IMPROVING LABOUR PRODUCTIVITY IN CONSTRUCTION.

A HYBRID MACHINE LEARNING APPROACH.

O BOKOR

PhD

2022

IMPROVING LABOUR PRODUCTIVITY IN CONSTRUCTION. A HYBRID MACHINE LEARNING APPROACH.

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A thesis submitted in partial fulfilment of the requirements of the University of Northumbria at Newcastle for the degree of Doctor of Philosophy

Research undertaken in the Faculty of Engineering and Environment

January 2022

ABSTRACT

Achieving less than ideal productivity is a problem the construction industry faces in most advanced countries, including the UK. One way to change this is to improve on-site execution by, for example, more accurate planning of construction operations. Despite continuous efforts for automation, mechanisation, and off-site production, the construction industry can still be considered labour-intensive. Therefore, understanding labour productivity and the factors influencing it is vital to better planning.

Owing to their versatility, durability, long service life, and being low maintenance, bricklaying works are ubiquitous, especially in housing and public projects, for example, schools. These operations are also especially labour-intensive. Consequently, an examination of bricklaying works is important for better planning and management of most construction projects. Ultimately, any gains in this operation could lead to an overall increase in site-based productivity.

The aim of the research project is to provide a better understanding of the bricklaying process and how it can be modelled, descriptively and normatively, to find a modelling approach that allows for a better examination of the effects of various factors on bricklaying productivity.

A number of factors influence on-site productivity. This research project focuses on those that are known in advance, in the pre-planning phase of the construction projects. These are the worker and wall characteristics.

To analyse bricklaying operations, a hybrid model is created. The effects of the above-mentioned factors on labour productivity are investigated with the help of the artificial neural network component, while the discrete-event simulation part models the process of block- and bricklaying. The model is built and tested with the help of real-life data collected at two construction projects by conducting a traditional work study. When the productivity rates were measured, note was made of the bricklayer working on the course, and the wall section where they worked. Site supervisors filled in the questionnaires asking about operative characteristics, while the wall characteristics were determined based on the drawings and specifications.

The resulting model can be used to provide more accurate productivity rate predictions for more precise time and cost estimates, and improved project planning in bricklaying.

ACKNOWLEDGEMENT

First and foremost, I would like to thank my supervisors, Dr Laura Florez-Perez, Dr Giovanni Pesce, Dr Barry Gledson, and Dr Allan Osborne, for their valuable guidance, contributions, and support, without which this research project could not have been completed. I would also like to thank Professor David Greenwood and Professor Rosie Parnell for their helpful recommendations and advice. I wish to thank Dr Nima Gerami Seresht for the invaluable assistance with modelling.

I am grateful to all the research participants for their contributions, time, and for sharing their knowledge.

Finally, I would like to express my gratitude to my family and friends for their unwavering support and encouragement.

DECLARATION

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas, and contributions from the work of others.

Any ethical clearance for the research presented in this commentary has been approved. Approval has been sought and granted through the Researcher's submission to Northumbria University's Ethics Online System. Final approval was granted on 10 April 2019 (Submission Ref. 7925).

I declare that the word count of the main body of this thesis is 56,513 words.

Name: ORSOLYA BOKOR

Date: 22/09/2022

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CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 Productivity

The global construction industry plays a key role in the world's economic performance, its output in 2020 was 10.7 trillion USD (Robinson *et al.*, 2021). In the UK, 6% of the GDP comes from this sector, and if the services of architects and surveyors and the construction-related manufacturers were included, the figure would be twice as great (Green, 2020). However, it has not evolved like other sectors, its productivity lags behind them (Barbosa *et al.*, 2017). Achieving less than ideal productivity is a problem most advanced countries face, including the UK (Green, 2016). Improving productivity has been an objective of every report on the construction sector since the second world war proving that this is not a recent development (Murray and Langford, 2003). One way to change this is to improve on-site execution by, for example, more accurate planning of construction operations (Barbosa *et al.*, 2017).

Another global issue is the shortage of skilled workers (Karimi *et al.*, 2017; Hasan *et al.*, 2018; Construction Skills Network, 2021). Moreover, in the UK the workforce is aging, the level of new entry is low, and a great amount of the workers are from overseas (Housing Communities and Local Government Committee, 2019; Green, 2020; Brooks and McIlwaine, 2021). Consequently, having more realistic productivity rates and resource usage information available to practitioners is essential. With the help of these, more precise schedules and cost calculations can be made, and better resource management can be achieved.

One of the most common concerns within construction-related research is that of productivity (Dolage and Chan, 2013; Yi and Chan, 2014). A substantial portion of these studies have focused on determining the factors that affect productivity, especially labour productivity, and categorising them based on various criteria. Extensive lists of the collected influencing factors have been presented. For example, Tsehayae and Robinson Fayek (2014) produced a list of 169 such factors, grouping them based on levels: from individual activities to the global scale. In some cases, research projects concentrate on how only one factor – such as project management (Chan and Ejohwomu, 2018) – affects productivity. Several studies focus on productivity in a single country (for example, the study of productivity in Oman by Jarkas et al. (2015)), while some investigate the factors in multiple countries looking for commonalities and differences (for instance, Sweis et al. (2008)).

Usually, either a systematic review of the literature is performed (for instance, Hasan et. al (2018) or Yi and Chan (2014)) or a combination of literature review and survey research is applied (see Naoum (2016)). The results of the surveys are likely to depend on the group of stakeholders responding, as different groups may consider different factors as more or less important. Therefore, Hasan et al. (2018) suggested the inclusion of several such groups. There are some studies (for example, Kazaz et al. (2016)) revealing the craftsmen's point of view, whereas others (for instance, Proverbs et al. (1998)) instead present the contractors' perspective. In their research project, Tsehayae and Robinson Fayek (2014) included both craftsmen and contractors. Additionally, El-Gohary and Aziz (2014) investigated the points of view of clients, contractors, as well as consultants.

Despite continuous efforts for automation, mechanisation, and off-site production, the construction industry is still labour-intensive. Therefore, understanding labour productivity and the factors influencing it are vital to better planning. Some construction operations are especially labour-intensive. For example, in the case of bricklaying works, an operation found on most sites, mechanisation is mostly limited to material handling. Consequently, an examination of bricklaying works is essential for better planning and management of most construction projects. Ultimately, any gains in this operation could lead to an overall increase in site-based productivity.

1.1.2 Bricklaying works

Bricklaying works have been an important part of construction projects for a long time. For instance, in England bricks have been used since the early 13th century (Kinniburgh and Vallance, 1948). The brickwork built today might be simpler than it used to be, owing to its versatility, durability, long service life, and being low maintenance, it is still ubiquitous, especially, in housing and public projects, for example, schools. Consequently, studies about masonry works are important. There have been research projects focusing on these works, for instance, Thomas and Sakarcan (1994) developed the factor model to calculate productivity rates. The factors they considered were work type, physical elements, construction methods, design requirements, and gang size. These were coefficients added to the base unit rate (Thomas and Sakarcan, 1994). In an earlier study of Sanders and Thomas (1993), the environmental factor of weather was taken into account, as well. Later, in the model of Thomas and Zavrski (1999) the complexity of design (as work content) was among the influencing factors. They introduced a difficulty scale for bricklaying works and evaluated the projects according to these criteria. A multiple regression model quantifying the effects of the factors was later proposed by Thomas and Sudhakumar (2014). In this, the affecting factors in the model entailed overtime, weather parameters, number of workers, and Thomas and Zavrski's (1999) project-level work content scale.

In Anand and Ramamurthy’s study (2003) various block and brick sample walls were built in a laboratory setting. The measured productivity rates were meant as baseline rates because they were considered to be unaffected by the factors typical of live construction sites. Nevertheless, workers’ attributes may still influence the rates. This is taken into account in, for example, Olomolaiye’s (1988), Sweis et al.’s (2008) and Florez’s (2017) research. Olomolaiye (1988) studied how the skills and motivation of workers affect their productivity. In his research, skill was defined as a combination of experience, training, and natural ability. It was concluded that skills had a greater influence on productivity than motivation (Olomolaiye, 1988). Sweis et al.’s (2008) definition of skill contained training, work ethics, and motivation. They showed that the skill factor is among the ones causing varying productivity rates. Florez (2017) also considered characteristics of bricklayers (compatibility, craft, and suitability) important when allocating squads to certain tasks. In this model, skill was defined as ‘ability of a worker to perform certain tasks well’ (Florez, 2017, p. 876).

To get better productivity rate estimates for bricklaying works in the planning phase of the construction projects, a model needs to be developed. This model can also be used to investigate the effects of influencing factors (worker and wall characteristics) on the productivity rate and to help in the selection of the most suitable labour resource allocation options, i.e., how best to assign workers to walls. Machine learning methods can be applied in the case of the former, while simulation can be of use for the latter purpose.

1.1.3 Machine learning

Artificial intelligence (AI) can be used to link the virtual and physical worlds, and with the help of intelligent systems, complex, nonlinear problems can be solved (Darko *et al.*, 2020). These systems can learn from data and make predictions and generalisations based on the acquired knowledge; this is called machine learning (ML), which is a sub-field of AI (Bilal *et al.*, 2016). Since the relationship between the influencing factors and construction productivity and the combined effect of the factors – due to the interrelationships between the factors – are complex, modelling is challenging (Chao and Skibniewski, 1994; Horner and Talhouni, 1995). Therefore, construction productivity studies can benefit from the application of ML methods, such as artificial neural networks (ANNs).

ANNs imitate the human brain and central nervous system (Boussabaine and Kirkham, 2008). Their main components are neurons, which are organised into three different layers, which are connected in the following order: input, hidden, and output layers (Moselhi *et al.*, 1991). The input variables are fed into the input layer, then the signal is transmitted to the output layer through the hidden layers, and it gets modified by weights, biases, and transfer functions on its way (Flood and Kartam, 1994a). ANNs work like a black box, meaning that their workings are hidden from the user (Adeli, 2001).

One advantage of ANNs is that they can be trained with even imperfect datasets, and provide quick and generalised solutions to problems (Flood and Kartam, 1994a). Another is that ANNs can be applied when the relationships between the independent and dependent variables are subject to uncertainty (Di Franco and Santurro, 2020).

Due to these favourable characteristics, ANNs have been used in construction management studies. El-Gohary et al. (2017) used ANNs to gain more accurate productivity rates for concrete works. Tsehayae and Robinson Fayek (2016) analysed the productivity influencing factors for the same trade. Badawy et al. (2021) developed an ANN model to be able to predict the productivity rate of reinforcing works based on physical attributes of the works (for example, the diameter of the rebar). Gerek et al. (2015) created two ANN models to study the productivity of bricklaying gangs. The chosen factors were mostly gang (for example, experience) and management-related with a couple factors regarding the design of the walls (Gerek *et al.*, 2015). To further improve the capabilities of ANNs, they can be combined with other methods. For example, neurofuzzy models are the product of marrying ANN with fuzzy logic (FL). Omar and Robinson Fayek's (2016) fuzzy neural network models were created to identify and quantify the relationships between the functional and behavioural competencies (i.e., knowledge and skills stemming from the organisations and the individuals) and the projects' key performance indicators.

1.1.4 Simulation

In such instances, when it would be too risky, costly or lengthy to make experiments with the actual system, a model needs to be developed (Law, 2015). This can be used to test theories, to see how the system changes due to the change of certain variables. This model can either be a physical or a mathematical one (Law, 2015). In the case of construction processes, the latter is required. In some cases, a mathematical model can be analytical, which is able to provide an exact solution. However, when only a numeric evaluation is possible, a simulation model is preferred (Law, 2015).

The link-node model developed by Teicholz in 1963 can be considered as the first example for construction simulation (AbouRizk *et al.*, 2011). In the past decades, numerous different models were presented. The examples used in these studies were mostly machine-driven works, such as earthworks (see, for example, Alzraiee et al. (2012)), reinforced concrete works (see, for instance, Khanzadi et al. (2018)), or civil engineering works (see, for example, AbouRizk (2010)). However, due to labour resources (especially skilled) being scarce, more complex, less predictable and involving more risks than plants or materials, it is probably more important to model labour-intensive works, such as bricklaying works, with simulation.

There are three basic simulation methods: discrete-event simulation (DES), system dynamics (SD), and agent-based modelling (ABM) (Borshchev, 2013; Raoufi and Robinson

Fayek, 2020). Discrete-event simulation has been used for the longest time in construction and is possibly the most widespread simulation method (AbouRizk *et al.*, 2011). It concentrates on the process itself. Passive objects, called entities, go through the workflow, where they get created, held, queued, and released. For example, Kim et al. (2021) applied DES to obtain the duration of in-situ concrete works taking gang size and spatial conflicts into account.

System dynamics developed by Forrester (1961) is a top-down method. It focuses on the affecting factors, their effects and interrelationships. Both qualitative and quantitative models can be created using system dynamics (Kunc, 2017). The former is a causal loop diagram showing balancing and reinforcing relationships, while in case of the latter, the model is comprised of stocks and flows, and the relationships are expressed using equations. With the help of SD, Al-Kofahi et al. (2020) studied how and to what extent owner-liable change orders affect labour productivity.

The third basic simulation method is agent-based modelling, which – in contrast with system dynamics – has a bottom-up approach. Global behaviour emerges from the interaction and behaviour of the individual agents, which are heterogeneous and have various attributes. For instance, Watkins et al. (2009) used ABM to determine how site congestion affects productivity with two agent types being defined: workers (with variables such as skill level) and activities.

There are several examples for the individual application of the basic simulation methods; however, it can be more beneficial to combine them. This way, the individual advantages of each method can be united, while their individual disadvantages can perhaps be overcome. Different elements of a system can be modelled with the help of different methods and such combinations can potentially provide better representations of reality (Borshchev and Filippov, 2004; Borshchev, 2013). For example, Khanzadi et al. (2018) used an integrated SD-ABM simulation approach to study how site congestion affects productivity.

1.2 Research aim and objectives

The aim of the research project is to provide a better understanding of the bricklaying process and how it can be modelled, descriptively and normatively, to find a modelling approach that allows for a better examination of the effects of various factors on bricklaying productivity. To achieve this, the following objectives are set:

1. To explore how construction productivity can be modelled. This entails examining various methods used on different levels of productivity and selecting the most suitable modelling approach that fits the aim of the study.
2. To study bricklaying works, bricklayers' characteristics, and gang composition. This includes taking time measurements and observations so as to gather knowledge on

the workflow of the operation, various materials, different wall types, bricklayers, and resource allocation. This is necessary for determining the building blocks of the model and assembling the data table fed into the model.

3. To investigate the factors influencing construction labour productivity. This entails the selection of the most relevant factors in the planning phase of construction projects, and brickwork in particular.
4. To create the model using the selected method including the chosen factors.
5. To analyse how the selected factors affect productivity. This can be achieved with the help of the model and statistical analyses.
6. To test the model by running it with model project data. This includes creating model wall sections, bricklayers, and bricklaying gangs. This enables testing the resource allocation implications of bricklaying gang compositions.

1.3 Contributions

As shown in section 1.1, there is a need for accurate productivity rates; however, most existing models do not take the human component into account, that is, how worker-related factors may affect productivity rates. This research project considers both worker and wall characteristics, which are known in the planning phase of construction projects.

A hybrid DES-ANN model is developed to better estimate the bricklaying process duration in the planning phase of the project, taking the previously mentioned factors into account. Better productivity estimates can lead to more realistic schedules and cost calculations. In addition, the model is capable of testing resource allocation options to find the optimal one, thus resources can be better planned and managed. While, in this thesis, the model is applied for bricklaying works and a certain set of factors that influence productivity are considered, by following the same steps different factors or different operations can be modelled.

As part of this research project, with the help of the developed model and extensive statistical analyses, the effects of the chosen factors on productivity are examined. Understanding the effects of these worker and wall-related factors can also aid project planning.

The frameworks developed for the two model components (artificial neural networks and simulation) are also contributions of this research project. These can be used individually or in combination for hybrid models to model construction productivity.

1.4 Research process

Figure 1.1 – from left to right – shows the steps of the research process together with the details and output of each step and the corresponding research objectives. The first step is to set the aim and objectives of the research project. Next comes an extensive literature

review concentrating on the following topics: construction productivity, labour productivity, productivity influencing factors and modelling methods applied in productivity studies, and research on bricklaying productivity. As a result of this step, the modelling method fitting the research aim can be chosen along with the productivity influencing factors to be included in the study. The next step is the collection and processing of data. This consisted of structured observations of brickwork on construction projects, where the site managers are also asked to evaluate the bricklayers, and interviews with bricklaying experts. The data collection provides the dataset used for both modelling and analysis and the description of the bricklaying process. The influencing factors selected during the literature review stage are refined and complemented in this step. After the collected data is processed, modelling can start: the hybrid DES-ANN model is created. In the next step, model project data are input into the model, which produces process durations as output. At the analysis stage, the effects of the influencing factors on productivity are determined based on the sensitivity analysis of the ANN model component and the statistical analysis of the collected data. Moreover, the output of the simulation runs is also analysed to compare different resource allocation options. Finally, the conclusions are drawn based on the analyses to provide contribution to both knowledge and practice.

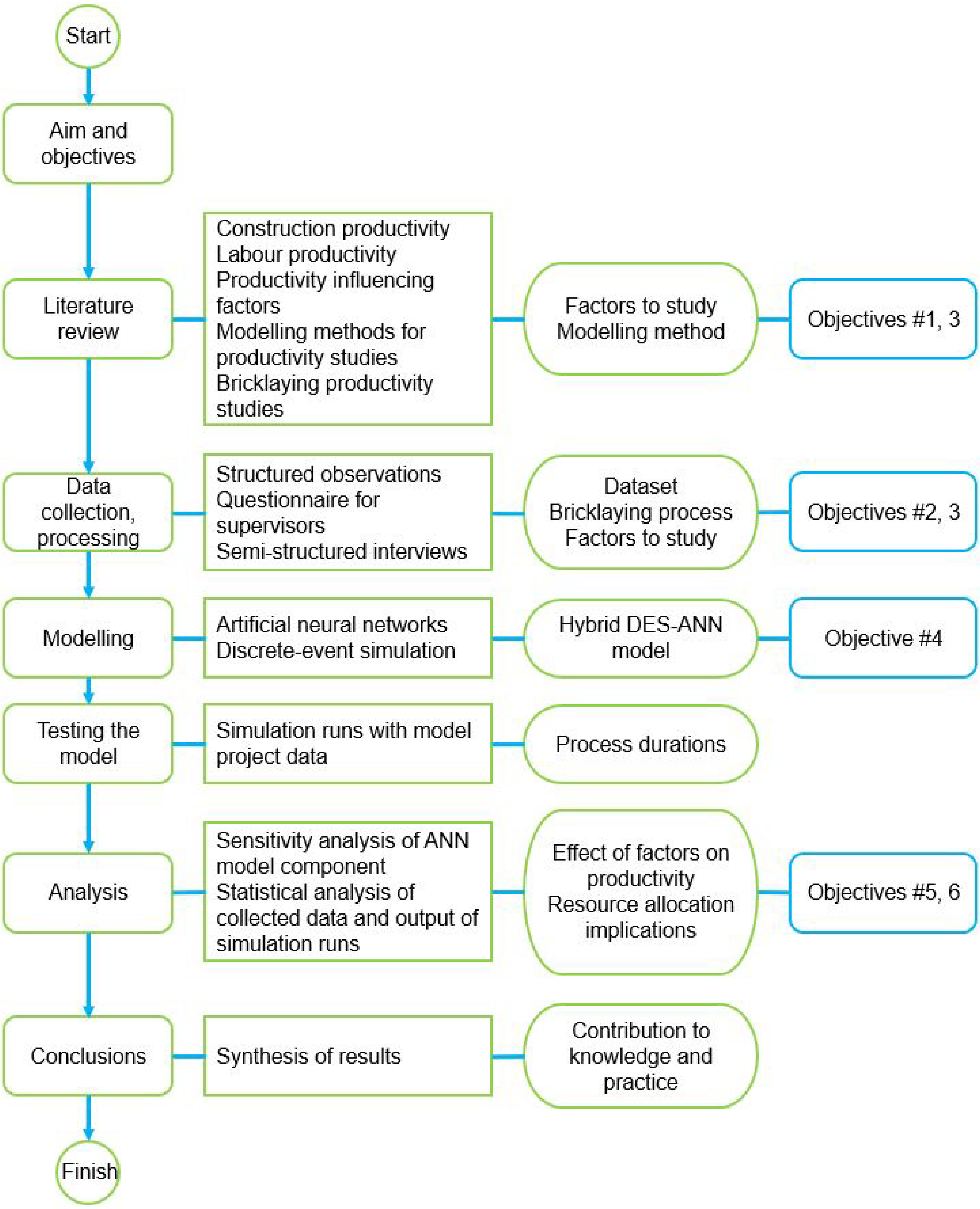


Figure 1.1. Research process

1.5 Overview of the thesis

The purpose of the current chapter is to briefly describe the context of the research, introduce the research project and show how it contributes to the body of knowledge.

The next chapter gives an overview of the literature relevant to the research topic. It starts with the introduction of general productivity concepts and skill shortage. Then comes a comprehensive discussion of productivity studies, first, with respect to the productivity influencing factors collected, second, the most commonly used methods, such as statistical analysis, genetic algorithms, and expert systems, are presented together with numerous examples for their application. Machine learning and simulation methods are extensively discussed with special attention to hybrid models, where different methods are combined. The chapter ends with an exhaustive review of bricklaying productivity studies.

The third chapter discusses the decisions made about conducting the research from the philosophical considerations, through research design, to research methods. Data collection and processing are also included in this chapter.

The developed hybrid model combining artificial neural networks (ANN) with discrete-event simulation (DES) is discussed in three parts. Chapter 4 explains which productivity influencing factors were selected for the model and describes these in detail. The process of brickwork construction used in the model is also described. The ANN model component is presented in Chapter 5, which also includes the framework developed for modelling productivity with ANN. The DES model component is discussed in Chapter 7, which entails the framework developed for construction simulation modelling for productivity studies. Furthermore, this chapter describes the details of the model project.

The sixth chapter details the statistical analyses used for examining the collected productivity data and their results.

Chapter 8 discusses the results of both the sensitivity analysis of the ANN model component and the statistical analyses. In addition, it presents the results and analysis of the output of the DES model component.

The conclusions drawn from the study and recommendations for further investigation of the topic can be found in Chapter 9.

1.6 Chapter summary

This chapter aimed to give a brief overview of the research project, which investigates construction labour productivity of bricklaying operations. First, the background of the research was presented. After an introduction to construction productivity and bricklaying operations, the methods selected for modelling were described, starting with machine learning, then simulation. The next section discussed the research aim and the objectives set to achieve this aim. Then the research's contribution to knowledge and practice were presented. The steps of the research project together with their details, output, and link to the research objectives were explained next. The final section gave an overview of the thesis listing its chapters with their brief contents.

CHAPTER 2

LITERATURE REVIEW – CONSTRUCTION PRODUCTIVITY STUDIES

2.1 Productivity

2.1.1 General concepts

The global construction industry has a significant output (10.7 trillion USD in 2020); therefore it is an important part of the world's economy (Hillebrandt, 2000; Barbosa *et al.*, 2017; Robinson *et al.*, 2021). In the UK, this contribution to the GDP is 6%; however, this does not include plant hire, construction-related manufacturing, and the services of architects, engineers, and surveyors, which account for approximately the same output share (Green, 2020). In May-June 2020, construction output sharply decreased due to the COVID-19 pandemic; however, it is expected to return to 2019 levels in the first half of 2022 (Construction Skills Network, 2021). In addition, the built environment affects other industries and their productivity by having an influence on people's happiness, health, and safety (Green, 2016).

The construction industry can still be considered labour-intensive. In the UK, it employs more than 7% of the labour force (2.3 million people), and further hundreds of thousands of people work in related businesses (Green, 2020). The workforce is expected to grow 1% annually, this way, by 2025 construction workforce is predicted to reach 2.84 million (Construction Skills Network, 2021). These people buy goods and services of other sectors, which ultimately generates employment in those sectors, as well (Hillebrandt, 2000). This way the economy as a whole is affected by the construction industry but the construction industry is also affected by the economy (Hillebrandt, 2000). Therefore, the fluctuations of the output of the construction industry are a result of the fluctuations of the economy as a whole plus the unique quality of the product, the built environment (Hillebrandt, 2000). Due to this two-way relationship, according to Green (2016), the construction industry should not be studied in isolation but as a part of the economy, and the goal should be the improvement of the economy as a whole (Green, 2016). Despite this, the construction industry is often used by governments to boost the economy, to reduce the fluctuations, even though this is a complicated endeavour as the effects of the measures are delayed (Hillebrandt, 2000).

Owing to the nature of construction projects, the industry is in the public eye, and the public often feels that its performance does not meet the expectations (Morton and Loss, 2008). Furthermore, from time to time, the construction industry is accused of not changing (Murray and Langford, 2003). For instance, Rudyard Kipling mentioned this in his poem, The Truthful Song (Kipling, 1910):

“The Bricklayer:—
I tell this tale which is strictly true,
Just by way of convincing you
How very little since things were made
Things have altered in the building trade.”

It is true that there are aspects of construction that have not changed, but others have (Morton and Loss, 2008). For example, the basic idea of bricklaying was the same in ancient Egypt; however, now the mass production of bricks is quality-controlled (Morton and Loss, 2008).

Construction productivity has been the subject of multiple avenues of research, such as academic (vast number of books, countless conference and journal papers), industrial (conducted by, for example, The Chartered Institute of Building, the Construction Industry Training Board, the Construction Leadership Council, McKinsey Global Institute), and governmental (numerous reports, for example, the Latham report (1994) and the Egan report (1998)). All these studies have attempted to answer the question why the construction industry’s productivity is lagging behind other sectors and how it could be helped. Global construction labour productivity has only grown by an average of 1% over the past 20 years (Barbosa *et al.*, 2017). In the UK, this number is smaller or even negative, therefore, it lags behind other developed nations (Green, 2016).

In general, productivity is calculated as the ratio of the total output and the weighted average of the inputs (Samuelson and Nordhaus, 2010). In the case of single factor productivity, only one input type is considered, for example, labour productivity is the output per unit of labour, usually a time dimension. While total factor productivity is the output divided by the total input (Samuelson and Nordhaus, 2010). Productivity can also be calculated on various levels determining both the output and the input. Bernold and AbouRizk (2010) defined four different layers: process, production, accounting, and economic. Ayele and Robinson Fayek (2018) proposed similar levels: activity, project, and industry. The productivity measure on the lowest level is typically physical, for instance, m^2/h (Bernold and AbouRizk, 2010; Chan and Gao, 2019). Examples for further levels can be seen in Table 2.1. The productivity measured on the lower levels can be aggregated to get the productivity indicators of the higher layers (Chan and Gao, 2019).

Level	**Productivity measure**	**Dimension example**
Process	physical output/input	m^2/h
Production	output/cost	$m^2/£$
Accounting	value added/input	£/h
Economic	income/input	income/management h

Table 2.1 Examples for productivity measures on different levels (based on Bernold and AbouRizk (2010))

Table 2.2 shows examples for various labour productivity measures used for different purposes listed by Horner and Talhouni (1995). In these cases, the output is the same; however, the inputs are different. The third measure reflects the effects of intrinsic variables, such as the ones characterising the workforce (for example, their skills), or the work performed (for example, its complexity), and the environment (project characteristics). The second measure includes the impact of both management and operatives (Horner and Talhouni, 1995).

Formula	**Input**	**Purpose**
Output/Total time	Total time	Tendering purposes
Output/Available time	= Total time – Unavoidable delays	Delay claims
Output/Productive time	= Available time – Avoidable delays	Research purposes

Table 2.2 Labour productivity measures with different time inputs (based on Horner and Talhouni (1995))

As evidenced above, a great number of variations of the basic productivity ratio exist. Tangen (2005) included many more examples in their study and argued that the mathematical formulae derived from these definitions tend to cover only a fraction of the real meaning of productivity. Depending on the purpose of determining productivity, various outputs and inputs are measured over different time periods (Thomas and Kramer, 1988; Horner and Duff, 2001). Then either the calculated productivity is compared to a standard or its changes over time are investigated (Tangen, 2005).

Productivity can increase in five ways (Tangen, 2005):

- the output remains the same but the input decreases,
- the output increases, while the input remains the same,
- the output increases and the input decreases,
- both the output and the input decrease but the decrease of the latter is proportionately greater,
- both the output and the input increase but the increase of the former is proportionately greater.

Productivity and performance both appear in the literature; however, they are not synonyms. Performance is a broader term including the concepts related to cost, speed, flexibility, dependability, and quality objectives that considers the success of different levels (activities, project, company etc.) (Tangen, 2005). Soewin and Chinda's (2020) construction performance index contained even more factors, such as health and safety and client satisfaction, 10 in total, divided into 57 items.

2.1.2 Skilled labour shortage in the UK

Construction labour productivity depends on the people involved in the projects to a great extent. The people are the industry's greatest, most critical assets (Construction Task Force, 1998; Bernold and AbouRizk, 2010). It is important for research to focus on labour productivity and investigate why there could be such great differences between the productivity of different workers, or the same ones at different times (Horner and Talhouni, 1995; Horner and Duff, 2001). The Egan Report (1998) also suggested that only a fraction of the possible labour efficiency is achieved. Operatives and white-collar workers are equally needed for increasing productivity (Murray and Langford, 2003). However, the number of skilled labour is decreasing.

In the 19th and the beginning of the 20th century, the number of apprentices was limited in order to prevent an oversupply of trained craftsmen (Morton and Loss, 2008). However, due to the increase in construction projects in the post-war era, there was a skill shortage, which has been present since then (Morton and Loss, 2008; Farmer, 2016; Parsons and Rubinsohn, 2021). Owing to the industry not being attractive enough for young people, the level of new entrants is low, while the current labour force is ageing leading to a significant decrease in available workforce (Farmer, 2016; Brooks and McIlwaine, 2021). Furthermore, many workers leave the industry in recession periods (Morton and Loss, 2008). The influx of migrant workers seemed to have provided a solution; however, a great portion of them have left due to Brexit (Winterbotham *et al.*, 2021).

A viable way to tackle skill shortage is the application of modern methods of construction (MMC). However, the relationship between MMC and skill shortage resembles the chicken-egg problem: it is not clear which one was first (Construction Skills Network, 2020). Although MMC is largely synonymous with pre-manufacturing, it has categories for on-site productivity improvement, as well (Housing Communities and Local Government Committee, 2019). In addition, the effectiveness of advanced technologies depends on the people using them (Morton and Loss, 2008). The high level of digitalisation typical of MMC can also make the industry more attractive for young people, thus raising the level of new entrants (Housing Communities and Local Government Committee, 2019). Furthermore, a greater extent of pre-manufacturing means that different skills are needed (Morton and Loss, 2008). Upskilling, reskilling, cross-skilling, and multiskilling are required (Moehler *et al.*, 2008; Construction Skills Network, 2020). Various cross-training strategies can be utilised to train single-skilled workers to be multiskilled, whose employment may result in reduced construction times and costs with an added benefit of increased safety (Nasirian *et al.*, 2019). Multi-skilled labour can be well used in off-site construction (Barkokebas *et al.*, 2020). However, it can also be beneficial to mix multi-skilled with single-skilled operatives in on-site construction gangs (Ahmadian Fard Fini *et al.*, 2016).

Despite the technological advances, construction projects are still labour-intensive. To meet the growing demand set by the increasing construction output, a competent, skilled, and trained workforce is crucial (Construction Skills Network, 2021). According to the Construction Skills Network's (2021) report, over the next 5 years, 216,800 workers will need to be recruited in the UK. Bricklayers have the fourth highest annual recruitment requirement after wood trades and interior fit-out, electrical trades, and labourers (Construction Skills Network, 2021). Owing to the ever-growing number of workers, on-site workforce organisation matters. By improving on-site execution, the productivity of the construction industry may also increase (Barbosa *et al.*, 2017). Productivity growth is vital for economic growth, to improve the standard of living (Green, 2016).

2.1.3 Why study labour productivity?

As evidenced above, the output of the construction industry is crucial to a nation's and also to the global economy. An important way to improve construction productivity is through the people working in the industry (Construction Task Force, 1998; Barbosa *et al.*, 2017; Construction Skills Network, 2021). However, the supply of skilled labour has not matched the growing demand due to the ever-increasing number of construction projects. Therefore, it is crucial to manage skilled labour appropriately. Furthermore, the industry's productivity is the aggregation of the productivity of the lower levels. Consequently, it is important to focus on the micro level, that is where productivity improvement can happen (Pekuri *et al.*, 2011). Understanding the productivity of the gangs through modelling is the key to strategies for productivity improvement on the higher levels (Thomas *et al.*, 1990). For this, both the workers and the work to be performed need to be studied (Hasan *et al.*, 2018).
The coming sections introduce studies collecting the factors influencing productivity, methods applied to investigate the effects of the factors on productivity, and the research efforts concentrating on the productivity of bricklaying operations.

2.2 Productivity influencing factors

The number and type of factors in the studies depend on the objectives of the research. If the goal is to present a collection of factors, a great number of factors are amassed, while in the case of modelling a specific operation, only a much smaller subset of factors is included because the high number of factors would make modelling impossibly complex, and ultimately, unusable. Furthermore, it might be too difficult to collect data for certain variables (Horner and Talhouni, 1995; AbouRizk *et al.*, 2016). Graham and Smith (2004) suggested that at each stage the model should only entail known and significant variables. This provides one possible categorisation of factors; however, there are numerous other ways. Due to productivity being measured at industry, project, and activity levels, the factors affecting productivity can also be collected for the levels separately (Yi and Chan, 2014).

Another possibility is to consider the time the impact of the factor is present, this way factors can have short-term effects, long-term effects, and long-term effects with ripple effect (Moselhi and Khan, 2012).

The list of factors might be different in different countries, in developed and developing countries. Hasan et al. (2018) argues that a few important factors are the same regardless of the country. The significance of certain factors can also be different depending on who ranks them: craftsmen's opinion might differ from that of managers, or consultants.

There are numerous studies providing a systematic review of productivity literature. For example, Hamza et al. (2019) compiled a list of the highest ranking influencing factors in the literature. Worker experience, motivation, and skills were in the top 5 (Hamza *et al.*, 2019). Usually, after collecting the factors, various project stakeholders are asked to express their opinions about the importance, impact, or severity of the factors. This is most commonly done through questionnaires but other methods, for instance, interviews are used sometimes. Table 2.3 contains a number of such studies conducted in various countries.

Study	**Country**	**Perspective**
Naoum (2016)	UK	Contractors
Tsehayae and Robinson Fayek (2014)	Canada	Contractors Craftsmen
Maqsoom et al. (2019)	Pakistan	Contractors
Dai et al. (2009)	USA	Craftsmen
Kazaz et al. (2016)	Turkey	Craftsmen
Hai and Van Tam (2019)	Vietnam	Craftsmen
Alaghbari et al. (2019)	Yemen	Consultants Academics
El-Gohary and Aziz (2014)	Egypt	Clients Contractors Consultants
Durdyev and Mbachu (2011)	New Zealand	Contractors Consultants

Table 2.3 Examples for studies with collections of productivity influencing factors

Naoum (2016) divided the 46 factors into 5 categories (pre-construction activities, activities during construction, motivational and social, organisational, management-related) and interviewed contract and site managers in the UK. Pre-construction planning was found to be the most important factor based on the ranking by the relative importance index (Naoum, 2016).

Tsehayae and Robinson Fayek (2014) compiled a list of 169 factors influencing productivity from the activity level through the project and organisation levels to the global level. Their survey showed that project managers and craftsmen regarded different factors important. The biggest difference in the case of building projects was in the ranking of gang competence and experience, which had a high rank for positive effect in the trade respondents' list. Similarly, in the case of industrial projects, good relationship between the members of the gang was regarded important for positive effect by the craftsmen; however, project managers considered other factors to be more significant (Tsehayae and Robinson Fayek, 2014).

Maqsoom et al. (2019) collected 55 factors that have an impact on time delays and invited contractors to rate the importance of each of them. The responses were analysed against firm size and industry experience. There were significant differences between the groups, regarding, for example, the factors related to skilled labour. Due to an increase in the number of construction projects in Pakistan, skill shortage emerged, making it difficult for young and small firms to find skilled labour. This was their biggest issue, while more mature companies felt that more accurate planning of projects was needed to better estimate durations (Maqsoom *et al.*, 2019).

Dai et al. (2009) asked craftsmen about their perception of the 83 identified factors, which were generally from the activity level. The workers' qualification was among the areas which was most likely to contribute to productivity improvement. It was argued that it was important to include craftsmen in efforts aiming to increase productivity (Dai *et al.*, 2009). Kazaz et al. (2016) also studied the craftsmen's perspective. Based on the relative importance index of the 37 factors, they found that the organisational factors (such as quality of site management) and – as an individual factor – having social insurance were considered the most important factors (Kazaz *et al.*, 2016). Craftsmen were asked to rate the impact of 43 factors by Hai and Van Tam (2019), as well. The experience of the workers was ranked highest overall, and the group of gang-related factors was found to be the most important by the respondents (Hai and Van Tam, 2019).

Alaghbari et al. (2019) chose to study the perspective of consultants and academics; however, experience and skills of the workers ranked first out of the 52 factors in this case, as well. The technical and technological factor group, including, for instance, the complexity of design, had the highest rank among the groups (Alaghbari *et al.*, 2019). Out of the 30 factors consultants, contractors, and clients asked by El-Gohary and Aziz (2014) also found labour experience and skills to be the most important productivity influencing factor. The perspective of consultants and contractors was also studied by Durdyev and Mbachu (2011). Level of experience and skills ranked high in this case, as well. However, project management related factors were considered to be more important out of a collection of 56. Factors internal to the project were found to contribute more to on-site productivity than external ones (Durdyev and Mbachu, 2011).

The number of factors in the above studies demonstrates that a great amount of them can be collected; however, it is not practical to use all of them when modelling construction operations. In addition, this also shows that worker-related factors are among the most important ones in such long lists. Despite this, Hasan et al. (2018) recommended even more labour-related factors to be included in productivity studies.

There are research efforts focusing on factors affecting the motivation of workers, which ultimately, impacts their productivity. One example is Raoufi and Robinson Fayek's (2018a) research, which considered the motivation of gangs, not individual operatives. Gangs were in the focus in Loganathan and Forsythe's (2020) study, as well. They developed a framework to investigate the role of teamwork in construction gangs in improving productivity. The inputs were characteristics of tasks (for example, difficulty) and gangs (for example, composition).

After the subset of factors is chosen, corresponding data needs to be collected, finally, their effects can be analysed using various methods. The next section introduces the methods most commonly applied in productivity studies.

2.3 Productivity studies: applied methods

2.3.1 Methods to measure efficiency and productivity

In the case of productivity studies, as with any other research, data need to be collected. These can come from various sources and are different on different levels. An obvious source on the activity and project levels is the construction site. Here different observations can be made for different purposes. One such aim is to investigate the efficiency of the operatives. Efficiency is determined by the utilisation of the available resources, hence connected to the denominator of the productivity ratio (Tangen, 2005) (see Table 2.2.). One way to measure this is to do activity sampling. The most commonly used method is work sampling (Thomas and Daily, 1983). This entails a great number of short, random, non-continuous observations over a period of time (Olomolaiye *et al.*, 1998). The main concept is that these occurrences follow the same distribution as the entire operation (Olomolaiye *et al.*, 1998). The goal is to measure time utilisation (Thomas *et al.*, 1984). Typically, productive and unproductive categories are chosen; however, more activity groups can be defined to facilitate a better analysis (Wandahl and Skovbogaard, 2017). In the case of each observation, the category is noted (Bernold and AbouRizk, 2010). The number of necessary observations depends on the desired accuracy, confidence level, and the estimated proportion of the smallest category (Meyers, 1992).

Hajikazemi et al. (2017) applied work sampling to measure the efficiency of electrical installations at eight Norwegian construction projects. On average, approximately 60% of the time was spent on value-adding activities, 30% on preparation, and 10% was the time loss (Hajikazemi *et al.*, 2017). The results of Josephson and Björkman's (2013) study showed a different ratio. In the case of the selected eight Swedish projects, on average, direct work was performed 13% of the work day, while preparation took 52%, and 35% was waste (Josephson and Björkman, 2013). Wandahl and Skovbogaard's (2017) study produced different results for the observed pre-fabricated façade panel installation works in Denmark. In this case, the productive work added up to 30%, while the contributory work was 50%, and the waste 20% (Wandahl and Skovbogaard, 2017).

Another method to study time utilisation is five-minute rating. While work sampling can be used on the project level, five-minute rating is better suited to measure the efficiency on the process level (Gong *et al.*, 2011). Gangs should be observed for at least as many minutes as the number of members but at least for five minutes (Thomas and Daily, 1983). At each observation interval, it should be noted whether the given operative is active for at least half of the interval (Dozzi and AbouRizk, 1993). This means that in the case of five-minute rating there are only two categories: working and not working (Gong *et al.*, 2011). Gong et al. (2011) analysed almost 40 years' worth of work sampling and five-minute rating data collected at various construction sites in the USA. Results of the former indicated that operatives spend 44% of their time on value-adding work, 31% on supportive activities and 25% was the time loss. Five-minute rating showed a 55% efficiency. They found that the direct work ratio had not changed significantly over time, and that while project type did not affect it significantly, it was significantly higher in the case of certain activities, for example, masonry, and it decreased significantly with the increase in the number of members of the gang (Gong *et al.*, 2011).

It is important to note that highly active workers are not necessarily highly productive because their output might not be high (Thomas *et al.*, 1984; Gong *et al.*, 2011). It is possible that due to a new method or equipment, the proportion of direct work decreases, which can even result in a negative correlation between value-adding work and productivity (Josephson and Björkman, 2013).

Time data for productivity studies can come from various sources. One possibility is to gather historical or current data from contractors. This typically means daily output data. Another option is to perform a time study. Taylor (1911) recommended scientific studies to be conducted in order to set standard times for jobs. First, the work needs to be broken down into elements, and then the time spent on each element should be measured (Taylor, 1911). Time studies can benefit from the use of image capturing. This way fewer observers are needed, and the recorded video can be more easily, reliably, and thoroughly analysed (Bernold and AbouRizk, 2010).

Mani et al. (2014) used a combination of fixed and moving camcorders to record electrical installations. The measurements of the activity elements were made while watching the footage. Then probability distribution functions were fitted to the collected data to determine the optimal productivity of the works (Mani *et al.*, 2014). Forsythe and Sepasgozar (2019) investigated prefabricated timber cassette installation with the help of time-lapse photography. Statistical analysis was performed on the collected crane cycle times to recommend changes to improve productivity (Forsythe and Sepasgozar, 2019). Mao et al. (2018) complemented the time study with collecting data from questionnaires completed at regular intervals and from wearing a smart band measuring the workers' heart rate to assess the physical and psychological state of bricklayers.

2.3.2 Methods to investigate the effects of the influencing factors

A vast number of studies explored the effects of various factors on productivity. Experimenting on the real system would involve too high risks, costs, and time; therefore models need to be developed (Law, 2015). In general, models can be physical or mathematical. The latter is suitable for modelling construction processes (Law, 2015). With these models, the individual and combined influence of the selected factors can be determined. These models can take various shapes and forms and can be different on different levels of productivity. The most popular methods are discussed below.

2.3.2.1 Statistical analysis

Statistical analyses are not only used to determine the influencing factors but also to determine the effects of these factors. Among the possible choices, regression analysis is one of the most preferred ones. By using regression models, the dependent output variable – productivity in this case – can be predicted based on the independent predictor variables, i.e., the various influencing factors. Karimi et al. (2017) investigated the effects of the availability of skilled labour on schedule performance and project productivity by performing a series of linear regression analyses. They found that increased craft recruiting difficulty leads to increased schedule overruns and decreased project productivity (Karimi *et al.*, 2017). Gurmu (2019) ran both linear and logistic regression analyses to study the influence of material management practices on project productivity. The developed model can help project managers to plan appropriate material management practices on multi-story building projects (Gurmu, 2019). Gurmu and Aibinu (2017) used a similar methodology to investigate how equipment management practices may enhance project productivity. Jarkas (2016) applied multiple regression analysis to examine the effects of various buildability factors on formwork labour productivity. Variability of beam sizes and usable floor area were found to be most important among them (Jarkas, 2016). Chih et al. (2017) also used regression analysis in their study, which concluded that good supervisor-worker relationship meant the presence of positive feelings, which – through stronger job embeddedness – could lead to better productivity. Raoufi and Robinson Fayek's (2018b) research applied hierarchical regression analysis to determine which situational/contextual factors (for example, foreman knowledge) can affect the relationship between motivation and gang productivity. According to this, the characteristics and skills of the foremen play an important part in the motivation-performance relationship (Raoufi and Robinson Fayek, 2018b).

2.3.2.2 Artificial intelligence

Artificial intelligence (AI) can help actively connect the physical and virtual worlds (Darko *et al.*, 2020). While AI was established as a research field in the 1950s, it has only been used in construction research since the 1970s with a sharp increase in the number of publications in the 21st century (Darko *et al.*, 2020). Intelligent systems can be applied to solve complex, nonlinear problems (Darko *et al.*, 2020). They are capable of quick and accurate analysis of vast amounts of data (Darko *et al.*, 2020). They can also to learn from big data and use the acquired knowledge to make predictions and generalisations (Darko *et al.*, 2020). This is called machine learning (ML) (Bilal *et al.*, 2016). Many methods – including artificial neural network (ANN) and genetic algorithms (GA) – belong to this sub-field of AI. Their application in productivity research is discussed in detail in Section 2.4.

2.3.2.3 Simulation

Mathematical models can be analytical and provide exact solutions but sometimes only a numeric evaluation is possible, in which cases, simulation can be useful (Law, 2015). Simulation is suitable for studying complex systems by making models of them and experimenting with them as if they were physical models (White and Ingalls, 2017). The observations made during the running of these tests are then used to understand these complicated systems, make generalisations, optimisations, and recommendations for improvement (AbouRizk and Mohamed, 2000; White and Ingalls, 2017). Teicholz's link-node model developed in 1963, which helped with the selection of the equipment used for earthworks, could be considered the forerunner of construction simulation (AbouRizk *et al.*, 2011). Simulation too has been evolving with the development of computers. The various methods selected for productivity studies will be introduced in *Section 2.5*.

2.3.2.4 Fuzzy logic

Problems in the construction industry are not only complex but also include a high degree of uncertainty. Fuzzy logic (FL) is capable of modelling this uncertainty (Robinson Fayek, 2020). Fuzzy sets can be used when owing to subjective or vague measures, imprecise, nonstatistical data or incomplete information, the boundaries of the parameters' states are not sharp (Zadeh, 1980; Robinson Fayek, 2020).

Ayyub and Haldar (1984) proposed the use of FL for including uncertainties given in linguistic terms in project schedules. Weather conditions and the experience of the workers were arbitrarily selected as factors in their example. The modified activity durations were calculated based on the frequency of occurrence of the factors, their negative effects on the duration and the membership functions (Ayyub and Haldar, 1984). Robinson Fayek and Oduba (2005) analysed two activities from a real-life industrial construction project with the help of FL, collected the factors affecting productivity (in two sub-models to decrease the size of the model) and the related 'if-then' rules. Triangular and trapezoidal membership functions were used, complete with experts' estimates for the endpoints. These results were then compared to actual project data (Robinson Fayek and Oduba, 2005). With the number of factors increasing, the amount of rules grows exponentially; therefore, Shaheen et al. (2009) proposed to gather the related factors under blocks. Lorterapong and Moselhi (1996) introduced FNET (fuzzy network scheduling), in case there is no available historical data or fair expert estimate. The proposed method produces more realistic results in the backward pass, affecting criticality, than previous efforts of using fuzzy sets in network scheduling (Lorterapong and Moselhi, 1996). Guo et al. (2017) applied FL to forecast the duration of wind-sensitive activities of wind turbine construction projects. Using their proposed system, schedulers can calculate activity durations based on wind data given in linguistic and qualitative terms (Guo *et al.*, 2017).

2.3.2.5 Genetic algorithms (GA)

Genetic algorithms are metaheuristic algorithms used for nonlinear, complex optimisations that work on the principles of natural selection present in biological evolution (Al-Bazi and Dawood, 2010; Mirahadi and Zayed, 2016; Hyun *et al.*, 2021). Selvam et al. (2020) used GA to determine the optimal duration and cost of different work packages affected by various influencing factors and project constraints. Hyun et al. (2021), Rashid et al. (2020), and Al-Bazi and Dawood (2010) developed models to optimise the worker allocation in manufacturing for construction. The first one sought to provide an optimal solution in the case of various objectives (for example, limited number of workers, or pre-determined output), while the other two did the optimisation with regards to a single objective, production time and costs respectively (Al-Bazi and Dawood, 2010; Rashid *et al.*, 2020; Hyun *et al.*, 2021). There are models where GA is combined with another method to depict the system more accurately. For example, Rashid et al. (2020) and Al-Bazi and Dawood (2010) used discrete-event simulation to model the process of modular unit and precast concrete element production, respectively. Mahdavian and Shojaei (2020) also combined GA and discrete-event simulation to optimise resource allocation. The GA component provided the set of available resources based on cost information, while the start and completion times were determined by the simulation part (Mahdavian and Shojaei, 2020).

2.3.2.6 Expert systems (ES)

At the core of expert systems (ES) is a logically structured knowledge base (Olomolaiye *et al.*, 1998). This library contains data and experience from past projects and rules of thumb (Boussabaine, 2001a). The users need to answer a series of questions, which were determined based on an understanding of how decisions are made by practitioners (Olomolaiye *et al.*, 1998). Moselhi and Nicholas (1990) proposed an expert system for scheduling and planning of building construction projects. Its duration modifier module added the influence of different factors, such as overtime, to the unimpacted duration to gain a more realistic one. The system could be used, for example, for analysing how the changes in the project environment would affect the project duration and costs (Moselhi and Nicholas, 1990). Rao et al. (2005) developed an expert system, which can systematically analyse productivity and offer possible corrective actions.

2.3.2.7 Multi-criteria decision analysis methods (MCDA)

Certain methods are more suited for productivity studies conducted at the industry level. Multi-criteria decision analysis methods are applied to aid the selection of the most appropriate alternative out of numerous options based on subjective criteria, where the variants are often described by uncertain and inaccurate data (Wątróbski *et al.*, 2019).

The Decision Making Trial and Evaluation Laboratory (DEMATEL) is an MCDA method that can analyse the direct and indirect connections between system elements (Nasirzadeh, Rostamnezhad, *et al.*, 2020). This method does not assume that the factors are independent of each other (Chaturvedi *et al.*, 2018). Chaturvedi et al. (2018) used DEMATEL to assess labour productivity in the Indian construction industry based on the cause and effect relationships of the influencing factors. They found safety to be the most important factor (Chaturvedi *et al.*, 2018). Nasirzadeh et al. (2020) applied DEMATEL for a similar purpose in the case of Australian construction projects. Level of skill and experience was ranked first among the most important factors (Nasirzadeh, Rostamnezhad, *et al.*, 2020). Shahpari et al. (2020) combined DEMATEL with other MCDA methods (Analytic Network Process and Technique for Order of Preference by Similarity to Ideal Solution) to assess the productivity of prefabricated and in-situ construction systems in Iran. Management and planning were found to be of greatest importance (Shahpari *et al.*, 2020).

Data envelopment analysis (DEA) is a non-parametric method used to determine a decision-making unit's (for example, a country's) relative efficiency (Hu and Liu, 2018). The indicators exist in a multi-input multi-output system (Li *et al.*, 2019). Hu and Liu (2018) applied DEA to measure the overall performance of the construction industry in different regions of China. With the help of this method, Li et al. (2019) measured the change in workforce productivity in various regions of the USA between 2006 and 2016.

Stochastic frontier analysis (SFA) is used for the same purpose as DEA; however, this is a parametric method (Nazarko and Chodakowska, 2017). De Jorge Moreno et al. (2016) developed three models based on SFA to study the technical efficiency of the Spanish construction industry. The skills of the workers were found to be an important factor (De Jorge Moreno *et al.*, 2016). Nazarko and Chodakowska (2017) compared the results of DEA and SFA models when measuring technical efficiency in EU countries. They concluded that the higher labour costs characteristic of old EU countries does not mean higher efficiency as well (Nazarko and Chodakowska, 2017).

2.4 Machine learning (ML)

The relationship between the influencing factors and the productivity rate, and especially the factors' combined effects are complex, thus making modelling challenging (Chao and Skibniewski, 1994). Owing to this, productivity studies can benefit from the application of machine learning methods. This section gives an overview of the most widely used options. ML systems are capable of making predictions on new data inputs based on what they have learnt from previous input data (Di Franco and Santurro, 2020). In this, they are similar to some statistical methods, regression, for instance. However, while in the case of regression analysis, the function describing the relationship between the variables is assumed and the coefficients are determined through iteration, in the case of ML, this function is approximated by the ML system (Boussabaine and Kirkham, 2008).

2.4.1 Artificial neural networks (ANNs)

Artificial neural networks (ANNs) have been used in construction studies since the late 1980s (Flood and Kartam, 1994a; Adeli, 2001). There is a wide range of applications in the field of construction management because ANNs can be trained to learn from even imperfect datasets, and provide quick and generalised solutions to a problem (Flood and Kartam, 1994a). ANNs can be used for modelling problems in which functional relationships between dependent and independent variables are subject to uncertainty, not understood, or may vary with time (Di Franco and Santurro, 2020).

Moselhi and Khan (2012) studied concrete formwork installation productivity by using ANN, fuzzy subtractive clustering, and stepwise regression analysis and comparing the results. Significance ranking of the influencing factors was performed, as well. Temperature and the type of the structure ranked highest (Moselhi and Khan, 2012). The same dataset and input variables were used by Nasirzadeh et al. (2020) and Golnaraghi et al. (2019). The former aimed to use ANN to gain prediction intervals for labour productivity, while the latter compared the results obtained with the help of four different network configurations (Golnaraghi *et al.*, 2019; Nasirzadeh, Kabir, *et al.*, 2020). The output of the ANN by Portas and AbouRizk (1997) was also an interval (referred to as a zone) containing a small range of productivity values for concrete formwork operations.

El-Gohary et al. (2017) sought to gain more accurate productivity rates for concrete works. Tsehayae and Robinson Fayek (2016) analysed the productivity influencing factors for the same trade. Badawy et al. (2021) created an ANN model to be able to predict the productivity rate of reinforcing works based on physical attributes of the works (for example, the diameter of the rebar).

Oral and Oral (2010) applied self-organising maps to investigate the effects of various influencing factors and to forecast construction productivity in the case of concrete works, formwork installation, and reinforcing works. Oral et al. (2016) compared the application of self-organising maps and artificial bee colony to predict productivity rates for ceramic tiling works. Heravi and Eslamdoost (2015) analysed the factors affecting productivity for power plant projects. They found supervision, proper coordination, and effective communication to be the most important ones. Moselhi et al. (2005) also investigated projects as a whole, rather than specific trades, and developed a model to understand the effect of change orders on labour productivity. Fan et al. (2021) also used physical characteristics complemented with cost data to attempt to forecast the project duration.

2.4.2 Hybrid ANN models

To enhance the capabilities of an ANN approach, it is possible to use it combined with other methods, thus creating a hybrid model. One option is to complement ANNs with construction simulation. Song and AbouRizk (2008) modelled steel drafting and fabrication by embedding ANNs into their discrete-event simulation model to estimate the duration of the individual activities. To provide accurate productivity estimates for earthworks, Chao and Skibniewski (1994) generated the activity durations fed into the ANN model with the help of discrete-event simulation.

ANN-FL hybrid models are referred to as neurofuzzy (Boussabaine, 2001a). FL is suitable for modelling subjective variables in the ANN models. The aim of Mirahadi and Zayed's (2016) study was to gain more accurate productivity rates for concrete works. To this end, they used both crisp and fuzzy input variables, which were fed into the model through simulation. The output layer was also fuzzy. Moreover, a genetic algorithm-based optimisation was used for the fine-tuning of the model (Mirahadi and Zayed, 2016). The output of the ANN model for concrete formwork operations by Portas and AbouRizk (1997) was an interval (referred to as a zone) containing a small range of productivity values measured on a fuzzy scale. Boussabaine (2001b) developed a neurofuzzy model to be able to better estimate project durations based on the selected project characteristics used as fuzzy input variables. Omar and Robinson Fayek's (2016) fuzzy neural network models were created to identify and quantify the relationships between the functional and behavioural competencies (i.e., knowledge and skills stemming from the organisations and the individuals) and the projects' key performance indicators.

2.4.3 Random forest (RF)

Random forest is a nonparametric, nonlinear regression algorithm, which creates a number of classification and regression trees from a random sample of the original dataset (Liu *et al.*, 2018; Momade *et al.*, 2020; Awada *et al.*, 2021). The output of RF is determined based on combining the output of these, individual decision trees (Momade *et al.*, 2020). Liu et al. (2018) studied the effects of meteorological factors on the productivity of scaffolding works. They compared a generalised additive model and an RF model, and found that RF is better suited for the task and is capable of further analysis of the combined impact of the environmental factors (Liu *et al.*, 2018). Momade et al. (2020) investigated the effects of various factors on the productivity of construction operatives working on residential projects. They compared an RF model with a support vector machine (SVM) one. SVM is also a nonlinear machine learning method, which can be used for regression and classification problems. In this study, the workers' salary was used as a productivity measure. Operative characteristics, such as experience, training, and skills, were found to have the greatest impact on productivity. The SVM model provided more accurate labour productivity predictions than the RF model (Momade *et al.*, 2020).

2.5 Simulation

2.5.1 Basic simulation methods

One of the basic simulation methods available is discrete-event simulation (DES), which focuses on, and models the process itself. DES is based on the concept of entities and resources to describe their flow and sharing across a system. Entities are passive objects (no interaction or characteristics are attached to them) and they travel through the workflow where they are processed, delayed, queued, seized, and divided. The first notable construction simulation tool using DES was Halpin's CYCLic Operations Network (CYCLONE) in 1973, which was intended to be a general-purpose simulation system (AbouRizk *et al.*, 2011). Martinez (2010) has described a methodology for conducting DES and pointed out the possible problems one may encounter when modelling, which could put the model's validity in jeopardy. Activity durations in DES models can be described by probability distribution functions like the ones used in Program Evaluation and Review Technique (PERT). Law (2015) attempted to collect all the available functions (ranging from uniform to Weibull, including the Johnson and Pearson systems) with their properties and explained their usage in the case of simulation. AbouRizk and Halpin (1992, p. 537) suggested that flexible functions were needed due to the 'diversified nature of construction duration data', and advised using the beta function because of its familiarity in the construction field. Hajdu and Bokor (2016) argued that a careful three-point estimation was more important than the type of distribution function selected. Monte Carlo simulations performed on hypothetical and real-life projects showed that a 10% difference in the three-point estimation could cause greater deviations than the chosen distributions (Hajdu and Bokor, 2016). Ahmed et al. (2021) used DES to model concurrent construction operations with resource constraints to find optimal workflow and resource allocation for minimal duration. Kim et al. (2021) applied DES to obtain the duration of in-situ concrete works taking gang size and spatial conflicts into account.

Another basic simulation method is system dynamics (SD), as developed by Forrester (1961). SD is a top-down method that concentrates on the various influencing factors and the relationships among them to show the entire system's workings and behaviour with feedback loops. SD can be used for both qualitative and quantitative modelling: the former focuses on creating a causal loop diagram (balancing and reinforcing relationships), while the latter determines stocks and flows and expresses the links with equations (Kunc, 2017). SD is a model that works with aggregates, that is, the items in the same stock are considered equal, and the system is defined as a set of structural dependencies. Mawdesley and Al-Jibouri (2009) used SD to determine which areas should be improved by management to increase productivity. The model contained planning, control, motivation, safety, and disruptions as the most significant factors. Several strategies were tested, and it was found that the first two needed the management's particular attention (Mawdesley and Al-Jibouri, 2009). Soewin and Chinda (2020) applied SD to determine the construction performance index and maturity level of construction companies based on 57 factors grouped into 10 major categories. They found that besides the traditional measures of time, cost, and quality, the internal stakeholders group – containing factors such as labour productivity, competence, and teamwork – was also key to achieving higher levels of maturity (Soewin and Chinda, 2020). With the help of SD, Al-Kofahi et al. (2020) studied how and to what extent owner-liable change orders affect labour productivity.

In contrast to SD, agent-based modelling (ABM) has a bottom-up approach – there is no global system behaviour. The system's behaviour emerges from how individual, heterogeneous agents interact with each other and their environment based on defined rules (Watkins *et al.*, 2009). Siebers et al. (2010) argue that ABM had an advantage over DES, in cases where the focus is not on the process but on how the individual agents, who can learn and adapt, affect the system. Son et al. (2015) emphasise similar positive properties through examples of project teams in large-scale construction projects. They recommend ABM for modelling, for instance, the international construction market with countries and firms as agents (Son *et al.*, 2015). Watkins et al. (2009) used ABM to determine how site congestion affects productivity with two agent types being defined: workers (with variables such as skill level) and activities. Dabirian et al. (2021) built on this model to quantify the productivity loss caused by site congestion. Hsu et al. (2016) used ABM to assess team member selection models. In their research, the agents were the workers with attributes such as experience and skills. It was concluded that interdependence-based selection is preferable to skill-based assignment (Hsu *et al.*, 2016). With the help of ABM, Kiomjian et al. (2020) studied how gang composition and project scheduling affect knowledge sharing, which in turn has an impact on the activity duration. Higher levels of knowledge sharing was found in the case of more diverse gangs, which could lead to greater productivity gains (Kiomjian *et al.*, 2020).

2.5.2 Hybrid simulation approaches

The approaches described above are often used individually but can also be applied in combination. A benefit of the combined approach is to use the various advantages of each method and to balance its shortcomings. The most suitable approach should be selected for each component of the model and, depending on the question that needs to be answered, such combinations will provide more accurate representations of reality (Borshchev and Filippov, 2004; Borshchev, 2013). Furthermore, the three basic simulation methods can be mixed with other methods, such as Artificial Neural Networks (ANNs) or Fuzzy Logic (FL) (Balaban *et al.*, 2014), which can also be considered hybrid approaches (AbouRizk, 2010; Nojedehi and Nasirzadeh, 2017).

Fahrland (1970) suggested the combination of DES and SD to create improved, more realistic, and efficient models with many possible applications ranging from aerospace missions to nuclear power plant start-ups. While DES concentrates on the process, and deals with issues at the operational level, SD is suitable for modelling at the strategic level; thus, complementing each other (Peña-Mora *et al.*, 2008). With the help of combined DES-SD systems, it is possible to coordinate managerial and operational decisions to increase productivity (Peña-Mora *et al.*, 2008; Alvanchi *et al.*, 2011). In the interest of obtaining more realistic project duration data, Alzraiee et al. (2015) complemented DES with SD, as well. The latter was used to take the influencing factors (for instance, weather and overtime) into consideration (Alzraiee *et al.*, 2015).

DES can also be combined with ABM. In operational research, instead of pure ABM, often a hybrid model is used where the entities of the DES are active, ABM agents (Siebers *et al.*, 2010). Shehab et al. (2020) paired DES with ABM in a hybrid simulation model, where the DES component modelled the construction operation, and the ABM part modelled the construction gangs.

Lättilä et al. (2010) urged that researchers should combine SD with ABM to combine the positive features of both approaches. They also mentioned that both systems could be used to model the same problem and then the results could be compared (Lättilä *et al.*, 2010). Nasirzadeh et al. (2018) proposed an integrated SD-ABM simulation approach to model construction workers' safety behaviour and its effect on the project duration. In the ABM model, contractors were chosen as agents, and each of them had their SD models showing the influencing factors. There was a constant flow of information between the models (Nasirzadeh *et al.*, 2018). Khanzadi et al. (2018) also used an integrated SD-ABM simulation approach to see how site congestion affects productivity.

Additionally, Borshchev (2013) provided an example for combining all three basic methods where DES is used to model the supply chain process, SD describes the market, and agents represent the participants.

Raoufi et al. (2016) provided an extensive overview of the combinations of FL with DES, SD and ABM in construction, showing the advantages of integrating FL into the basic methods and giving advice on the appropriate choice of a hybrid technique. AbouRizk and Sawhney (1993) developed the Subjective and Interactive Duration Estimation System (SIDES) with the aim of determining more realistic beta distribution functions for activity durations in DES with the help of FL. The users of the application had to define the two endpoints of the function; however, fitting was based on the selected influencing factors expressed in linguistic terms (AbouRizk and Sawhney, 1993). Zhang et al. (2005) also suggest the application of FL in DES in cases when there is no field data to use. Even when there is, FL could be used to incorporate 'vagueness, imprecision and subjectivity' (Zhang *et al.*, 2005, p. 727).

Nojedehi and Nasirzadeh (2017) also combined SD with FL, while the former part of the model contained the most important factors influencing labour productivity; the latter component was used to express the effect of those factors that could not have been done with crisp values. With the help of the model, possible solutions for improving productivity were tested to contribute to better managerial decisions (Nojedehi and Nasirzadeh, 2017).

Raoufi and Robinson Fayek (2015) combined FL with ABM to investigate how gang performance is affected by the workers' personality and the interactions between the workers and their environment. Two layers of agents were defined: workers and gangs. The 'what-if' rules of agent behaviour were expressed in linguistic terms, which were translated using FL (Raoufi and Robinson Fayek, 2015).

2.6 Productivity studies of block and bricklaying operations

The fundamental principles of masonry works have not changed for millennia (Gilbreth, 1909). Bricks and brickwork were discussed in various collections of the architectural knowledge of the given era, for example, in Vitruvius' Ten Books on Architecture from the 1st century BC or in Yingzao Fashi from early 12th century China (Vitruvius, 1914; Chong, 2006). In the beginning of the 20th century, Gilbreth (1909) published a book on bricklaying, which contained a motion study. All the movements of typical bricklaying operations were listed, and – in order to increase productivity – the sequences were optimised by omitting the unnecessary ones (Gilbreth, 1909). The tools used by bricklayers today (right side of Figure 2.1) are very similar or the same as the ones that can be seen in Gilbreth's book (left side of Figure 2.1).

Figure 2.1 Top: Trowel, Bottom: Brick clamp (Left: Gilbreth (1909, pp. 8&118), Right: Photos taken by Orsolya Bokor in 2019)

In the post-war era, productivity became important as the number of construction projects increased to a great extent. For example, the Building Research Station conducted studies of masonry works. One of these compared the productivity of laying bricks and blocks of various sizes and analysed productive and non-productive times (Kinniburgh and Vallance, 1948). Another one also mentioned that the size of the unit was important with regards to productivity, alongside motivation, the technique of laying, and the organisation of the works on site (Forbes and Mayer, 1968). Based on on-site observations and video analysis, Whitehead (1973) proposed improvements to the bricklaying technique to increase productivity.

There have been several studies modelling bricklaying productivity. Some investigated the effects of a few factors, while others included a number of factors. Table 2.4 contains the most common factors from the selected studies. These factors are divided into categories called design, gang, management, site, and external. In these studies, various methods were used to analyse the impact of the chosen factors on productivity.

Thomas and Yiakoumis (1987) proposed the application of the factor model, which focused on gang-level productivity. The effects of the influencing factors were quantified with the help of regression analyses. Based on these and the learning curve effect, productivity curves could be defined, and then used to forecast actual productivity. The goal was to be able to explain the variability of daily productivity. The model was developed as a general one, not specifically for masonry works; however, block laying was one of the activities observed for data collection. The paper showed an example of the application of the model to determine the effects of changes in temperature and relative humidity (Thomas and Yiakoumis, 1987). Later, the factor model was further developed.

Sanders and Thomas (1991) compiled a list of factors (concentrating mostly on design-related ones) influencing masonry productivity. With the help of the variance analysis, they concluded that design requirement factors – for example, the number of cuts – had considerable impact on productivity (Sanders and Thomas, 1991). A regression model was created based on these factors with gang size added to them (Sanders and Thomas, 1993). The calculated coefficients were used in Thomas and Sakarcan's (1994) productivity forecasts. Their conceptual factor model contained more factors than Sanders and Thomas' (1991) list. However, they argued that predictions about productivity can only be made based on factors that can be predicted in advance. These factors are related to the work to be performed, while the work environment cannot be predicted (Thomas and Sakarcan, 1994).

Thomas and Završki (1999) proposed a work content scale for masonry projects. This essentially described the difficulty of the works on the project level. The 1 (the least complex design) to 5 (the most complex design) scale was based on the number of cuts, openings, and non-perpendicular corners, and the extent of ornamental work (Thomas and Završki, 1999). Since daily productivity was measured in all of Thomas' above-mentioned studies, wall or course difficulty could not be used.

Sweis et al. (2009) further developed Thomas and Sakarcan's (1994) factor model by adding a group of factors, called indirect causes, which included, for example, acceleration. They used the complexity scale of Thomas and Završki (1999) to describe the difficulty of the projects. Their objective was to determine a baseline productivity rate based on the work to be done factors, and to calculate the normal variation, which happens due to the work environment factors. They recommended management action when the variation was abnormal. Normal variation was determined with the help of multiple regression analysis, where the work environment factors were binary independent variables (Sweis *et al.*, 2009). In another study, Sweis et al. (2008) compared baseline productivity rates of masonry works in the US, UK, and Jordan based on data collected on project sites in these countries. Here they also used Thomas and Završki's (1999) difficulty scale to characterise the projects. They attributed the differences between baseline values to a function of construction methods, materials, site management, sociological and cultural factors, and craft skills.

Training, work ethic, and motivation were included in the latter. They found that the productivity of skilled bricklayers was similar in all three countries; however, due to manual material handling practice in Jordan, a great number of unskilled labourers had to be employed on the sites causing variations in baseline productivity (Sweis *et al.*, 2008).

Thomas and Sudhakumar (2014) used multiple regression analysis to model masonry productivity. One of the selected influencing factors was work content from Thomas and Završki's (1999) model, which was found to have significant effect on productivity. Apart from a couple of gang-related ones, the majority of the factors considered were ones that are unknown at the time of pre-construction planning.

Hendrickson et al. (1987) developed an expert system called MASON to estimate block and bricklaying activity durations. First, the maximum productivity rate was determined, then this was adjusted, decreased based on the answers given to the questions about the selected factors. The majority of the factors considered were regarding the work to be performed. Gang-related questions were concerned with gang composition and whether the operatives were union members (Hendrickson *et al.*, 1987).

Models based on machine learning were also developed. Gerek et al. (2015) created two artificial neural network models to study the productivity of bricklaying gangs. The chosen factors were mostly gang (for example, experience) and management-related with a couple ones regarding the design of the walls. By ranking the factors, they found that brick type and working time had the greatest effect on productivity (Gerek *et al.*, 2015). Aswed (2016) developed an artificial neural network model, as well. Factors were selected from all categories shown in Table 2.4; however, most of them were gang and design-related. According to the sensitivity analysis performed, the ones with the greatest impact were from these categories (Aswed, 2016). Al-Somaydaii (2016) used a support vector machine learning algorithm to investigate bricklaying productivity. The majority of the factors were either gang or site-related, however, there were no design-related ones (Al-Somaydaii, 2016).

Karthik and Kameswara Rao (2019) conducted a survey research to find the most important factors influencing bricklaying productivity. Their study included factors from every category shown in Table 2.4; however, there were very few design-related ones. The relative importance indices showed gang-related factors to be the most important category with experience and skills being first in the overall ranking (Karthik and Kameswara Rao, 2019).

Horner and Talhouni (1995) reported that daily productivity of bricklaying gangs could be twice as much one day as the day before, and even five times as much on one site as on another. They divided the factors contributing to these variations into three categories: people, project and site-related. In the first group were the worker's skill, speed, and the quality of their work. Problems can be overcome fast with good skills, and good quality work can make rework unnecessary. It was emphasised that the selection and training of the operatives is crucial (Horner and Talhouni, 1995).

Despite attempts at mechanisation, masonry works remain highly labour-intensive. Mortlock and Whitehead (1970) devoted a section in their study to introduce several bricklaying machines from various countries, such as the US, the UK, and the Netherlands. There are examples for experimenting with bricklaying robots at universities (Pritschow *et al.*, 1996; Aguiar and Behdinan, 2015). However, industrial application has only just begun (Melenbrink *et al.*, 2020). Owing to this and the aforementioned shortage of skilled labour, it is crucial to investigate the effects of gang-related, especially worker-related, factors on productivity. For instance, experience, health, and good relationships between the workers appeared in Aswed's (2016) and Al-Somaydaii's (2016) studies. The following examples concentrate on the impact of worker-related factors.

Olomolaiye (1990) studied the effect of bricklayers' motivation on their productivity. Besides financial incentives, several other factors were included among the motivating variables, such as good relationships among the members of the bricklaying gangs. It was found that motivation did not influence the productivity rate; however, it did have an effect on the percentage of productive time. It was argued that skills, which are the product of natural ability, training, and experience, and are reflected in speed, could affect productivity (Olomolaiye, 1990). Therefore, Olomolaiye et al. (1996) investigated how skill – defined as a function of time it takes to lay a brick – affected the output of bricklayers. Based on the results of the simulation, the critical activities of the bricklaying process were found with the actual laying the brick task having the greatest influence on the output. Different gang sizes were also examined, and the 2 bricklayer+1 labourer configuration was found to be optimal (Olomolaiye *et al.*, 1996).

Florez (2017) used a different definition for skill: the ability to perform a task well. This model was developed to match the walls with masons with appropriate skills, while aiming for minimum activity durations and keeping the costs within budget. The walls were divided into easy and difficult categories. Furthermore, the relationships between the members of the gang were also considered (Florez, 2017). This was further explored by Florez et al. (2020), who found that personality characteristics could affect productivity, that the members of the gang should be compatible.

The factors selected for this study have a gray background in Table 2.4. As the research project concentrates on pre-construction planning, the values of the chosen factors need to be known in advance, hence they are from the design and gang-related categories. Difficulty of works and brick type belong to the former, while skills, which are further broken down into sub-factors, and experience are in the latter group. Section 4.1 explains the selection of the factors in detail and also provides the definitions used in this study.

Factor cat.	Factor	Thomas and Yiakoumis (1987)	Sanders and Thomas (1991)	Thomas and Sakarcan (1994)	Sweis et al. (2009)	Thomas and Sudhakumar (2014)	Gerek et al. (2015)	Karthik and Kameswara Rao (2019)	Aswed (2016)	Al-Somaydaii (2016)	Horner and Talhouni (1995)	Hendricksen et al. (1987)
D	Buildability	●									●	
E S	Variability of design		●									
I	Structure											●
G N	Building element		●									●
	Size								●			●
	Specifications	●		●	●						●	
	Design features		●	●	●							●
	Finish											●
	Difficulty of works			●	●	●		●			●	
	Brick/block type						●					●
	Brick/block size			●	●							●

Factor cat.	Factor	Thomas and Yiakoumis (1987)	Sanders and Thomas (1991)	Thomas and Sakarcan (1994)	Sweis et al. (2009)	Thomas and Sudhakumar (2014)	Gerek et al. (2015)	Karthik and Kameswara Rao (2019)	Aswed (2016)	Al-Somaydaii (2016)	Horner and Talhouni (1995)	Hendricksen et al. (1987)
	Mortar type						●		●			●
	Design changes				●			●			●	
G	Gang size	●	●			●			●	●	●	
A N	Gang composition					●	●					●
G	Skills							●			●	
	Age						●		●	●		
	Experience						●	●	●	●		
	Execution							●		●	●	
	Intra-gang relationships							●		●		
	Physical, mental health								●	●		
	Union										●	●
	Motivation							●		●	●	
	Absenteeism	●						●			●	

Factor cat.	Factor	Thomas and Yiakoumis (1987)	Sanders and Thomas (1991)	Thomas and Sakarcan (1994)	Sweis et al. (2009)	Thomas and Sudhakumar (2014)	Gerek et al. (2015)	Karthik and Kameswara Rao (2019)	Aswed (2016)	Al-Somaydaii (2016)	Horner and Talhouni (1995)	Hendricksen et al. (1987)
MANAGEMENT	Management methods	●						●			●	
	Supervision			●	●			●				
	Work schedule	●		●	●			●			●	
	Shift work				●							
	Working days, hours						●				●	
	Breaktime						●					
	Overtime				●	●	●	●				
	Acceleration				●						●	
	Manning level	●			●							
	Wage type[1]					●	●					
	Wage						●	●	●			

[1] Wage type refers to the way the workers are contracted (direct labour, subcontracted) and paid (lump sum, weekly, daily)

Factor cat.	Factor	Thomas and Yiakoumis (1987)	Sanders and Thomas (1991)	Thomas and Sakarcan (1994)	Sweis et al. (2009)	Thomas and Sudhakumar (2014)	Gerek et al. (2015)	Karthik and Kameswara Rao (2019)	Aswed (2016)	Al-Somaydaii (2016)	Horner and Talhouni (1995)	Hendricksen et al. (1987)
S I	Site organisation	●							●	●		
T	Congestion	●		●	●			●			●	
E	Disruptions		●								●	
	Rework			●	●	●		●				
	Equipment			●	●			●			●	
	Tools			●	●			●				
	Material availability			●	●	●		●	●	●	●	
	Health and safety							●				
	Site security								●	●		
EXT.	Weather	●	●	●	●	●		●	●	●	●	●

Table 2.4 Influencing factors in bricklaying productivity models (cat.=category, EXT.=external)

2.7 Chapter summary

To give context to the research project on construction labour productivity, this chapter provided an overview of construction productivity concepts and the skill shortage in the UK. The bulk of the chapter discussed productivity studies. First, research efforts on collecting and categorising productivity influencing factors were introduced. Then the various methods – such as statistical analysis, fuzzy logic, genetic algorithms, and expert systems – used for modelling productivity were presented complete with examples for their application. Machine learning and simulation methods were discussed in more detail as these were selected for modelling bricklaying productivity in this research project. Artificial neural networks, a machine learning approach, were chosen for one component of the model because they can handle complexity and uncertainty characterising construction, learn from even imperfect input data, and make predictions – in this case, for productivity – for new input data. The use of ANNs will be discussed in detail in Chapter 5. For the other component of the model, discrete-event simulation was selected, which is suitable for modelling a construction process, providing the process duration and information on resource usage and allocation. Creating hybrid models – as shown by the examples – is beneficial because by combining the methods, their advantages are also combined, while their shortcomings can be balanced out. Chapter 7 will introduce the DES component and show the connection between the model components. The final section of this chapter provided a comprehensive discussion of the published bricklaying productivity studies, complete with a table listing and categorising the productivity influencing factors selected for these studies. The factors chosen for this research project will be discussed in Chapter 4.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

To be able to demonstrate how the aim and objectives of the research project were achieved, the steps of the research process need to be articulated. The components of the research project are shown in Figure 3.1. Details are listed in the middle row, while the output of each step can be seen in the bottom row.

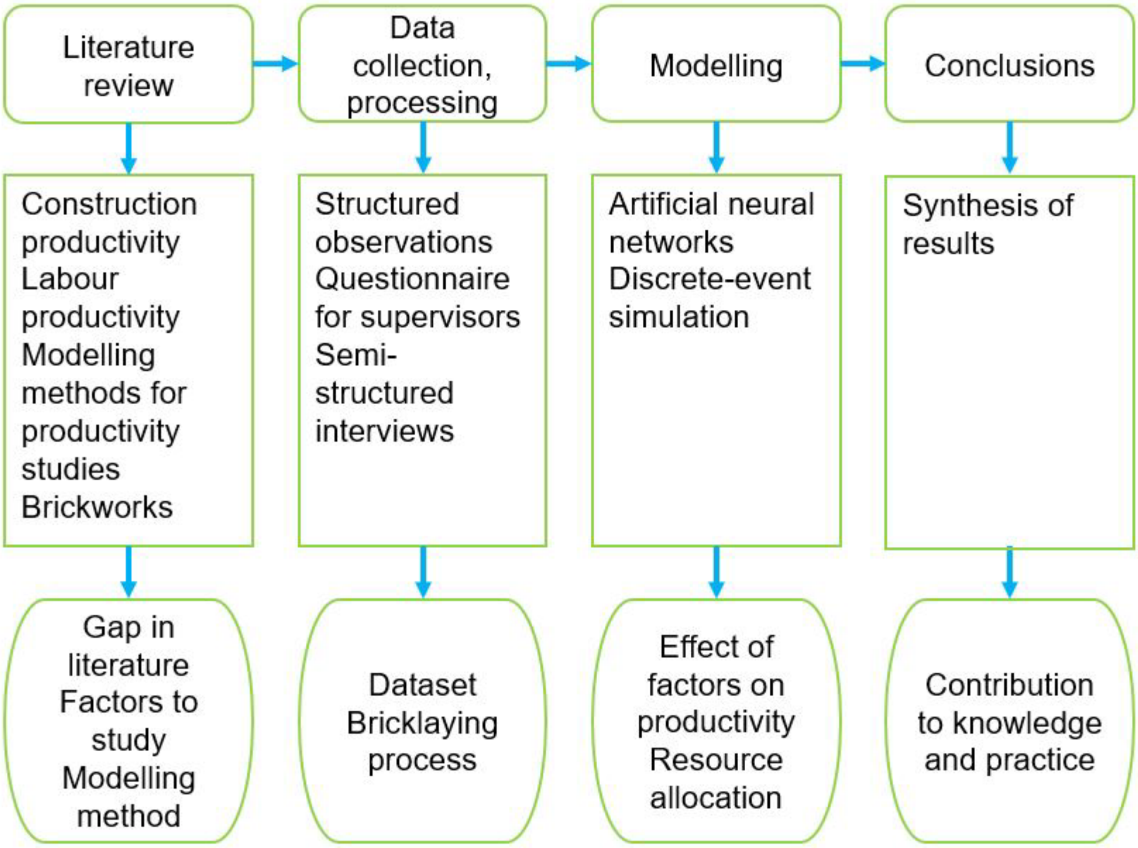


Figure 3.1 Steps of the research project

It is important to choose the appropriate methods to achieve the objectives of the research. However, these methods do not exist in a vacuum, they all have theoretical underpinnings, which should also be considered. Dealing with theory is critical for two reasons: one, it provides the foundation for the research, the rules by which it is conducted, and two, theory facilitates the understanding of the findings (Crotty, 1998; Bryman, 2016). Today there is a variety of options for conducting and interpreting research, there is not one single scientific method (Fellows and Liu, 2015). Therefore, the appropriate theoretical background has to be chosen and made explicit in the research.

This chapter aims to introduce the theoretical considerations behind the research as well as how it was conducted in practice.

3.2 Research decisions

The four basic elements of the research process according to Crotty (1998) can be seen in Figure 3.2. Method (e.g., non-participant observations) is the technique applied for collecting and analysing data. Methodology (e.g., survey research) is the design or process explaining the selection of methods, and the link between them and the outcomes. The philosophical view (e.g., positivism) affecting the methodology and giving context to the research process is referred to as theoretical perspective. The way that knowledge is understood and explained belongs in the element of epistemology (Crotty, 1998).

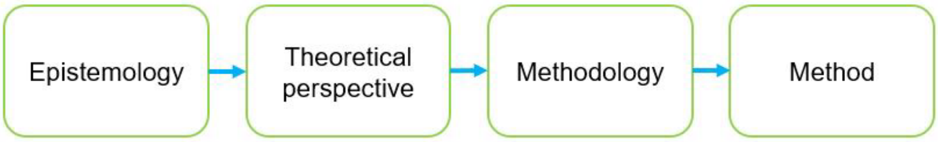


Figure 3.2 Four elements of research (Adapted from (Crotty, 1998))

Three of these four elements in Crotty's (1998) model also appear in Creswell and Creswell's (2018) framework. In this case, the theoretical perspective is called philosophical worldview, while methodology is labelled as designs. Using this framework, the research approach emerges from the interaction of the three components (Creswell and Creswell, 2018).

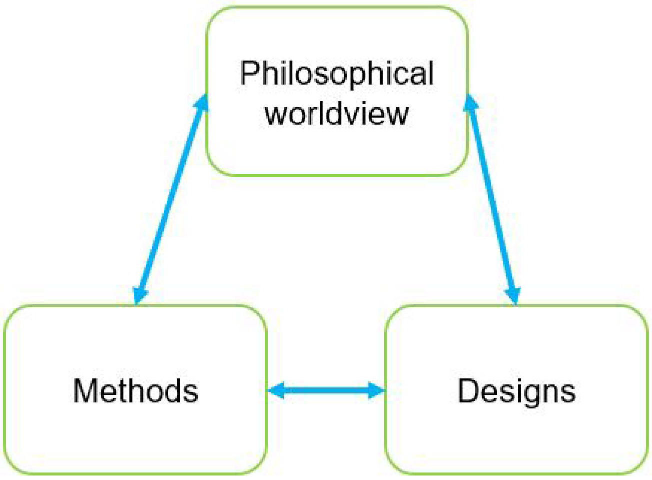


Figure 3.3 Research approach (Adapted from (Creswell and Creswell, 2018))

Saunders et al. (2016) illustrated the questions that need to be answered when deciding about how to conduct a research project with the metaphor of a 'research onion' (see Figure 3.4). The techniques used for data collection and analysis are often the only issues considered; however, those only comprise the centre of the onion, and the outer layers are also important (Saunders *et al.*, 2016).

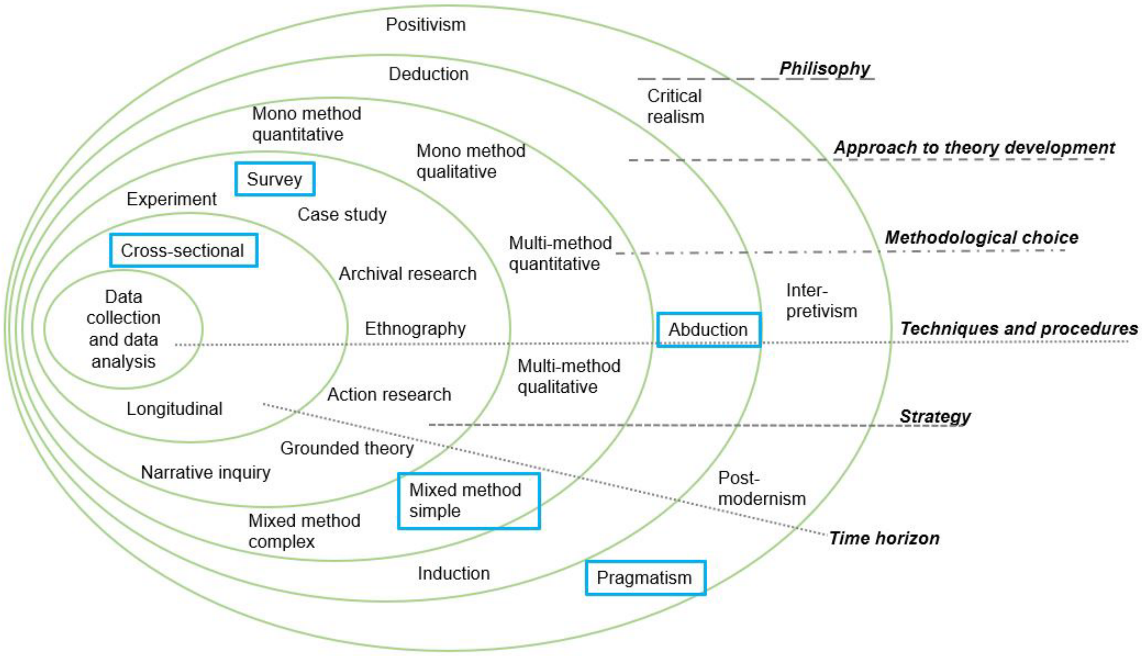


Figure 3.4 Research onion (Adapted from (Saunders et al., 2016))

The research onion is a useful tool because its layers frame the decisions about the research. Therefore, the following sections are structured using these layers to explain and justify the choices made in this research project, which are shown in blue frames in Figure 3.4.

3.2.1 Research philosophy

As a result of the research project, new knowledge is developed. In the course of that, several assumptions have to be made. Research philosophy deals with the system of these assumptions (Saunders *et al.*, 2016). Crotty (1998) calls this element theoretical perspective, while it appears as philosophical worldview in Creswell and Creswell's (2018) framework. Bryman (2016) refers to it as an epistemological consideration.

Saunders et al. (2016) explain the various philosophies using three different types of research assumptions made during the research. The first one is ontology, which is concerned with the nature of reality. Epistemology refers to what kind of knowledge can be considered acceptable. Similar to business and management in their case, construction management is also multidisciplinary, hence, for example, various types of data can be accepted as legitimate. Lastly, axiology refers to how values are dealt with, how the values of the researcher and those of the participants affect the research (Saunders *et al.*, 2016).

The aforementioned assumptions can be placed on a scale going from objectivism to subjectivism (Saunders *et al.*, 2016). In Crotty's (1998) model this is the epistemology element, while Bryman (2016) discusses them under ontological considerations. Objectivism views everything as tangible objects, which exist independently of experiences or interpretations (Bryman, 2016; Saunders *et al.*, 2016). There is only one true reality, which can be observed and measured by the researchers, who remain detached and exclude their own values from their research (Saunders *et al.*, 2016). Constructionism rejects the idea of universal truth, and believes that the same phenomenon can be interpreted in various ways by different researchers (Crotty, 1998). In the case of subjectivism, the meaning assigned to objects does not come from the interaction with the given object, it is rather a social construct (Crotty, 1998). The values of the researcher are integrated into the research (Saunders *et al.*, 2016).

Several research philosophies exist. The two most prominent and opposing ones are positivism and interpretivism (Crotty, 1998). The former is typically favoured within the natural sciences, while the latter, the social sciences (Bryman, 2016). Table 3.1 shows examples of several research philosophies, of which some will be explained further in the following sections.

	Positivism, post-positivism	**Realism**	**Interpretivism**	**Post-modernism**	**Pragmatism**	**Critical inquiry**	**Feminism**	**Transformative**
(Saunders *et al.*, 2016)	●	●	●	●	●			
(Crotty, 1998)	●		●	●	●	●	●	
(Creswell and Creswell, 2018)	●		●		●			●
(Bryman, 2016)	●	●	●	●				

Table 3.1 Research philosophies discussed in different sources

Positivist research assumes that there are natural laws, which can be discovered by bias-free observations carried out according to the scientific method (Crotty, 1998; Bryman, 2016; Saunders *et al.*, 2016). Positivism is deterministic, meaning that the outcomes are the result of causes (Creswell and Creswell, 2018). The data from the observations are used to verify a hypothesis formulated based on theory (Saunders *et al.*, 2016). The collected data can also provide the basis for laws (Bryman, 2016). Fellows and Liu (2015) argue that while this philosophical stance can be applied for investigating the natural laws of the universe, usually, the observations taken and means of measurements can affect the object of the study. Saunders et al. (2016), therefore, mentions that – despite best efforts – it is practically impossible for the researcher to exclude their values from the research.

Similarly to positivism, realism also assumes that there is one true reality, which exists separately from the researchers' interpretations (Bryman, 2016). Both Bryman (2016) and Saunders et al. (2016) differentiate between two forms of realism: empirical (or naïve) and critical realism. The former assumes that this reality can be understood by applying suitable methods (Bryman, 2016). Critical realists accept that there is a distinction between the object of their research and their descriptions, interpretations of it (Bryman, 2016; Saunders *et al.*, 2016). Hypothetical entities, which are entailed in mechanisms and could not be observed but their effects can be, are also admissible for them (Bryman, 2016). Context, in which the cause and effect happens, is important for critical realists (Bryman, 2016). While positivists believe that their concepts of reality are direct reflections of reality, critical relativists assert that they are merely a way of knowing that reality (Bryman, 2016).

Interpretivism, in short, is the opposite of positivism. It is based on the notion that people and the social world are fundamentally different from the objects of the positivist research in the natural sciences; therefore, a different research logic is required when investigating them (Bryman, 2016). Interpretivists collect the interpretations of their research subjects on the investigated issues. These are then interpreted by them, and then interpreted once again within the theory of the discipline (Bryman, 2016). Researchers do not attempt to detach themselves from their research, their beliefs and values are integrated into their studies (Saunders *et al.*, 2016). Interpretivism is often a preferred philosophical stance in management research (Fellows and Liu, 2015; Saunders *et al.*, 2016).

Pragmatist researchers do not wish to subscribe to any of the offered extremes on the philosophical scale (Creswell and Creswell, 2018). They start with the research problem and would like to choose the methods most appropriate to meet the objectives of the research regardless of those being quantitative or qualitative (Feilzer, 2010; Saunders *et al.*, 2016). Therefore, these studies are typically mixed-method ones (Creswell and Creswell, 2018). The objectives are usually contributions to practice (Saunders *et al.*, 2016). Pragmatists accept uncertainty and acknowledge that the findings are not absolute but relative (Feilzer, 2010). To understand a phenomenon, practical consequences and empirical findings need to be studied (Johnson and Onwuegbuzie, 2004).

As construction management draws from both the natural and the social sciences, different philosophical stances are adopted in research in this field (Dainty, 2008). Dainty (2008) argues that the paradigms of both sciences should be acceptable, and ideally they should be used in combination with each other.

In light of this, pragmatism seems to be the appropriate choice. Due to this research project being in the field of construction management, thus in the middle between natural and social sciences, and because the output of it is intended to be a contribution to construction practice, the pragmatist philosophical stance was chosen.

3.2.2 Research approach

The chosen philosophical perspective determines the choices in the inner layers of the research onion. Table 3.2 shows examples for typical combinations.

Philosophy	**Approach**	**Methodology**
Positivism	Deduction	Quantitative
Interpretivism	Induction	Qualitative
Pragmatism	Deduction, induction, abduction	Mixed

Table 3.2. Philosophy-approach-methodology interaction (Based on (Saunders et al., 2016))

The second layer of Saunders et al.'s (2016) research onion shown in Figure 3.4 is the approach to theory development. Based on this, the research can be deductive, inductive, or abductive.

The difference between induction and deduction is the sequence of the steps of the research process. In the case of deduction, first a hypothesis is formulated based on the literature review and theoretical considerations, then comes the data collection resulting in findings, which either confirm or refute this hypothesis (Bryman, 2016). If the hypothesis (general statement) proves to be correct, then the specific statements coming from the general one are also true (Fellows and Liu, 2015). However, deduction might not advance knowledge, as it works within the limits of the extant knowledge (Fellows and Liu, 2015).

It is crucial that the conditions under which the hypothesis will likely to be confirmed are precisely specified and held constant throughout the data collection (Saunders *et al.*, 2016). This way it is ensured that the changes in the dependent variable have indeed been caused by the changes of the selected independent variables (Saunders *et al.*, 2016). It is also important that these variables are precisely defined and can be measured (Saunders *et al.*, 2016). The findings can only be generalised, if the sample size was sufficient (Saunders *et al.*, 2016). Deduction is usually applied in natural sciences (Saunders *et al.*, 2016).

In the case of induction, the sequence is just the opposite of the one described for deduction (Bryman, 2016). Here the observations come first, and the general statement comes as a conclusion from the findings (Bryman, 2016). Induction can advance knowledge, as it can yield hypotheses and push the limits of extant knowledge (Fellows and Liu, 2015). Induction is typically used in the social sciences, where the goal is to better understand the problem (Saunders *et al.*, 2016). The conditions are not strictly specified to allow room for new ones to be included (Saunders *et al.*, 2016). The sample size is not so crucial as it is dictated by the chosen method and the richness of the data collected (Saunders *et al.*, 2016).

The third approach is abduction, which is the combination of deduction and induction (Saunders *et al.*, 2016). The research starts as it would in the case of deduction; however, there are surprises among the findings making it necessary to formulate theories that can possibly explain these unexpected results (Fellows and Liu, 2015). Alternatively, it can start as induction would, then after the conceptual framework is ready, it is tested by a new round of data collection (Saunders *et al.*, 2016). Abduction allows for continuous movement between data and theory in order for new knowledge to be developed or existing theories to be modified (Saunders *et al.*, 2016; Awuzie and McDermott, 2017). Axelrod (2007) argues that applying simulation in the research means that both deduction and induction are used. The modelling starts in a deductive way, with a theory; however, the output of the simulation model can be analysed inductively (Axelrod, 2007).

Based on the above, the abductive approach was chosen for this research as both the existing literature and the observations informed formulating theory.

3.2.3 Research design

The next layer of the research onion in Figure 3.4 contains the possible methodological choices. Based on this, quantitative, qualitative, or mixed methods research design can be followed, where mixed methods refer to a combination of quantitative and qualitative methods. Figure 3.5 shows the methodological choices based on how many and what type of techniques are used for data collection and analysis. The selected methodology (simple mixed methods) is framed in blue.

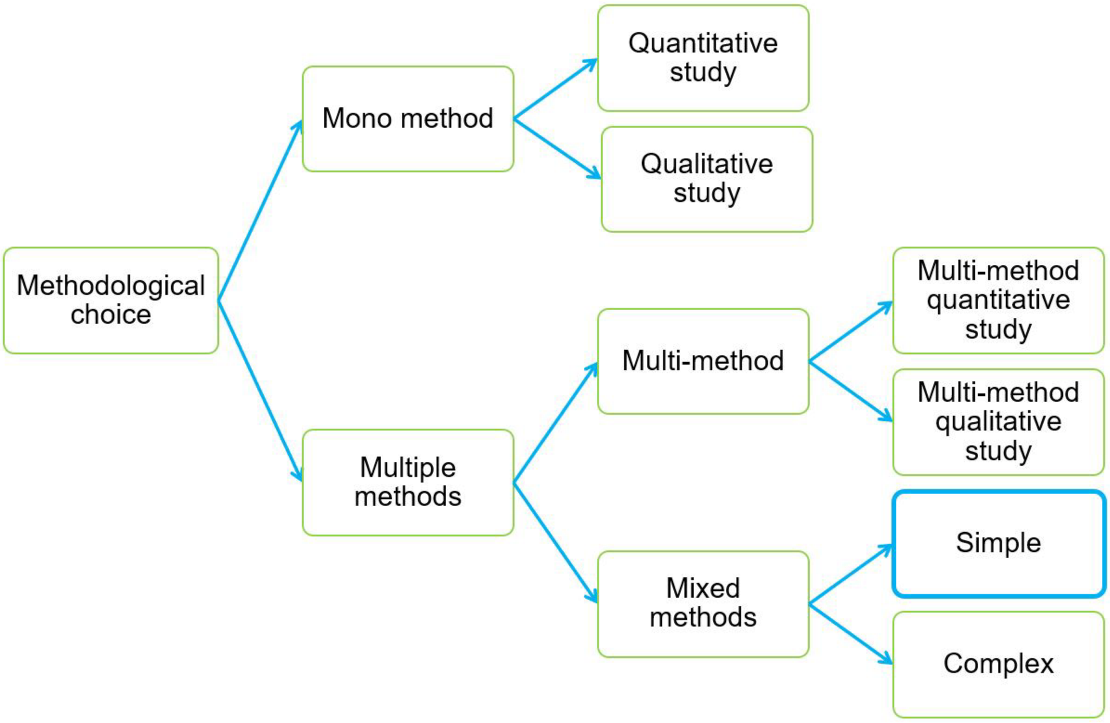


Figure 3.5 Methodological choices (Adapted from (Saunders et al., 2016))

If one procedure is applied for data collection and the subsequent analysis, then the study is called mono method. Within that quantitative and qualitative mono method studies are differentiated based on the type of the technique used. Another option is to apply multiple methods for data collection and analysis. If all chosen techniques are of one type, either quantitative or qualitative, then the study is a multi-method one. If both quantitative and qualitative methods are applied within one study, then that is a mixed methods research (Saunders *et al.*, 2016).

Table 3.2 shows likely combinations of philosophies, approaches, and methodologies.

Quantitative research is most likely positivist; however, it can be associated with realism, or pragmatism, as well (Saunders *et al.*, 2016). It usually adopts a deductive approach, an objectivist ontology, and a value-free axiology (Fellows and Liu, 2015; Bryman, 2016). Quantitative studies typically deal with numbers, they measure quantifiable variables, and analyse them using a range of statistical techniques to prove a theory (Saunders *et al.*, 2016).

Qualitative research is typically interpretivist; however, it can be realist or pragmatist as well (Saunders *et al.*, 2016). These studies often start with an inductive approach, but may also use deduction in certain phases (Saunders *et al.*, 2016). In qualitative studies, researchers focus on investigating social phenomena through the interpretations of the participants in order to better understand them (Bryman, 2016).

Mixed methods research is the combination of the previously mentioned quantitative and qualitative research designs. Simple and complex types are differentiated based on how the combination is handled (Saunders *et al.*, 2016). In the case of the former, the qualitative and quantitative components are running concurrently in one single data collection and corresponding analysis phase, whereas in the case of the latter, the components are sequential (Saunders *et al.*, 2016). If there are two phases: one qualitative and one quantitative, the research design can be sequential exploratory or sequential explanatory depending on which comes first. If the qualitative phase precedes the quantitative one, the study has a sequential exploratory research design (Saunders *et al.*, 2016). The research design can also be multi-phased (Saunders *et al.*, 2016). Mixed methods research can be either realist or pragmatist (Saunders *et al.*, 2016). It can adopt any approach, it can be deductive, inductive or abductive (Saunders *et al.*, 2016).

In this research project, both quantitative and qualitative methods are applied for data collection and analysis in one phase; therefore, concurrent mixed methods research design was chosen.

3.2.4 Research strategy

The fourth layer of the research onion shown in Figure 3.4 includes the strategies that can be chosen within the selected research design. The research strategy provides the methodological connection between the philosophical stance and the methods intended for data collection and analysis (Saunders *et al.*, 2016). It is an action plan to achieve the research objectives and answer the research question (Crotty, 1998).

By selecting the research design, the set of possible research strategies is given. Experimental and Survey Research are examples of quantitative options, qualitative ones also include Survey Research as well as Action Research, Ethnography, and Grounded Theory, and Case Study Research frequently encompasses Mixed Methods Research Design (Saunders *et al.*, 2016).

The decision of choosing the appropriate strategy is driven by the research questions and objectives; however, the available resources and access to potential data sources affect the selection as well (Saunders *et al.*, 2016).

The selected research strategy was Survey Research. Two survey methods were employed: structured observations and semi-structured interviews.

3.2.5 Research time horizon

A further choice within the research onion framework in Figure 3.4 concerns the time horizon of the research. Cross-sectional studies investigate a certain phenomenon at a particular point in time, while longitudinal studies focus on change (Saunders *et al.*, 2016). According to Bryman (2016), cross-sectional and longitudinal designs are research methodologies with the former being another term for survey research and the latter being an extension of survey research. Saunders et al. (2016) argue that while cross-sectional studies are mostly associated with survey research, they can also use qualitative or mixed methods strategies. Due to this research project being interested in the effects of certain factors on productivity, but not how this effect may change over time, the study can be categorised as cross-sectional.

3.2.6 Research methods

At the core of the research onion are the techniques and procedures used for data collection and analysis. The selected methods should be in line with the choices made in the outer layers of the research onion depicted in Figure 3.4. The structured observations and interviews used for data collection and the artificial neural networks, simulation and statistical analysis chosen for data analysis are described in the coming sections.

3.3 Sampling

In the majority of cases, it is not possible to collect and analyse data from every possible project, person, or case; a sample of them needs to be selected (Saunders *et al.*, 2016). The findings of the research can only be generalised if the sample is representative of the population of interest (Bryman, 2016).

The two main types of sampling techniques are probability and non-probability sampling (Saunders *et al.*, 2016). A possible categorisation of the different sampling options can be seen in Figure 3.6, where the selected technique (purposive) is framed in blue.

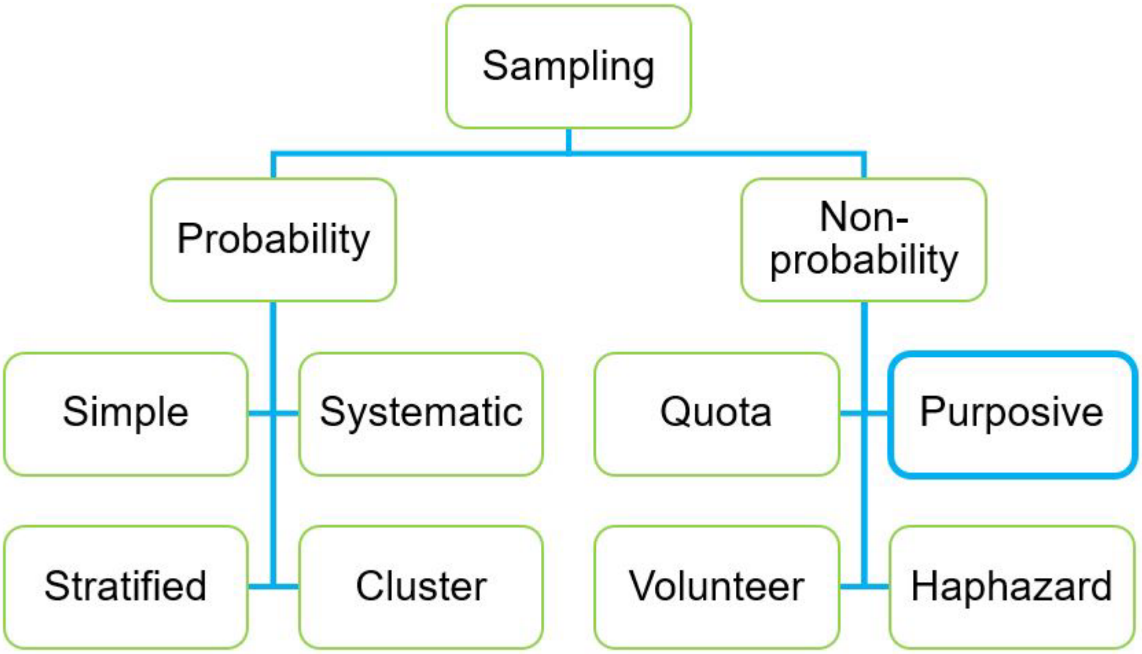


Figure 3.6 Sampling techniques (Adapted from (Saunders et al., 2016))

In the case of probability sampling, the selection is random; the chance of being included is the same for every member of the population (Fellows and Liu, 2015). Sometimes this is not possible as the sampling frame cannot be constructed (Bryman, 2016). In such instances, a type of non-probability sampling can be chosen. Most of these techniques involve subjective judgement (Saunders *et al.*, 2016).

This study focuses on the productivity of bricklayers; therefore, this trade constitutes the population of the research. Owing to most of the data collection being done through structured observations, the sampling was two-fold (Bryman, 2016). First, the appropriate projects were identified where access was negotiated, and then observations took place. Due to time and cost constraints, the study was limited to the investigation of projects in North East England, UK. The projects were chosen as a result of purposive sampling. Project managers and members of the CIOB's local hub were contacted to get information about projects involving substantial masonry works taking place during the doctorate timeframe. Finding projects with a significant amount of bricklaying was important as it allowed for a great number of observations of the same bricklayers. Based on these criteria, two projects were selected. These are introduced in Section 3.5.1.2. The pilot project described in detail in Section 3.5.1.1 was chosen through convenience sampling as it took place on the university campus.

The second component of sampling was the sampling taking place on site. This can be further broken down into two elements: choosing the time of the observations and the operation observed. According to Mundel (1985), sampling for the observations can be divided into two categories: intensive and extensive. The former means that for a limited period the same operation is observed, while the latter refers to the operation being observed at intervals for an extensive period of time. The time component of the on-site sampling is based on the observation schedule, which is discussed in detail in Section 3.5.1. Lastly, every effort was made to observe all bricklayers on the sites for an equal amount of time. However, not all bricklayers were performing all the different kinds of works. In addition, one company experienced high turnover.

The experts for the interviews were selected through purposive sampling. Since the interviews were conducted in person, the geographical constraint was the same as mentioned above for the projects. Bricklaying lecturers in the colleges in North East England were contacted via email. The interviews were scheduled with the respondents.

3.4 Ethical considerations

The considerations and choices described in the previous sections make the planning of the research process possible. After the necessary theoretical considerations, the theory needs to be put into practice, and the actual data collection and analysis can start. However, before the data collection can commence, several ethical issues need to be considered. It is essential to ensure that the participants are not harmed, their privacy is not invaded, and they make an informed consent to participation (Bryman, 2016).

The ethical risk level of the research project was designated medium because even though people participated in the research, they were not considered to be vulnerable. In addition, the data collection involves acquiring commercially sensitive information.

The ethical considerations can be divided into two main categories. The first includes measures to ensure the protection of personal and commercial data. Apart from the researcher and the supervisory team, no one has access to either the physical (e.g., drawings) or the digital data (e.g., photos) collected. This also means that the productivity rates measured by observing the subcontractors have not been shared with the contractors. Furthermore, the bricklayers were not informed about how their supervisors evaluated them.

The other group of issues are concerned with the researcher's behaviour on site. The participants of the study were informed about the details of the study, and signed consent forms to confirm that they agreed to be included in it.

Ultimately, the research project was approved by the Faculty Research Ethics Committee of Northumbria University's Faculty of Engineering end Environment in advance of the data collection commencing. The research process was conducted in compliance with the ethical guidelines of Northumbria University.

3.5 Data collection

For model development and analysis, data was collected in three ways. First, structured observations were conducted on two construction projects to study the process of bricklaying operations, bricklayers, and to take time measurements of the construction. The exact location and the bricklayer were always noted together with the time measurements. The usual organisation of masonry works was also observed. Secondly, the supervisors of the observed bricklayers were asked to evaluate the bricklayers based on pre-defined factors. These were necessary to study the effects of the factors on the productivity rate. Thirdly, semi-structured interviews with experts were conducted discussing the bricklaying process, bricklayers, and walls. The answers provided by the interviewees were used to better understand what was seen during the observations, to confirm the conclusions drawn from them, and to help with finalising the bricklaying process and the factors used in the model.

3.5.1 Structured observations

Structured observations allow data to be collected in a natural setting (Saunders *et al.*, 2016). As opposed to participant observations, in this case, the researcher is detached, does not take part in the observed activities (Saunders *et al.*, 2016). That is why they are also called non-participatory or non-participant observations (Dainty, 2008; Bryman, 2016). Early examples for structured observations are time and motion studies (Saunders *et al.*, 2016). The first ones were conducted based on Frederick W. Taylor's idea at the turn of the 20th century. Taylor (1919) proposed the adoption of scientific management in manufacturing, but also shared examples from construction. According to this, precise instructions have to be developed for every task and the workers have to be trained to perform the operations in that exact way. To achieve this, first the managers have to study how skilled workers do their jobs, break down the tasks into elementary motions, and measure the time it takes to perform each. Based on the collected data, the unnecessary movements need to be eliminated and the standard time for the task set (Taylor, 1919). Sanford Thompson worked for Taylor and in six years starting from 1896 he studied the eight most important construction trades including masonry. Due to this experience, he was able to improve Taylor's method (Taylor, 1911). Frank Gilbreth, who was originally asked to co-author a book with Thompson on the time and motion studies of masonry works, published his own book on bricklaying (Wrege *et al.*, 1997). In this, among other topics, he detailed the exact movements masons have to make when building a wall (Gilbreth, 1909). These were the findings of the earliest motion study of bricklaying. Gilbreth also created a system of motions that can be used for any activity: these are the therbligs (his name backwards) (Mundel, 1985).

The British Standard – BS3138:1992 (withdrawn without replacement on 10/02/2020) – uses the term work study as a summary term for all studies that investigate activities in order to make them more efficient. It refers to motion study as method study, and lists time study as a technique for work measurement. Time study is in the category of direct observations as the observer is physically present on site, while at other times the activities are recorded, and then analysed later, away from the site. The exact definitions in BS3138:1992 are the following (British Standards Institution, 1992):

- Work study: "The systematic examination of activities in order to improve the effective use of human and other resources".
- Method study: "The systematic recording and critical examination of ways of doing things in order to make improvements".
- Time study: "Observation, recording and rating of human work to establish the times required by a qualified worker to perform specified work under stated conditions at a defined rate of working. Times are recorded by direct observation, using a time measuring device; ratings are made simultaneously. Basic times are then derived by extension."

The last definition contains an element typically used in time studies: the rating. This means that during the observations the observer notes a percentage value together with each measurement. When selecting this value, the observer should consider the working conditions, the difficulty of the job, skills, effectiveness, and speed of the operatives but most importantly, their efforts (Mundel, 1985; Meyers, 1992; Olomolaiye *et al.*, 1998). The rating reflects how the measured time compares to a standard time (Mundel, 1985). Determining the correct ratings requires experienced observers (Olomolaiye *et al.*, 1998). In the case of this research project, rating was not used directly as the objective of the study was to determine the effect of the selected factors, most of which are considered when determining the rating, on the productivity rates.

Structured observations are conducted based on a set of rules, hence these are also called systematic observations (Bryman, 2016).

In the case of this research project, bricklaying works were observed. Because the process of bricklaying was to be modelled, a precise description of it was required. Performing observations, after reviewing the technical literature, aided this. However, for this project, the process did not need to be broken down into motions, as the goal was not to make it more efficient by omitting certain movements. Therefore, determining only the activities and their sequence was sufficient. Then, time measurements of performing these tasks were taken, with special emphasis on the laying bricks activity. Whenever it was possible, the time it took to build one course was measured, as this was long enough time to be meaningful and used for generalisation, but also short enough to measure. Always the net time was measured; however, note was made of any interruptions to the work, if there were any. Other tasks, such as preparation and jointing, were also observed and measured.

Bryman (2016) emphasised the importance of the observation schedule. The schedule of the observations of this research project was dependent upon the schedule of the construction projects visited, which determined what kind of works it was possible to observe and at which part of the site. The observation schedule needed to be flexible to follow the changes made to the project schedules. Sometimes the weather or equipment failure changed the plans on the day, on rare occasions even to the point of making observations impossible. The observations took place on different days of the week and at different times (morning, middle of the day, afternoon). The exact times were scheduled around the workers' break times. Varying times and days were chosen in order to decrease time error (Saunders *et al.*, 2016). Horner and Talhouni (1995) argued that there could be significant differences between the measurements taken on different days, on different sites, of different gangs. They have advised longer periods of observation to reduce this variability (Horner and Talhouni, 1995). In the case of this research project, the observations were conducted from when bricklaying works started to when they finished on site.

Another way of performing site observations is to use equipment to capture images or video, for example, by mounting these at certain locations on site or utilising the site's own surveillance system, then these photos or videos can be analysed either manually or automatically (Yang *et al.*, 2015; Kim and Chi, 2020; Ahmadian Fard Fini *et al.*, 2021). In this case, too many video cameras would have been needed to cover every façade of all the buildings that were constructed simultaneously. Therefore, the observations were carried out in person, by a single observer. Photos were taken to be used during data processing.

Taylor (1911) did not agree with Thompson concealing the stopwatches while conducting his studies, he argued that since the results of the measurements ultimately affected the workers, they should be informed about them. However, he accepted the advantages this can have when the observed workers are not affected by the results (Taylor, 1911). In this research project, the stopwatch application of a mobile phone was used. Although it was not concealed, its purpose was not obvious to the observed operatives.

The reactive effect is when the participant's behaviour changes due to being observed (Bryman, 2016). Finding the suitable place for the observations on the narrow scaffolding is not an easy task as – apart from the aforementioned phenomenon – it should also be considered that the observer cannot stand in the way of other operatives, who are working on the building. The participants were informed about the observations, but they took place from an appropriate distance so as not to cause unnecessary stress for the workers. Sometimes it was not possible to stay hidden, the experience was that the operatives forgot about being observed after some time passed. In addition, since the observations took place over a course of several months, the bricklayers got accustomed to the observer being on site, and sometimes they did not even notice their presence. Hajikazemi et al. (2017) reported a similar experience. However, on a few occasions, when a concealed position could not be found, the bricklayers became curious and wished to talk, which resulted in them not working as normal, making the measurements difficult.

3.5.1.1 Pilot study

Pilot observations were made at a school building construction project (Project A). The site visits took place from mid-September to mid-October 2018.
The building was an annex to an already existing building on a University Campus. The façade of the building was constructed using a steel framing system with brick and glass panels. The brickwork was quite unique because the brick bonding was the Flemish bond, which is common for historic buildings but not for modern ones. Here it was chosen to match the Flemish bond used for the original building. In the case of the new walls, the brickwork was only ½ brick thick instead of 1 brick thick, as it would be with traditional Flemish bond. *Figure 3.7* shows how the Flemish bond looks like.

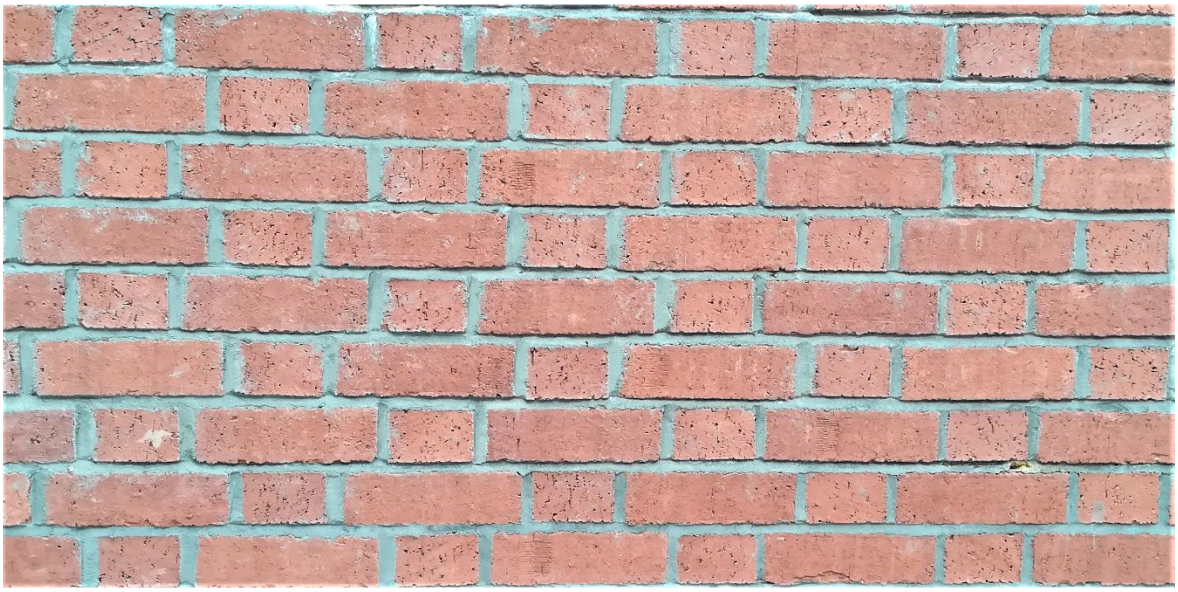


Figure 3.7 Flemish bond on Project A (photo taken by Orsolya Bokor in 2018)

Another interesting feature of the project was that 1/6 of the bricks had special shapes.
The unique features of this project and the short amount of time that could be spent on site did not allow for the time measurements made here to be used together with the measurements from the other projects. However, the observations made on this site were important for determining the bricklaying process and for establishing the way future observations were made.

3.5.1.2 Projects

The majority of the observations took place at two projects (Projects B and C). As mentioned before, they were both in North East England. Project B was a £30m sports complex construction project, which entailed the construction of one, steel-framed sports hall. On the ground floor, the external infills were cavity walls, where the inner leaf was a 100mm-thick block wall with rounded pointing and the outer leaf was a brick wall constructed of perforated Staffordshire blue engineering bricks with recessed pointing. The two leaves were tied together, and insulation was placed between them. The rest of the façade had metal cladding. The internal partition walls were 140mm-thick block walls with rounded pointing. In the case of all the walls, simple stretcher bond was used. Figures 3.8 and 3.9 show a block and a blue brick wall section, respectively.

Figure 3.8. Blockwork on Project B (photo taken by Orsolya Bokor in 2019)

Figure 3.9 Blue bricks on Project B (photo taken by Orsolya Bokor in 2019)

At this project, masonry works were subcontracted and performed by one masonry contractor. On average, eight bricklayers and four labourers were on site. 20 site visits took place between mid-November 2018 and mid-March 2019.

Project C, a £80m student accommodation complex, comprised of the construction of 12 buildings. Three buildings had little to no brickwork. Five buildings had brick façades; however, they were constructed using prefabricated modules with brick slip finishes. The remaining four buildings had brick façades, as well, and these were constructed in the traditional way, on site. Steel framing system was used for the external walls. The outer leaf was the brick wall, which was tied to the inner leaf with the help of channels mounted on the insulation, which only partially filled the cavity. There were two types of bricks used for these buildings. One was a stock brick with a single frogging in various shades of red, the other was a gray, solid concrete brick. The brick slips on the prefabricated modules matched these bricks in appearance. In the case of both bricks, simple, stretcher bond was used. The pointing was recessed on the red brick façades, and a combination of rounded and recessed on the gray brick walls. Red and gray brick wall sections can be seen in Figures 3.10 and 3.11, respectively.

Figure 3.10 Red bricks on Project C (photo taken by Orsolya Bokor in 2019)

Figure 3.11 Gray bricks on Project C (photo taken by Orsolya Bokor in 2019)

The bricklaying works of the two red brick and the two gray brick buildings were subcontracted to two different masonry contractors. On average, ten bricklayers and four labourers were on site. 27 site visits took place between mid-February and mid-June 2019. Table 3.3 gives a detailed description of the bricks and blocks used on the two projects.

Material	Type	Size	Dry density
Red brick	Stock bricks with a single frogging	215x102x65mm	1650 kg/m^3
Gray brick	Solid, concrete bricks	215x100x65mm	2100 kg/m^3
Blue brick	Perforated Staffordshire engineering bricks	215x102.5x65mm	1800 kg/m^3
Block of external wall	Solid, concrete blocks	440x215x100mm	2050 kg/m^3
Block of internal wall	Solid, concrete blocks	440x215x140mm	2050 kg/m^3

Table 3.3 Summary of material properties

3.5.2 Questionnaire for supervisors

To complement the data collected via observations, the supervisors of the bricklayers were also asked to evaluate the operatives by filling in a questionnaire.

In the case of questionnaires, the respondents have to answer the same set of questions (Saunders *et al.*, 2016). Self-completed questionnaires are sent to the respondents, for example, via email, and they answer at their own leisure, and return the answers (Bryman, 2016). Another possibility is for the researcher to ask the questions face-to-face, via phone, or online (Saunders *et al.*, 2016). This can be considered a structured interview (Bryman, 2016). The questions can be divided into two categories: open and closed (Fellows and Liu, 2015). Open questions allow the respondents to answer freely, in the form of their choice (Fellows and Liu, 2015). Closed questions, on the other hand, have a fixed number of answers determined by the researcher, from which the respondent can choose (Fellows and Liu, 2015).

In the case of this research project, the supervisors filled in the questionnaire consisting of closed questions during one of the site visits. The questionnaire asked them to put the operatives into one of three categories regarding each factor. The factors were the following:

- Quality: the quality of the work performed by the operative,
- Perceived speed: the pace with which the operative is working,
- Knowledge: technical knowledge, the operative knows how to build different walls,
- Independence: it refers to the operative knowing how to proceed, whether they can work without constant supervision.

The factors will be discussed in more detail in Section 4.1.2.
Table 3.4 shows the categories the supervisors could choose from regarding the factors. The experience of the bricklayers – expressed as the number of years spent working in construction – was also added to the table.

Factors	**Categories/Scale**		
	1	**2**	**3**
Quality	Acceptable	Good	Excellent
Perceived speed	Slow	Normal	Fast
Knowledge	Need to be improved	Adequate	Excellent
Independence	No	Medium	Yes

Table 3.4 Summary of factors in the questionnaire

The supervisors were chosen to evaluate the bricklayers as they were familiar with their work and could also be objective about their performance.

3.5.3 Semi-structured interviews

As the final part of data collection, semi-structured interviews were also conducted.
Based on how rigid the framework of the interview is, interviews can be categorised as structured, semi-structured, and unstructured (Fellows and Liu, 2015). In the case of structured interviews, the interviewer asks the questions verbatim, in the same order from all respondents. Unstructured and semi-structured interviews are also called qualitative research interviews (Saunders *et al.*, 2016). Unstructured interviews are similar to conversations, where the interviewer has a few notes aiding them to cover the topics (Bryman, 2016). As its name suggests, semi-structured interviews are halfway between structured and unstructured interviews. The interviewer usually has an interview guide, a list of questions they would like to ask (Bryman, 2016). However, additional questions can also be asked (Bryman, 2016). Despite this, the questions asked are mostly the same in the case of all the interviews (Bryman, 2016). Probing questions are often used in qualitative interviews. These are asked to further explore responses which are important to the topic (Saunders *et al.*, 2016).
In the case of this research project, two semi-structured interviews were conducted with purposively selected experts. The experts were both bricklaying lecturers at colleges with substantial industry experience. The mostly open-ended questions had been prepared in advance and had been divided into three categories: process, walls, and bricklayers (see Appendix B). The questions in the first group served to better understand the process of wall construction as it had been observed on site. Furthermore, questions about whether the process was the same at other parts of the country and Europe and if it had changed

over time were also answered. The second group of questions regarding the walls was used to map the most important wall characteristics. These helped with confirming and finalising the levels used in the difficulty factor and deciding what other wall factors to include in the model. The last group of questions focused on the bricklayers. Most of them concentrated on the skills of the bricklayers to help in finalising the worker characteristics used in the model. Some questions were concerned with the organisation of the work on site.

3.6 Data processing

Before the data analysis could begin, the collected data needed to be processed.
During the observations, field notes were taken. The majority of these were measurements. The most important ones of them were those of the laying bricks activity. It meant that the number of bricks laid and the time it took to perform this task were written down. ½ bricks were counted as whole bricks because the time it takes to lay them is the same for both. In addition, note was made of the bricklayer whose work was measured, and the location (building, floor, number of course) of the given course, as well. Based on these pieces of information, data tables were compiled. The rows represent the measurements. The first column contains the productivity rate. As mentioned in Table 2.2, the productivity rate best fitting research purposes is equal to the output divided by the productive time. In this case, the number of bricks laid were divided by the net times measured during the observations, as discussed in Section 3.5.1. The dimension of this continuous variable is bricks/hour. Next to this value come the factors one by one. These are all ordinal variables measured on a scale of 1 to 3. First of these are the worker characteristics: the quality, perceived speed, knowledge, independence scores given by the supervisors in the evaluation, and the experience category. With the help of the floor plans and elevations provided by the contractors, each wall section was given an ID, which was also included in the data table. The wall characteristics – the course difficulty and the material – have their own columns, as well.
Table 3.5 shows a few examples from the final, simplified data table, which contains the productivity rates with the corresponding values of the seven factors. Altogether there are 129 rows in this table; therefore, the ID runs from 1 to 129. (The examples in Table 3.5 appear transposed to better fit the page.)

ID	16	32	48
Productivity rate [bricks/h]	75	100	120
Quality	1	3	2
Perceived speed	2	3	1
Knowledge	1	3	3
Independence	1	3	3
Experience	1	3	2
Course difficulty	1	1	2
Brick type	1	3	2

Table 3.5 Examples from the data table

In some cases, only one measurement could be made for the two bricklayers working on a course. However, in the data table individual measurements were needed. Therefore, these time measurements were divided by two for the two bricklayers, and the average of the scores for quality, perceived speed, knowledge, independence, and experience was calculated. This meant that half-scores appeared in the data table for some factors.
After the first phase of modelling, to improve the accuracy of the model, six datapoints (#62, 78, 79, 81, 82, and 84) were removed. This will be explained in detail in Chapter 5. Table 3.6 shows the number of datapoints for each category. The distribution of the datapoints among the categories is not uniform because the bricklayers on each site were a given, and even though every effort was made to take the same amount of observations of the various bricklayers, due to the construction schedule and unexpected events, such as equipment breakdown, this was not always possible.

Factor/Scale	1	1.5	2	2.5	3
Quality (Q)	24	0	36	8	55
Perceived speed (PS)	10	0	36	18	59
Knowledge (K)	24	14	24	12	49
Independence (I)	14	14	26	16	53
Experience (E)	22	14	43	4	40
Course difficulty (CD)	83	0	34	0	6
Brick type (BT)	61	0	38	0	24

Table 3.6 Number of datapoints for each value of the factors

The time measurements of the other activities, such as the mounting of the profiles, were entered into a separate data table. In this case, the scores of the bricklayers performing the tasks were not part of the table, and the type of brick was only noted for the jointing activity.

The task durations of these activities were calculated as the average of the time measurements.
The time measurements (taken at Project B) for blockwork were processed in the same manner as those for brickwork. However, this data table was not used in later stages of the research project, as the collected data would not have been enough for the first part of the modelling. After adding more observations to these in the future, the data could be used for modelling blockwork and a comparison with brickwork would be possible.

3.7 Modelling

After the data table was ready, modelling could start. The developed model was a hybrid comprised of artificial neural network (ANN) and discrete-event simulation (DES) components. The former was used to determine the productivity rate for the activity laying bricks. The networks were trained and tested with the data in the assembled final data table, and the best performing networks were chosen. Then a model project was defined, and input into these. The output of this part of the model was used as the input for the simulation component. The effects of the selected factors were also examined with the help of the ANN model component. DES was used to model the process of brickwork to obtain the process duration and to examine the various resource allocation options.
Modelling is briefly introduced in this section. More details about the selected factors and the bricklaying process will be provided in Chapter 4, while Chapters 5 and 7 will explain the ANN and DES model components, respectively.

3.7.1 Artificial neural networks

ANN modelling was chosen to explore the relationship between the factors and the productivity rate because it is able to handle these complex links, learn from even imperfect datasets, and capable of making generalisations based on them (Chao and Skibniewski, 1994; Flood and Kartam, 1994a).
In the feedforward networks created, the input, hidden, and output layers of the ANN were connected in this order. The input layer consisted of one neuron for each of the seven factors, while the output layer had one neuron for the forecasted productivity rate. The network was trained in a supervised way, meaning that the values of the input variables and the targeted output values were fed into it. The values came from the data table produced during the data processing explained in the previous section.
Hundreds of networks were created by changing various settings. One of them was the number of hidden neurons and layers. The networks had hidden neurons between 5 and 20 in one or two layers. Other than modifying the network architecture, six different learning algorithms, according to which the weights and biases are calculated in the network, were also tested. Finally, various transfer functions, which change the value of the input going

into the neurons, were checked; different combinations of tangent sigmoid, log-sigmoid, and linear activation functions were used.
The created networks were ranked based on their correlation coefficients, the mean squared errors, and the mean absolute percentage errors, and the best performing networks were chosen. Sensitivity analysis was run on these networks to determine how the factors affect the productivity rate.
A model project was created with model bricklayers and wall sections. These became the input for the ANN component. The output provided by the above-mentioned networks for the model project input was used as the input for the DES model component.

3.7.2 Simulation

Simulation can be well used to model construction operations, as this way the uncertainties, dependencies, and complicated behaviour inherent to construction can be captured. In addition, simulation allows for experimenting on systems (Law, 2015; White and Ingalls, 2017). Discrete-event simulation is a simulation method that was chosen because it focuses on the process itself, and can provide the process duration, which was the purpose of the model. Moreover, resource allocation options can also be tested with the help of DES.
Due to two methods being combined in a hybrid model, the structure and the interaction points had to be defined. The ANN and DES components made up a sequential structure, as the ANN part was run first, and its output became the input of the DES component, which provided the final output of the model. The interface variable, i.e., where the two components were linked, was the productivity rate of the activity laying bricks calculated by the ANN component and input into the DES component.
For building the model, first, the process of brickwork was defined based on the observations and the interviews. The steps of the workflow became the tasks defined in the DES model. The duration of these activities was determined next. The duration of the activity laying bricks was provided by the ANN model for the model project data input, while the durations of the other tasks were from the data table assembled based on the observations. Finally, the labour resources were assigned to the tasks. Various model bricklaying gangs were created and tested to investigate which pairings were the most productive.

3.8 Statistical analysis

As mentioned before, the ANN model component was used to examine the effects of the factors on the productivity rate. However, ANN works as a black box, where the calculations are hidden from the users (Boussabaine, 1996; Adeli, 2001). Therefore, to complement these, statistical analyses were also performed to investigate the effects of the factors individually and together on the productivity rate in a more transparent way. In order for the results to be comparable to those of the ANN model component, the same data table was used. The analysis and the results will be presented in Chapter 6 in detail.

First, the normality of the distribution of data in each category of the factors and the homogeneity of the variances of each group needed to be checked because the outcome of these determines whether parametric or non-parametric tests should be used to study the effects of the factors on the productivity rate. To examine normality, Kolmogorov-Smirnov and Shapiro-Wilk tests were run, and the skewness and kurtosis values were studied. The homogeneity of the variances was checked using Levene's and Hartley's tests. Due to not all categories following a normal distribution and having homogeneous variances, both parametric and non-parametric tests were performed. From the former group the F-statistic of the one-way analysis of variance, in the case of homogeneous variances, and the F-statistic of the Welch's test and the Brown-Forsythe's test, in the case of heterogeneous variances, was examined to determine which factors had a significant effect on the productivity rate. In addition, planned contrasts were also performed to study which categories were significantly different from the others within a given factor. From the non-parametric tests, Kruskal-Wallis tests were performed to find the factors with a significant impact on the productivity rate. These were complemented by pairwise comparisons to determine the categories that were significantly different from the others.

Finally, regression analysis was also performed to examine how each factor influenced the productivity rate. Some of the models created included all the factors, while others were comprised of only selected factors.

Statistical analysis was also performed on the process duration data generated with the DES model component for the model project data input. The same tests were performed as mentioned above, except for the regression analysis. The results will be discussed in Chapter 8.

3.9 Chapter summary

This chapter discussed the decisions – from the philosophical considerations, through research design, to research methods – made about conducting the research with the help of the 'research onion'. Data collection and processing were also presented in detail.

For modelling bricklaying works, it was necessary to collect information on bricklaying operations and bricklayers. This was achieved in multiple ways. The most prominent one was through structured observations, which took place on two construction sites in North East England from mid-November 2018 to mid-June 2019. Three different masonry sub-contractors worked with the three different materials used; therefore, altogether 21 bricklayers were observed. Based on the time measurements and the evaluation of the bricklayers by their supervisors, the data table was produced, which was used for the modelling and was also analysed with statistical methods. Besides the measurements, the process of bricklaying was also observed because the steps had to be determined for the sequence defined in the simulation model. Semi-structured interviews with experts were also conducted. The questions were mostly open-ended and were divided into three categories: process, wall, and bricklayers. The responses were used to better understand these topics. For example, the ones in the process group helped finalise and verify the workflow in the DES model component. Modelling was also briefly discussed in this chapter, it will be presented in detail in Chapters 4, 5, and 7. The particulars of the statistical analyses can be found in Chapters 6 and 8.

CHAPTER 4

MODELLING PART 1: PRODUCTIVITY INFLUENCING FACTORS AND THE BRICKLAYING PROCESS

4.1 Determining the factors

4.1.1 Important labour productivity influencing factors

Labour productivity, in general, is influenced by a great number of factors. As detailed in Chapter 2, considerable research efforts have been devoted to list and categorise these, and to determine the most important ones. The rankings may differ from country to country or depending on, for example, which stakeholder group's (contractors, craftsmen etc.) point of view they represent. Usually, when modelling construction operations or specific works, a smaller subset of factors is selected in order for the model to be useful and still manageable. Graham and Smith (2004) recommended that at each stage only the known and significant variables should be included in the model. However, not every factor lends itself to simple measuring (Horner and Talhouni, 1995).

One possible way to divide the productivity influencing factors is based on how they can be taken into account in the planning phase of construction projects:

- known in advance: These are the factors that can be considered in the planning phase because they are known and can be regarded as constant, as in they are not going to change during construction.
- unknown, can be changed: These factors are unknown prior to construction, therefore, cannot be taken into consideration, when planning the construction phase. However, for instance, with proper management, they can either be avoided, or handled when they arise.
- unknown, cannot be changed: These factors are unknown prior to construction, and while their effects might be mitigated, their causes cannot be modified.

Table 2.4 in Section 2.6 summarised the productivity impacting factors collected by studies of bricklaying works. These were categorised into design, gang, management, site-related, and external factors. Design-related factors (e.g., difficulty of works), most of the gang-related factors (e.g., experience of workers), and part of the management-related factors (e.g., working days and hours) belong to the first group in the categorisation above because these are known in the planning phase of the project. The second group (unknown, can be changed) includes site-related factors, such as, site congestion as these issues can be overcome during construction. On the other hand, the external factors, for example, the weather, cannot be changed. Thomas and Sakarcan (1994) suggested that factors that can be predicted in advance can be used for forecasts. In line with this, this study focuses on factors that belong to the first category because it aims to help better plan projects; therefore, the factors considered are known prior to construction.

Hasan et al. (2018) argued that productivity could only be improved by studying the work itself and the workers performing the work. This recommendation has been confirmed by various productivity research efforts, which found that the skills and experience of workers to be one of the most important productivity influencing factors. See, for example, Tsehayae and Robinson Fayek's (2014), Hamza et al.'s (2019), or Karthik and Kameswara Rao's (2019) studies. Alaghbari et al. (2019) found that technical factors, such as design complexity, were also important along with experience and skills.

Despite skills and experience ranking high in numerous studies and the general shortage of trained construction workers, most of the bricklaying productivity models did not include these factors. For example, the factor model developed by Thomas and Yiakoumis (1987) and further improved by Thomas and Sakarcan (1994) and Sweis et al. (2009) did not take these factors into account; however, it did include design-related ones. The latter study used the work complexity scale determined by Thomas and Završki (1999) as did Thomas and Sudhakumar (2014). Experience and a few design-related factors were included by Gerek et al. (2015), Aswed (2016), and Al-Somaydaii (2016) but not skills.

Even though skills ranked high in a number of studies, it was not explained what exactly was meant by the term. When skill shortage is mentioned, or government policies, skills are usually measured by qualification levels (Vogl and Abdel-Wahab, 2015). In the case of a handful of studies, skills were included and defined, as well. One such model is Olomolaiye's (1988), where skills were the function of natural mental and physical abilities, training, and experience, which are reflected in speed. Another example is Florez's (2017) study, where skill was defined as being good at specific works. This model considers which type of walls the given bricklayer is better suited to: brick or block walls, detailed or non-detailed walls. Wall difficulty was also considered (Florez, 2017).

Horner and Talhouni (1995) argued that great variations in daily bricklaying output was due to people, project, and site-related factors. The first group contained factors such as the quality of work, the speed, and skills of workers, which made the selection and training of workers important. In this case, skills were meant as the ability to solve problems. Adequate quality was required to avoid wasteful rework, while speed was seen as something that would come and go with experience. Based on the conducted interviews described in Section 3.5, bricklaying training in the UK seems to agree with this, as the practical assessments of the students are marked based on quality: the work needs to be within the acceptable tolerances set by the National House Building Council based on the British Standard. Students learn to build walls of proper quality and are hoped to improve speed in time. This is the opposite of what Gilbreth (1909) recommended. He suggested that speed was more important and the skills would come with time (Gilbreth, 1909). Now students are also trained to build different types of walls (different bonds, straight and curved walls, decorations), using various materials (bricks, blocks), how to read and interpret drawings, and do necessary calculations.

4.1.2 Factors used in the artificial neural network (ANN) model component

Based on the above, this study aimed to explore how worker- and design-related factors affect bricklaying productivity. Out of the worker-related factors skills and experience were chosen. Skills were broken down into a further four factors: quality, perceived speed, knowledge, and independence. From the design-related factors, course difficulty and brick type were selected.

Quality, perceived speed, and knowledge were mentioned in previous studies, while independence was not. The bricklayers working on the observed projects were evaluated by their supervisors based on these characteristics. The categories of them are explained in Table 4.1. Following on from the nature of the evaluation, these factors are subjective.

Quality refers to the quality of the work performed by the bricklayer. The categories go from acceptable to excellent as below acceptable quality, the work needs to be redone. Therefore, it is assumed that the quality of the bricklayer's work have to be acceptable at least for them to be employed as a bricklayer on a project. Perceived speed is the pace with which the bricklayer is usually working in the supervisor's opinion. Knowledge refers to the bricklayer's technical knowledge, whether they are familiar with how to construct various wall types, using different bricks etc. Independence means that the bricklayer is capable of working on their own, without the need for constant supervision, after finishing one wall section, they are able to find what to do next.

Determining the experience category was based on the number of years the bricklayer has worked in construction. Bricklayers with less than 10 years of experience were put into the first category, and with more than 30 years into the third one.

Factors	**Categories**		
	1	**2**	**3**
Quality	Acceptable	Good	Excellent
Perceived speed	Slow	Normal	Fast
Knowledge	Need to be improved	Adequate	Excellent
Independence	No	Medium	Yes
Experience	Limited	Medium	Substantial

Table 4.1 Summary of bricklayer-related factors

Altogether the work of 21 bricklayers was observed on the two projects. Table 4.2 shows their distribution among the categories of the worker-related factors.

Factor/Scale	1	2	3
Quality (Q)	4	3	14
Perceived speed (PS)	1	11	9
Knowledge (K)	4	6	11
Independence (I)	3	4	14
Experience (E)	5	6	10

Table 4.2 Distribution of bricklayers among the categories of the factors

Two design-related factors were considered: course difficulty and brick type.
Most of the studies mentioned above and in Chapter 2 collected daily output data; however, as Horner and Talhouni (1995) observed, there could be great variations between these datapoints. Their suggestion was to have longer intervals between the productivity calculations (Horner and Talhouni, 1995). However, it is worth considering that if the "readings" are closer to each other, then they are impacted by potentially fewer factors, which may also be observed. Consequently, in this study, the time it took to measure a course of brickwork was measured. As a result of this, the difficulty levels also needed to be determined per course. The basis of categorisation was Thomas and Završki's (1999) work content scale, which has been used – as shown before – in numerous bricklaying studies. However, it was developed for describing projects, not individual courses because it was paired with daily output measurements. Here, three course difficulty levels were defined: easy, medium, and difficult. These are illustrated in Table 4.3. The courses belonging to the easy category are the straight ones with only half-cuts. In the work content scale, level 1 projects predominantly have long, straight walls (Thomas and Završki, 1999). Medium courses are divided by openings, such as doors and windows, and might have corners or movement joints within them. Ordinary openings at regular intervals describe most walls in the work content scale (Thomas and Završki, 1999). The most difficult courses are characterised by custom cuts next to decorative elements (for example, an arch), various vents, or, for instance, because the top edge of the last course at the top of the building is not horizontal. These all need to be measured individually. In the work content scale, some ornamental work differentiates level 3 from level 2. Levels 4 and 5 contain walls with extensive ornamental work, non-perpendicular corners, and various sized units (Thomas and Završki, 1999). Since such walls were not observed, these levels were not used in this study.

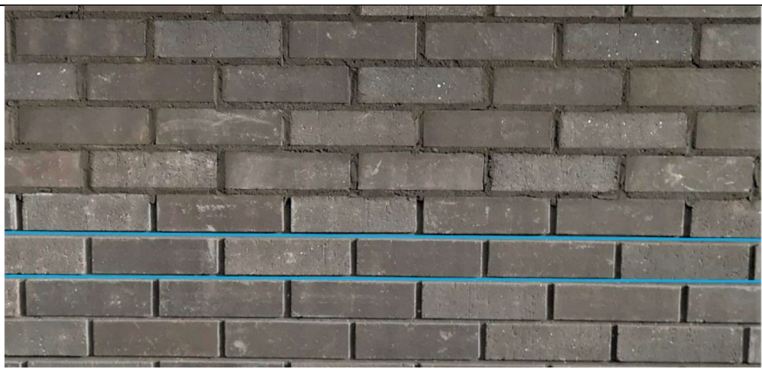
1		**Easy** Half-cuts only Straight courses
2		**Medium** Openings (windows, doors) within the course Corners, movement joints Half-cuts only
3		**Difficult** Custom cuts next to vents, decorative elements, at the top of the building

Table 4.3 Course difficulty levels (Photos taken by Orsolya Bokor in 2019)

The other design-related factor selected in this study is brick type. The construction of three different types of brick walls was observed. Table 4.4 summarises the most important characteristics of the bricks. The order red-gray-blue reflects the difficulty of building with these bricks based on the site observations and interviews.

1		**Red bricks** stock brick, single frogging, various shades of red, 215x102x65mm, dry density: 1650 kg/m^3
2		**Gray bricks** concrete brick, solid, gray, 215x100x65mm, dry density: 2100 kg/m^3
3		**Blue bricks** Staffordshire engineering brick, perforated, blue, 215x102.5x65mm dry density: 1800 kg/m^3

Table 4.4 Brick types (Photos taken by Orsolya Bokor in 2019)

The red bricks are stock bricks, meaning that there could be easily detectable size differences between the individual bricks making it harder to keep the vertical joints running nicely down the entire façade in perfect lines. However, these irregularities in size also allow for slight irregularities in the final wall to be aesthetically acceptable. In addition, these are the easiest to work with because of they absorb water from the mortar quickly helping with setting. Furthermore, the frogging (the indentation on the top of the bricks) prevents floating and makes it easier to cut.

The gray bricks are solid concrete bricks, which makes them uniform, hence easier to lay them to a line. On the other hand, their water absorption is lower making setting slower. Moreover, the lack of frogging means that they are more prone to floating and can be easily moved inadvertently before the mortar sets.

The blue bricks are engineering bricks used for their low water absorption characteristic. However, this also means that the setting of the mortar takes the longest in their case, and they easily float, as well. Fewer courses can be laid at the same time. Also, jointing is the most difficult in the case of blue brick walls. This is the bricklayers' least favourite brick to work with.

4.2 The process of bricklaying

For the discrete-event simulation (DES) component of the model, the steps of wall section construction need to be determined. In this study, the process of building the outer leaf of a cavity wall is used as an example because this was observed during data collection. The basic principle is the same for any kind of wall construction; therefore, the model can be easily adjusted to other types of walls.

The projects where the observations took place were introduced in Section 3.5.1. Altogether three different types of bricks were used for the brick façades as shown in Table 4.4. A sample cavity wall section can be seen in Figure 4.1. The inner leaf in this case was a steel framing system. The insulation partially filled the cavity. The outer leaf was connected to the insulation through ties placed in the channels mounted to it. The photo shows the red bricks used in the case of two buildings, while in the case of another two buildings, gray bricks were used instead of the red ones, but the layers were the same. In the case of the sports hall, a 100mm-thick solid, concrete block wall served as the inner leaf, while blue bricks made up the outer wythe. The insulation partially filled the cavity. Ties connected the two leaves. These were embedded in the mortar beds on both sides.

Figure 4.1 Cavity wall construction (Photo taken by Orsolya Bokor in 2019)

The steps of building the outer brick leaf of a cavity wall are shown in Figure 4.2. The process described here is based on site observations and interviews.

Figure 4.2 Process of brick wall construction

The first task is preparation. This means that the necessary materials and tools need to be placed in front of the given wall section. This includes stacking bricks and placing mortar (or spot) boards. However, other materials, such as various ties, weeps, damp proof course, different tapes, movement joint fillers, are also needed. All these can be stored on loading platforms of the scaffolding; therefore, this step means that the materials are moved from there to the wall section. Usually, during the construction, pallets of bricks and mortar tubs are transported to the loading platforms from material depots on site by designated labourers using forklifts. Preparation can either be done by labourers or bricklayers depending on gang composition. Generally, the supply of bricks and mortar is continuous, as often not the whole amount needed for a wall section would fit in front of it. If there are labourers to bring the materials, then this can be done parallel to the construction of the wall. However, if one of the bricklayers is responsible for this, then at times they have to stop laying bricks to get the materials interrupting the process. The necessary tools and equipment include, for instance, various trowels, spirit levels, profiles, lines, measuring tapes, boxcutters, chisels, hammers, brick clamps, depending on the jointing type, chariot jointers.

Once all the necessary tools and materials are available by the wall section to be built, the metal or wooden profiles need to be mounted. Figure 4.3 shows one in use with pink line attached to it. The profiles on either side of the future wall section mark the start and finish points of the courses. They also need to be perfectly vertical; therefore, their position is checked by a spirit level. The markings on the profiles ensure the gauge, i.e., that every course is of the same height. The line, which is used for making sure that the courses are level, is stretched between the two profiles at the correct level in order for the outer top edge of the bricks to be laid to it.

Figure 4.3 Profile and line (Photo taken by Orsolya Bokor in 2019)

Laying bricks takes up the most time in the process, the productivity of this task determines the productivity of the process; therefore, the observations were focused on this. The borders of the wall section are usually corners or movement joints. The line cannot be stretched over more than 30-40 bricks, otherwise there would be considerable sagging resulting in level issues. The height of the wall section is determined by the lifts. Approximately 1.5 m of brickwork can be built by the bricklayers standing on the same level of the scaffolding. The number of courses that can be laid in a day depends on the type of brick, mortar, and the weather. On every floor there is a damp proof course guiding the water from the cavity through the weeps to the outer side of the wall. This black membrane can be seen in Figure 4.4 before it was cut to fit the outer plane of the wall. The weep is circled in red in the photo. About every fourth brick is removed – usually before jointing is started – in this course, and hessian sheets are woven through them. These are used to clean the cavity from the mortar that falls in during the construction of the wall section.

Figure 4.4 Hessian, weep, damp proof course (Photo taken by Orsolya Bokor in 2019)

The laying starts by spreading mortar in the length of approximately three bricks, then the bricks are placed one by one with one end of them covered in mortar for the vertical joints. The face of the bricks is constantly cleaned of excess mortar, while from the back mortar is usually removed at the end of each course. If the bricks need to be cut, either a brick cutter or a combination of hammer and chisel are used. After the entire course is laid, the line needs to be moved into its next position, and the laying starts again. From time to time, the plumb (verticality) of the built part of the section needs to be checked by a spirit level.
Two types of ties are used, and both need to be placed in-between courses. One is for providing connection between the two leaves of the wall. The other ties the neighbouring wall sections together. Figure 4.5 shows both types.

Figure 4.5 Ties (Photo taken by Orsolya Bokor in 2019)

After the courses of the wall section have been laid, the profiles can be removed. The last step is jointing, i.e., the tidying of the joints. The time that needs to pass between the laying of the bricks and jointing depends on the type of the brick, the mortar, and the weather. The type of jointing determines the tools that are used for this task. The different jointing options are shown in Table 4.5.

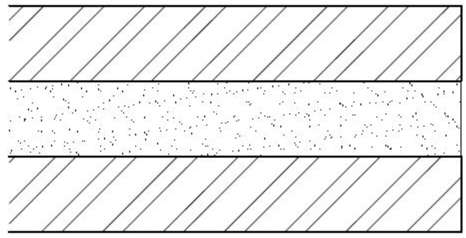
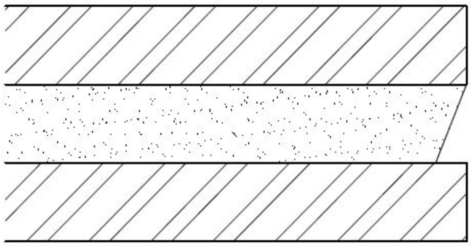
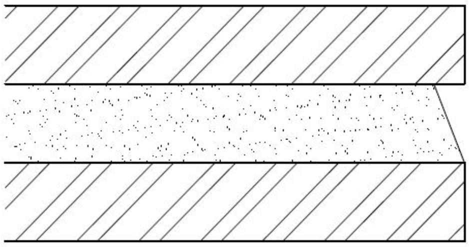
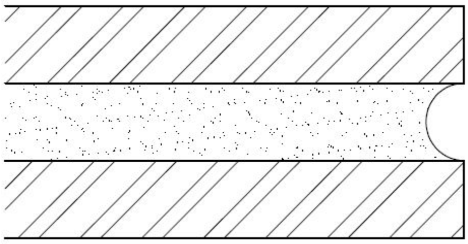
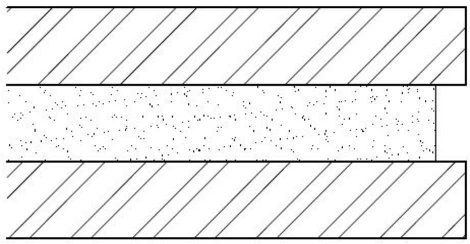
	Flush
	Struck
	Weather-struck and cut
	Rounded or tooled
	Recessed

Table 4.5 Types of jointing (based on Carruthers and Coote (2013)*)*

In the case of the observed projects, recessed joints were created with the help of chariot jointers. The only exception was the vertical joint of the gray brick walls, which were rounded, shaped by jointing irons. Jointing is usually done from the top of the wall section, moving down. First the vertical, then the horizontal joints are tidied. After jointing, the brick surface is brushed to remove any mortar specks or other stains.

Figure 4.6 shows a blue brick wall section, where jointing has not been done in the top five courses (above the red line) but has been finished in the lower section (below the red line).

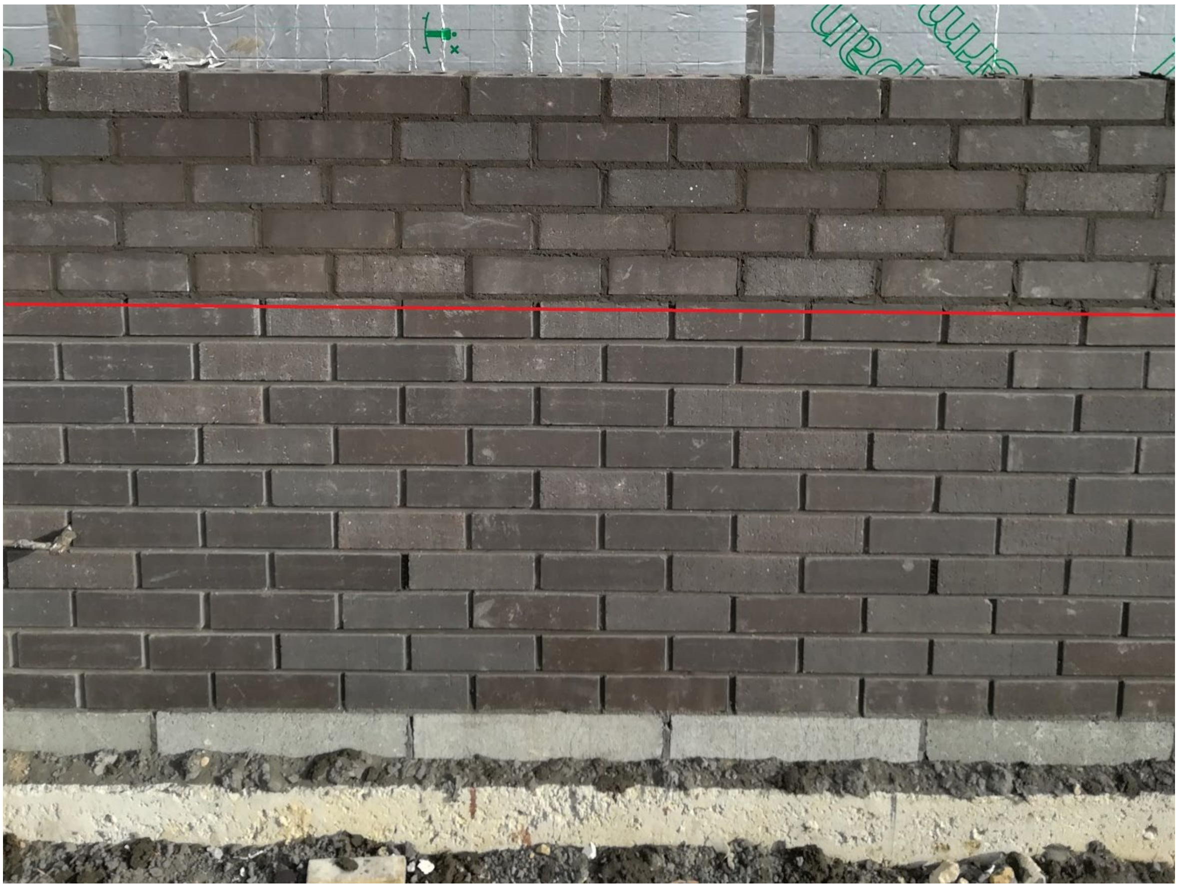


Figure 4.6 Brick wall before and after jointing (Photo taken by Orsolya Bokor in 2019)

Based on the observations and the interviews, it can be stated that usually two bricklayers work on a wall section, going from opposite directions. Therefore, in this study, the term bricklaying gang refers to a gang of two bricklayers.

4.3 The hybrid DES-ANN model

The basic building blocks of the model were introduced above. Figure 4.7 shows the structure of the model. It consists of two main components: an artificial neural network (ANN) and a discrete-event simulation (DES) part, thus creating a hybrid DES-ANN model.

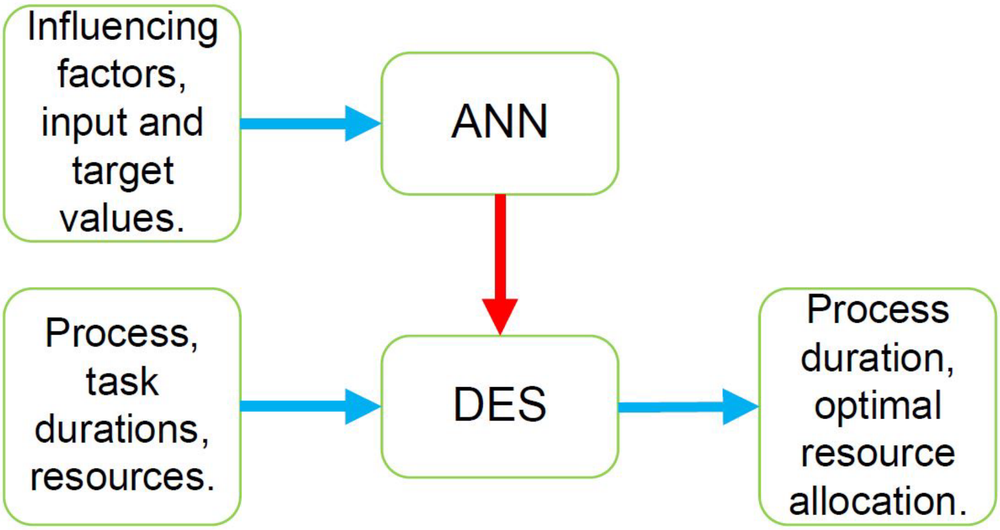


Figure 4.7 The hybrid DES-ANN model structure

As detailed in Section 3.6 a data table was compiled based on the measurements of the work study, the supervisors' evaluation of the workers, and the observations concerning the wall types. This way each productivity rate measurement for the laying bricks task (in bricks/hour) had a corresponding value for the worker-related factors (quality, perceived speed, knowledge, independence, and experience) and the wall-related factors (course difficulty and brick type). This data table was used to train, test, and validate the ANN model component. This part of the model provided the duration for the laying bricks task in the DES model component. The ANN model component is described in detail in Chapter 5.

The steps of the bricklaying process shown in Figure 4.2 were the tasks defined in the DES model component. The task durations were determined based on the measurements obtained through the site observations, and for the laying bricks task by the ANN part of the model. The necessary labour resources were assigned to the tasks based on the site observations. The DES part of the model provided the process duration and the optimal way of labour resource allocation. The DES model component is described in detail in Chapter 7.

It is worth noting that the process duration that the DES model component provides is the productive time. Usually, the total time needed for construction includes unavoidable and avoidable delays on top of the productive time (Horner and Talhouni, 1995; Greenwood and Shaglouf, 1997). Total time can be considered as the sum of productive, unproductive, supervision, and relaxation time (Olomolaiye, 1988). Relaxation includes the official breaks, for instance, for lunch. This always needs to be part of the working day. Supervision time refers to receiving instructions and discussing issues with the supervisors. Unproductive time can stem from many sources. It might be unavoidable, for example, due to the weather. For instance, brickwork should not be built in freezing conditions. Avoidable delays, such as ones owing to material shortage or equipment breakdown, can be avoided or handled well with proper site management.

4.4 Chapter summary

This is the first of three chapters discussing the developed hybrid model combining discrete-event simulation (DES) and artificial neural networks (ANNs). The first part dealt with the productivity influencing factors chosen for this study. This was done based on the literature review, the observations, and the interviews conducted. Since the model aims to help construction project planning, those factors were considered which can be known in the planning phase of the projects. Due to this, worker (quality, perceived speed, knowledge, independence, experience) and wall-related (course difficulty, brick type) factors were selected, which were explained in detail. Then the bricklaying process was presented, discussing the steps, and illustrating it with photos from the observations. Finally, the DES-ANN hybrid model was briefly introduced. The model will be discussed in detail in Chapters 5 and 7.

CHAPTER 5

MODELLING PART 2: ARTIFICAL NEURAL NETWORK COMPONENT

5.1 Artificial neural networks (ANNs)

5.1.1 Selection of artificial neural networks

In productivity studies, the effects of different factors on the productivity rates are analysed. However, these relationships between the various factors and the productivity rate, and especially the factors' combined effects are complex, thus making modelling challenging (Chao and Skibniewski, 1994). Owing to this, productivity studies can benefit from artificial neural networks (ANNs). ANNs can be trained to learn from even imperfect datasets and provide quick and generalised solutions to a problem (Flood and Kartam, 1994a). ANNs can be used for modelling problems in which functional relationships between dependent and independent variables are subject to uncertainty, not understood, or may vary with time (Di Franco and Santurro, 2020). For all the above-mentioned reasons, they can perform better than traditional, statistical methods (Boussabaine, 1996) or even optimisation algorithms, which can operate slowly when the problem at hand involves a large number of variables (Flood and Kartam, 1994a) or when generalisation and patterns extracted from large datasets are the bottom line. Consequently, in this study, ANNs were selected to predict the bricklayers' productivity rate based on the chosen worker and wall characteristics, and to determine the effects of these factors on the productivity rate and the interrelationships between the factors.

5.1.2 Introduction to artificial neural networks

Artificial neural networks – similar to the human brain and the central nervous system – are able to learn and generalise from examples (Boussabaine and Kirkham, 2008). The components of the network are called neurons, processing elements, or nodes (Moselhi *et al.*, 1991; Boussabaine, 1996). These neurons are organised into three types of layers: input, hidden, and output layers. In any given network, there is one input layer, and one output layer, while the number of hidden layers varies. Figure 5.1 shows the topology of an ANN model.

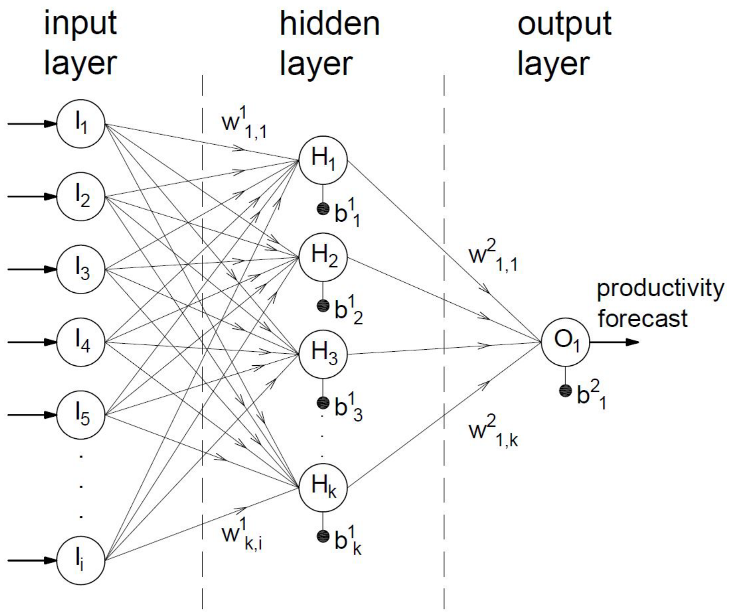


Figure 5.1: ANN model architecture

As can be seen in Figure 5.1, the neurons in the network are connected to each other. Each of these links have a weight (w) showing the strength of the connections (Boussabaine, 1996). The input variables are fed into the input layer, then the signal arrives to the nodes of the hidden layer through the links, and finally, it is transmitted to the output layer. However, the weights of the connections modify the signal that arrives at the output neurons (Flood and Kartam, 1994a). Equations (1) and (2) give the value of the signal at the hidden and the output layer respectively in the network depicted in Figure 5.1 (Flood and Kartam, 1994a).

$$h_n = f_h\left(\sum_{x=1}^{i} w_{n,x}^1 * i_x + b_n^1\right) \tag{1}$$

$$o_1 = f_o\left(\sum_{n=1}^{k} w_{1,n}^2 * h_n + b_1^2\right) \tag{2}$$

where f: transfer function, w: weight, b: bias.

The learning method determines how the weights change over the course of the training (Boussabaine, 1996).

Based on what the network has learnt, it will be able to predict the outcome when presented with new input data points (Boussabaine and Kirkham, 2008). ANNs work like a black box, where the magic happens in the hidden layer, hidden from the user (Boussabaine, 1996; Adeli, 2001). This is in contrast with classic statistical analysis, for example, regression analysis, where the relationships between the dependent and independent variables are apparent. In the case of regression analysis, the class of the relationship needs to be determined beforehand, and frequently linear relationships are assumed (Sonmez, 1996).

However, in construction management problems, the relationship between the input and the output is typically complex due to unknown combined effects (Chao and Skibniewski, 1994) and ANNs are well-suited to handle such cases. Despite this, interpreting the data using both ANNs and statistical analysis can be beneficial as a fuller picture can be obtained.

5.2 Application of ANN for productivity analysis

The steps of developing an ANN model are shown in Figure 5.2. As with any other model, it starts with **problem definition**. Based on that, the input and output variables can be determined. These can be continuous, categorical, or, in the case of neuro-fuzzy networks, even fuzzy ones.

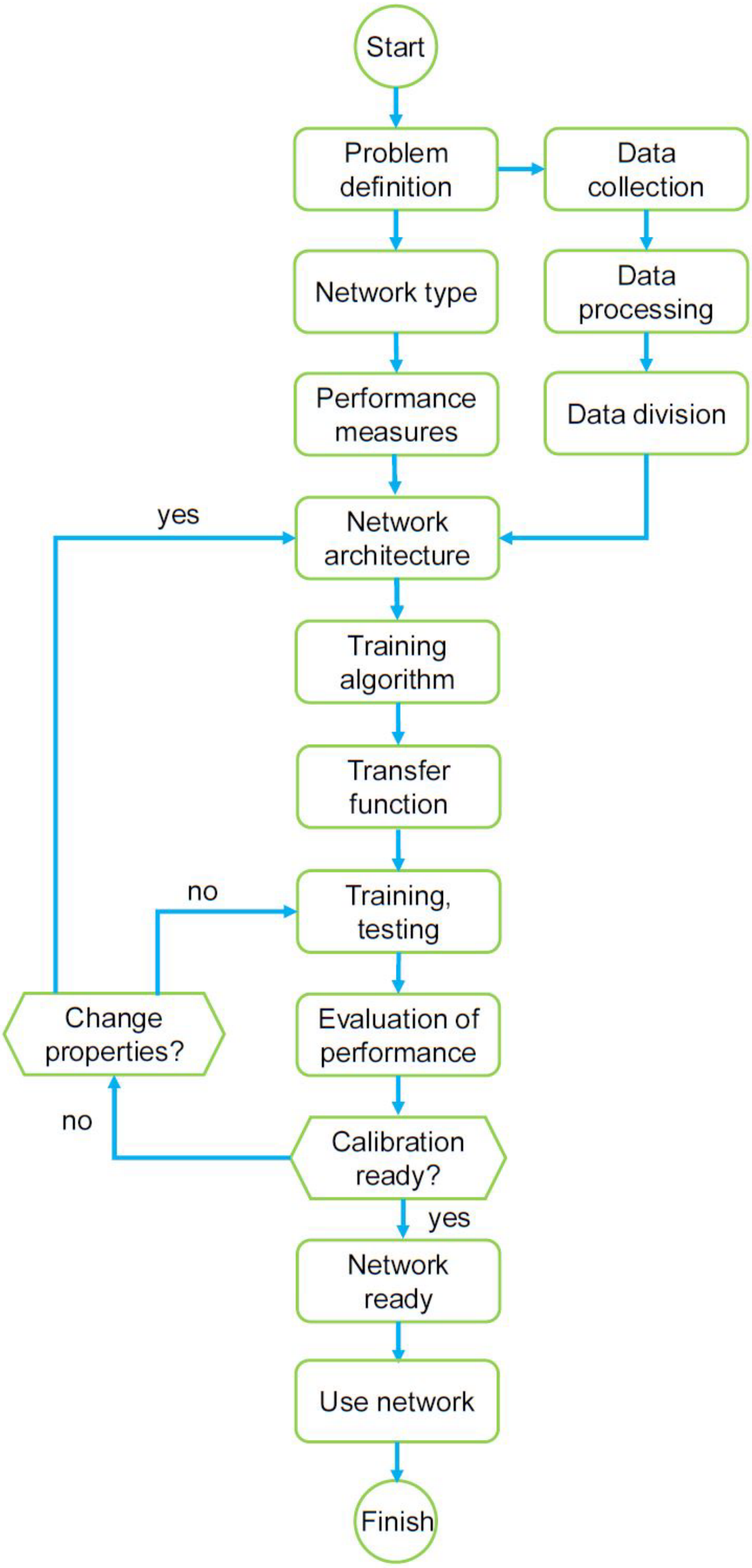


Figure 5.2 Steps of developing an ANN model

The selection of the variables informs the **data collection**. Patel and Jha (2015) suggest the minimum number of data points to be equal to the product of the neurons in each layer. Too few training data points can cause underfitting, meaning that the network is not able to learn properly (Flood and Kartam, 1994a). For example, in the case of productivity studies, especially if the data collection is done through work studies, it can be challenging to amass a substantial dataset. If the variables are scaled differently, normalisation of the data might be needed as part of **data processing** (Flood and Kartam, 1994a, 1994b). The next step is **data division**, where the collected data set is sorted into training and testing data. In most of the studies, one of the following training-testing ratios is applied: 80-20%, 75-25%, or 70-30%. There could be a third set of data used for validating. In these cases, typically half of the testing set becomes the validating set. The number of data subsets is determined by the selected training algorithm. Normally, the dataset is divided randomly. However, it is essential that all subsets are representative of the collected data (Hagan *et al.*, 2014). In addition, Chao and Skibniewski (1994) found that having extremes in the training dataset helped the performance of the model. One way to improve the generalisation properties of the model is to use k-fold cross-validation (Amari *et al.*, 1997; Adeli and Wu, 1998). This means that the dataset is divided into k sets. In each instance, k-1 sets are used for training, while the remaining set is used for testing. This is repeated k times to make each set the test dataset once. The performance measures are determined as the average of the errors produced by each network (Adeli and Wu, 1998).

After the input and output variables are defined, the **network type** has to be chosen. One option is to select a basic network paradigm, another is to define a new one (Moselhi *et al.*, 1991). The network can learn in three different ways. In the case of supervised learning, both the input and the output dataset is presented to the network, which calculates a predicted output for each input set, and then it is compared to the desired output (Flood and Kartam, 1994a). Another option is to provide a grade as an output, this is called reinforcement learning (Boussabaine, 1996). In the case of unsupervised learning, the targeted output dataset is not given to the network (Boussabaine, 1996). For example, self-organising maps belong to this category (Oral *et al.*, 2016). Based on the direction of the connections, there are feedforward and recurrent networks. Feedback loops can be found in the latter (Forbes *et al.*, 2004). The networks can also be static or dynamic. In the case of the former, the values of the input variables remain constant, while in the case of the latter, these values change over time (Flood and Kartam, 1994b).

Deterministic and stochastic networks can be distinguished, as well. In probabilistic neural networks probability density functions are used (Specht, 1990). The advantage of probabilistic neural networks is that they can be trained fast on sparse datasets (Sawhney and Mund, 2002; Tam *et al.*, 2005). Feedforward backpropagation networks are the most commonly used ones, see, for example, El-Gohary et al. (2017), or Tsehayae and Robinson Fayek (2016). Moselhi et al. (1991) chose backpropagation for its high accuracy and high interpolative performance. Other types include the radial basis used by, for instance, Moselhi and Khan (2012). Gerek et al. (2015) compared the performance of these two types of networks and found that the radial basis network was more appropriate for their bricklaying example. Golnaraghi et al. (2019) investigated the application of the general regression network, and the adaptive neuro-fuzzy inference system in addition to the two above-mentioned networks. The backpropagation network suited the formwork assembly activity the best as presented in their paper (Golnaraghi *et al.*, 2019). Oral et al. (2016) used the self-organising map approach for a ceramic tiling activity. Bailey and Thompson (1990) presented the characteristics of many network paradigms.

In the case of supervised learning, over the course of the training of the network, the difference between the targeted and the predicted output is calculated, typically, with the help of statistical tools. This will be later used to evaluate the performance of the given network configuration. The most commonly used **performance measures** are the mean squared error (or the root-mean-square error) (3), the mean absolute percentage error (4), the mean absolute error (5), and the correlation coefficient.

$$mse = \frac{1}{N} * \sum_{i=1}^{N} (observed\ value_i - predicted\ value_i)^2 \tag{3}$$

$$mape = \frac{1}{N} * \sum_{i=1}^{N} \frac{|observed\ value_i - predicted\ value_i|}{observed\ value_i} * 100\% \tag{4}$$

$$mae = \frac{1}{N} * \sum_{i=1}^{N} |observed\ value_i - predicted\ value_i| \tag{5}$$

where N: number of observations.

The optimal network configuration can be obtained by following a trial-and-error approach, as there are no formal rules concerning this (Boussabaine and Kirkham, 2008; El-Gohary *et al.*, 2017). To determine the **network architecture**, decisions have to be made concerning the number of hidden layers and the number of neurons in each of these layers. Deep neural networks have numerous hidden layers (Darko *et al.*, 2020). These are able to process datasets consisting of multiple arrays, e.g., images. They can learn from and extract complex visual patterns from pictures or videos (Darko *et al.*, 2020). However, in the case of function fitting problems, shallow networks do suffice (MathWorks United Kingdom, no date b). These usually have one or two hidden layers. It is worth starting with one hidden layer (Boussabaine and Kirkham, 2008). Two layers, however, can provide greater flexibility (Flood and Kartam, 1994a). Having too few hidden neurons in the network might lead to underfitting, and produce high error values (Flood and Kartam, 1994a; El-Gohary *et al.*, 2017). On the other hand, too many hidden nodes can lead to overfitting, in which case the error values are low; however, the network cannot work well outside the training patterns (Flood and Kartam, 1994a; El-Gohary *et al.*, 2017). At the start, the number of hidden neurons can be set at 2/3 or 70-90% of the input neurons, or at the average of the number of input and output nodes (Boussabaine and Kirkham, 2008; El-Gohary *et al.*, 2017). Having more than 2-2.5 times as many hidden neurons as input nodes might cause instability in the network (Patel and Jha, 2015; Ayhan and Tokdemir, 2019). Probabilistic neural networks typically have one hidden layer with as many neurons as training patterns (Sawhney and Mund, 2002; Tam *et al.*, 2005).

The **training algorithm** or learning rule determines the way in which the weights and biases (denoted by w and b respectively in Figures 5.1 and 5.3) are recalculated over the course of training (Moselhi *et al.*, 1991). Selection depends on many factors, including the network type, and the dataset. In the case of backpropagation networks, the application of the generalised delta rule used to be widespread (Bailey and Thompson, 1990; Adeli, 2001). Adeli (2001) recommended choosing the adaptive conjugate gradient algorithm instead. Several models use the Levenberg-Marquardt algorithm due to it being fast and powerful, see, for example, Gerek et al. (2015). Another option is the Bayesian Regularisation algorithm suggested for small and noisy datasets, see, for example, Golnaraghi et al. (2019). Heravi and Eslamdoost (2015) compared the application of Bayesian Regularisation and scaled conjugate gradient learning rule and found that the former has better generalisation performance. In the case of radial basis networks, the Gaussian function is the most commonly used (Adeli, 2001). For examples, see Gerek et al. (2015) and Moselhi and Khan (2012). Multilayer networks' performance surface may have several local minimum points, but it is important to ensure that the global minimum point has been found (Hagan *et al.*, 2014). To this end, use can be made of algorithms with adaptive learning rates (MathWorks United Kingdom, no date c). Another option is to attempt to smooth out the trajectory's oscillations with momentum (Hagan *et al.*, 2014).

The output of the neurons is calculated based on the weights of the connections. Then a **transfer** or activation **function** is applied to this result (Flood and Kartam, 1994a). These functions can be linear, threshold, or sigmoid, which is the most widely used (Boussabaine and Kirkham, 2008). Portas and AbouRizk (1997) selected a sigmoid, while Tsehayae and Robinson Fayek (2016) applied a hyperbolic sigmoid transfer function. Heravi et al. (2015) experimented with different combinations of log-sigmoid, tan-sigmoid, and linear functions. They found that the log-sigmoid functions performed well with Bayesian Regularisation, while the tan-sigmoid function failed with the same algorithm (Heravi and Eslamdoost, 2015). Gerek et al. (2015) used saturating linear and linear activation functions in their two-layer feedforward network.

After making the decisions regarding the initial settings of the network, the **training** and the **testing** could start. Next comes the **evaluation of the performance** of the network configuration using the selected measures. If the performance is not satisfactory, there are two options. If the performance is below expectations, the network attributes need to be changed and the training and testing run again. The modifications are preferably made one at a time in order for the effect of the change to be able to be observed. The other option, in the case of better performing networks, is to retrain the network with the same configuration – i.e., without **changing** its **properties** – to see if using different weights during training could help enhance the performance. This cycle continues until the optimal network configuration is found; the **calibration** is **ready**. When that happens, the **network** is **ready**, it can be used with new datasets to predict solutions and values (see Figure 5.2).

5.3 ANN for bricklaying

The previous section described the process of creating an ANN model. This section explains the decisions made in the case of the model introduced in this study. The steps of the flowchart in Figure 5.2 are followed in this section, as well.

The reason for developing this ANN model is to calculate the productivity rates based on the selected factors and to see how these factors affect the bricklayers' productivity. In this case, only those factors that can be known during the planning phase of a construction project are considered, particularly, worker and wall characteristics. These factors, which include, for example, the experience of the bricklayers and the type of brick used for the wall, comprise the input neurons of the ANN model. The output neuron is the forecasted productivity rate. Figure 5.3 shows an example for an ANN defined in this research. In this case there are two hidden layers, each comprised of five hidden neurons.

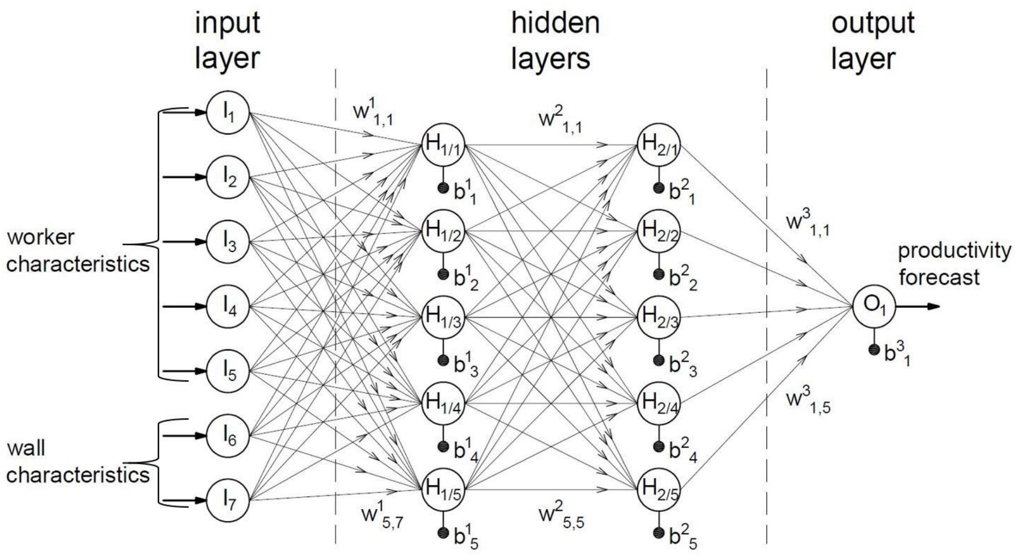


Figure 5.3 Example for bricklaying ANN model architecture (w: weight, b: bias)

The data collection took place at two construction projects by conducting a traditional work study. When the productivity rates were measured, note was made of the bricklayer working on the course, and the wall section where they worked. Based on these measurements, the data table was produced. In every row of this table, there is one productivity rate measured in bricks/hour together with the corresponding worker and wall attributes. There are five operative characteristics: quality, perceived speed, knowledge, independence, and experience, which are ordinal variables measured on a scale of one to three. The values of the first four attributes were determined by the bricklayers' supervisors, while the factor experience reflects the number of years the bricklayers spent in construction. There are two wall attributes: course difficulty and brick type, which are ordinal variables measured on a scale of one to three. The values of these factors were determined based on the observations and the drawings. Table 5.1 shows the selected factors and their scales. A more detailed description of the data collection can be found in Section 3.5, while the variables are explained in more detail in Section 4.1.2.

Factor/Scale	1	2	3
Quality	Acceptable	Good	Excellent
Perceived speed	Slow	Normal	Fast
Knowledge	Need to be improved	Adequate	Excellent
Independence	No	Medium	Yes
Experience	Limited	Medium	Substantial
Course difficulty	Easy	Medium	Difficult
Brick type	Red	Gray	Blue

Table 5.1. Selected factors and their scales

Data processing included producing the data table based on the measurements obtained during data collection. This is explained in more detail in Section 3.6. The data table was the basis of determining the input and target matrices. Since the variables were scaled differently, normalisation of the data was needed (Flood and Kartam, 1994a, 1994b).

The next step was data division. In order to improve the generalisation properties of the model, 10-fold cross-validation was used. This meant that the dataset was divided into 10 sets, which were equal in numbers as much as possible. In the case of each fold, one of the sets was used for testing, while the other nine were used for training.

Following the other branch in Figure 5.2, the selection of the network type came after the problem definition. The above-mentioned input variables are static, they do not change over time. The target output was measured; therefore, the training of the network is supervised. There are no feedback loops in the network, a feedforward network is defined. Due to its accuracy and high interpolative performance, backpropagation was selected.

The mean squared error (mse), the mean absolute percentage error (mape), and the correlation coefficient (R) were used to evaluate the network configurations. In the case of each fold, the following steps needed to be followed, and the best possible configurations found.

One of the chosen network configurations can be seen in Figure 5.3. There are seven input neurons (one for each input variable mentioned before) and one output neuron (the forecasted productivity rate). The example shows two hidden layers. Configurations with one hidden layer were also investigated. Based on the recommendations mentioned in the previous section, the number of hidden neurons was chosen between 5 and 20. In the case of two hidden layers, 5 and 10 neurons per layer were chosen.

In this research, altogether six training algorithms were selected. The most frequently used Levenberg-Marquardt (lm) algorithm was the first choice for its speed and power. The Bayesian Regularisation (br) algorithm recommended for noisy and small datasets was selected also for preventing overfitting. Two training algorithms (gradient descent with adaptive learning rate backpropagation (gda) and gradient descent with momentum and adaptive learning rate backpropagation (gdx)) with adaptive learning rates were chosen, as well, for their ability to enhance performance by amending the learning rate. The Broyden-Fletcher-Goldfarb-Shanno quasi-Newton backpropagation (bfg) was selected for its speed (MathWorks United Kingdom, no date a). The scaled conjugate gradient (scg) algorithm was chosen for its efficiency (Hagan *et al.*, 2014).

Corresponding to the training algorithms, activation functions needed to be chosen. Sigmoid functions are the most commonly used and best resemble the behaviour of biological neurons (Boussabaine and Kirkham, 2008). They are advised in the case of backpropagation by Bailey and Thompson (1990). Therefore, in this study, log-sigmoid (logsig) and tangent sigmoid (tansig) activation functions were selected for the first, or in the case of two hidden layers, the first two layers, and a linear (purelin) transfer function was applied for the final layer.

In the case of each fold, the number of hidden layers and neurons, the training algorithms, and transfer functions were changed until the best performing networks were found. Then the average of the performance measures of the ten selected networks was calculated.

5.4 Finding the most suitable ANN

Numerous different ANNs were created with the help of the MATLAB R2021a software running on a Lenovo laptop with 8 GB of RAM, Intel®Core™ i5-7200U processor on a 64-bit Windows 10 Home operating system. MATLAB was chosen because it can handle developing ANNs, is user-friendly, and the full version was available at the university.

The best performing network configurations of each fold are listed in Table 5.2. For example, the best network for fold #1 has an input layer of seven neurons for the seven factors, one hidden layer with five neurons, and one output neuron for the forecasted productivity rate. The chosen training algorithm is the scaled conjugate gradient. The transfer functions applied to the output of layers 1 (input), 2 (hidden layer) are the tangent sigmoid and the linear functions, respectively. The correlation coefficient of the training data subset is 0.82, while that of the test data subset is 0.58. For the entire dataset, the R value is 0.79. The mean squared error for the entire dataset is 0.0647. The mean absolute percentage error for the entire dataset is 21.21%, for the training dataset, it is 20.55%, while for the test dataset it is 28.18%. It took the software 2 seconds to calculate these results.

Fold	Network architecture		Training algorithm	Transfer function			Correlation coefficient, R			Mean squared error	Mean absolute % error			Training time, [s]
	Number of hidden layers	Number of neurons/ hidden layer		Layer 1	Layer 2	Layer 3	Training	Test	All	Dataset	Dataset	Training	Test	
1	1	5	scg	tansig	purelin	-	0.82	0.58	0.79	0.0647	21.21	20.55	28.18	2
2	1	5	lm	tansig	purelin	-	0.83	0.47	0.79	0.0653	20.76	18.97	42.22	<1
3	1	5	lm	tansig	purelin	-	0.77	0.89	0.80	0.0638	24.01	22.57	36.61	<1
4	1	5	lm	tansig	purelin	-	0.80	0.81	0.79	0.0645	24.42	22.97	34.31	<1
5	2	5	lm	tansig	tansig	purelin	0.81	0.22	0.76	0.0743	25.28	22.78	50.75	<1
6	1	5	lm	tansig	purelin	-	0.81	0.67	0.79	0.065	21.49	21.55	21.06	<1
7	1	5	lm	tansig	purelin	-	0.81	0.67	0.79	0.0654	21.37	21.98	15.66	<1
8	1	5	lm	tansig	purelin	-	0.80	0.80	0.79	0.0644	21.25	21.63	18.15	<1
9	1	5	lm	tansig	purelin	-	0.80	0.77	0.80	0.0638	21.79	22.55	12.51	<1
10	1	5	lm	tansig	purelin	-	0.81	0.41	0.80	0.0636	23.33	22.49	29.47	<1
average							0.81	0.63	0.79	0.0655	22.49	21.80	28.89	

Table 5.2 Summary of the most suitable network configurations in each fold (gray background: fold selected for further analysis)

The average mean absolute percentage error across the 10 folds is above 20%. This is higher than ideal, therefore the networks for folds 7, 8, and 9, which had the lowest mean absolute percentage error, were chosen for further analysis. Figures 5.4, 5.6, and 5.8 show the productivity rates predicted by the model and the observed productivity rates. The orange 45-degree line depicts the ideal situation where the output and target values are equal. The further away the points are from this line, the higher the error, i.e., the difference between the predicted and target values. Figures 5.5, 5.7, and 5.9 show the error frequency histograms of the three selected networks. In each case, the datapoints which produced an error in the top 5% were checked. Based on this, six datapoints were finally removed from the dataset in order to improve the performance of the model. The excluded datapoints – #62, 78, 79, 81, 82, and 84 – are shown in red in Figures 5.4, 5.6, and 5.8.

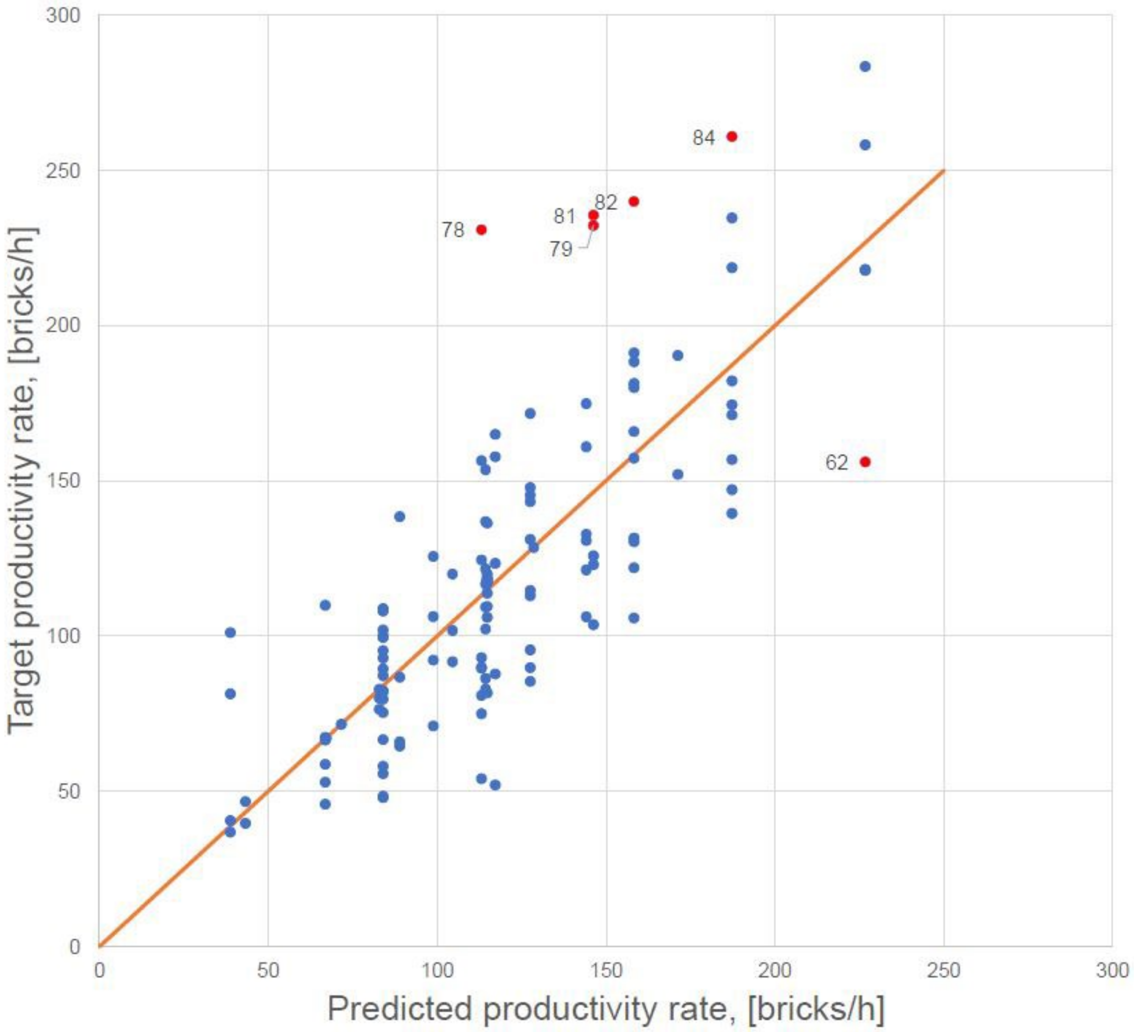


Figure 5.4 Predicted and observed productivity rates based on Fold #7

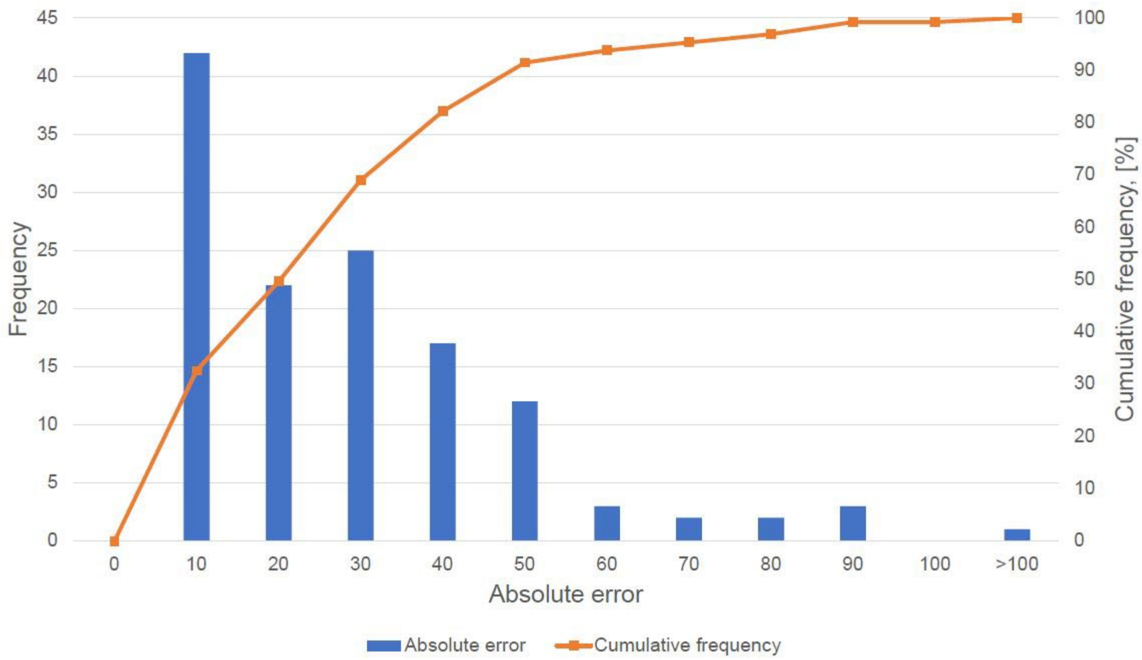


Figure 5.5. Frequency of absolute errors of Fold #7

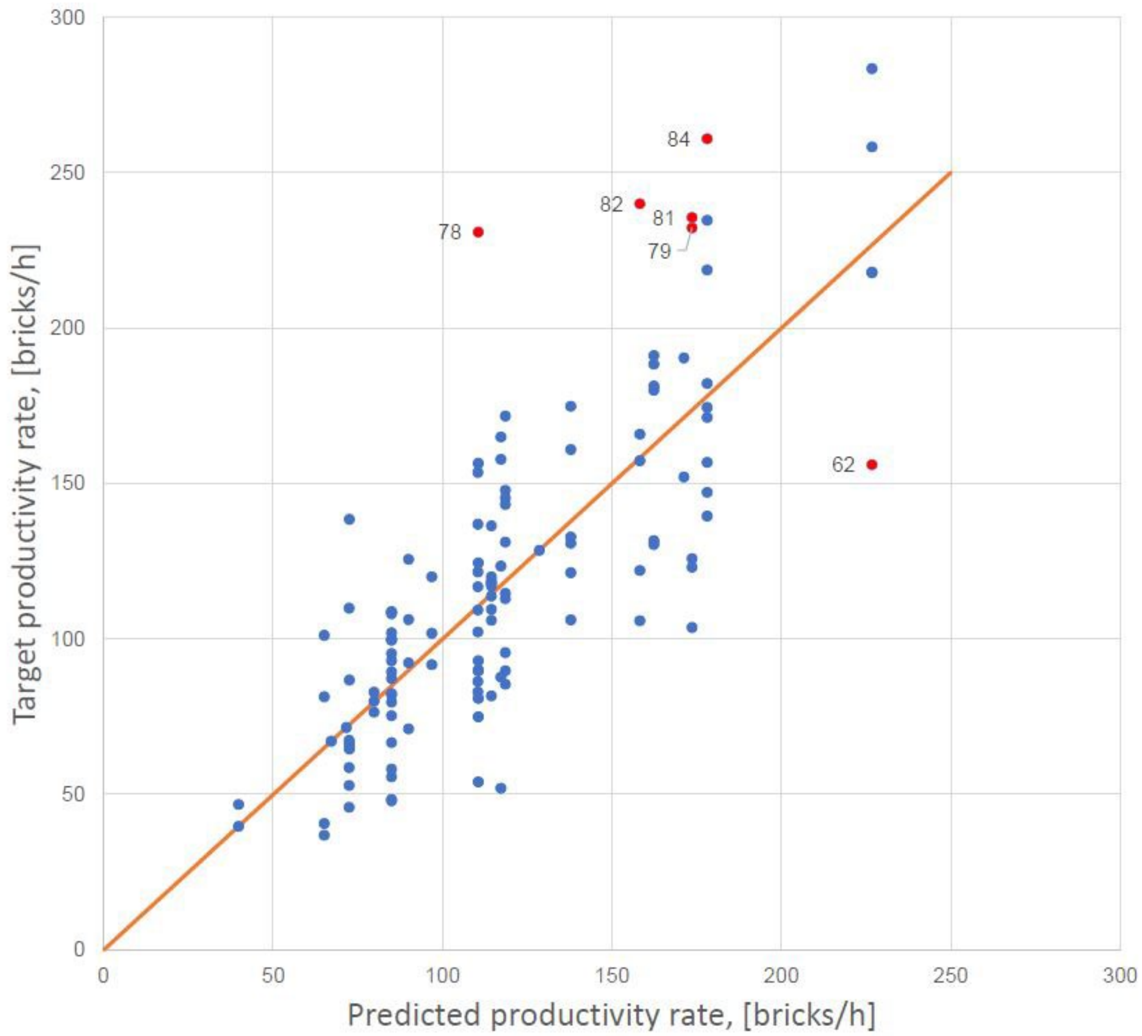


Figure 5.6 Predicted and observed productivity rates based on Fold #8

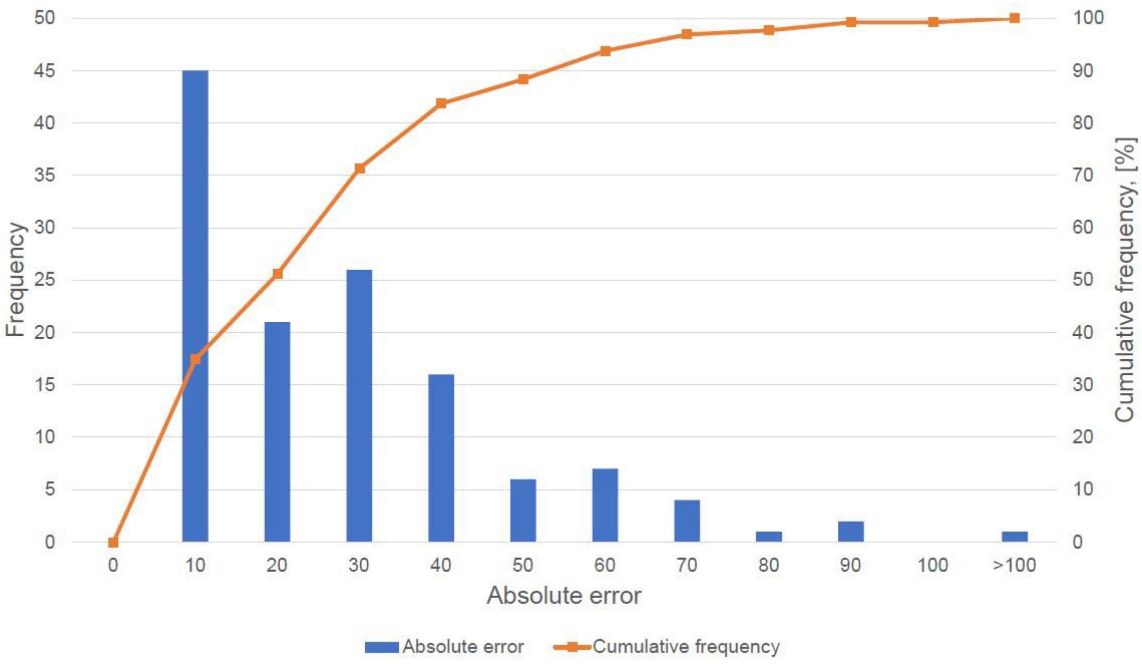


Figure 5.7 Frequency of absolute errors of Fold #8

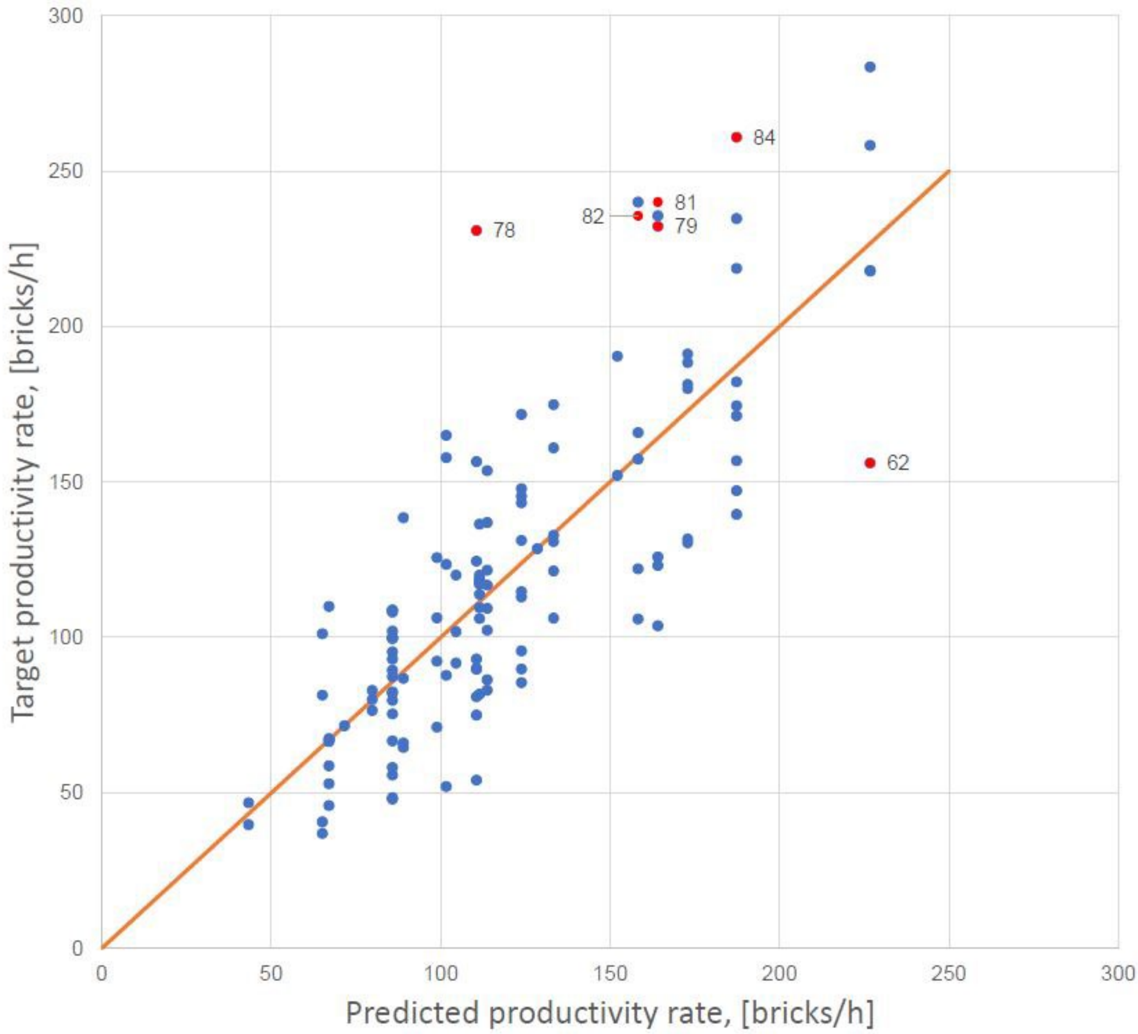


Figure 5.8 Predicted and observed productivity rates based on Fold #9

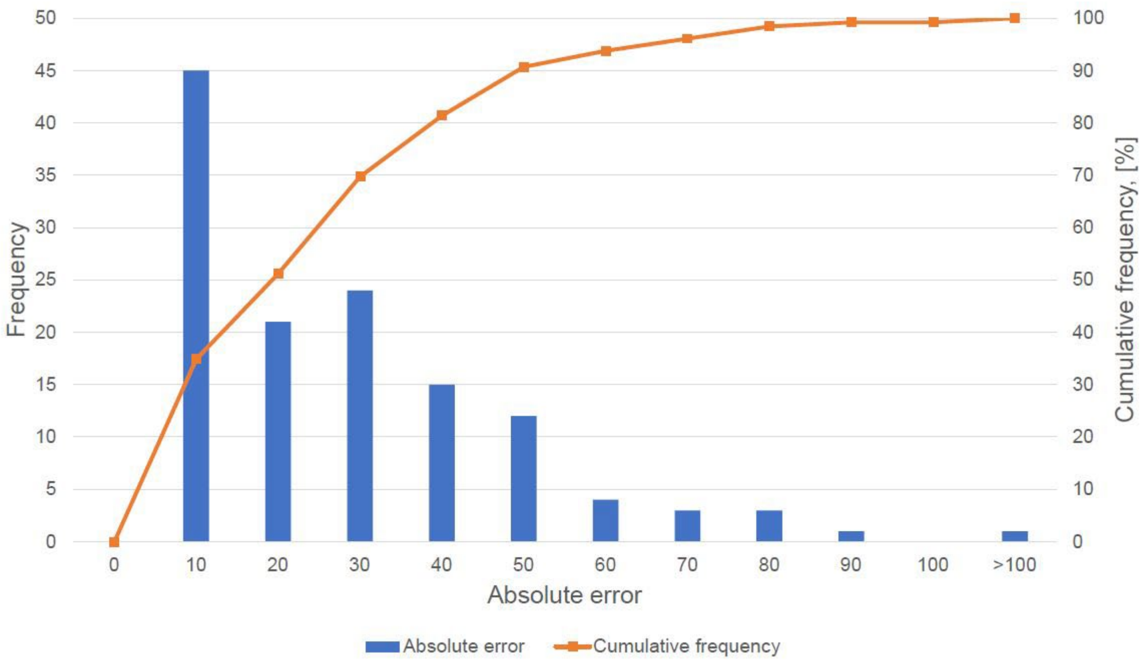


Figure 5.9 Frequency of absolute errors of Fold #9

As a result of removing six datapoints, the final dataset consisted of 123 datapoints. The distribution of datapoints over the values of each factor can be seen in Table 5.3.

Factor/Scale	**1**	**1.5**	**2**	**2.5**	**3**
Quality (Q)	24	0	36	8	55
Perceived speed (PS)	10	0	36	18	59
Knowledge (K)	24	14	24	12	49
Independence (I)	14	14	26	16	53
Experience (E)	22	14	43	4	40
Course difficulty (CD)	83	0	34	0	6
Brick type (BT)	61	0	38	0	24

Table 5.3 Number of datapoints at each value of the factors in the final dataset

After the final dataset was determined, it was again divided into ten folds, and the same process was followed as described before. Hundreds of feedforward networks were created with seven input neurons for the seven input variables listed in Table 5.1 and one output neuron for the forecasted productivity rate. Different hidden layer configurations were tested: 5 to 20 hidden neurons in one hidden layer and 5 or 10 neurons in two hidden layers. Six training algorithms were selected: Levenberg-Marquardt (lm) algorithm (with various learning rates and momentum settings), Bayesian Regularisation (br) algorithm, gradient descent with adaptive learning rate backpropagation (gda), gradient descent with momentum and adaptive learning rate backpropagation (gdx), Broyden-Fletcher-Goldfarb-Shanno quasi-Newton backpropagation (bfg), and scaled conjugate gradient (scg) algorithm. Linear transfer function was chosen for the final layer, and mostly the tangent sigmoid (tansig) function was used for the previous layers; however, the log-sigmoid (logsig) and linear activation functions were also tested for those layers, as well. By using the above-mentioned settings, many configurations were tested for each fold. The best performing network for each fold can be seen in Table 5.4. Both the average correlation coefficient and the average mean absolute error improved in comparison with the values shown in Table 5.2.

The next step was to find the overall best performing network that would be part of the hybrid DES-ANN model. The top 20 are listed in ascending order of the mean absolute error of the test dataset in Table 5.5. All of them are from fold #1, as that had the lowest mean absolute percentage error. It can be seen that most of the networks listed have the same correlation coefficients and error values, which were chosen as the performance measures to evaluate the networks by. Therefore, the results of the sensitivity analysis were also used to determine the most appropriate network, which would be part of the model.

Fold	Network architecture		Training algorithm	Transfer function			Correlation coefficient, R			Mean squared error	Mean absolute % error			Training time, [s]
	Number of hidden layers	Number of neurons/ hidden layer		Layer 1	Layer 2	Layer 3	Training	Test	All	Dataset	Dataset	Training	Test	
1	1	20	gda	tansig	purelin	-	0.86	0.83	0.86	0.0381	11.06	11.87	1.21	3
2	1	5	scg	tansig	purelin	-	0.87	0.48	0.86	0.038	12.60	13.24	6.92	1
3	1	5	lm	tansig	purelin	-	0.87	0.66	0.85	0.0384	14.95	13.12	31.11	<1
4	2	10	gda	tansig	tansig	purelin	0.85	0.9	0.85	0.0386	13.64	13.00	17.99	1
5	1	15	gda	tansig	purelin	-	0.87	0.54	0.85	0.0385	13.62	12.49	25.97	1
6	2	5	gda	tansig	tansig	purelin	0.86	0.52	0.85	0.0404	14.57	13.68	21.73	2
7	2	5	gda	tansig	tansig	purelin	0.87	0.65	0.85	0.0386	11.89	11.91	11.55	1
8	2	5	gda	tansig	tansig	purelin	0.82	0.93	0.84	0.0417	14.36	14.20	15.69	1
9	1	20	scg	tansig	purelin	-	0.86	0.84	0.85	0.0412	11.47	13.59	10.97	<1
10	1	15	gda	tansig	purelin	-	0.86	0.84	0.85	0.0387	14.20	13.25	19.54	1
average							0.86	0.72	0.85	0.0392	13.24	13.04	16.27	

Table 5.4 Summary of the most suitable network configurations in each fold (gray background: fold selected for further analysis)

#	Fold	Network architecture		Training algorithm	Transfer function			Correlation coefficient, R			Mean squared error	Mean absolute % error			Training time, [s]
		Number of hidden layers	Number of neurons/ hidden layer		Layer 1	Layer 2	Layer 3	Training	Test	All	Dataset	Dataset	Training	Test	
1	1	2	5	gdx	tansig	tansig	purelin	0.86	0.83	0.85	0.0392	11.81	12.79	0.0520	2
2	1	2	10	gdx	tansig	tansig	purelin	0.86	0.82	0.86	0.0382	11.34	12.27	0.0756	2
3	1	1	15	gdx	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1781	2
4	1	1	15	scg	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1831	<1
5	1	1	10	scg	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1832	<1
6	1	1	20	scg	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1832	<1
7	1	2	5	bfg	tansig	tansig	purelin	0.86	0.82	0.86	0.0383	11.38	12.34	0.1833	<1
8	1	1	15	bfg	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	0.18	0.1833	<1
9	1	1	20	bfg	tansig	purelin	-	0.86	0.82	0.85	0.0383	11.38	12.34	0.1834	<1
10	1	2	5	lm	tansig	tansig	purelin	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1
11	1	2	10	bfg	tansig	tansig	purelin	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1
12	1	1	10	lm	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1
13	1	1	15	lm	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1

#	Fold	Network architecture		Training algorithm	Transfer function			Correlation coefficient, R			Mean squared error	Mean absolute % error			Training time, [s]
		Number of hidden layers	Number of neurons/ hidden layer		Layer 1	Layer 2	Layer 3	Training	Test	All	Dataset	Dataset	Training	Test	
14	1	1	20	lm	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1
15	1	1	5	lm	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	1
16	1	2	10	lm	tansig	tansig	purelin	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1
17	1	1	10	bfg	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	<1
18	1	1	5	bfg	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.38	12.34	0.1834	1
19	1	2	5	scg	tansig	tansig	purelin	0.86	0.82	0.86	0.0383	11.38	12.34	0.1837	<1
20	1	1	10	gdx	tansig	purelin	-	0.86	0.82	0.86	0.0383	11.35	12.32	0.3344	2

Table 5.5 The best performing network configurations (gray background: network selected for further analysis)

5.5 Sensitivity analysis

To understand the effect of the input variables on the output variable, i.e., the productivity rate, sensitivity analysis was performed. This meant that at one time one input variable's value was changed, while all others were fixed at their mean value, and this was repeated seven times for the seven factors (Sonmez, 1996; Sonmez and Rowings, 1998).
In the first case, the given input variable's value was chosen to be equal to its minimum value (1), then to its maximum value (3), and the output values were recorded. The difference between the two output values was also calculated. This was performed in the case of all the networks listed in Table 5.5. Some of them produced negative output, which is not acceptable as the productivity rate must be a positive number. Therefore, these networks were discarded. After this elimination, the first three networks – #4, #9, and #11 in Table 5.5 – were kept and used for further analysis. The main features of networks A, B, and C can be seen in Table 5.6.

Network	**Network architecture**		**Training algorithm**	**Transfer function**		
	Number of hidden layers	**Number of neurons/ hidden layer**		**Layer 1**	**Layer 2**	**Layer 3**
Network A	1	15	scg	tansig	purelin	-
Network B	1	20	bfg	tansig	purelin	-
Network C	2	10	bfg	tansig	tansig	purelin

Table 5.6 The final three networks

Table 5.7 contains the results of the first round of the sensitivity analysis for networks A to C. The table shows the productivity rates calculated in the given network. For example, in the case of quality, the output of network A was 112.7 bricks/h, when the value of quality was set at 1, while the values of all other factors were their mean values, and the output was 153.3 bricks/h, when the value of quality was 3, while that of the other factors remained the same. The difference between these two output values is 40.6 bricks/h, which can be seen in the fourth column.

Factor	Network A			Network B			Network C		
	Output for			Output for			Output for		
	min.	max.	diff.	min.	max.	diff.	min.	max.	diff.
Q	112.7	153.3	40.6	135.9	102.1	-33.8	106.3	138.8	32.5
PS	202.4	146.8	-55.6	111.0	135.3	24.3	112.7	116.9	4.2
K	200.9	93.9	-107.0	162.9	131.7	-31.2	106.1	156.2	50.1
I	47.9	112.6	64.7	89.3	129.1	39.8	148.0	103.4	-44.6
E	76.6	179.6	103.1	17.3	153.5	136.2	113.1	178.1	65.0
CD	123.1	35.2	-87.9	133.2	37.1	-96.1	168.3	96.0	-72.3
BT	128.9	126.5	-2.3	190.2	81.1	-109.1	102.1	38.7	-63.4

Table 5.7 Results of sensitivity analysis for networks A-C (productivity rates in bricks/h)

While the values may be different, it can be seen that in the case of experience, course difficulty, and brick type, the differences by all three networks have the same sign. These factors are coloured in gray in Table 5.7. The sign of the difference value shows that with experience increasing, the productivity rate also increases, while in the case of course difficulty and brick type, the effect is the opposite. For example, the more difficult the course, the lower the productivity rate. The first four factors provided more varied results. Further analysis was needed.

In the second round of sensitivity analysis, basically the same principle was used as in the first one: only one factor's values were changed, while the values of the other factors were kept at their mean values. However, in this case, the value of the selected factor was changed by 0.1 increments between 1 and 3 to see how the productivity rate changes due to the changes in the chosen factor. The output of the three networks were depicted in graphs, which can be seen in Figures 5.10 through 5.16.

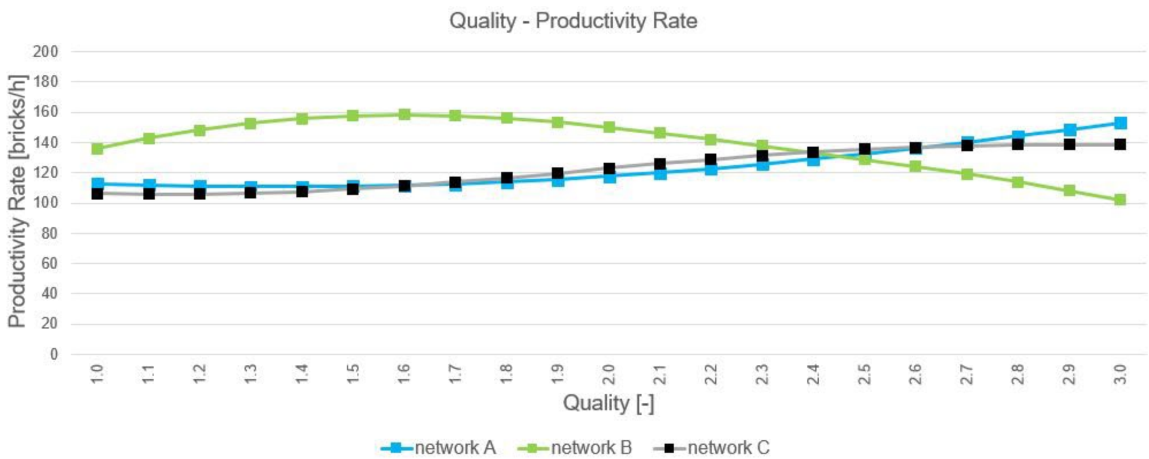


Figure 5.10 Quality-productivity rate

Figure 5.10 shows how the productivity rate changes if the value of the quality factor is changed between 1 and 3. Networks A and C provided similar results suggesting that the productivity rate increases as the value of quality increases.

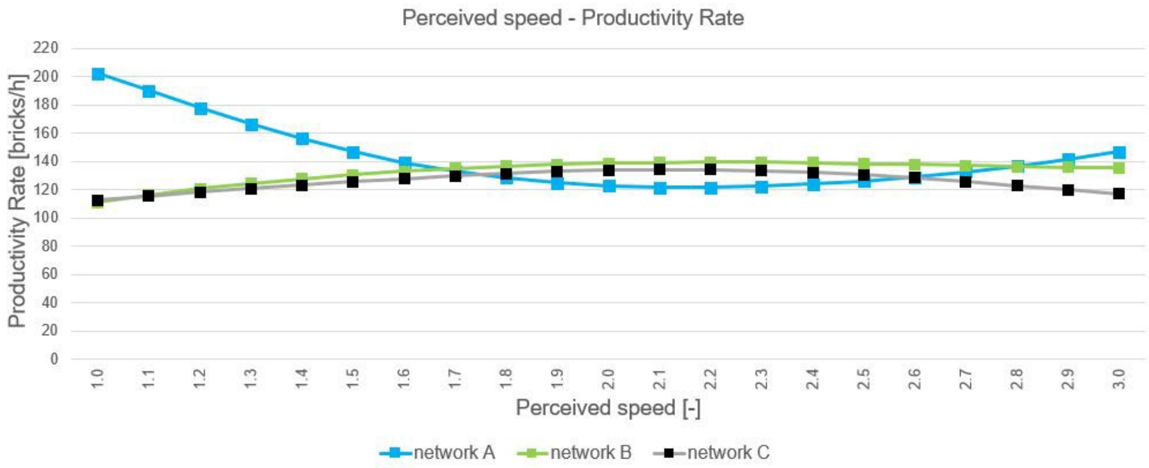


Figure 5.11 Perceived speed-productivity rate

In the case of perceived speed, – as can be seen in Figure 5.11 – the output of networks B and C were close showing the same trend of a slight increase in productivity as the factor's value increases.

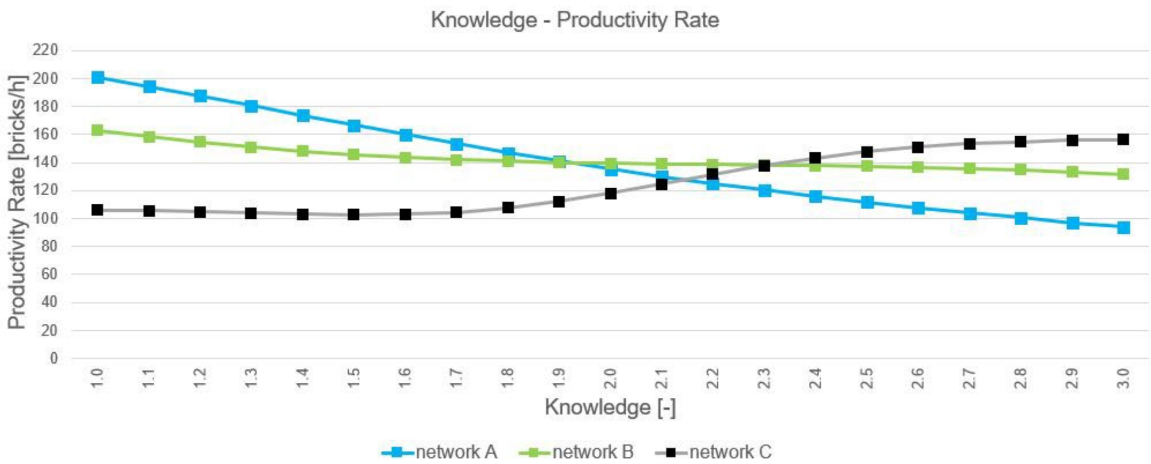


Figure 5.12 Knowledge-productivity rate

For the knowledge factor, the outputs are more varied; however, networks A and B suggest a decrease in the productivity rate as knowledge increases (see Figure 5.12).

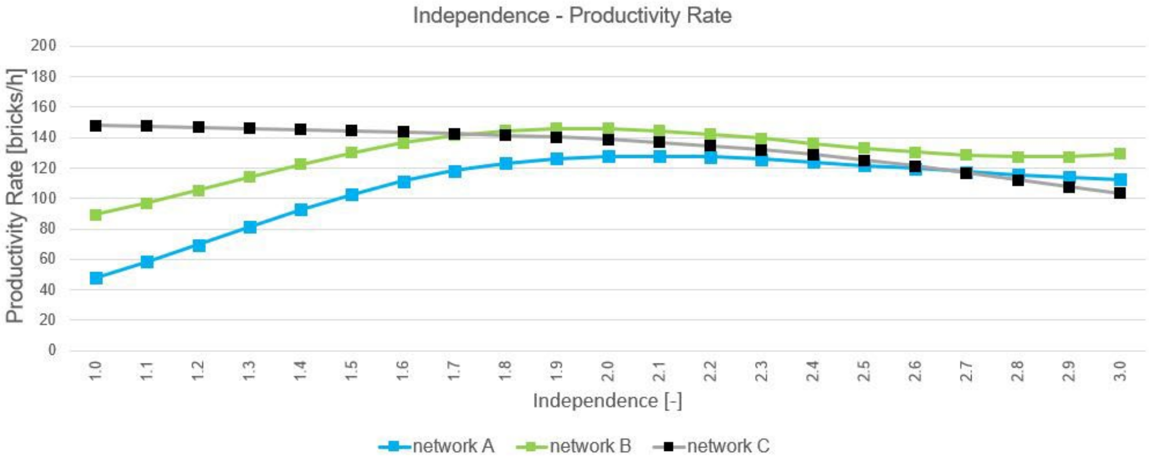


Figure 5.13 Independence-productivity rate

In the case of independence (see Figure 5.13), similar outputs were provided by all three networks in the right side of the graph. Networks A and B show an increasing trend.

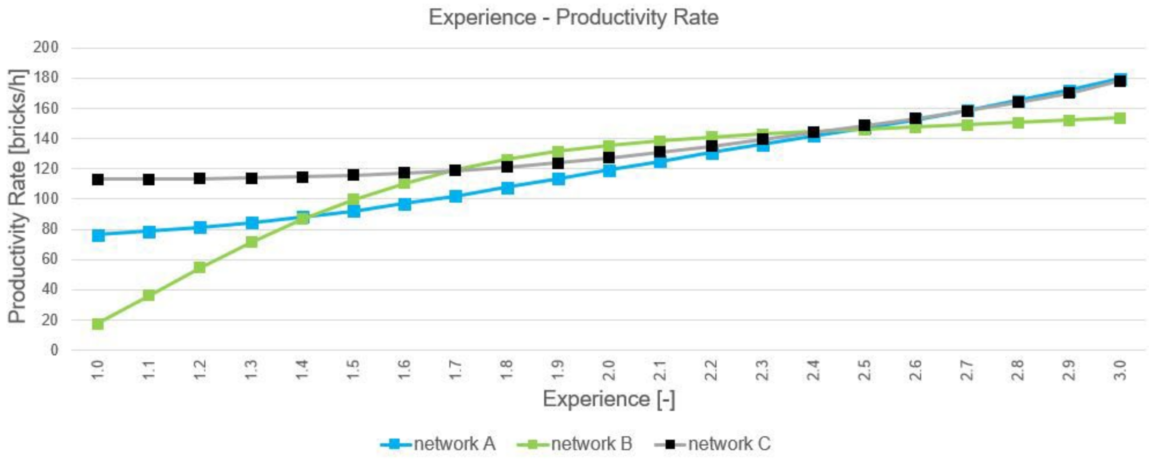


Figure 5.14 Experience-productivity rate

As could be seen in Table 5.7 and here in Figure 5.14, the productivity rates provided by all three networks show an increase as experience increases. Networks A and C produced more similar results.

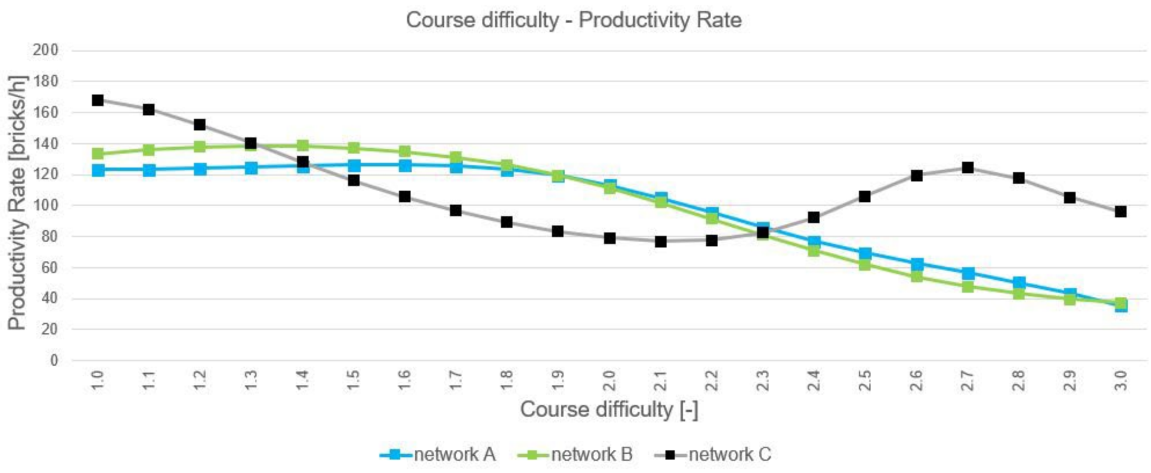


Figure 5.15 Course difficulty-productivity rate

In the case of course difficulty, the output of networks A and B were close showing the same trend of decreasing productivity as the factor's value increases (see Figure 5.15).

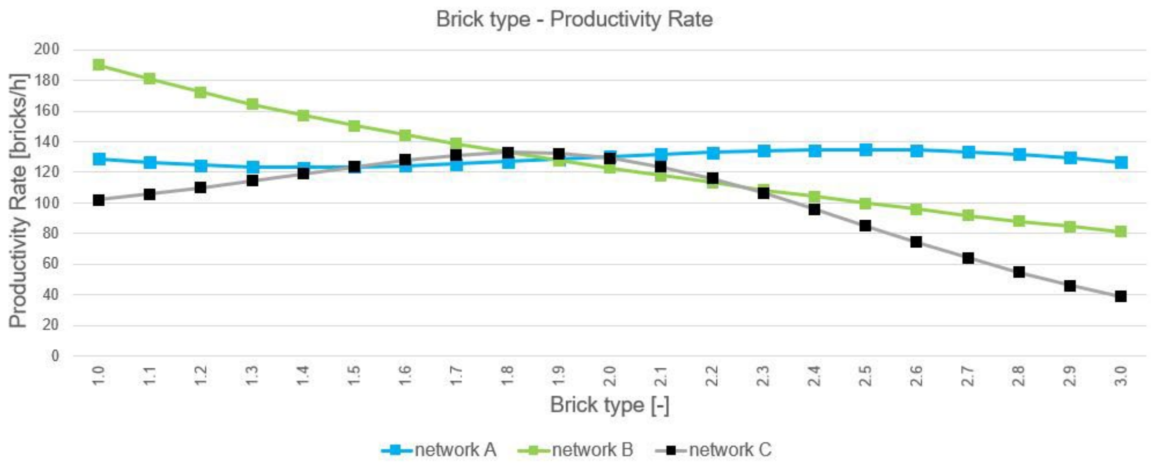


Figure 5.16 Brick type-productivity rate

For the brick type factor, the outputs shown in Figure 5.16 are also more varied; however, all three networks suggest a decrease in the productivity rate as the value of brick type increases.

5.6 Chapter summary

This is the second of three chapters discussing the developed hybrid DES-ANN model. The first one was Chapter 4, which provided an overview of the model, while Chapter 7 will discuss the DES part of the model and the link between the two components. In this chapter, first, artificial neural networks were introduced describing the concept and the general workings of the networks. Then the framework developed for productivity modelling with ANN was presented. The steps of creating an ANN model were explained in detail, showing the options that need to be considered. In the next section, the choices made for the ANN component of the model were explained using the framework. Hundreds of feedforward networks were created, which had different architecture (one or two hidden layers, varying number of hidden neurons), were trained by different backpropagation learning algorithms (altogether six different ones were selected) and used different transfer functions (combinations of various sigmoid and linear functions were chosen). The data table was divided into 10 equal sets for the 10-fold validation, which meant that each time the network was trained using 9 folds and tested using the remaining fold. This was repeated 10 times until all folds were used for testing once. The networks were ranked based on the selected performance measures (mean squared error, mean absolute percentage error, and correlation coefficient). Since the accuracy of the model was not ideal, six datapoints were removed from the data table, and then hundreds of networks were created the same way as before. These were ranked and the three best performing ones were chosen for sensitivity analysis. The output of the analysis was used to analyse the effects of the factors on the productivity rate.

CHAPTER 6

STATISTICAL ANALYSIS OF THE COLLECTED PRODUCTIVITY DATA

6.1 The data table and descriptive statistics

The aim of the statistical analysis is to determine the effect of the following factors on the productivity rate of bricklaying works: quality (Q), perceived speed (PS), knowledge (K), independence (I), experience (E), course difficulty (CD), and brick type (BT). These were described in detail in Section 4.1.2.

The data table used for the analyses contains 123 data points for productivity rates and the corresponding values of the above-mentioned factors. The dataset on which the analyses were performed was the same as the one used to for the artificial neural network component of the model. The process of obtaining the dataset was described in Section 5.4. The descriptive statistics for the productivity rates can be seen in Table 6.1 and the histogram in Figure 6.1.

	Productivity Rate
Number of data points	123
Minimum [bricks/h]	36.89
Maximum [bricks/h]	283.5
Mean [bricks/h]	114.8
Standard Deviation [bricks/h]	46.62
Variance [(bricks/h)^2]	2174
Skewness	0.926
Standard Error of Skewness	0.218
Kurtosis	1.197
Standard Error of Kurtosis	0.433

Table 6.1 Descriptive statistics for productivity rate

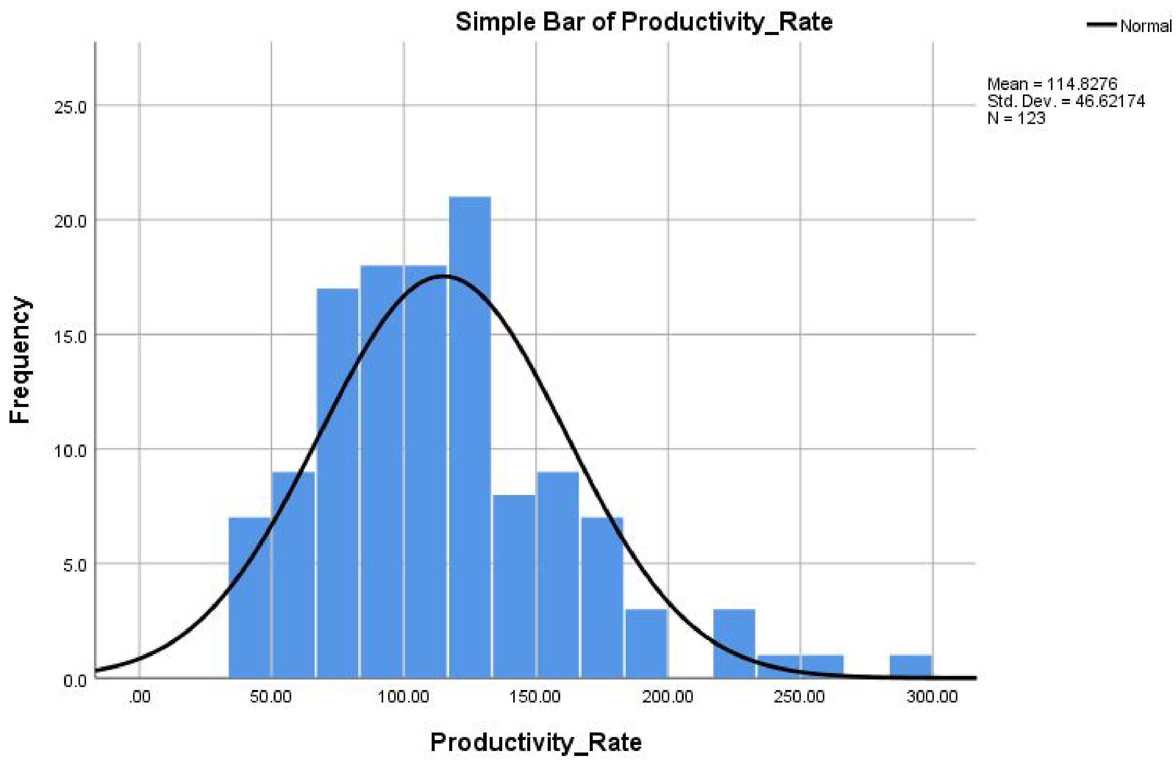


Figure 6.1 Histogram of productivity rate [bricks/h]

Table 6.2 contains the list of the factors with their scales explained. Moreover, it shows the abbreviations used later in this chapter. For example, Q1 stands for acceptable quality, when the value of the quality factor equals 1. In the case of some factors, there are half values as well, such as Q2.5. This is the average of Q2 and Q3. More details on this can be found in Section 3.6.

Factor/Scale	**1**	**2**	**3**
Quality (Q)	Acceptable (Q1)	Good (Q2)	Excellent (Q3)
Perceived speed (PS)	Slow (PS1)	Normal (PS2)	Fast (PS3)
Knowledge (K)	Need to be improved (K1)	Adequate (K2)	Excellent (K3)
Independence (I)	No (I1)	Medium (I2)	Yes (I3)
Experience (E)	Limited (E1)	Medium (E2)	Substantial (E3)
Course difficulty (CD)	Easy (CD1)	Medium (CD2)	Difficult (CD3)
Brick type (BT)	Red (BT1)	Gray (BT2)	Blue (BT3)

Table 6.2 Factors and their scales

Table 6.3 shows the number of datapoints for each value of the factors. Even though every effort was made to have an equal number of observations of the various bricklayers and wall sections, in the final data table the number of datapoints per factor group is uneven. This was explained in detail in Section 3.6.

Factor/Scale	**1**	**1.5**	**2**	**2.5**	**3**
Quality (Q)	24	0	36	8	55
Perceived speed (PS)	10	0	36	18	59
Knowledge (K)	24	14	24	12	49
Independence (I)	14	14	26	16	53
Experience (E)	22	14	43	4	40
Course difficulty (CD)	83	0	34	0	6
Brick type (BT)	61	0	38	0	24

Table 6.3 Number of datapoints for each value of the factors

The level of measurement is different for different variables. While the productivity rate, the dependent variable, can be considered continuous, the independent variables, the factors, are ordinal.

The analyses were performed according to Field (2009) and using IBM SPSS Statistics 26 and MS Excel 2016 software. The level of significance is 0.05, unless stated otherwise.

Table 6.4 contains the most common abbreviations and notations used in the coming tables.

Abbreviation	**Meaning**
Sig.	significance
df	degrees of freedom
t	result of t-test, t-value
R^2	coefficient of determination

Table 6.4 Common abbreviations

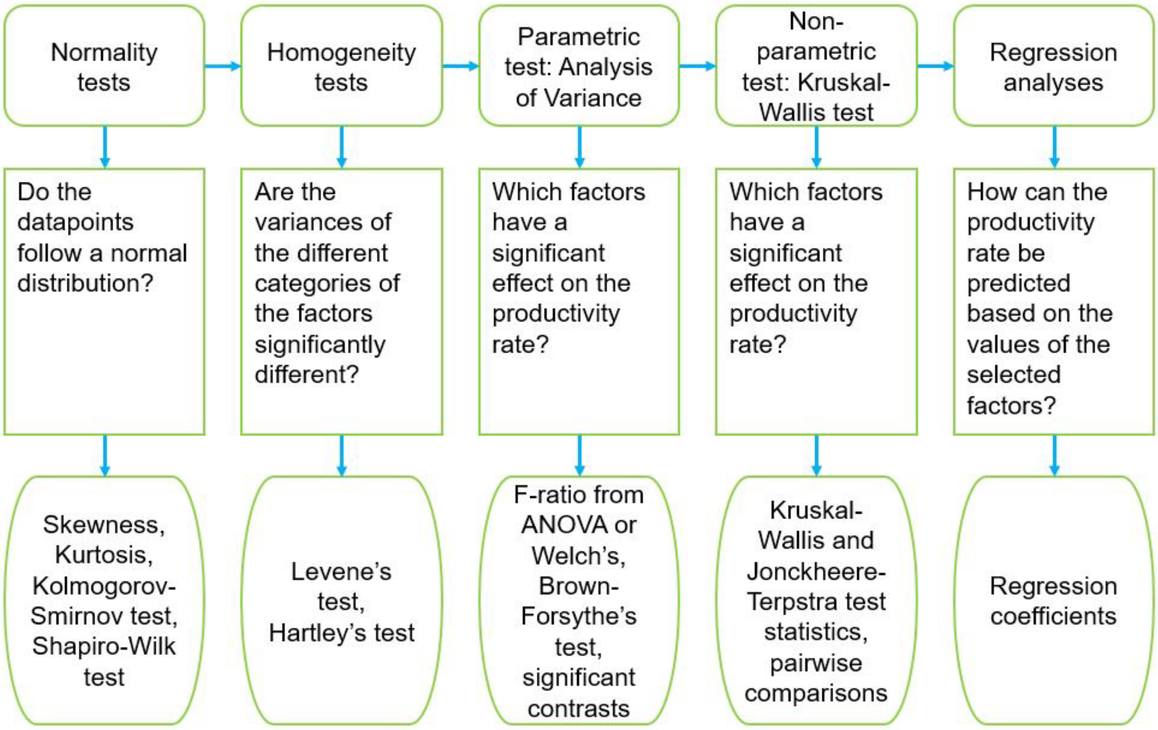


Figure 6.2 Steps of the statistical analysis

Figure 6.2 shows the statistical analysis performed and detailed in this chapter. The tests listed in the top row were run in order for the questions in the middle row to be answered. The bottom row contains the output of the analyses. The coming sections describe the steps in detail.

6.2 Normality and homogeneity

For parametric tests, it needs to be determined whether the variables follow a normal distribution, and their variances are homogenous between the categories of the factors. These assumptions of normality and homogeneity need to be met in order for the F statistic, the output of the tests, to be reliable.

The productivity rates at every level of each variable were checked for normality because for the tests, this is what matters, and not the overall normality. The analyses included running the Kolmogorov-Smirnov and Shapiro-Wilk tests and checking the skewness and kurtosis. Table 6.6 shows the results of the aforementioned tests. In the case of the Kolmogorov-Smirnov and Shapiro-Wilks tests, if the test is significant, the scores are significantly different from the normal distribution. In most cases, the two tests give the same results. When they differ, the final decision can be made based on the other skewness and kurtosis values and the histograms.

In the case of skewness and kurtosis, first, standardised z-scores were calculated based on (1) and (2).

$$z_{skewness} = \frac{S-0}{SE_{skewness}} \quad (1)$$

$$z_{kurtosis} = \frac{K-0}{SE_{kurtosis}} \quad (2)$$

where S: skewness, $SE_{skewness}$: standard error of skewness, K: kurtosis, $SE_{kurtosis}$: standard error of kurtosis.

Then these values were compared to the value of the normal distribution ($z_{critical}$). If the absolute value of $z_{skewness}$ or $z_{kurtosis}$ is greater than $z_{critical}$=1.96, then the value is significant, meaning that the distribution is not normal. Tables 6.5 shows the results of these tests, as well.

Based on the above tests, it can be concluded that the following categories are significantly non-normal: Q3, PS3, K3, I3, E3, CD2. In these cases, the normality condition for parametric tests is not met.

	Kolmogorov-Smirnov			Shapiro-Wilk			Skewness				Kurtosis				Final
Factor	**D**	**Sig.**	**Normal**	**D**	**Sig.**	**Normal**	**Skewness**	**Standard error of skewness**	$z_{skewness}$	**Normal**	**Kurtosis**	**Standard error of kurtosis**	$z_{kurtosis}$	**Normal**	**Normal**
Q1	0.160	0.112	yes	0.915	0.046	no	0.618	0.472	1.309	yes	-0.755	0.918	-0.822	yes	yes
Q2	0.092	0.200	yes	0.985	0.885	yes	0.071	0.393	0.181	yes	-0.150	0.768	-0.195	yes	yes
Q2.5	0.185	0.200	yes	0.907	0.335	yes	-0.625	0.752	-0.831	yes	-0.685	1.481	-0.463	yes	yes
Q3	0.173	0.000	no	0.925	0.002	no	0.951	0.322	2.953	no	0.431	0.634	0.680	yes	no
PS1	0.231	0.139	yes	0.858	0.072	yes	-1.160	0.687	-1.689	yes	3.604	1.334	2.702	no	yes
PS2	0.094	0.200	yes	0.971	0.451	yes	0.372	0.393	0.947	yes	-0.440	0.768	-0.573	yes	yes
PS2.5	0.103	0.200	yes	0.970	0.799	yes	-0.042	0.536	-0.078	yes	-0.736	1.038	-0.709	yes	yes
PS3	0.140	0.006	no	0.947	0.012	no	0.776	0.311	2.495	no	0.150	0.613	0.245	yes	no
K1	0.160	0.112	yes	0.915	0.046	no	0.618	0.472	1.309	yes	-0.755	0.918	-0.822	yes	yes
K1.5	0.137	0.200	yes	0.948	0.533	yes	0.044	0.597	0.074	yes	-1.112	1.154	-0.964	yes	yes
K2	0.104	0.200	yes	0.933	0.114	yes	0.793	0.472	1.680	yes	0.091	0.918	0.099	yes	yes
K2.5	0.186	0.200	yes	0.916	0.258	yes	0.053	0.637	0.083	yes	-1.322	1.232	-1.073	yes	yes
K3	0.201	0.000	no	0.877	0.000	no	1.457	0.340	4.285	no	2.551	0.668	3.819	no	no
I1	0.189	0.190	yes	0.915	0.185	yes	0.114	0.597	0.191	yes	-1.463	1.154	-1.268	yes	yes
I1.5	0.137	0.200	yes	0.948	0.533	yes	0.044	0.597	0.074	yes	-1.112	1.154	-0.964	yes	yes
I2	0.129	0.200	yes	0.932	0.086	yes	0.800	0.456	1.754	yes	-0.790	0.887	-0.891	yes	yes

	Kolmogorov-Smirnov			Shapiro-Wilk			Skewness				Kurtosis				Final
Factor	**D**	**Sig.**	**Normal**	**D**	**Sig.**	**Normal**	**Skewness**	**Standard error of skewness**	$z_{skewness}$	**Normal**	**Kurtosis**	**Standard error of kurtosis**	$z_{kurtosis}$	**Normal**	**Normal**
I2.5	0.127	0.200	yes	0.961	0.689	yes	-0.517	0.564	-0.917	yes	0.141	1.091	0.129	yes	yes
I3	0.189	0.000	no	0.889	0.000	no	1.390	0.327	4.251	no	2.532	0.644	3.932	no	no
E1	0.109	0.200	yes	0.970	0.709	yes	0.388	0.491	0.790	yes	-0.328	0.953	-0.344	yes	yes
E1.5	0.137	0.200	yes	0.948	0.533	yes	0.044	0.597	0.074	yes	-1.112	1.154	-0.964	yes	yes
E2	0.100	0.200	yes	0.978	0.571	yes	0.384	0.361	1.064	yes	0.426	0.709	0.601	yes	yes
E2.5	0.281	-		0.877	0.326	yes	0.317	1.014	0.313	yes	-4.067	2.619	-1.553	yes	yes
E3	0.184	0.002	no	0.916	0.006	no	0.994	0.374	2.658	no	0.534	0.733	0.729	yes	no
CD1	0.102	0.032	no	0.972	0.070	yes	0.545	0.264	2.064	no	0.104	0.523	0.199	yes	yes
CD2	0.170	0.014	no	0.908	0.008	no	1.083	0.403	2.687	no	1.130	0.788	1.434	yes	no
CD3	0.227	0.200	yes	0.870	0.228	yes	-0.702	0.845	-0.831	yes	-1.666	1.741	-0.957	yes	yes
BT1	0.082	0.200	yes	0.969	0.122	yes	0.619	0.306	2.023	no	0.197	0.604	0.326	yes	yes
BT2	0.115	0.200	yes	0.973	0.474	yes	0.084	0.383	0.219	yes	0.064	0.750	0.085	yes	yes

Table 6.5 Results of the normality tests (D: test statistic, gray background: non-normal distribution)

Besides normality, the homogeneity of variance should also be checked. Two tests were performed to this end: Levene's and Hartley's.

Table 6.6 shows the results of Levene's test. If the test is significant, the variances of different categories are significantly different, they are not homogeneous.

Factor	F	df_1	df_2	Sig.	Homogenous
Q	7.058	3	119	0.000	no
PS	6.766	3	119	0.000	no
K	0.362	4	118	0.835	yes
I	0.798	4	118	0.529	yes
E	3.017	4	118	0.021	no
CD	2.473	2	120	0.089	yes
BT	9.158	2	120	0.000	no

Table 6.6 Results of Levene's test (F: Levene test statistic, gray background: heterogeneity of variance)

To double-check the results, Hartley's F_{max} was also calculated for all factors. This is the ratio of the biggest and the smallest variance per factor. This value is then compared to a critical value, which is determined based on the number of variances compared and the number of cases per category. Then the F_{max} values were compared to the critical values. If the F_{max} value is greater than the critical, it is significant, meaning that the variances are heterogeneous. Since the numbers of cases in each group are different, the critical values were calculated for both the number of cases in the category with the smallest and also with the biggest variance. The F_{max} values were either greater or smaller than both of these values for all factors, except for the course difficulty. Here the F_{max} value was between the calculated critical values. The critical value determined for the smallest variance was high due to the low number of cases for CD3. The results are summarised in Table 6.7. The critical column shows the smaller value out of the two calculated ones in the homogenous cases, and the greater one, in the heterogeneous ones.

Factor	Variance					Hartley's F_{max}	Critical	Homogeneous
	1	1.5	2	2.5	3	biggest/smallest		
Q	2080	-	603	2385	3275	5.434	2.502	no
PS	192	-	1298	1460	3111	16.189	6.310	no
K	2080	1111	1992	2372	2526	2.274	2.336	yes
I	2201	1111	2612	1382	2576	2.351	3.160	yes
E	828	1111	1767	987	3261	3.938	3.464	no
CD	1692	-	3236	-	330	9.806	10.800	yes
BT	2786	-	1075	-	512	5.444	2.785	no

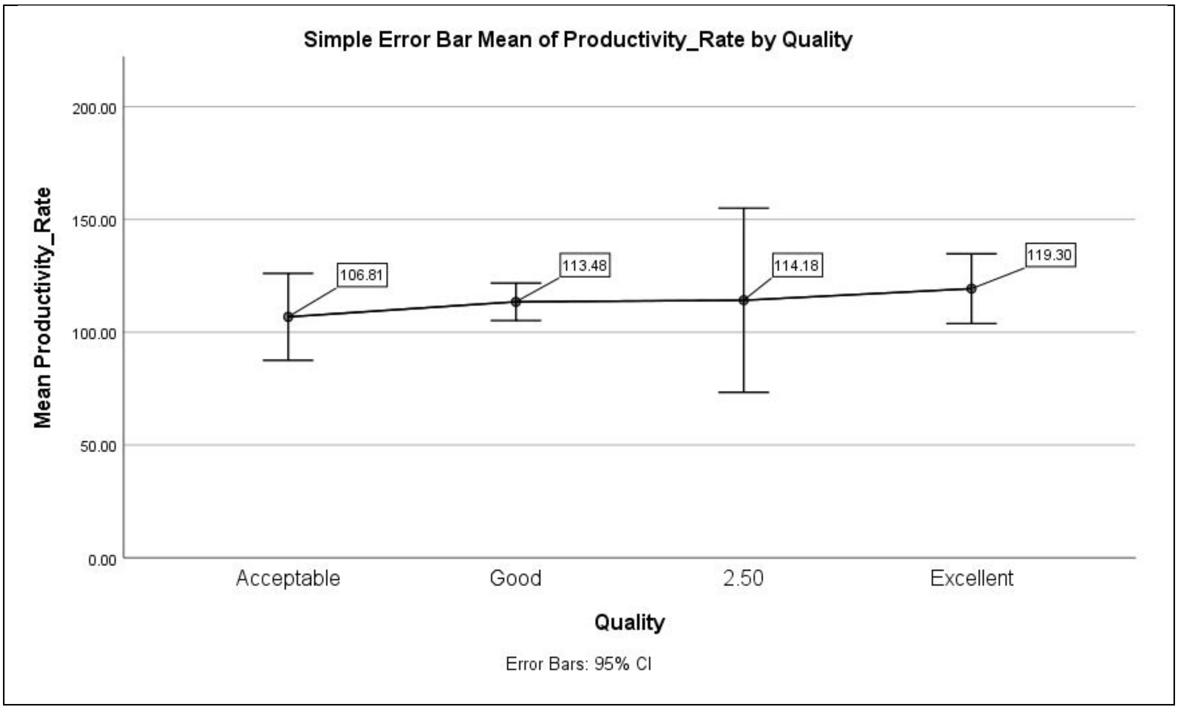
Table 6.7 Results of Hartley's test (gray background: heterogeneity of variance)

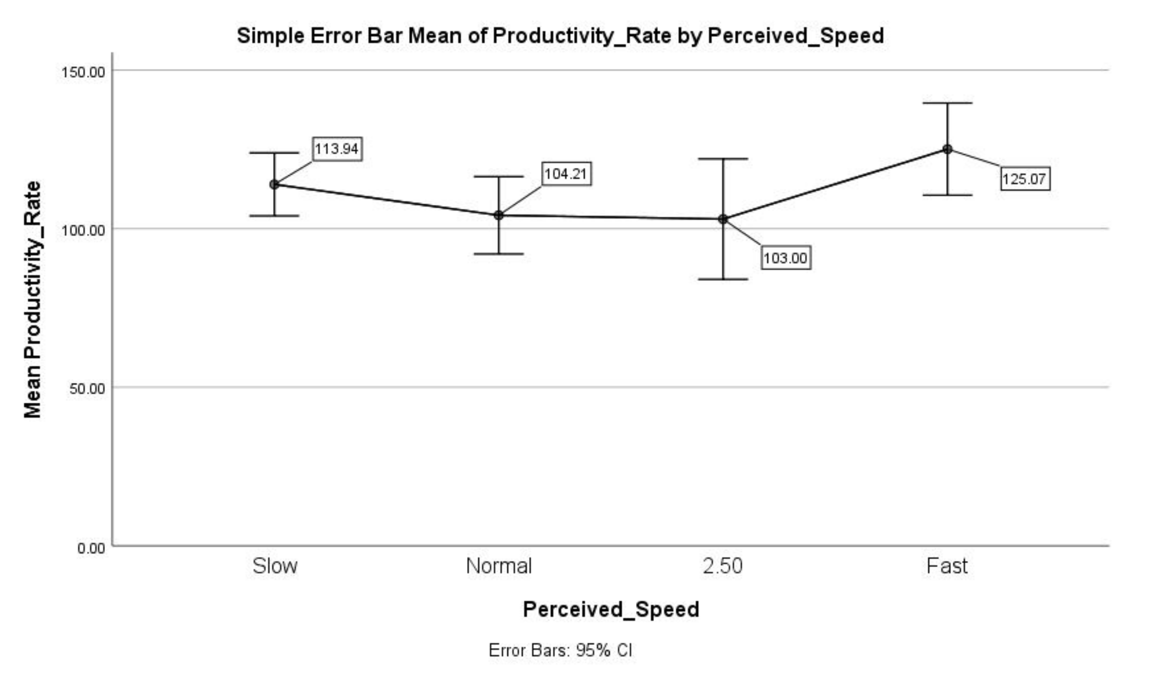
Based on the above tests, it can be concluded that the variances are significantly different in the case of the following factors: quality, perceived speed, experience, and brick type. The results of Levene's and Hartley's tests are the same, the homogeneity of variance condition of parametric tests is only met in the case of knowledge, independence, and course difficulty.

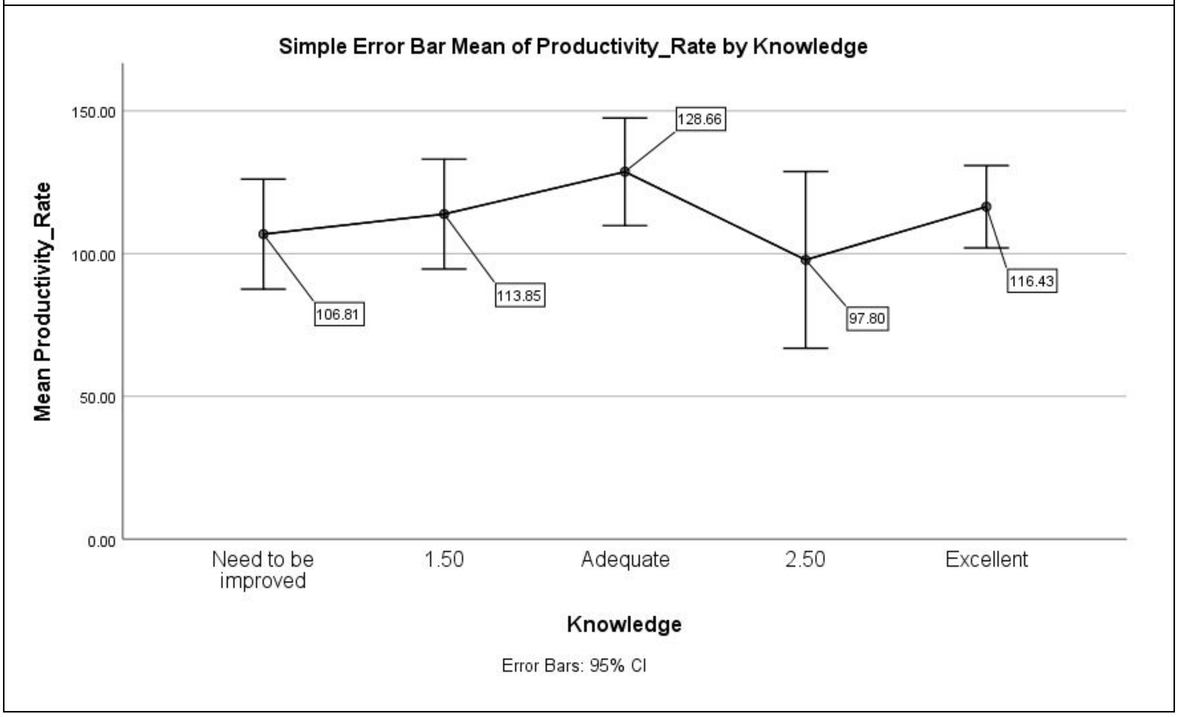
6.3 One-way analysis of variance (ANOVA)

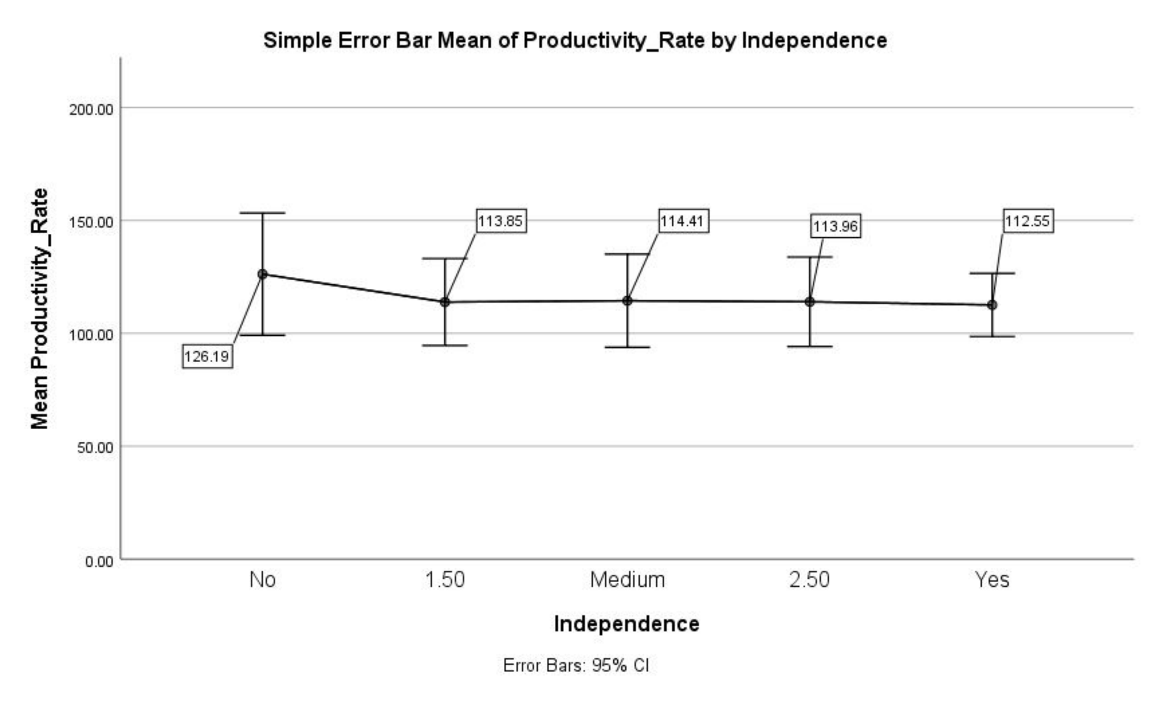
ANOVA is used to determine whether the selected factors have an influence on the dependent variable, i.e., the productivity rate. It is a parametric test; therefore, it assumes a normal distribution. In the case of unequal sample sizes, ANOVA is also sensitive to the violation of the homogeneity of variance. That is why the tests of the previous chapter were performed. From the results we can conclude that while the scores of some categories follow a normal distribution, and the variances of the groups in some factors are homogenous, others are non-normal and heterogeneous. Due to this, both parametric and non-parametric tests were performed to determine whether the productivity rate is affected by the factors. In the case of both types of tests, the categories within one factor were compared to each other.

The error bars showing the 95% confidence intervals for the different groups of each factor can be seen in Figure 6.3. The mean productivity rate values for every category are labelled.




Simple Error Bar Mean of Productivity_Rate by Perceived_Speed
150.00
100.00
50.00
0.00
Mean Productivity_Rate
113.94
104.21
103.00
125.07
Slow
Normal
2.50
Fast
Perceived_Speed
Error Bars: 95% CI


Simple Error Bar Mean of Productivity_Rate by Knowledge
150.00
100.00
50.00
0.00
Mean Productivity_Rate
128.66
106.81
113.85
97.80
116.43
Need to be improved
1.50
Adequate
2.50
Excellent
Knowledge
Error Bars: 95% CI


Simple Error Bar Mean of Productivity_Rate by Independence
Mean Productivity_Rate
200.00
150.00
100.00
50.00
0.00
126.19
113.85
114.41
113.96
112.55
No
1.50
Medium
2.50
Yes
Independence
Error Bars: 95% CI


Simple Error Bar Mean of Productivity_Rate by Experience
Mean Productivity_Rate
150.00
100.00
50.00
0.00
91.03
113.85
122.90
65.04
124.57
Limited
1.50
Medium
2.50
Substantial
Experience
Error Bars: 95% CI

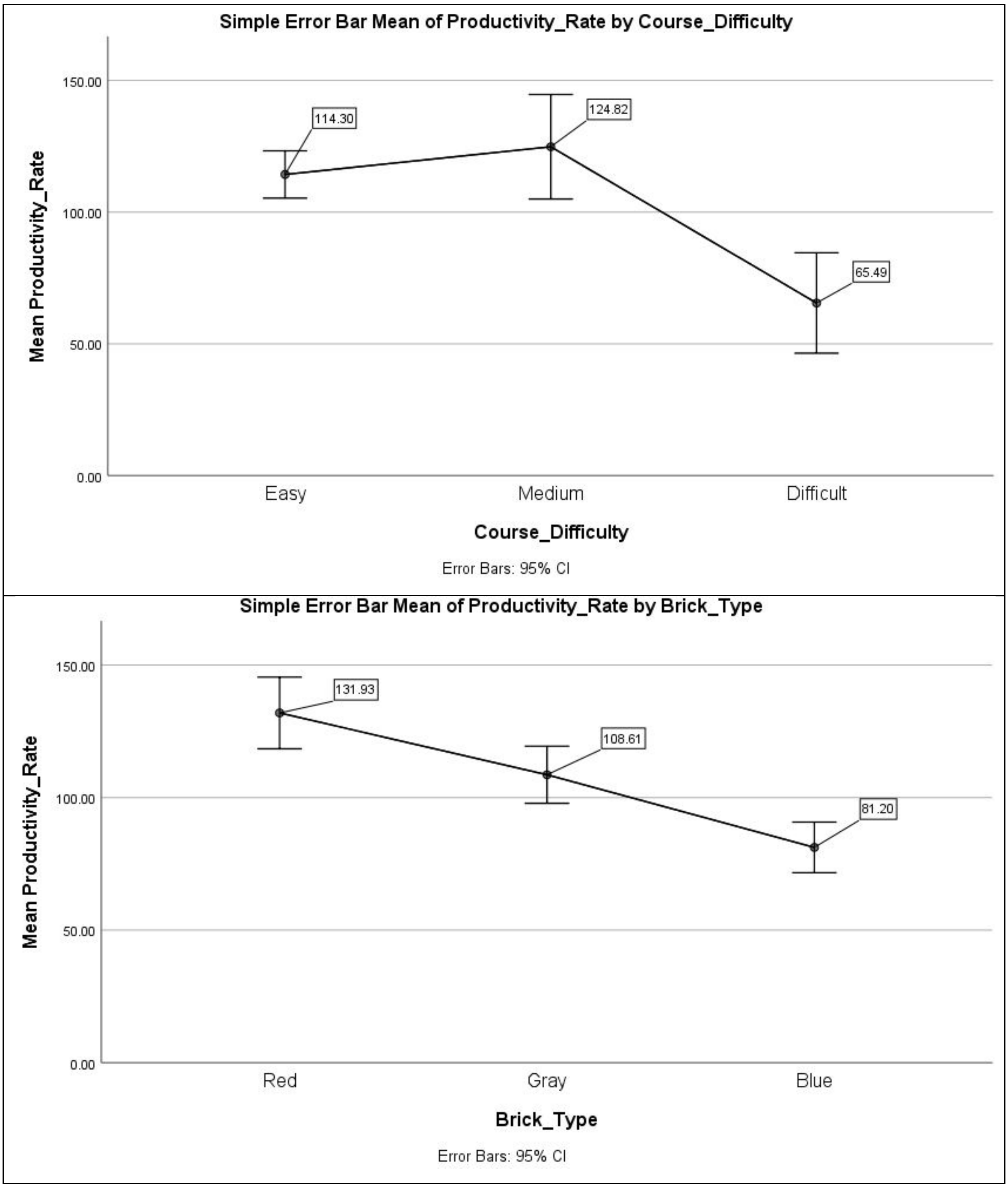


Figure 6.3 Error bars

Table 6.8 summarises the tests that were performed and the main results. If the variances of the categories are significantly different from each other, Welch's F has to be checked. If this is significant, that means that the factor has an effect on the dependent variable, which is now the productivity rate. This is the case for experience and brick type. Table 6.10 contains the results of Welch's test. The effect size was calculated according to (3) (Horn, 2006). The effects were determined based on Table 6.10. For perceived speed, the Welch F was not significant; however, the Brown-Forsythe F was. This can be due to an extreme mean. The implications of this are the same as those of Welch's F being significant. Table 6.11 contains the results for this test. The effect sizes were calculated according to (3) and the effects were determined based on Table 6.9.

Factor	Variances	ANOVA/Robust tests	Significant contrasts	Significant post-hoc tests
Q	significantly different	Welch's, Brown-Forsythe's: not significant		
PS	significantly different	Welch's: not significant Brown-Forsythe's: significant	▪ PS3 vs. PS1&PS2&PS2.5 ▪ PS2.5 vs. PS3	
K	not significantly different	ANOVA: not significant	▪ K2 vs. K2.5&K3	
I	not significantly different	ANOVA: not significant		
E	significantly different	Welch's, Brown-Forsythe's: significant	▪ E3 vs. E1&E1.5&E2&E2.5 ▪ E2 vs. E1&E1.5 ▪ E1.5 vs. E1 ▪ E1 vs. E1.5&E2&E2.5&E3 ▪ E2 vs. E2.5&E3 ▪ E2.5 vs. E3	Games-Howell E1vE2 E1vE3
CD	not significantly different	ANOVA: significant	▪ CD2 vs. CD3 ▪ CD3 vs. CD1&CD2	Hochberg, Gabriel CD1vCD3 CD2vCD3
BT	significantly different	Welch's, Brown-Forsythe's: significant	▪ BT1 vs. BT2&BT3 ▪ BT2 vs. BT3 ▪ BT3 vs. BT1&BT2 ▪ BT1 vs. BT2	Games-Howell BT1vBT2 BT1vBT3 BT2vBT3

Table 6.8 Parametric test results (gray background: factor has an effect on the productivity rate)

$$\omega^2 = \frac{df_1 * (F-1)}{df_1 * (F-1) + N} \qquad (3)$$

where F: Welch's/Brown-Forsythe F, N: sample size.

Effect size (ω^2)	Effect
> 0.01	small
> 0.06	medium
> 0.14	large

Table 6.9 Effect sizes

Factor	Welch's F	df_1	df_2	Sig.	Effect size	Effect
Q	0.343	3	27.544	0.794		
PS	1.981	3	47.254	0.130		
E	5.522	4	19.706	0.004	0.1282	medium
BT	20.505	2	75.489	0.000	0.2408	large

Table 6.10 Results for Welch's test (gray background: factor has an effect on the productivity rate)

Factor	Brown-Forsythe F	df_1	df_2	Sig.	Effect size	Effect
Q	0.442	3	41.994	0.724		
PS	3.225	3	95.555	0.026	0.0515	small
E	4.856	4	64.073	0.002	0.1114	medium
BT	18.150	2	118.726	0.000	0.2181	large

Table 6.11 Results for Brown-Forsythe's test (gray background: factor has an effect on the productivity rate)

In the case of the variances being homogenous, the ANOVA table has to be looked at. This was the case for knowledge, independence, and course difficulty. The test was significant only for course difficulty. The results can be seen in Table 6.12. The effect size was calculated based on (4), and the effect was determined according to Table 6.9.

$$\omega^2 = \frac{SS_M - df_M * MS_R}{SS_T + MS_R} \tag{4}$$

where SS_M: between group effect (sum of squares model), df_M: degrees of freedom for the effect, MS_R: residual mean squared error, SS_T: total amount of variance in the data (sum of squares total)

Factor	F-ratio	Sig.	SS_M	SS_T	MS_R	df_M	Effect size	Effect
K	1.127	0.347						
I	0.237	0.917						
CD	4.374	0.015	18017	265178	2060	2	0.052	small

Table 6.12 Results for ANOVA (gray background: factor has an effect on the productivity rate)

Table 6.13 shows the main ANOVA summary table for course difficulty. The combined between group effect is the overall effect due to the model, while the within groups effect is the unsystematic variation in the data existing due to individual differences between the groups. Since the F-ratio value corresponding to the former is significant, course difficulty has a significant effect on the productivity rate. The F-ratio of the quadratic term is significant suggesting a quadratic trend.

Course Difficulty			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		18017	2	9008	4.374	0.015
	Linear Term	Unweighted	13329	1	13329	6.472	0.012
		Weighted	1562	1	1562	0.758	0.386
		Deviation	16455	1	16455	7.989	0.006
	Quadratic Term	Unweighted	16455	1	16455	7.989	0.006
		Weighted	16455	1	16455	7.989	0.006
Within Groups			247161	120	2060		
Total			265178	122			

Table 6.13 ANOVA results for course difficulty

Since the previous tests only show that the given factor has some effect on the dependent variable, planned contrasts and post-hoc tests were used to see where the differences lie. Tables 6.14-16 summarise the orthogonal contrasts tested for the factors. For instance, in the case of the quality factor, first, the highest score was selected as a baseline, and the other three categories were compared to this. Then the second highest score was compared to the two lower scores. Last, the lowest and second lowest scores were compared to each other. Then another set of comparisons were performed. This time the lowest score was chosen as the baseline and compared to the higher scores. Then the second lowest was compared to the two higher scores, and finally the two higher scores were compared to each other. The comparisons were defined based on the same logic in the case of the other factors as well. The significant contrasts are listed in Table 6.8.

		I	II	III		I	II	III
Q, PS	**1**	1	1	1		-3	0	0
	2	1	1	-1		1	-2	0
	2.5	1	-2	0		1	1	-1
	3	-3	0	0		1	1	1

Table 6.14 Contrasts for the quality and perceived speed variables

		I	II	III	IV		I	II	III	IV
K, I, E	**1**	1	1	1	1		-4	0	0	0
	1.5	1	1	1	-1		1	-3	0	0
	2	1	1	-2	0		1	1	-2	0
	2.5	1	-3	0	0		1	1	1	-1
	3	-4	0	0	0		1	1	1	1

Table 6.15 Contrasts for the knowledge, independence and experience variables

		I	II		I	II
CD, BT	**1**	-2	0		1	1
	2	1	-1		1	-1
	3	1	1		-2	0

Table 6.16 Contrasts for the course difficulty and brick type variables

The results for those contrasts that were significant are shown in Table 6.18. It also lists the effect sizes, which were calculated according to (5), while the effects were determined based on Table 6.17.

$$r = \sqrt{\frac{t^2}{t^2 + df}} \qquad (5)$$

Effect size (r)	Effect
> 0.1	small
> 0.3	medium
> 0.5	large

Table 6.17 Effect sizes

Comparisons	t	Sig.	2-tailed/ 1-tailed	df	Effect size	Effect
PS3 vs. PS1&PS2&PS2.5	-2.187	0.031	2-tailed	85.845	0.230	small
PS2.5 vs. PS3	1.907	0.032	1-tailed	41.187	0.285	small
K2 vs. K2.5&K3	-1.781	0.039	1-tailed	118	0.162	small
E3 vs. E1&E1.5&E2&E2.5	-2.551	0.014	2-tailed	45.285	0.355	medium
E2 vs. E1&E1.5	-2.439	0.017	2-tailed	66.241	0.287	small
E1.5 vs. E1	-2.11	0.045	2-tailed	24.802	0.390	medium
E1 vs. E1.5&E2&E2.5&E3	1.920	0.033	1-tailed	28.868	0.337	medium
E2 vs. E2.5&E3	-2.532	0.027	2-tailed	11.499	0.598	large
E2.5 vs. E3	3.286	0.020	2-tailed	5.266	0.820	large

Comparisons	t	Sig.	2-tailed/ 1-tailed	df	Effect size	Effect
CD2 vs. CD3	-2.952	0.004	2-tailed	120	0.260	small
CD3 vs. CD1&CD2	2.831	0.005	2-tailed	120	0.250	small
BT1 vs. BT2&BT3	-4.858	0.000	2-tailed	90.294	0.455	medium
BT2 vs. BT3	-3.891	0.000	2-tailed	59.457	0.451	medium
BT3 vs. BT1&BT2	6.192	0.000	2-tailed	68.052	0.600	large
BT1 vs. BT2	2.712	0.008	2-tailed	97	0.266	small

Table 6.18 Results for the significant contrasts

For post-hoc tests, in the case of homogenous variances, Hochberg's GT2 and Gabriel's procedures were selected as they can deal with unequal sample sizes. The Games-Howell procedure was chosen for heterogeneous variances because that can also handle different sample sizes. The significant tests are listed in Table 6.8. These are similar to the significant contrasts.

Based on the parametric tests performed, it can be concluded that brick type and experience have the most significant effects on the productivity out of the seven factors. The productivity rate significantly decreases from red bricks (BT1) to gray bricks (BT2) to blue bricks (BT3). This is consistent with how the brick type factor was defined as a difficulty scale. Experience has a reverse effect. The productivity rate increases significantly with more years spent working in construction. According to the Brown-Forsythe's test, perceived speed also has a significant effect on productivity. Based on the significant contrasts, the bricklayers who were deemed fastest (PS3) by their supervisors tend to work significantly faster than the ones in the lower categories. This shows a consistency between the time measurements and the supervisors' evaluation. According to the ANOVA, course difficulty significantly affects the productivity rate. Based on the significant contrasts, difficult courses (CD3) take significantly longer to build, than the courses in the other two categories.

6.4 Non-parametric tests

Due to some categories following normal distribution, while others are non-normal, and some factors having homogenous variances, while others are heterogeneous, both parametric and non-parametric tests were performed. The summary of the latter tests performed can be seen in Table 6.19.

To see whether the productivity rate is affected by the various factors, one-way ANOVA tests were performed. Their non-parametric equivalent is the Kruskal-Wallis test. If it is significant, the given factor significantly affects the dependent variable. In this case, experience, course difficulty, and brick type significantly affect the productivity rate. The details are shown in Table 6.19.

Factor	Kruskal-Wallis			Jonckheere-Terpstra	
	H	**df**	**Sig.**	**z**	**Sig.**
Q	1.295	3	0.730	0.402	0.688
PS	3.337	3	0.343	1.140	0.254
K	4.137	4	0.388	0.135	0.893
I	1.931	4	0.748	-1.120	0.263
E	14.277	4	0.006	1.590	0.112
CD	10.065	2	0.007	-0.799	0.424
BT	22.265	2	0.000	-4.696	0.000

Table 6.19 Tests run and their main results (H: Kruskal-Wallis test statistic, z: standardised Jonckheere-Terpstra test statistic, gray background: factor has an effect on the productivity rate)

The Kruskal-Wallis test can determine if the factor has an effect on the dependent variable, however, it cannot determine trends. Jonckheere-Terpstra tests were performed to determine whether the categories' order is meaningful. The results of this test can be seen in Table 6.19, while the effect size and the effect of the factor producing a significant test statistic are shown in Table 6.20. The effect size was calculated according to (6). The effect was determined based on Table 6.17. According to the results, the productivity rate significantly decreases (because the z value is negative) with choosing different bricks (red→gray→blue).

$$r = \frac{z}{\sqrt{N}} \tag{6}$$

where z: standardised Jonckheere-Terpstra test statistic, N: sample/group size.

Factor	z	Sig.	Effect size	Effect
BT	-4.696	0.000	-0.423	medium

Table 6.20 Results of the Jonckheere-Terpstra test

In the case of those factors, where the Kruskal-Wallis test was significant, pairwise comparisons were performed. The details of the significant ones can be seen in Table 6.21. The significance column contains the adjusted significance values, which are determined based on the Bonferroni correction. To minimise the Type I errors, the scores' significance values were multiplied by the number of possible comparisons for each factor. For instance, in the case of brick type, there were three possible comparisons (BT1vBT2, BT1vBT3, BT2vBT3); therefore, the original significance value was multiplied by 3. Then these corrected significance values were compared to the 0.05 significance level. The effect size was calculated according to (6). The effect was determined based on Table 6.17.

Contrast	2-tailed/ 1-tailed	z	Sig.	N	Effect size	Effect
E1vE2	2-tailed	-2.907	0.036	65	-0.361	medium
E2.5vE2	1-tailed	2.674	0.038	47	0.390	medium
CD1vCD3	2-tailed	2.994	0.008	89	0.317	medium
CD2vCD3	2-tailed	3.143	0.005	40	0.497	medium
BT1vBT3	2-tailed	4.712	0.000	85	0.511	large
BT2vBT3	2-tailed	2.934	0.010	62	0.373	medium

Table 6.21 Results of the pairwise comparisons (z: standardised test statistic, N: group size)

Based on the non-parametric tests performed, it can be concluded that experience, course difficulty, and brick type significantly affect the productivity rate. This is the same result as that of the parametric tests. Pairwise comparisons show that building a difficult course (CD3) is significantly slower than constructing the other two, and that building with blue bricks (BT3) also takes significantly longer than laying the other two brick types.

6.5 Regression analysis

By using regression analysis, the dependent output variable – the productivity rate in this case – can be predicted based on the independent predictor variables, i.e., the selected influencing factors. In the case of linear regression, the target value of the output variable can be calculated based on the linear equation (7).

$$Y = b_0 + b_1 * X_1 + b_2 * X_2 + \cdots + b_k * X_k + \varepsilon \qquad (7)$$

where Y: target value of the dependent variable, b: regression coefficients, X: values of the predictor variables, k: number of predictors, ε: error, difference between observed and predicted output value.

The predictors in regression analysis can be either continuous or binary. In this case, the independent variables are ordinal; however, they were handled as continuous. It can be worthwhile treating ordinal variables as continuous to examine the linear component associated with them and to avoid overlooking possible relationships (Pasta, 2009).

6.5.1 Simple regression analysis

First, simple regression analyses were performed to see which factors affect the productivity rate on their own. The results can be seen in Table 6.22. R^2 (coefficient of determination) shows how much of the variation of the productivity rate can be explained by the given factor. For example, brick type accounts for 25.6% of the variation in the model. The F-ratio being significant means that the model predicts the productivity rate significantly better than using the mean value. In case the t-test is significant, it can be concluded that the factor makes a significant contribution to predicting the productivity rate. Based on the above and

Table 6.22, experience and brick type are the two factors that can be used to predict the productivity rate significantly well.

Factor	R^2	F-ratio	Sig.	Sig.?
Q	0.01	1.233	0.269	no
PS	0.021	2.591	0.110	no
K	0.002	0.188	0.665	no
I	0.005	0.584	0.446	no
E	0.039	4.906	0.029	yes
CD	0.006	0.717	0.399	no
BT	0.175	25.629	0.000	yes

Table 6.22 Results of simple regression analyses (gray background: significant t-test)

6.5.2 Multiple regression analysis

After simple regression analyses, several multiple regression analyses were performed. When determining the order in which the factors were added to the model, first, the results of the simple regression analyses were used. The factors were added in descending order of their F-ratio values: brick type, experience, perceived speed, quality, course difficulty, independence, knowledge. Based on the results, the order was changed according to the F-ratio of change values, course difficulty and independence moved to third and fourth positions respectively. This has not changed that model's parameters that included all the factors; however, it provided a better understanding of the intermediate models.

Three analyses were run. In the case of the first one, the factors were added to the model one by one. Then the backward method was applied for all the factors. In the case of the final test, quality and knowledge were not included in the model.

The top row of Figure 6.4 shows the main components of the multiple regression analysis, while the middle row lists the questions the part looks to answer, and, finally, the bottom row gives the output of each component.

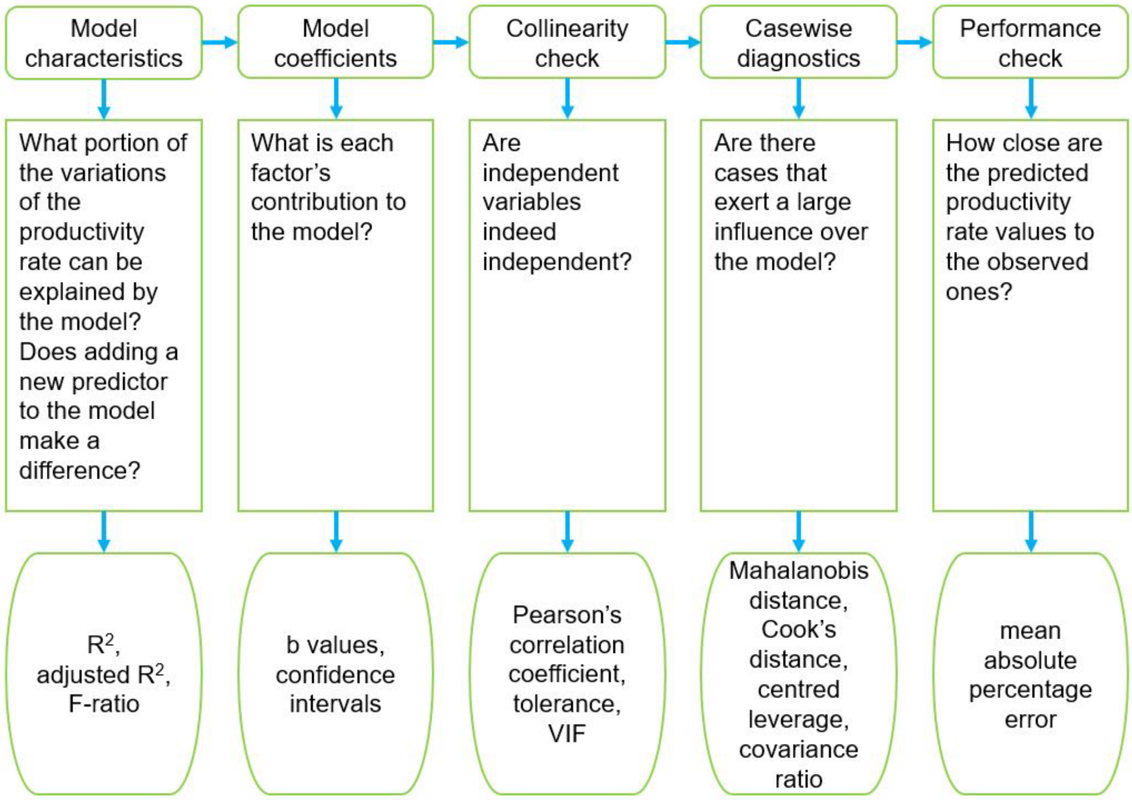


Figure 6.4 Steps of multiple regression analysis

6.5.2.1 Multiple regression analysis with all factors

Ideally, there should be no substantial correlation between the independent variables. This means that the Pearson's correlation coefficient should not be greater than 0.9. There is one pairing (knowledge-independence) where the correlation is higher than that. Table 6.23 shows the highest correlation coefficients.

Factor #1	Factor #2	Pearson's correlation coefficient	Sig.
K	I	0.924	0.000
Q	K	0.825	0.000
Q	I	0.720	0.000
E	K	0.687	0.000
BT	I	0.653	0.000
E	Q	0.651	0.000

Table 6.23 The highest Pearson's correlation coefficients

Table 6.24 gives the summary of the models. The first model had one predictor: the brick type. The second one also included the experience variable. Model 7 was created using all the factors. According to the R^2 value, Model 7 can explain 45.6% of the variations of the productivity rate. The adjusted R^2 shows that if Model 7 was applied to the whole population, rather than to the given sample, it could explain 42.2% of the variation. Where the F-ratio of change is significant, the change in R^2 is significant, meaning that adding a new predictor to the model makes a difference. This is the case for the first four models. The F-ratio represents the ratio of the improvement of the prediction relative to the inaccuracy that can still be found in the model. Here the F-ratio started to decrease after the second predictor had been added to the model.

Model	**Factors**	**R^2**	**Adjusted R^2**	**F-ratio of change**	**df_1**	**df_2**	**Sig. F-ratio of change**	**F-ratio**	**Sig. F-ratio**
1	BT	0.175	0.168	25.629	1	121	0.000	25.629	0.000
2	BT, E	0.350	0.339	32.354	1	120	0.000	32.312	0.000
3	BT, E, CD	0.386	0.371	6.989	1	119	0.009	24.946	0.000
4	BT, E, CD, I	0.424	0.405	7.811	1	118	0.006	21.733	0.000
5	BT, E, CD, I, PS	0.442	0.418	3.703	1	117	0.057	18.525	0.000
6	BT, E, CD, I, PS, Q	0.445	0.416	0.651	1	116	0.421	15.500	0.000
7	BT, E, CD, I, PS, Q, K	0.456	0.422	2.224	1	115	0.139	13.744	0.000

Table 6.24 Model summary

The Durbin-Watson statistic shows if the assumption of independent errors is tenable. The value should be between 1 and 3, preferably closer to 2. Here it is 1.072.

The parameters of Model 7 can be found in Table 6.25. The b values show each predictors' contribution to the model. If b is negative, there is a negative relationship between the outcome and the predictor. In case it is positive, the relationship is positive, as well. A significant t-test means that the predictor's contribution to the model is significant. In this case, brick type, experience, course difficulty, and independence make significant contributions to the model.

Ideally, the confidence interval should not cross zero. However, the confidence intervals of quality, perceived speed, and knowledge do cross zero.

To check whether there is collinearity in the data, the tolerance and variance inflation factor (VIF) values need to be examined. Table 6.25 also contains these values for Model 7. Tolerance should be greater than 0.1, and the VIF should not be greater than 10. Note that both rules were violated in the case of knowledge and independence.

	Unstandardised coefficients		Standardised coefficients	t	Sig.	95% confidence interval for b		Collinearity statistics	
Factor	**b**	**Standard error**	**Beta**			**Lower bound**	**Upper bound**	**Tolerance**	**VIF**
Constant	162.663	21.516		7.560	0.000	120.043	205.282		
BT	-58.265	6.942	-0.972	-8.393	0.000	-72.017	-44.514	0.353	2.836
E	34.699	7.634	0.544	4.545	0.000	19.578	49.821	0.331	3.023
CD	-25.904	6.532	-0.321	-3.965	0.000	-38.843	-12.964	0.721	1.387
I	41.504	16.031	0.632	2.589	0.011	9.750	73.258	0.079	12.586
PS	-13.315	8.504	-0.176	-1.566	0.120	-30.160	3.530	0.376	2.658
Q	1.297	10.544	0.021	0.123	0.902	-19.589	22.183	0.159	6.291
K	-24.083	16.148	-0.405	-1.491	0.139	-56.069	7.902	0.064	15.538

Table 6.25 Model parameters (gray background: significant t-test)

Table 6.27 lists those cases where the standard residual is less than -2, or greater than 2. There are seven cases listed, which is slightly over the 5% limit (123*0.05=6.15). Two cases (36 and 79) have a standardised residual of more than 2.5 or less than -2.5. This is slightly above the 1% limit (123*0.01=1.23). The listed cases were checked separately to see whether they have any undue influence on the model. The critical value of the Mahalanobis distance was determined based on the number of predictors and the sample size (Barnett and Lewis, 1978). Since the table only contains the critical values for maximum five predictors, the corresponding value, 20, is chosen as the critical value for this analysis. The Cook's distance should not exceed 1. The leverage, in this case, should be less than 0.1301, while the covariance ratio should be between 0.8049 and 1.195. Table 6.26 summarises the critical values of each measure of influence. Based on Tables 6.26 and 6.27, it can be seen that the seven listed cases satisfy the first three conditions but the covariance ratios of cases 36, 77, 78, and 79 are not within the calculated limits.

Lower bound		Measure of influence		Upper bound
		Mahalanobis Distance	<	20
		Cook's Distance	<	1
		Centred Leverage	<	$2 * \frac{k+1}{N} = 2 * \frac{7+1}{123} = 0.1301$
$1 - 3 * \frac{k+1}{N} = 1 - 3 * \frac{7+1}{123} = 0.8049$	<	Covariance Ratio	<	$1 + 3 * \frac{k+1}{N} = 1 + 3 * \frac{7+1}{123} = 1.195$

Table 6.26 Limits for casewise diagnostics (k: number of predictors, N: sample size)

Case Number	Standard Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Covariance Ratio
12	-2.254	12.035	0.085	0.099	0.800
36	-2.622	10.901	0.103	0.089	0.687
50	-2.167	10.901	0.070	0.089	0.821
76	2.033	5.480	0.031	0.045	0.831
77	2.484	5.480	0.046	0.045	0.710
78	2.409	7.321	0.057	0.060	0.737
79	3.120	7.321	0.096	0.060	0.537

Table 6.27 Results of casewise diagnostics

Figure 6.5 shows the predicted and observed productivity rates. The predicted values are calculated based on the coefficients, b-values, listed in Table 6.25. The orange line depicts the ideal/theoretical situation where the predicted values are equal to the observed ones.

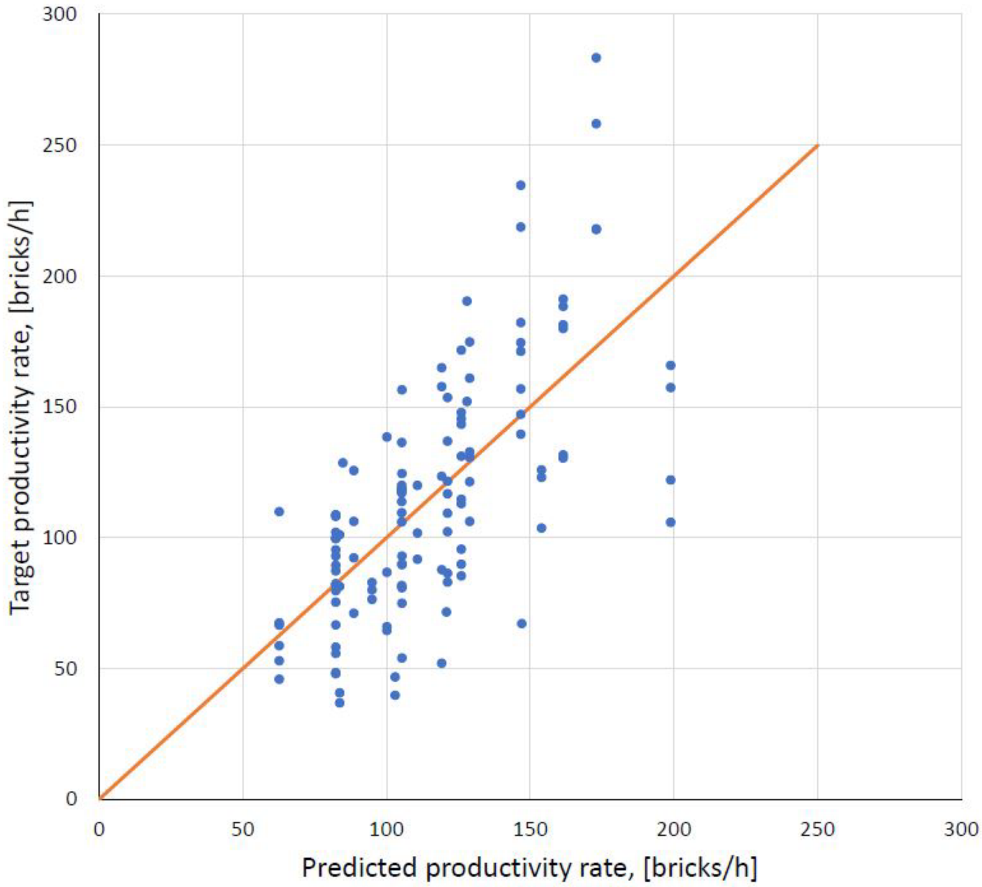


Figure 6.5 Predicted and observed productivity rates based on Model 7

Based on the observed and predicted values of the productivity rate, the mean absolute percentage error can be calculated using (8).

$$mape = \frac{1}{N} * \sum_{i=1}^{N} \frac{|observed\ value_i - predicted\ value_i|}{observed\ value_i} * 100\% \qquad (8)$$

The mape for Model 7 is 27.37%.

6.5.2.2 Multiple regression analysis with all factors (backward method)

In the case of this method, first, all factors are included in the model, then at each step one factor is excluded. The factors are considered for removal in ascending order of their partial correlations. The ones meeting the removal criterion (probability of F ≥0.1) are excluded one by one. In this case, only quality was removed.

Table 6.28 gives the summary of the models. The first model includes all the factors, while the second one includes all of them but quality. According to the R^2 value, Model 2 can explain 45.5% of the variations of the productivity rate. The adjusted R^2 shows that if Model

2 was applied to the whole population, rather than to the given sample, it could explain 42.7% of the variation. Where the F-ratio of change is significant, the change in R^2 is significant, meaning that adding a new predictor to the model makes a difference. This is the case for the first model. The F-ratio represents the ratio of the improvement of the prediction relative to the inaccuracy that can still be found in the model. Here the F-ratio increased after quality had been removed from the model.

Model	**Factors**	**R^2**	**Adjusted R^2**	**F-ratio of change**	**df_1**	**df_2**	**Sig. F-ratio of change**	**F-ratio**	**Sig. F-ratio**
1	BT, E, CD, I, PS, Q, K	0.456	0.422	13.744	7	115	0.000	13.744	0.000
2	BT, E, CD, I, PS, K	0.455	0.427	0.015	1	115	0.902	16.169	0.000

Table 6.28 Model summary

The Durbin-Watson statistic shows if the assumption of independent errors is tenable. The value should be between 1 and 3, preferably closer to 2. Here it is 1.071.

The parameters of Model 2 can be found in Table 6.29. The b values show each predictors' contribution to the model. If b is negative, there is a negative relationship between the outcome and the predictor. In case it is positive, the relationship is positive as well. A significant t-test means that the predictor's contribution to the model is significant. In this case, only knowledge does not make a significant contribution to the model.

Ideally, the confidence interval should not cross zero. However, the confidence interval of knowledge does cross zero.

To check whether there is collinearity in the data, the tolerance and VIF values need to be examined. Table 6.29 also contains these values for Model 2. Tolerance should be greater than 0.1, and the largest VIF should not be greater than 10. Note that both rules were violated in the case of knowledge and independence.

	Unstandardised coefficients		Standardised coefficients	t	Sig.	95% confidence interval for b		Collinearity statistics	
Factor	**b**	**Standard error**	**Beta**			**Lower bound**	**Upper bound**	**Tolerance**	**VIF**
Constant	161.954	20.643		7.845	0.000	121.068	202.840		
PS	-12.623	6.348	-0.167	-1.988	0.049	-25.197	-0.049	0.669	1.494
K	-23.010	13.532	-0.387	-1.700	0.092	-49.812	3.791	0.091	11.005
I	41.653	15.917	0.634	2.617	0.010	10.128	73.179	0.080	12.514
E	34.503	7.433	0.541	4.642	0.000	19.781	49.225	0.346	2.890
CD	-26.021	6.435	-0.323	-4.044	0.000	-38.766	-13.275	0.737	1.357
BT	-58.363	6.867	-0.974	-8.498	0.000	-71.965	-44.761	0.357	2.799

Table 6.29 Model parameters (gray background: significant t-test)

Table 6.31 lists those cases where the standard residual is less than -2, or greater than 2. There are seven cases listed, which is slightly above the 5% limit (123*0.05=6.15). Cases 36, 77, and 79 have a standardised residual of more than 2.5 or less than -2.5. This can be accepted as within the 1% limit (123*0.01=1.23). The listed cases are checked separately to see whether they have any undue influence on the model. The critical value of the Mahalanobis distance is determined based on the number of predictors and the sample size and was determined to be 20 (Barnett and Lewis, 1978). Table 6.30 summarises the critical values of each measure of influence. Based on Tables 6.30 and 6.31, it can be seen that the seven listed cases satisfy the first three conditions but the covariance ratios of cases 36, 77, 78, and 79 are not within the calculated limits.

Lower bound		**Measure of influence**		**Upper bound**
		Mahalanobis Distance	<	20
		Cook's Distance	<	1
		Centred Leverage	<	$2 * \frac{k+1}{N} = 2 * \frac{6+1}{123} = 0.114$
$1 - 3 * \frac{k+1}{N} = 1 - 3 * \frac{6+1}{123} = 0.829$	<	Covariance Ratio	<	$1 + 3 * \frac{k+1}{N} = 1 + 3 * \frac{6+1}{123} = 1.171$

Table 6.30 Limits for casewise diagnostics (k: number of predictors, N: sample size)

Case Number	**Standard Residual**	**Mahalanobis Distance**	**Cook's Distance**	**Centred Leverage Value**	**Covariance Ratio**
12	-2.266	11.965	0.098	0.098	0.833
36	-2.643	10.166	0.111	0.083	0.724
50	-2.185	10.166	0.076	0.083	0.845
76	2.061	2.449	0.018	0.020	0.836
77	2.514	2.449	0.027	0.020	0.730
78	2.413	7.007	0.062	0.057	0.773
79	3.127	7.007	0.105	0.057	0.587

Table 6.31 Results of casewise diagnostics

Figure 6.6 shows the predicted and observed productivity rates. The predicted values are calculated based on the coefficients, b-values, listed in Table 6.29. The orange line depicts the ideal/theoretical situation where the predicted values are equal to the observed ones.

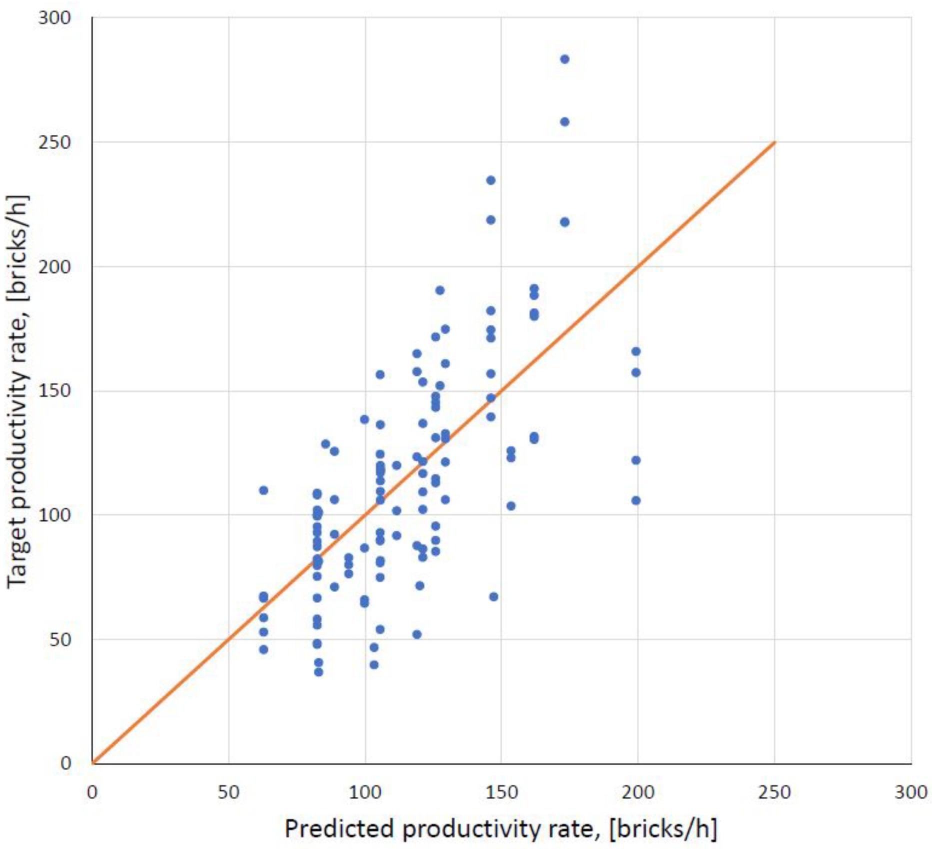


Figure 6.6 Predicted and observed productivity rates based on Model 2

The mean absolute percentage error was calculated using (8). It is 27.32% for Model 2.

6.5.2.3 Multiple regression analysis with selected factors

Adding the factors one by one to the model during the regression analysis described in Section 6.5.2.1 was useful also to see the results for each intermediate model. Model 5 containing 5 factors (perceived speed, independence, experience, course difficulty, brick type) satisfied the criteria (no substantial correlation between variables, significant t-tests, confidence interval not crossing zero, low level of collinearity); therefore, it was further examined.

Table 6.32 gives the summary of the model. According to the R^2 value, the model can explain 44.2% of the variations of the productivity rate. The adjusted R^2 shows that if the model was applied to the whole population, rather than to the given sample, it could explain 41.8% of the variation. Where the F-ratio of change is significant, the change in R^2 is significant, meaning that adding the predictors to the model makes a difference. The F-ratio represents the ratio of the improvement of the prediction relative to the inaccuracy that can still be found in the model.

Model	Factors	R^2	Adjusted R^2	F-ratio of change	df_1	df_2	Sig. F-ratio of change	F-ratio	Sig. F-ratio
1	PS, I, E, CD, BT	0.442	0.418	18.525	5	117	0.000	18.525	0.000

Table 6.32 Model summary

The Durbin-Watson statistic shows if the assumption of independent errors is tenable. The value should be between 1 and 3, preferably closer to 2. Here it is 1.069.

The parameters of the model can be found in Table 6.33. The b values show each predictors' contribution to the model. If b is negative, there is a negative relationship between the outcome and the predictor. In case it is positive, the relationship is positive as well. A significant t-test means that the predictor's contribution to the model is significant. In this case, perceived speed does not make a significant contribution to the model; however, the significance value is barely over the limit.

Ideally, the confidence interval should not cross zero. While the confidence interval of perceived speed does cross zero, the positive side of the interval is small compared to the entire interval.

To check whether there is collinearity in the data, the tolerance and VIF values need to be examined. Table 6.33 also contains these values for the model. Tolerance should be greater than 0.1, and the largest VIF should not be greater than 10. Note that none of the rules have been violated.

	Unstandardised coefficients		Standardised coefficients	t	Sig	95% confidence interval for b		Collinearity statistics	
Factor	**b**	**Std. error**	**Beta**			**Lower bound**	**Upper bound**	**Tolerance**	**VIF**
Constant	167.687	20.530		8.168	0.000	127.029	208.345		
PS	-12.309	6.397	-0.162	-1.924	0.057	-24.977	0.360	0.670	1.493
I	17.886	7.677	0.272	2.330	0.022	2.682	33.091	0.349	2.865
E	28.797	6.686	0.451	4.307	0.000	15.555	42.038	0.435	2.301
CD	-24.896	6.452	-0.309	-3.858	0.000	-37.675	-12.117	0.745	1.343
BT	-53.236	6.220	-0.889	-8.559	0.000	-65.554	-40.918	0.443	2.259

Table 6.33 Model parameters (gray background: significant t-test)

Table 6.35 lists those cases where the standard residual is less than -2, or greater than 2. There are six cases listed, which is slightly above the 5% limit (123*0.05=6.15). Cases 78 and 79 have a standardised residual of more than 2.5 or less than -2.5. This is above the 1% limit (123*0.01=1.23). The listed cases are checked separately to see whether they have any undue influence on the model. The critical value of the Mahalanobis distance is determined based on the number of predictors and the sample size and was determined to be 20 (Barnett and Lewis, 1978). Table 6.34 summarises the critical values of each measure of influence. Based on Tables 6.34 and 6.35 it can be seen that the seven listed cases satisfy the first three conditions but the covariance ratios of cases 36, 77, 78, and 79 are not within the calculated limits.

Lower bound		Measure of influence		Upper bound
		Mahalanobis Distance	<	20
		Cook's Distance	<	1
		Centred Leverage	<	$2 * \frac{k+1}{N} = 2 * \frac{5+1}{123} = 0.098$
$1 - 3 * \frac{k+1}{N} = 1 - 3 * \frac{5+1}{123} = 0.854$	<	Covariance Ratio	<	$1 + 3 * \frac{k+1}{N} = 1 + 3 * \frac{5+1}{123} = 1.146$

Table 6.34 Limits for casewise diagnostics (k: number of predictors, N: sample size)

Case Number	Standard Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Covariance Ratio
12	-2.130	11.365	0.095	0.093	0.899
36	-2.440	8.752	0.094	0.072	0.813
76	2.044	2.449	0.021	0.020	0.865
77	2.493	2.449	0.031	0.020	0.773
78	2.544	6.043	0.070	0.050	0.777
79	3.252	6.043	0.114	0.050	0.610

Table 6.35 Results of casewise diagnostics

Figure 6.7 shows the predicted and observed productivity rates. The predicted values are calculated based on the coefficients, b-values, listed in Table 6.33. The orange line depicts the ideal/theoretical situation where the predicted values are equal to the observed ones.

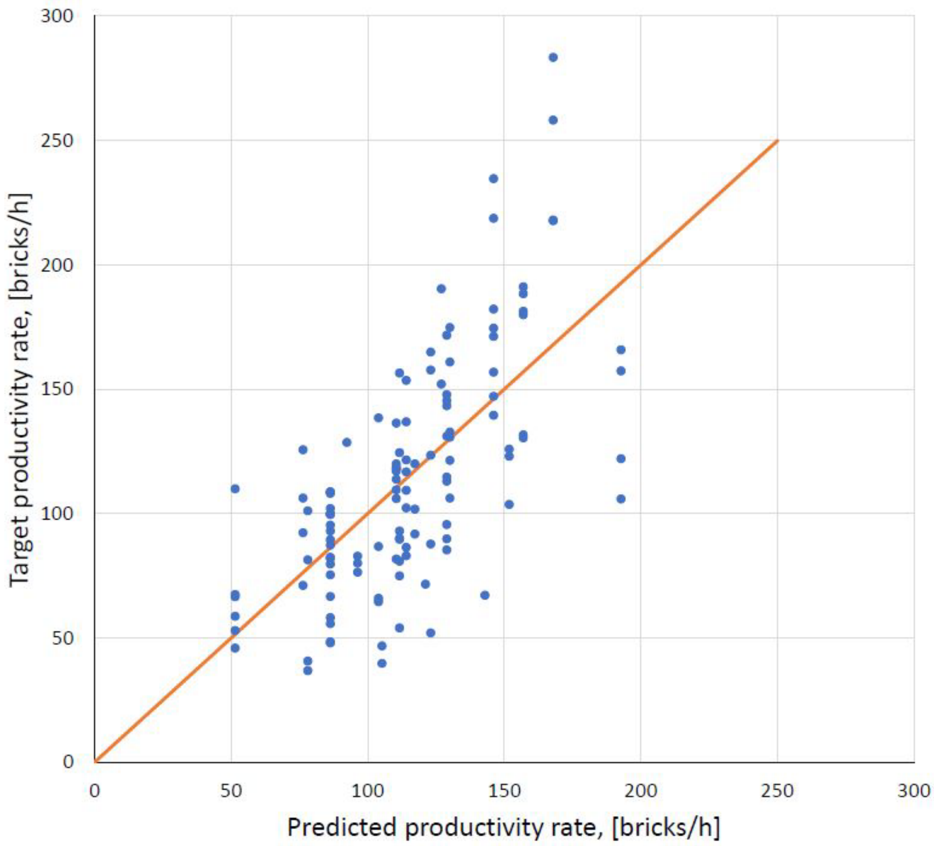


Figure 6.7 Predicted and observed productivity rates based on Model 1

The mean absolute percentage error was calculated using (8). It is 27.70% for Model 1.

6.5.3 Summary of regression analyses

Both simple and multiple regression analyses were performed on the data table. Multiple regression analyses were performed for all the factors and also only including selected factors.

The adjusted R^2 showing what percentage of the variation the model could explain, if applied to the whole population was approximately 42% for all multiple regression models. Due to the F-ratios being significant for all these models, this 42% that can be explained is a significant amount. Changing the factors included in the model did not modify the adjusted R^2 values.

The mean absolute percentage error was approximately 27%. This is not ideal. However, the models will not be used for prediction; therefore, this accuracy can be accepted. If they were to be used, the datapoints for which casewise diagnostics were performed would need to be further examined. The mean absolute percentage error for the ANN model component, which will be used for calculating the productivity rates, was 13%.

Table 6.36 summarises the results of the simple and multiple regression analyses. The top row shows whether the factor's contribution to the model is significant. The **+** sign in the bottom rows refers to a positive relationship between the factor and the productivity rate, while the **-** sign marks a negative, i.e., inverse, relationship. For example, the factor independence was not significant in the simple regression analysis, however, it was significant in the multiple regression models. According to the simple regression analysis, there is a negative relationship between independence and the productivity rate, however, the multiple regression analyses suggest a positive relationship, meaning that as independence increases, the productivity rate increases, as well. Based on the analyses, experience, brick type, independence, and course difficulty make significant contributions to the models, that is, these factors significantly predict the productivity rate. According to the sign of the b values, independence and experience have a positive relationship with the productivity rate, while in the case of course difficulty and brick type, the relationship is inverse, meaning that as these factors increase, the productivity rate decreases.

Factor	**Simple regression**	**Multiple regression**		
		All	**All, backward**	**Selected**
Quality	not significant	not significant	not included	not included
	+	+		
Perceived speed	not significant	not significant	significant	not significant
	+	-	-	-
Knowledge	not significant	not significant	not significant	not included
	+	-	-	
Independence	not significant	significant	significant	significant
	-	+	+	+
Experience	significant	significant	significant	significant
	+	+	+	+
Course difficulty	not significant	significant	significant	significant
	-	-	-	-
Brick type	significant	significant	significant	significant
	-	-	-	-

Table 6.36 Summary of the results of the regression analyses (gray background: factor's contribution to the model is significant)

6.6 Chapter summary

This chapter details the statistical analyses performed on the data table. As the normality and homogeneity tests showed that some groups of factors followed a normal distribution, while others were non-normal, and that in some cases the variances were homogeneous, while in others they were heterogeneous, both parametric (ANOVA, Welch's, Brown-Forsythe's) and non-parametric tests (Kruskal-Wallis, Jonckheere-Terpstra) were used to determine which factors had significant effects on the productivity rate. In addition, simple and multiple regression analyses were conducted to examine the relationship between the factors and the productivity rate. In Chapter 8, the results of the performed tests will be compared to those of the sensitivity analyses of the ANNs shown in Chapter 5.

CHAPTER 7

MODELLING PART 3: DISCRETE-EVENT SIMULATION COMPONENT

7.1 Simulation methods

Simulation is a method to make experiments on a system that does not exist yet, or one that does; however, conducting tests on it would be disruptive, costly, or dangerous for various reasons. Construction simulation can be useful due to these models being able to reflect the dynamic nature of construction processes and capture complicated behaviour, uncertainties, and dependencies.

There are three basic simulation methods: discrete-event simulation (DES), system dynamics (SD), and agent-based modelling (ABM) (Borshchev, 2013; Raoufi and Robinson Fayek, 2020). DES is process-focused, where a sequence of tasks is defined. The entities, which are passive, non-interacting objects without any specific features, are moving through this workflow, during which they are seized, queued, delayed, and released. Resources can be assigned to the tasks. Due to the low level of abstraction, DES can be well used for modelling on the operational level (Peña-Mora *et al.*, 2008).

SD can be used to model a system's behaviour and workings with feedback loops. It focuses on the various influencing factors and the relationships among them. In contrast to DES, in the case of SD, the level of abstraction is high as this method deals with aggregates (stocks and flows) and global trends (Borshchev and Filippov, 2004; Borshchev, 2013). Therefore, SD can be applied on the strategic level, to see how context-level variables affect the selected system (Alvanchi *et al.*, 2011).

While SD is a top-down method, ABM is a bottom-up approach, where the system's behaviour emerges from how individual agents interact with each other and their environment based on defined rules (Watkins *et al.*, 2009). The agents are heterogenous with different attributes. They are also adaptive, capable of changing and evolving (Watkins *et al.*, 2009). ABM can be used on all levels of abstraction (Borshchev and Filippov, 2004). Table 7.1 summarises the most important input necessary for the three basic simulation methods and the possible outputs these models can provide.

Methods	Input	Output
Discrete-event simulation (DES)	Tasks Activity durations Resources	Process duration Resource usage
System dynamics (SD)	Influencing factors Stocks and flows Feedback loops	Changes of factors over time Effects of factors
Agent-based modelling (ABM)	Agents Attributes Rules of behaviour	Behaviour of the system

Table 7.1 Input and output of basic simulation methods

7.2 Simulation framework

The steps of creating a construction simulation model can be seen in Figure 7.1. The first step is to analyse the **problem** that needs to be solved. Then the **question**, which the simulation results should answer, must be phrased. Depending on the **complexity** of the question or the part of reality to be modelled, the left (single method) or right (hybrid approach) path should be chosen. The next step is to select the most suitable simulation approach. The choice could be made based on the purpose of the investigation and the required level of abstraction.

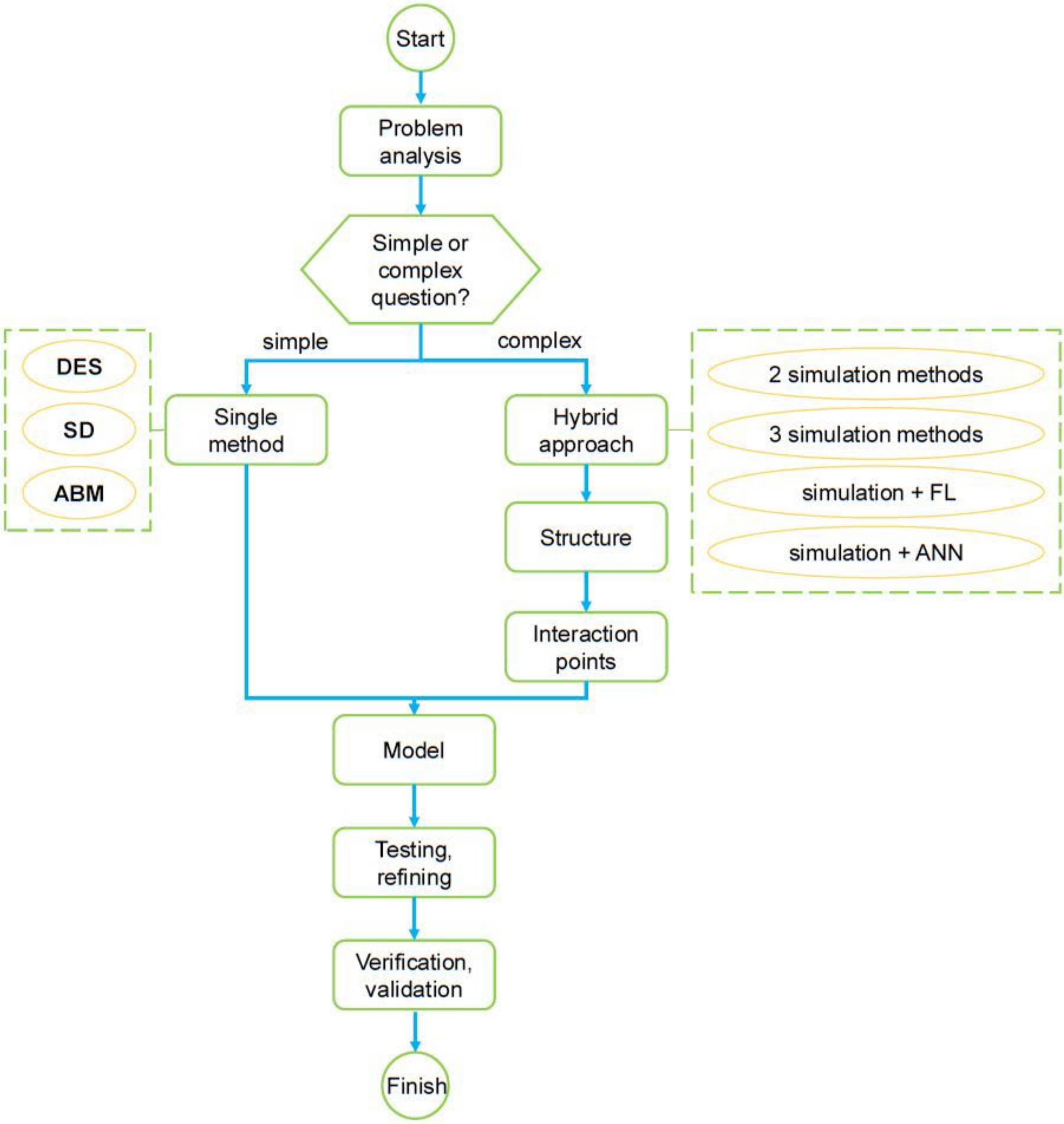


Figure 7.1 Simulation framework

If the focus is on the process itself, **DES** might be the most appropriate method, as it could be used on the operational level. It provides information on activity and project durations and resources. In DES, for instance, the workflow of masonry works can be modelled. Examples for descriptions of the workflow can be found in studies such as Florez and Castro-Lacouture's (2014) work, in the case of the construction masonry unit, or Dawood et al.'s (2001) paper, in the case of brickwork. If the objective is to see one factor's effect on activity durations in a process, it is probably enough to choose a proper probability distribution function for the activity distributions in DES. However, if the effects of several factors are to be taken into account, the combination of DES with another method could provide better results.

SD concentrates on causal relationships on a macro level and tracks the changes of the continuous variables. In the case of masonry, it could be used, for example, to include the factors influencing labour productivity. SD can be applied in both a qualitative and a quantitative way (Kunc, 2017). The former can be used, if the aim is to understand the workings of the system (Kunc, 2017). In the case of the latter, the system is expressed as a system of differential equations (Borshchev and Filippov, 2004).

ABM may be used at all levels of abstraction. By defining the agents with their attributes and rules of behaviour, the workings of the global system are revealed. The agents, for instance, could be bricklayers and labourers working on a project. The different wall sections could also be agents. For example, in Watkins et al.'s (2009) study, every worker and task were represented as agents.

In more simple cases, the basic simulation methods can be used on their own; however, in more complex cases, a combination of methods might be more appropriate. Different names exist for these combined approaches, including: 'hybrid', 'multi-method', and 'multi-paradigm' simulations (Mustafee *et al.*, 2015). Mosterman (1999) defined the composite of discrete and continuous simulation as 'hybrid simulation'. Balaban et al. (2014) argue that ABM might not be considered a paradigm; hence, those approaches where ABM is paired with another method may not be called multi-paradigm. According to them, there is also a distinction between mixed/hybrid and multi-methods (Balaban *et al.*, 2014). Both Mustafee et al.(2015) and Balaban et al. (2014) agree that proper definitions are needed. In this study, the term 'hybrid' refers to a combination of methods.

A **hybrid model** can be created in various ways. One is to combine any two of the above-mentioned basic simulation methods, or, perhaps, all three of them. Another option is to compose the model of a simulation part and another, such as fuzzy logic (FL) or artificial neural network (ANN), component. FL can be useful when the variables are subjective and could not be easily expressed with crisp values. ANN can be applied when the variables' combined effects are complex, and they are subject to uncertainty. The point of creating a hybrid model is to combine the advantages of the methods involved and to counterbalance their shortcomings.

If a hybrid solution seems appropriate, after choosing the most suitable approach, the **structure** must be determined. This means that the way the different components of the model are linked to each other needs to be defined. Moradi et al. (2015) defined three possible ways the DES and SD models could be linked. First is the hierarchical format (see Figure 7.2), which could either be SD- or DES-dominant (in Figure 7.2, Method2 is dominant). In this case, there is a vertical interaction between the strategic (SD) and operational (DES) models. The second one is the phase-to-phase format, where the two models run in separate phases. The third type is the integrated format (see Figure 7.3), which allows constant bidirectional interactions (Moradi *et al.*, 2015). Alvanchi et al. (2011) also identified three structures of DES-SD hybrid models similar to the ones mentioned above. These are the DES-dominant, SD-dominant (see Figure 7.2) and parallel modelling (see Figure 7.4). In the case of the first two, the direction of the interaction is towards the dominant part, while in parallel models, the interaction is bidirectional (Alvanchi *et al.*, 2011).

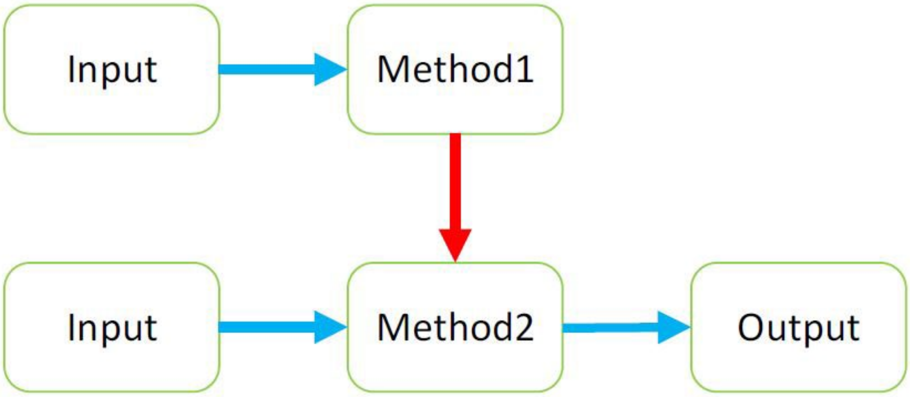


Figure 7.2 Sequential structure of hybrid simulation

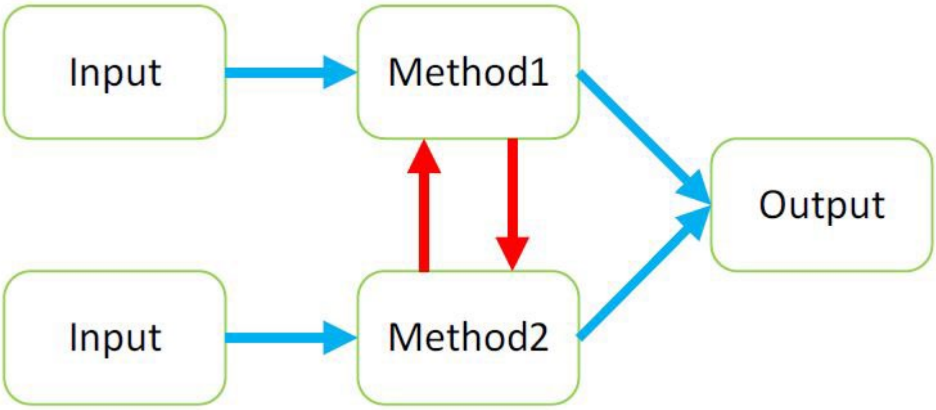


Figure 7.3 Integrated structure of hybrid simulation

Swinerd and McNaught (2012) defined three classes for SD-ABM hybrid simulation. Figure 7.3 shows how in the case of the integrated simulation, there is continuous feedback both ways between the two modules. Per Figure 7.2 sequential simulation means that first, the SD module runs, and its output becomes the input for the ABM module or vice versa. The third class is interfaced hybrid design (see Figure 7.4), where the modules run parallel and their outputs are combined (Swinerd and McNaught, 2012).

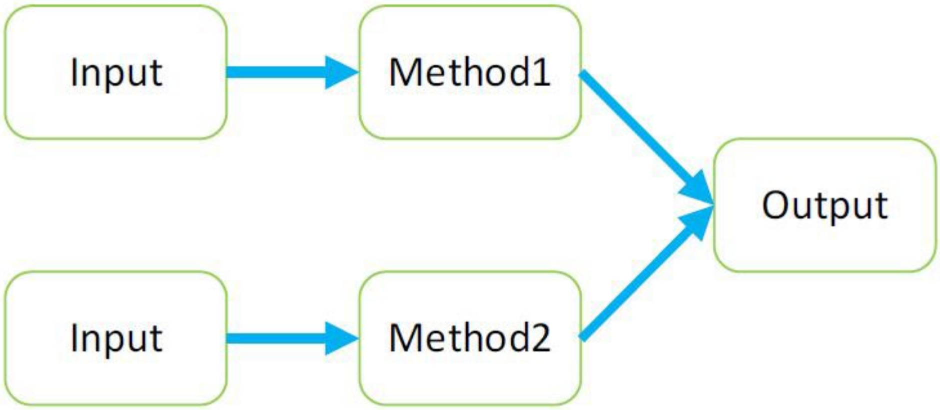


Figure 7.4 Parallel structure of hybrid simulation

Borshchev (2013) described the six most frequently used variations of the integrated structure (see Figure 7.3) and provided examples for all of them. These are the following:

- agents in an SD environment,
- agents interacting with a DES model,
- DES model linked to an SD model,
- SD inside every agent,
- DES inside every agent,
- agents as entities in a DES model.

Of the three structures that have been presented thus far, if they were to be theoretically ranked according to the level of interaction between the two components, parallel would be the lowest and integrated the highest. In the case of the parallel structure (see Figure 7.4), the components are running simultaneously, and their outputs are combined. The second possibility is the sequential structure (see Figure 7.2), which means that the output of one approach becomes the input of the other, and the final output comes from the second. The last option is the integrated structure (see Figure 7.3). In this case, the interaction between the components is bidirectional and continuous.

After the most suitable structure is selected, the next step in this branch (see Figure 7.1) is to define the **interaction points** between the components. These interface variables are the ones that may affect the variables in the other component. Creating hybrid models provides the opportunity of having dynamic variables, which would otherwise be static using a basic simulation method (Alvanchi *et al.*, 2011). Furthermore, applying a hybrid approach can mean the combination of a continuous (e.g. SD) and a discrete (e.g. DES) method, meaning that time advancement has to be defined (Alvanchi *et al.*, 2011; Alzraiee *et al.*, 2012). It is important, therefore, to be aware of how the interacting variables may change due to linking the components of the hybrid system. According to Alvanchi et al. (2011), there are five types of interactions:

- in case of one discrete and one continuous variable
    - a discrete change in the discrete variable causing a discrete change in the continuous one,
    - a discrete change in the discrete variable causing a change in the functional description of the continuous one,
    - a continuous change in the continuous variable causing a discrete change in the discrete one,
- in case of two continuous variables
    - a continuous change in one continuous variable causing a continuous change in the other,
- in case of two discrete variables
    - a discrete change in one discrete variable causing a discrete change in the other.

Based on the selected simulation approach, its structure and interaction points, if applicable, and the required input data, the simulation **model** could be produced. The necessary input information is listed in Table 7.1.

After the preliminary model is ready, it needs to be **tested** and **refined**. The improved model must be checked, as well. **Verification** confirms that the model is a correct reflection of reality; whereas **validation** is performed to show that the model's accuracy is adequate for the simulation problem. Verification and validation do not only happen at the end, but they are performed after every step in the model development process (Sargent, 2015).

7.3 Model for bricklaying

Using the flowchart shown in Figure 7.1, the choices for the first couple of steps were explained before, in Chapter 4. Since the goal was to obtain better time estimates for the scheduling of bricklaying works and to aid more efficient resource allocation, the complex path – i.e., a hybrid modelling approach – was selected. The model had two components: an ANN part, which was shown in detail in Chapter 5, and a DES part. The latter was chosen because its output coincides with the aim of the task. Based on Table 7.1, DES can simulate the process of bricklaying, by inputting the task durations and resource information, the process durations of various resource combinations can be compared.

The next step in the flowchart in Figure 7.1 is the selection of the structure of the hybrid model. In this study, a sequential structure (see Figure 7.2) was chosen. First, the ANN model component was trained based on the collected data, and then it was used to provide the task duration for the activity of laying bricks, which was fed into the DES part of the model together with the durations of the other tasks and resource information. This was done in order to gain the needed process duration and resource allocation information (see Figure 7.5).

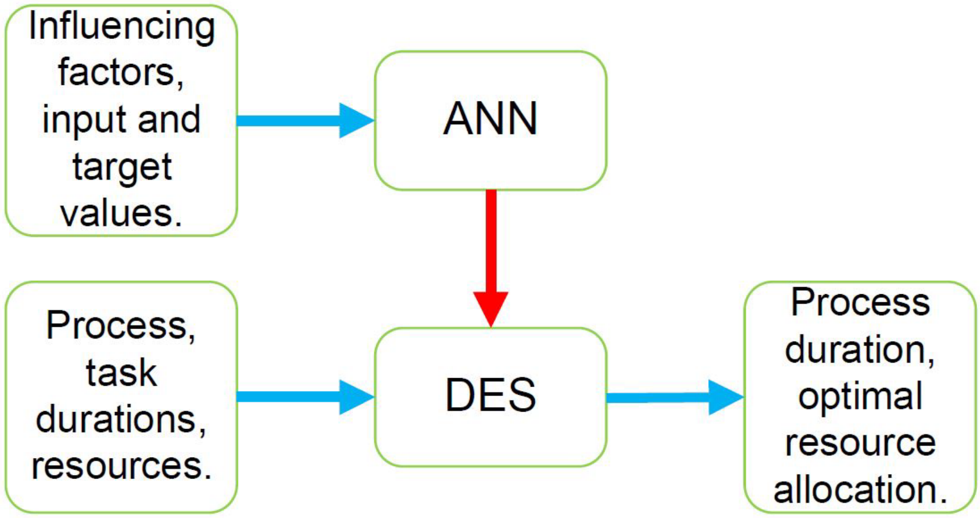


Figure 7.5 DES-ANN hybrid approach

The red arrow in Figure 7.5 denotes the direction of the interaction between the two model components. It was one-way, going from the ANN to the DES part. The interface variable, where the two components are linked, was the activity duration of the task laying bricks. The calculations to obtain these values will be shown in detail in Section 7.4.
The next step was to create the model. For this, in the case of DES, the process, the entities going through it, the task durations, and the resources were needed. The workflow for building the brick outer leaf of a cavity wall façade, which was explained in detail in Section 4.2, can be seen in Figure 7.6.

Figure 7.6 Process of bricklaying – DES model component

Activity preparation means that all necessary materials and tools are placed in front of the wall section to be built by, most commonly, labourers. This includes, for example, bricks, mortar boards, ties, weeps, movement joint fillers, trowels, spirit levels, profiles, and lines. Before the activity laying bricks can begin, profiles are mounted on both ends of the wall section, and the line is stretched between them (see activity profiles up). The main activity is the laying of the bricks, which shows actual progress. This task includes placing mortar, cutting bricks, if applicable, placing bricks, removing excess mortar, and moving the line up to the level of the next course. After the courses are laid, the profiles can be taken down (see activity profiles down). The last activity is the jointing, when the joints between the bricks are tidied up according to the required jointing type.

The entities in this case were the wall sections that needed to be built. The task durations and the resources assigned to each activity are summarised in Table 7.2, in the case of model wall section #1 built of red bricks (see Figure 7.8). For example, the task duration of the activity mounting of the profiles was expressed as a triangular distribution with a minimum value of 0.0788 h, a maximum value of 0.1463 h, and a most likely value of 0.1125 h. The triangular distribution was chosen in the case of four tasks. This distribution is commonly used in simulation modelling, and is a reasonable choice in a data-deficient environment (AbouRizk and Halpin, 1992; Thompson *et al.*, 2016). The duration of the mounting and dismounting of the profiles activities does not depend on the size of the wall section or the brick type. Therefore, the same values were used for all model wall sections (more on these in the next section). Most of the materials and tools placed in front of the wall section during preparation are the same regardless of the size of the wall section or the brick type. The size only affects the number of bricks that need to be supplied; however, the space is limited, and materials can be brought during the laying of the bricks by the labourers, if needed. Therefore, the same values were used for the task duration for all model wall sections. The amount of jointing that needs to be performed depends on the total length of the joints. Moreover, the time this task takes is dependent upon the type of the jointing and the brick. Therefore, different values were used for the various model wall sections and brick types.

Based on the observations, two labourers were assigned to the task preparation, while two bricklayers (one gang) were allocated for the other activities. The model bricklaying gangs defined will be explained in the coming section.

Task	**Duration, [h]**	**Resources**
Preparation	Triangular (0.1959, 0.3638, 0.2799)	2 labourers
Profiles up	Triangular (0.0788, 0.1463, 0.1125)	1 bricklaying gang
Laying bricks	Calculation shown in Section 7.4	1 bricklaying gang
Profiles down	Triangular (0.0394, 0.0731, 0.0563)	1 bricklaying gang
Jointing	Triangular (0.1750, 0.3249, 0.2499)	1 bricklaying gang

Table 7.2 Input of the DES model component for model wall section #1 built of red bricks

The DES model was created using the AnyLogic 8.7.5 (Personal Learning Edition) software running on a Lenovo laptop with 8 GB of RAM, Intel®Core™ i5-7200U processor on a 64-bit Windows 10 Home operating system. AnyLogic was selected early on in the research project when the simulation method had not yet been chosen because it is the leading simulation software in numerous industries, and it can handle all three basic simulation methods and any hybrid approach combining these methods.

7.4 Interaction point between the model components

As mentioned in the previous section, the interface variable between the ANN and DES model components was the task duration of the activity laying bricks. Since the DES model component will be used for running various resource allocation scenarios, model bricklayers and model wall sections needed to be defined. Their parameters were input into the ANN model, which gave the productivity rate of the given bricklayer for the specific course and brick type. Then this value was used to calculate the time it took to construct the model wall sections for individual bricklayers. In the next step, the activity duration for bricklaying gangs of two were determined. Finally, a beta distribution was fit, and this became the input of the DES component. The steps of the calculations are shown in Figure 7.7 and will be explained in detail in the sections below.

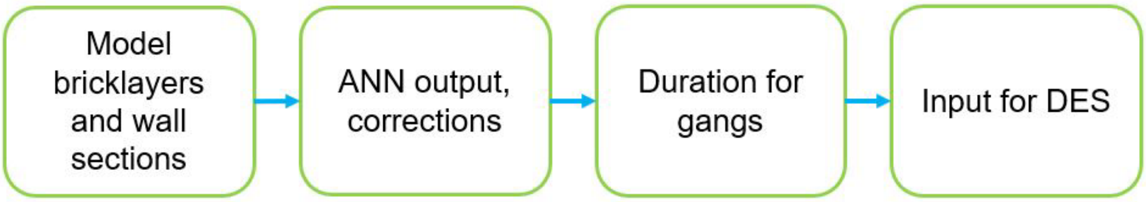


Figure 7.7 Steps of calculating the duration of the laying bricks activity

7.4.1 Model project: model bricklayers

As the input for the ANN model component, the created model bricklayers and model wall sections were used. Since both the sensitivity analysis of the ANN model and the statistical analysis of the collected data showed experience to be the most important factor for the bricklayers, the model bricklayers were configured based on that characteristic. There were six model bricklayers, two for each level of experience. One had lower, while the other higher marks in the other categories. Table 7.3 shows the model bricklayers defined.

Factors	**Model bricklayers**					
	BL1	**BL2**	**BL3**	**BL4**	**BL5**	**BL6**
Quality (Q)	1	2	2	3	3	3
Perceived speed (PS)	1	2	2	2	2	3
Knowledge (K)	1	2	2	3	2	3
Independence (I)	1	2	2	3	2	3
Experience (E)	1	1	2	2	3	3

Table 7.3 Model bricklayers

7.4.2 Model project: model wall sections

Model wall sections also had to be defined to have the input for the ANN model component. The three model wall sections – WS1, WS2, and WS3 – are shown in Figure 7.8, 7.9, and 7.10 respectively. These were modelled similarly to the wall sections constructed at the observed projects, where the data collection took place.

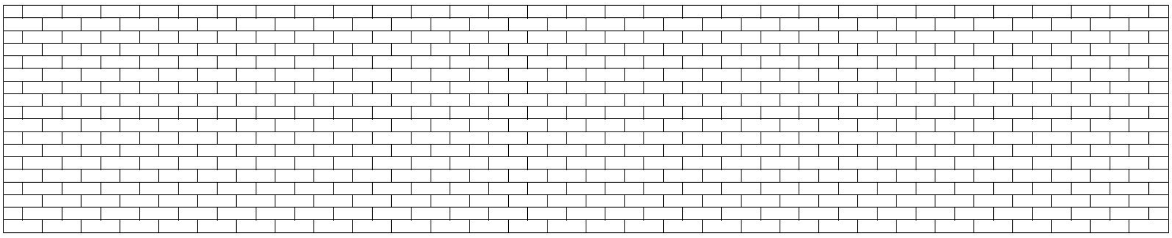


Figure 7.8 Model wall section – WS1

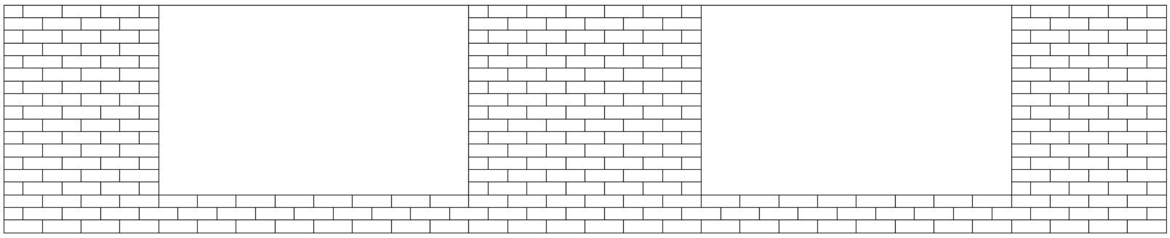


Figure 7.9 Model wall section – WS2

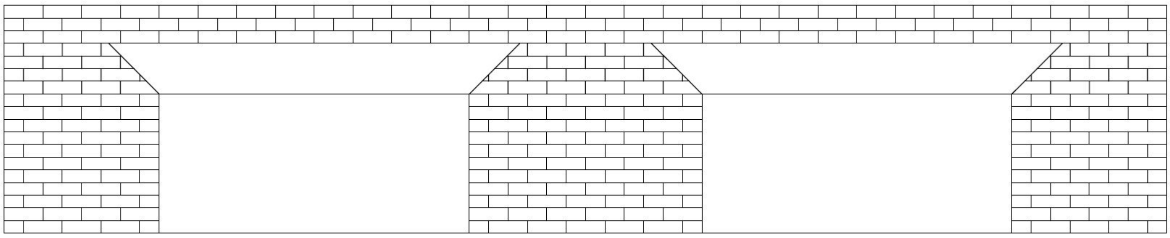


Figure 7.10 Model wall section – WS3

Not all wall sections were built of all three brick types (BT); therefore, only those combinations were used for the model wall sections, whose construction had been observed during the data collection. Table 7.4 contains the pairings of model wall sections and brick types applied in the study.

Model wall section	**Brick type**		
	Red (BT1)	**Gray (BT2)**	**Blue (BT3)**
WS1	●	●	●
WS2	●	●	
WS3	●		

Table 7.4 Model wall sections by brick type

The different wall sections contained courses of various difficulty levels. WS1 only had level 1 courses, WS2 had both level 1 and 2 courses, while WS3 had courses in all three categories. The course difficulty levels are explained in detail in Section 4.1.2. Table 7.5 contains the number of bricks per course difficulty level and in total in the model wall sections. For example, in the case of WS2, 91 bricks would need to be laid in level 1 courses and 234 bricks in level 2 courses, a total of 325 bricks.

Number of bricks	**Course difficulty (CD)**			**Total**
Model wall section	**1**	**2**	**3**	
WS1	549	0	0	549
WS2	91	234	0	325
WS3	91	172	58	321

Table 7.5 Number of bricks in model wall sections per course difficulty

7.4.3 Calculations

After defining the model bricklayers and wall sections, the productivity rates of the various combinations needed to be determined with the help of the ANN model component. Table 7.6 shows an example for the input for model bricklayer #5, model wall section #2 built of gray bricks.

	Q	**PS**	**K**	**I**	**E**	**CD**	**BT**
BL5_WS2.2	3	2	2	2	3	1	2
	3	2	2	2	3	2	2

Table 7.6 Example of the input for the ANN component

The output of the ANN model component was the productivity rate given in a dimension of bricks/hour. However, the duration of the laying bricks task was measured in hours; therefore, the number of bricks per course category had to be divided by the productivity rate and summed up for all types of courses. The results of these calculations are shown in Table 7.7, in the case of the example bricklayer-wall section combination shown in Table 7.6.

BL5_WS2.2	**Output of Network A**	**Output of Network C**	**Number of bricks**	**Duration based on Network A**	**Duration based on Network C**	**Mean duration**
	[bricks/h]	[bricks/h]	[bricks]	[h]	[h]	[h]
CD1	183.97	137.57	91	0.495	0.661	
CD2	139.62	101.66	234	1.676	2.302	
Σ				2.171	2.963	2.567

Table 7.7 Example for duration calculation for a single bricklayer

Table 7.7 includes the output of the ANN model component for the input contained by Table 7.6. ANN Networks A, B, and C were identified as the best performing ANN models and were described in detail in Section 5.5. All model bricklayer and model wall combinations were input into all three networks. In some instances, the output productivity rates were negative, which are, of course, not appropriate as negative amounts of bricks cannot be laid. In some other cases, while the output was not negative, it reflected a very low productivity rate, which was also very different from the output of the other two networks. In the case of both problems, corrections were made. To obtain more consistent results, the values were modified to the mean of the output of the other two networks. However, it could be observed that these phenomena mostly occurred in the case of the output of Network B. After corrections, the means were calculated for the output of all three networks and for the output of only networks A and C. These were compared, and it was found that the difference exceeded 10% in only a handful of cases; therefore, the output of Network B was not used in subsequent calculations. This way corrections were only necessary in 4 instances out of the 36 in total.

It is worth mentioning that in some cases all three models gave the same output for the same input. This typically happened in the case of model bricklayer #6 as around 20% of the observed bricklayers had the same attributes, and more than 20% of the observations were of them. Therefore, the networks were probably better trained for bricklayers with the most experience and the best skills.

The time it takes for one model bricklayer #5 (characteristics in Table 7.3) to build model wall section #2 (shown in Figure 7.9) of gray bricks (BT2) is 2.567 hours. However, bricklayers typically work in gangs of two. Therefore, the task duration needed to be calculated for the gangs, shown as step 3 in Figure 7.7. For this, first the model bricklayers had to be paired. Since the goal was to compare which pairings would perform better, the least experienced bricklayer with the lowest scores was put in a gang with the most experienced bricklayer with the highest scores and so on. Table 7.8 contains the model bricklaying gangs.

Model bricklaying gang (BG)	Bricklayer 1	Bricklayer 2
BG1	BL1	BL6
BG2	BL2	BL5
BG3	BL3	BL4

Table 7.8 Model bricklaying gangs

Table 7.9 and Equations (1) to (7) show how Equation (8), which was ultimately used to calculate the task duration for the gangs, was determined. The wall section they are working on is *1* unit in size. Since they are not working at the same speed, one of them builds *x* part of the wall, while the other *1-x*. When they are working together, it takes both bricklayers *t* time to build that part of the wall. However, if they worked alone on the given section, it would take them t_1 and t_2 time respectively. Equations (1) to (3) are based on the speed-distance-time formulae from physics. Equations (4) to (6) are derived from Equation (3), while Equation (7) is the combination of Equations (1), (2), and (6). Equation (8) shows the time (t) needed for the gang to build the given wall section expressed with the help of the individual times (t_1 and t_2), which were calculated in the previous step. For example, Table 7.7 contains the calculation of a value of t_2.

Bricklayer	**Quantity of wall section done**	**Time, if working together**	**Time, if working alone**	**Productivity rate**
Bricklayer 1	x	t	t_1	v_1
Bricklayer 2	1-x	t	t_2	v_2

Table 7.9 Calculation of the task duration for the gang

$$v_1 = \frac{1}{t_1} \tag{1}$$

$$v_2 = \frac{1}{t_2} \tag{2}$$

$$t = \frac{x}{v_1} = \frac{1-x}{v_2} \tag{3}$$

$$v_2 * x = v_1 - v_1 * x \tag{4}$$

$$(v_1 + v_2) * x = v_1 \tag{5}$$

$$\frac{x}{v_1} = \frac{1}{v_1 + v_2} \tag{6}$$

$$t = \frac{1}{\frac{1}{t_1} + \frac{1}{t_2}} \tag{7}$$

$$t = \frac{t_1 * t_2}{t_1 + t_2} \tag{8}$$

The last step in creating the input of the DES model component was to make the task duration stochastic. For this, the beta function was chosen as that is continuous, has lower and upper bounds, is flexible, and frequently used in construction modelling (AbouRizk and Halpin, 1992; Fente *et al.*, 2000). The shape of the function is determined by the shape parameters, α and β. For example, if these values are between -1 and 0, the function has a U shape, if they are greater than 1, it has a bell-shape (Fente *et al.*, 2000). The latter is the one usually defined. When α equals β, the shape is symmetrical. Parameters α and β can be calculated based on the minimum (a) and maximum (b) expected duration values and two of the following: mean (μ), mode (m), variance (σ^2), selected percentile (AbouRizk *et al.*, 1991). In this case, a symmetrical bell shape was chosen for the beta function with the minimum and maximum values determined as 70% and 130% of the durations calculated in the previous step (Hajdu and Bokor, 2016). Due to the symmetry, the mean is equal to the mode (Equation (9)). The variance was calculated based on Equation (10), which is the classic PERT formula (Hahn and Del Mar López Martín, 2015; Hajdu and Bokor, 2016). Equations (11) to (14) were used to determine the value of the shape parameters (AbouRizk *et al.*, 1991). The same shape parameters were assigned to the task durations in all cases, regardless of bricklayers or wall sections. Table 7.10 shows the values of the beta function parameters for the gang of model bricklayers 2 and 5 for model wall section #2 constructed from gray bricks.

$$\mu = m \tag{9}$$

$$\sigma^2 = \left(\frac{b-a}{6}\right)^2 = \left(\frac{1.3m-0.7m}{6}\right)^2 = 0.01m^2 \tag{10}$$

$$\xi = \frac{\mu - a}{b-a} = \frac{m-0.7m}{1.3m-0.7m} = 0.5 \tag{11}$$

$$\psi = \frac{\sigma^2}{(b-a)^2} = \frac{0.01m^2}{(1.3m-0.7m)^2} = 0.0278 \tag{12}$$

$$\beta = \frac{\xi * (1-\xi)^2}{\psi} + \xi - 1 = 4 \tag{13}$$

$$\alpha = \frac{\beta * \xi}{1-\xi} = 4 \tag{14}$$

WS2.2	**BL2**	**BL5**	**BL2+5 (BG2)**	**a (min)**	**b (max)**	**α**	**β**
duration, [h]	4.434	2.567	1.626	1.138	2.114		
shape parameter, [-]						4	4

Table 7.10 Calculation of the duration of activity laying bricks

7.5 Running the model

To build the DES model component, the bricklaying process shown in Figure 7.6 needed to be created in the simulation software. Then the task durations were calculated and input into the model. Finally, the labour resources were assigned to the activities. While the process was the same, the task durations and the assigned resources were different in different groups of runs. Two rounds of simulation runs were recorded and analysed.

7.5.1 First batch of simulation runs

In the first batch of simulation runs, the process durations were recorded after each run to examine the effects of the three factors shown in Table 7.11: model bricklaying gang, model wall section, and brick type. The aim was to investigate which model bricklaying gang worked faster, whether there was one that was better suited for a model wall section or a brick type.

Factor/Scale	**1**	**2**	**3**
Model bricklaying gang (BG)	BL1+BL6 (BG1)	BL2+BL5 (BG2)	BL3+BL4 (BG3)
Model wall section (WS)	Model wall section #1 (WS1)	Model wall section #2 (WS2)	Model wall section #3 (WS3)
Brick type (BT)	Red (BT1)	Gray (BT2)	Blue (BT3)

Table 7.11 Factors in the first batch of simulation runs

Altogether six model wall section and brick type combinations were defined. These are shown in Table 7.4. Three model bricklaying gangs were created (see Table 7.8). Therefore, 18 scenarios were tested in total with 100 simulation runs for each, resulting in 1800 runs. In each run, 50 model wall sections were built.

The workflow created in the simulation software was the same as the one shown in Figure 7.6. The task duration of the activity laying bricks was calculated based on the process described in the previous section. An example of the activity duration entered into the model can be seen in Table 7.10. A different activity duration needed to be calculated for all 18 scenarios. Table 7.2 contains an example for the activity durations of the other tasks. The activity duration of jointing was different for the six model wall section-brick type combinations. As for the resources, two labourers were assigned to the preparation activity, while one model bricklaying gang performed the other tasks.

7.5.2 Second batch of simulation runs

In the second batch of simulation runs, the process durations were recorded after each run to examine the effects of the three factors shown in Table 7.12: bricklaying gang composition, model wall section, and brick type. The aim was to investigate which bricklaying gang composition could achieve shorter process duration, whether one of them was better suited for a model wall section or a brick type.

Factor/Scale	1	2	3
Bricklaying gang composition (BLC)	Mixed (BLC1)	Straight (BLC2)	-
Model wall section (WS)	Model wall section #1 (WS1)	Model wall section #2 (WS2)	Model wall section #3 (WS3)
Brick type (BT)	Red (BT1)	Gray (BT2)	Blue (BT3)

Table 7.12 Factors in the second batch of simulation runs

The two types of bricklaying gang compositions are explained in Table 7.13. In the case of the mixed one, the same bricklaying gangs are defined as in the previous batch of simulation runs. The straight composition means that every model bricklayer is paired with another with the same skills and experience.

	Mixed (BLC1)	Straight (BLC2)
1	BL1+BL6	BL1+BL1
2	BL1+BL6	BL2+BL2
3	BL2+BL5	BL3+BL3
4	BL2+BL5	BL4+BL4
5	BL3+BL4	BL5+BL5
6	BL3+BL4	BL6+BL6

Table 7.13 Mixed and straight pairings of bricklayers

Altogether six model wall section and brick type combinations were defined. These are shown in Table 7.4. Two model bricklaying gang compositions were defined (see Table 7.13). Therefore, 12 scenarios were tested in total with 20 simulation runs for each, resulting in 240 runs. In each run, 100 model wall sections were built.

The workflow created in the simulation software was the same as the one shown in Figure 7.6. The task duration of the laying bricks activity was calculated based on the process described in the previous section. For a mixed bricklaying gang, an example of the activity duration entered into the model can be seen in Table 7.10. In the case of, for instance, the BL1+BL1 gang, the activity duration was first calculated for one BL1 bricklayer, then it was divided by 2 for the two bricklayers in the gang. A different activity duration needed to be calculated for the different bricklaying gangs in the case of every model wall-section-brick type combination. Table 7.2 contains an example for the activity duration of the other tasks. The activity duration of jointing was different for the six model wall section-brick type combinations. As for the resources, two labourers were assigned to the preparation activity, while six bricklaying gangs (see Table 7.13) performed the other tasks.

7.6 Chapter summary

This the third of three chapters discussing the developed hybrid DES-ANN model. Chapter 4 gave an overview of the model, while Chapter 5 discussed the ANN model component. In this chapter, first, simulation methods were introduced describing the concept of the methods. Then the framework developed for productivity modelling with simulation was presented. The steps of creating a simulation model were explained in detail, showing the options that need to be considered. In the next section, the choices made for the DES component of the model were explained using the framework. Building the DES model component started with defining the workflow of the bricklaying process, then the task durations were entered, finally the resources were assigned to the activities. For testing the model, a model project was defined, which consisted of creating model wall sections and model bricklayers. These provided the input data for the ANN model component, the output (productivity rate) of which became the input (task duration of activity laying bricks) for the DES model component. The calculations necessary for converting the ANNs' output into the DES' input were explained in detail. The last section discussed the two batches of simulation runs. The results from these runs and their analysis can be found in Chapter 8.

CHAPTER 8

SUMMARY RESULTS, ANALYSIS, AND DISCUSSION

8.1 Results of the analysis of the collected data

As detailed in Section 3.5, productivity measurements with the corresponding bricklayer and wall attributes were collected through structured observations at two construction sites. After processing the data as described in Section 3.6, the data table was used to train and test the ANN model component and statistical analyses were also performed on it. Chapters 5 and 6 contain the details respectively.

One of the questions that needed to be answered was how the productivity rate changed due to the changes of the selected factors introduced in Section 4.1.2. Table 8.1 summarises how the productivity rate changes when the value of the factor increases based on the statistical analyses and the sensitivity analysis of the ANN model component. For example, when the value of the independence factor increases, the productivity rate also increases, according to the multiple regression analyses and the ANN model component. Based on the simple regression analysis, there is an inverse relationship between independence and the productivity rate: when the value of the independence factor increases, the productivity rate decreases. In the case of regression analysis, the sign of the b values indicates the relationship between the dependent (productivity rate) and the independent variables (factors). If the b value is positive, the outcome, here the productivity rate, and the predictor, i.e., the factor, change the same way. If the t-test is significant, the predictor's contribution to the model is significant, meaning that it significantly predicts the productivity rate. In Table 8.1, these significant contributions are marked by underlining. For instance, the independence factor's contribution to the multiple regression models was significant. The simple regression analysis was described in Section 6.5.1, the results were shown in Table 6.22. The various multiple regression analyses performed were detailed in Section 6.5.2, and the b values and t-test results were included in Tables 6.25 (for all factors), 6.29 (for all factors, backward method), and 6.33 (for selected factors). The last column of Table 8.1 lists the conclusions drawn from the sensitivity analysis of the three selected, trained and tested artificial neural networks. The analysis was detailed in Section 5.5, and the corresponding graphs were Figures 5.10 through 5.16. In the case of the analyses listed in Table 8.1, productivity rate was given in bricks/h dimension; therefore, an increase means better productivity, quicker construction.

Factor	Simple regression analysis	Multiple regression analysis			ANN model component
		All factors	All factors, backward	Selected factors	
Quality	Increase	Increase	Not included	Not included	Increase
Perceived speed	Increase	Decrease	Decrease	Decrease	Increase
Knowledge	Increase	Decrease	Decrease	Not included	Decrease
Independence	Decrease	Increase	Increase	Increase	Increase
Experience	Increase	Increase	Increase	Increase	Increase
Course difficulty	Decrease	Decrease	Decrease	Decrease	Decrease
Brick type	Decrease	Decrease	Decrease	Decrease	Decrease

Table 8.1 Does the productivity rate increase or decrease when the factor's value increases?

It can be seen in Table 8.1 that all analyses showed the same results and all of them were significant, as well, in the case of experience, course difficulty, and brick type. Therefore, these three seem to be the most important factors affecting the productivity rate out of the seven listed factors.

Based on the results, the more experienced a bricklayer is, the more time they work in construction, the faster they can work. In contrast, for example, Horner and Talhouni (1995) argued that speed first increased, then decreased with experience. It was mentioned in the interviews that more experienced bricklayers might be less willing to adapt to the newer technologies, for instance, the thin-joint technology. However, the bricks and the technology used at the observed projects can be considered traditional. The observations suggested that more experienced bricklayers could work faster, achieving higher productivity because their movements had become almost automatic, they needed to check their work less, and were usually better organised, having all necessary materials and tools in the right place to minimise the need for unnecessary movements. Among the worker attributes included in the factors, experience seems to be the most essential.

Both wall characteristics – course difficulty and brick type – are significant, as well. Both show the same trend: construction tends to get slower as the difficulty of the laying of the courses or the usage of the materials increase. As described in Section 4.1.2, straight courses with only half-cuts are at one end of the scale, while courses with openings and custom cuts are on the other. The difference in difficulty makes a significant difference in construction time, as well. The same is true for the brick type, which also reflects a ranking in difficulty from red to blue bricks. As the results show, the laying of the blue bricks takes significantly longer than that of the red bricks.

Independence, defined as knowing what to do without constant supervision, also made a significant contribution to the multiple regression models. According to these and the ANN sensitivity analysis, the more independent the bricklayer, the higher their productivity rate. This can be because independence might also increase with time; therefore, the bricklayers are also more skilled, and can achieve higher productivity.

Perceived speed, which is a significant factor in one of the multiple regression models, shows mixed results. The values of this factor, quality, knowledge, and independence came from the questionnaire filled in by the bricklayers' supervisors and the variation might be due to the difference between the supervisors' subjective opinion and the objective time measurements.

According to the results, if quality increases, the productivity rate also increases. Both the interviews and the supervisors' evaluation suggested that more experienced bricklayers produced better quality work. Since they also tend to work faster, this might explain this result. The interviews suggested the need to balance between quality and speed. At the colleges, the students focus on keeping to the standards in order for the quality to be satisfactory and learn how to gain speed with time. This method is the opposite of what Gilbreth (1909) recommended. He believed that the bricklayers needed to be taught the most effective way of laying bricks possible, and they should perform the movements as quickly as possible, their skills would develop with practice.

Based on the analyses, knowledge seems to have an inverse relationship with productivity: as it increases, the productivity rate decreases. Only the result of the simple regression analysis and one ANN (network C) show an opposite, increasing trend. This would be more in line with the logical assumption that knowledge – similarly to independence and quality – also increases with time; therefore, a more knowledgeable bricklayer could be expected to work faster, as well.

In addition to the regression analyses, parametric (ANOVA/Welch's and Brown-Forsythe's tests) and non-parametric (Kruskal-Wallis) tests were also performed on the data table. As some groups of the factors followed a normal distribution, while others were non-normal, and some factors had homogeneous variances, while others had heterogeneous variances, both kinds of tests were run. The results of these can be seen in Table 8.2. It summarises the contents of Tables 6.8, 6.10, 6.11, and 6.12. The effects were calculated based on the parametric test results.

Factor	Parametric		Non-parametric
	ANOVA/Robust tests	**Effect**	**Kruskal-Wallis**
Quality	Not significant	-	Not significant
Perceived speed	Significant	Small	Not significant
Knowledge	Not significant	-	Not significant
Independence	Not significant	-	Not significant
Experience	Significant	Medium	Significant
Course difficulty	Significant	Small	Significant
Brick type	Significant	Large	Significant

Table 8.2 Results of parametric and non-parametric tests (gray background: factor's effect on the productivity rate is significant)

According to Table 8.2, both parametric and non-parametric tests showed that experience, course difficulty, and brick type had a significant effect on the productivity rate. These results are congruent with the ones mentioned previously in this section.

8.2 Analysis of DES model component output

8.2.1 Analysis of the output of the first batch of runs

8.2.1.1 Descriptive statistics and factors analysed

As explained in the Section 7.5.1, the DES model component was run 100 times for each bricklaying gang-brick type-model wall section configuration. The activity duration of the jointing task was determined by the brick type and model wall section combination, while the duration of the activity laying bricks was calculated based on the output of the ANN model component, where the model bricklayer, brick type and course difficulty characteristics were entered. The DES model component provided the project duration, which then needed to be divided by the total number of bricks (for the 50 wall sections) used for the built wall sections in order to compare the different configurations. This way the productivity rates were given in seconds/brick dimension. (This means that the higher the value, the slower the construction.) The descriptive statistics for these productivity rates can be seen in Table 8.3 and the histogram in Figure 8.1.

	Productivity Rate
Number of data points	1800
Minimum [s/brick]	15.65
Maximum [s/brick]	35.64
Mean [s/brick]	22.02
Standard Deviation [s/brick]	5.333
Variance [$(s/brick)^2$]	28.44
Skewness	1.246
Standard Error of Skewness	0.058
Kurtosis	0.446
Standard Error of Kurtosis	0.115

Table 8.3 Descriptive statistics for productivity rate

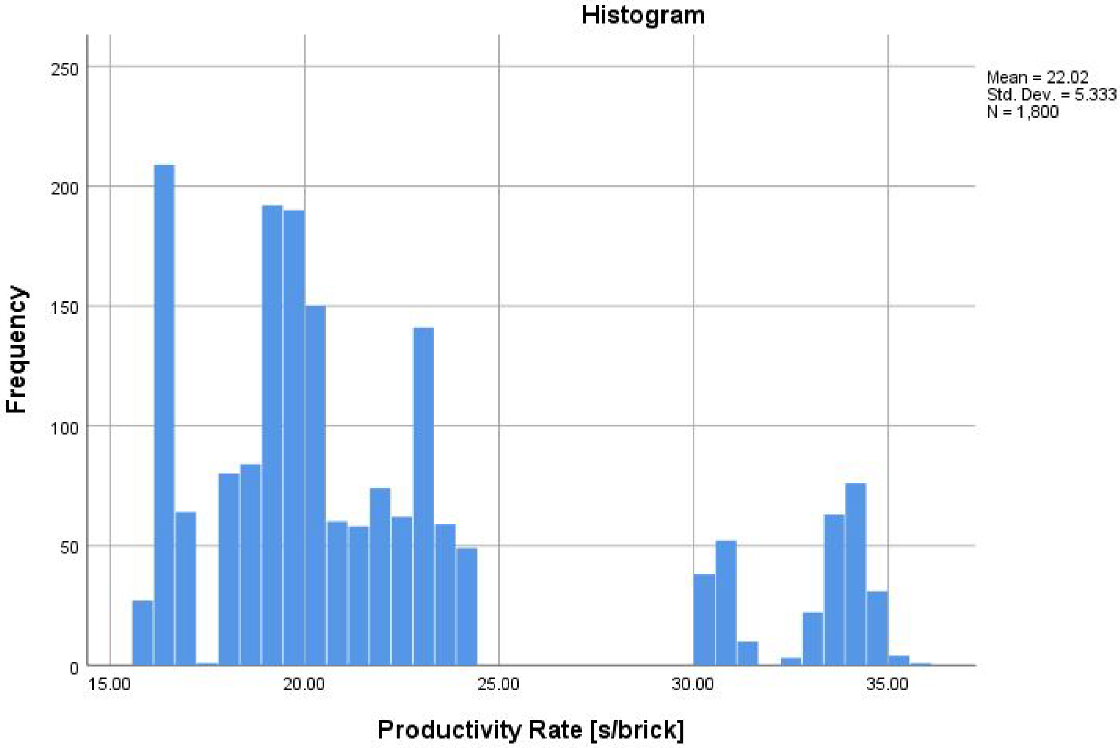


Figure 8.1 Histogram of productivity rate

Table 8.4 contains the list of factors with their scales explained. Moreover, it shows the abbreviations used later in this chapter. For example, WS1 stands for model wall section #1, and BG1 refers to the bricklaying gang composed of BL1 and BL6 model bricklayers introduced in Section 7.3.1.

Factor/Scale	1	2	3
Model bricklaying gang (BG)	BL1+BL6 (BG1)	BL2+BL5 (BG2)	BL3+BL4 (BG3)
Model wall section (WS)	Model wall section #1 (WS1)	Model wall section #2 (WS2)	Model wall section #3 (WS3)
Brick type (BT)	Red (BT1)	Gray (BT2)	Blue (BT3)

Table 8.4 Factors and their scales

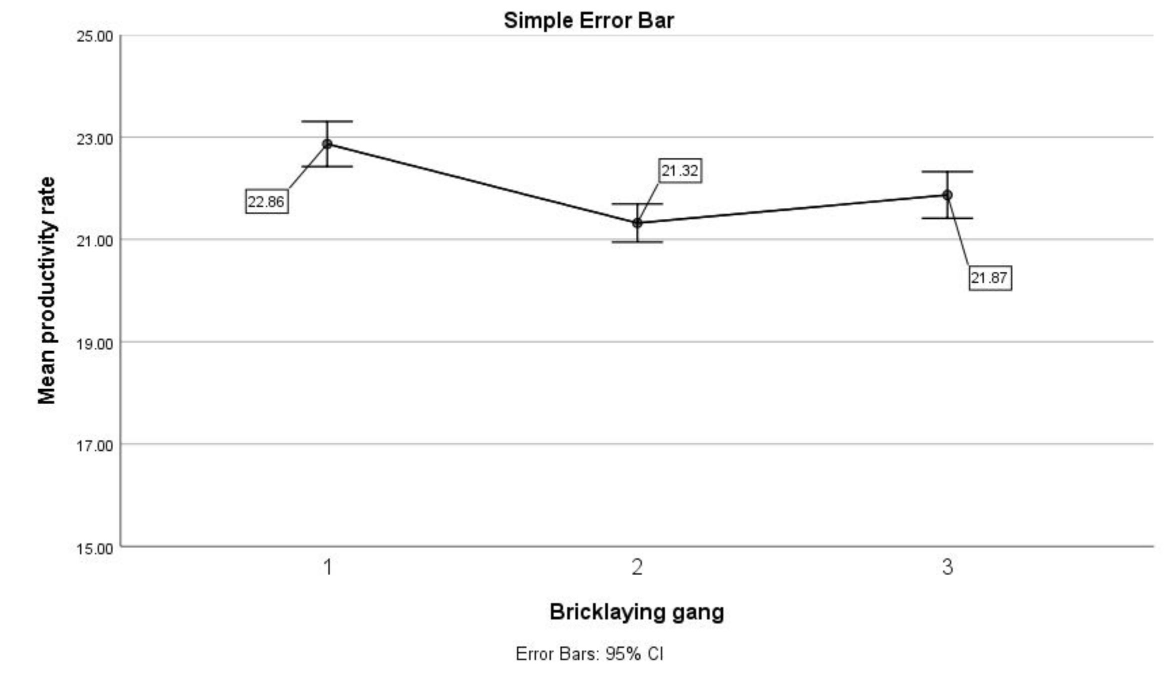
Statistical analyses were run to see how the above factors affect the productivity rates. The analyses were performed according to Field (2009) and using IBM SPSS Statistics 26 and MS Excel 2016 software. The level of significance is 0.05, unless stated otherwise.
Table 8.5 contains the most common abbreviations and notations used in the coming tables.

Abbreviation	Meaning
Sig.	significance
df	degrees of freedom

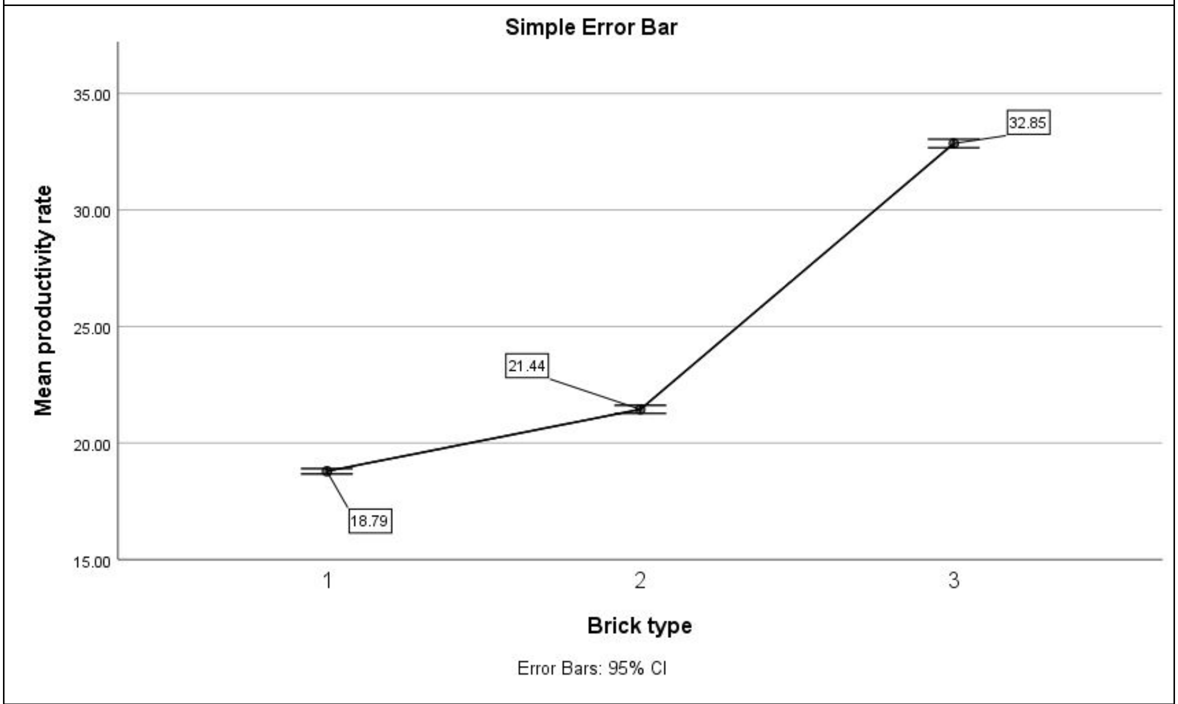
Table 8.5 Common abbreviations

8.2.1.2 Error bars

The error bars showing the 95% confidence intervals for the different groups of each factor can be seen in Figure 8.2. The mean productivity rate values in s/brick for every category are labelled. Due to the chosen dimension, the higher the value, the slower the works are performed. The following tests showed whether the differences between the categories were significant. Looking at the depicted means in the graphs below, trends can be observed. For example, in the case of brick type, blue bricks are laid slower than gray ones, and walls of red ones are the fastest to build. This is in line with the previously drawn conclusions. However, it is worth noting that these only show the means when the grouping is done for only one factor. For instance, the graph of the model wall sections suggests that the construction is quicker for the supposedly more difficult wall sections, that the more complex it is, the faster it can be built. This is most likely because the more difficult brick types are only used for the easier wall sections. In Figure 8.3, the mean productivity rates for the model wall sections are shown separately for the three brick types. As shown, the mean productivity rates increase from the easier to the more difficult wall sections and from the red to the blue bricks within one type of wall section. The possible effect of the assigned bricklaying gang is not shown. Figure 8.4 depicts the productivity rates in the same way as Figure 8.3; however, only for one model bricklaying gang (BG3). This graph suggests the same trends as the one in Figure 8.3.



Simple Error Bar
25.00
23.00
21.00
19.00
17.00
15.00
Mean productivity rate
22.86
21.32
21.87
1
2
3
Bricklaying gang
Error Bars: 95% CI



Simple Error Bar
35.00
30.00
25.00
20.00
15.00
Mean productivity rate
32.85
21.44
18.79
1
2
3
Brick type
Error Bars: 95% CI

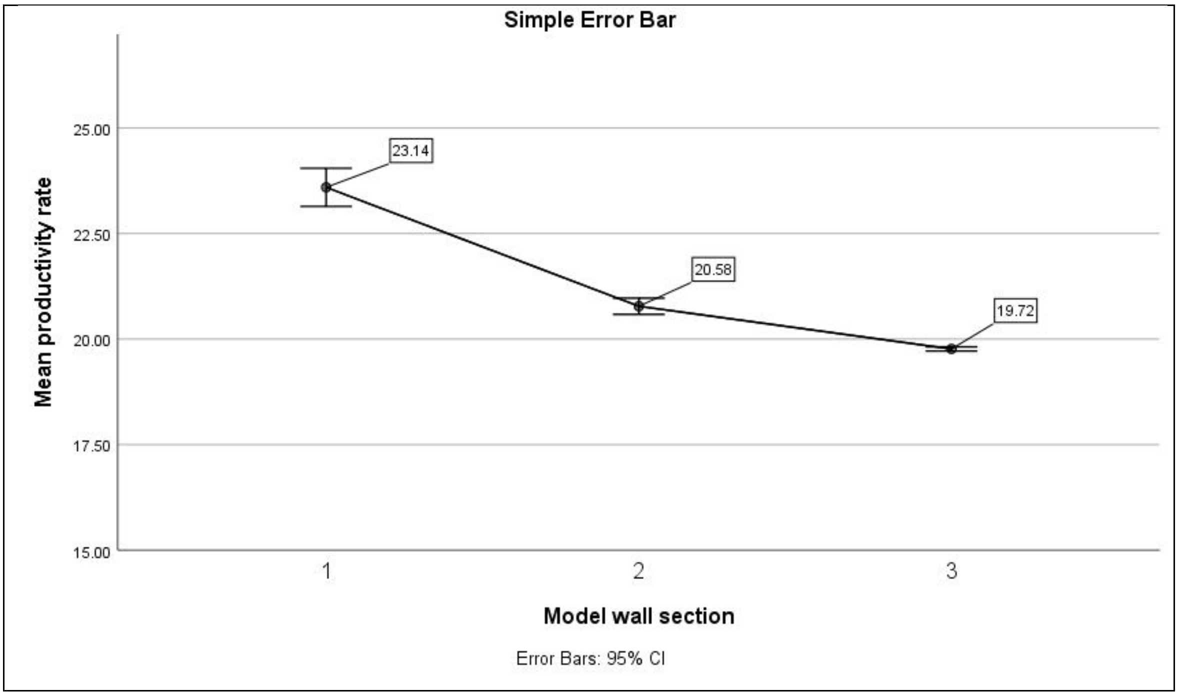


Figure 8.2 Error bars

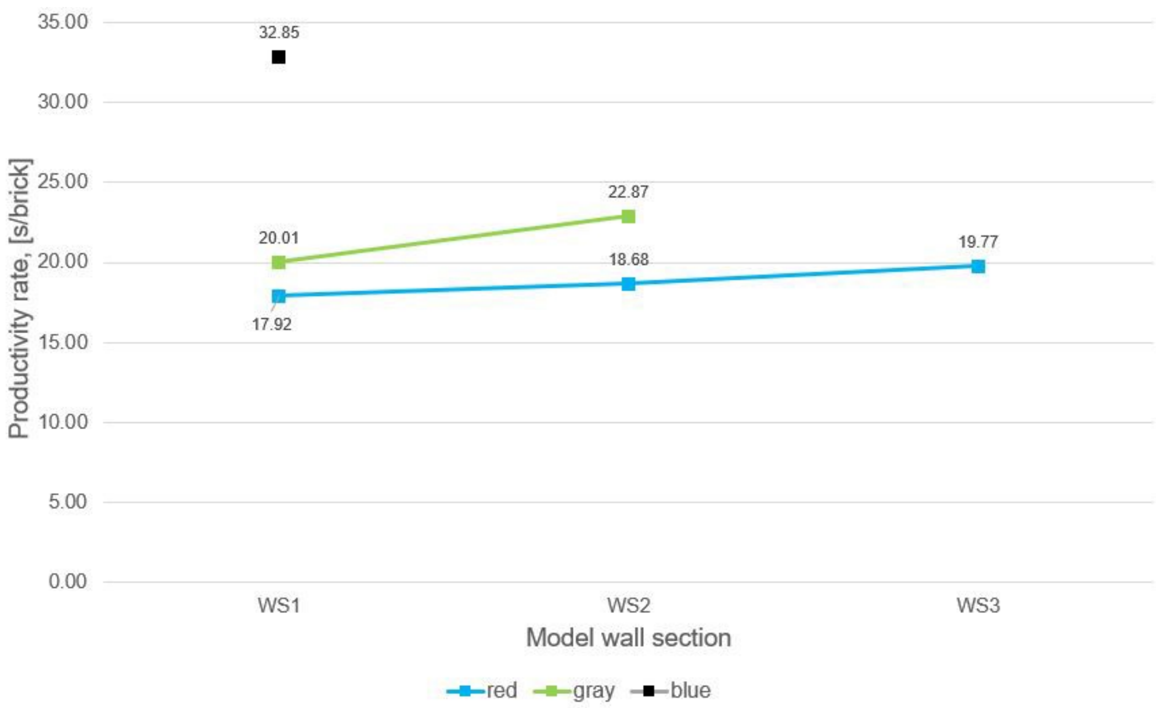


Figure 8.3 Mean productivity rates per model wall section for each brick type

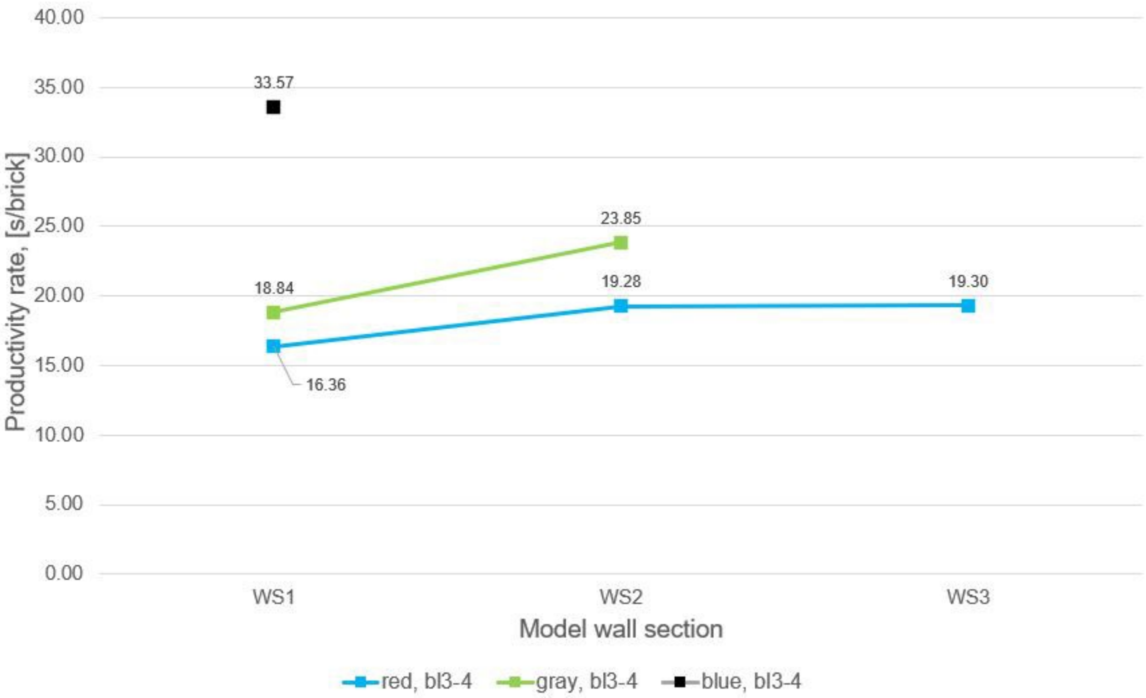


Figure 8.4 Mean productivity rates per model wall section for each brick type for the BG3 model bricklaying gang

8.2.1.3 Normality and homogeneity of variance

To select the appropriate tests, it needed to be determined whether the variables followed a normal distribution, and their variances were homogenous between the categories of the factors. These assumptions of normality and homogeneity need to be met, in the case of parametric tests, for the F statistic, the output of the tests, to be reliable.

The productivity rates at every level of each variable were checked for normality because for the tests, this is what matters, and not the overall normality. The analyses included running the Kolmogorov-Smirnov and Shapiro-Wilk tests. Based on the tests, it can be concluded that all the categories were significantly non-normal. Table 8.6 summarises the results of the normality tests.

Factor	Cat.	N	Kolmogorov-Smirnov		Shapiro-Wilk		Normal?
			D	Sig.	D	Sig.	
WS	WS1	900	0.180	0.000	0.828	0.000	no
	WS2	600	0.119	0.000	0.922	0.000	no
	WS3	300	0.055	0.031	0.984	0.002	no
BT	BT1	900	0.199	0.000	0.860	0.000	no
	BT2	600	0.184	0.000	0.837	0.000	no
	BT3	300	0.210	0.000	0.841	0.000	no
BG	BL1	600	0.287	0.000	0.770	0.000	no
	BL2	600	0.236	0.000	0.817	0.000	no
	BL3	600	0.311	0.000	0.755	0.000	no

Table 8.6 Results of the normality tests (D: test statistic, Cat.: category)

Besides normality, the homogeneity of variance was also checked by using Levene's test. Based on this test, it can be concluded that the variances are significantly different in the case of all the factors. The results are included in Table 8.7.

Factor	F	df_1	df_2	Sig.	Homogenous?
WS	979.451	2	1797	0.000	no
BT	53.718	2	1797	0.000	no
BG	11.808	2	1797	0.000	no

Table 8.7 Results of Levene's test (F: Levene test statistic)

8.2.1.4 Non-parametric tests

Since the tests showed that the distribution of the productivity rates was non-normal and the variances were heterogeneous, the criterion for parametric tests were not met. Therefore, non-parametric tests were performed to determine whether the productivity rate is affected by the factors. The categories within one factor were compared to each other. The Kruskal-Wallis test, the non-parametric equivalent of the one-way independent ANOVA, was used to see the differences between the categories. If it is significant, the given factor significantly affects the dependent variable. In this case, all factors were found to significantly affect the productivity rate. The details are shown in Table 8.8.

Factor	Kruskal-Wallis			Jonckheere-Terpstra		
	H	df	Sig.	z	Sig.	order
WS	26.316	2	0.000	-4.428	0.000	descending
BT	984.491	2	0.000	32.364	0.000	ascending
BG	89.952	2	0.000	-8.447	0.000	descending

Table 8.8 Results of the Kruskal-Wallis and Jonckheere-Terpstra tests (H: Kruskal-Wallis test statistic, z: standardised Jonckheere-Terpstra test statistic)

The Kruskal-Wallis test can determine if the factor has an effect on the dependent variable; however, it cannot show trends. Jonckheere-Terpstra tests were performed to determine whether the categories' order is meaningful. The sign of the test statistic indicates an ascending, in the case of a positive number, or a descending order of medians, in the case of a negative one. For example, in the case of brick type, the medians of the groups are in an ascending order from BT1 (red), through BT2 (gray) to BT3 (blue), that is, the productivity rate significantly increases, meaning that construction is slower. The results of this test can be seen in Table 8.8.

$$r = \frac{z}{\sqrt{N}} \tag{1}$$

where z: standardised Kruskal-Wallis test statistic, N: sample/group size.

Effect size (r)	Effect
> 0.1	small
> 0.3	medium
> 0.5	large

Table 8.9 Effect sizes

With the significant Kruskal-Wallis tests, pairwise comparisons were also performed. The details of the significant ones can be seen in Table 8.10. The significance column contains the adjusted significance values, which are determined based on the Bonferroni correction. To minimise the Type I errors, the scores' significance values were multiplied by the number of possible comparisons for each factor. For instance, in the case of brick type, there were three possible comparisons (BT1vBT2, BT1vBT3, BT2vBT3); therefore, the original significance value was multiplied by 3. Then these corrected significance values were compared to the 0.05 significance level. The effect size was calculated according to (1). The effect was determined based on Table 8.9.

Contrast	2-tailed/ 1-tailed	z	Sig.	N	Effect size	Effect
WS1vWS3	2-tailed	4.849	0.000	1200	0.140	small
WS2vWS3	2-tailed	4.613	0.000	900	0.154	small
BT1vBT2	2-tailed	-15.327	0.000	1500	-0.396	medium
BT1vBT3	2-tailed	-30.820	0.000	1200	-0.890	large
BT2vBT3	2-tailed	-17.634	0.000	900	-0.588	large
BG1vBG2	2-tailed	8.112	0.000	1200	0.234	small
BG1vBG3	2-tailed	8.311	0.000	1200	0.240	small

Table 8.10 Results of the pairwise comparisons (z: standardised test statistic, N: group size)

According to Table 8.10, the productivity rate for building with blue bricks (BT3) is significantly higher (meaning that construction is slower) than that of the other two materials. Moreover, the productivity rate for the gray bricks (BT2) is significantly higher than that of the red bricks (BT1). The productivity rates of the model bricklaying gangs #2 (BG2) and #3 (BG3) are significantly lower (meaning that they work faster) than that of model bricklaying gang #1.

Based on the non-parametric tests performed, it can be concluded that all three factors significantly affect the productivity rate.

8.2.1.5 Mean productivity rates per factor

During the simulation runs in this batch, the same amount of wall sections was built by the bricklaying gangs listed in Table 8.4. The mean productivity rates for the three model bricklaying gangs in the case of the different brick types and model wall sections are depicted in Figures 8.5 through 8.8. In the case of each model wall section a different bricklaying gang is most productive. Figure 8.7 shows that model bricklaying gang #2 can build model wall section #1 the fastest regardless of the brick type used. In the case of model wall section #2, model bricklaying gang #1 might be recommended regardless of brick type (see Figure 8.8), while the construction of model wall section #3 might benefit from model bricklaying gang #3. Figures 8.5 and 8.6 show that – apart from model wall section #2 – model bricklaying gang #1 tends to be the slowest. This gang is composed of the least and most experienced model bricklayers; therefore, it might be beneficial to have more balanced gangs, meaning pairing bricklayers with more similar scores. Figures 8.7 and 8.8 show that the performance of the other two model bricklaying gangs tends to be closer to each other, with bricklaying gang #2 doing slightly better. It can also be seen from these two graphs that – regardless of the wall section and the bricklaying gang – construction time increases from red bricks to gray bricks to blue bricks. This is consistent with the findings presented in the previous section and the test results shown in this one and can be explained by the more complicated nature of laying the bricks and executing the jointing. Figures 8.5 and 8.6 show the increasing difficulty of the model wall sections from #1 to #3 as the latter generally takes more time to build. However, this is not true for model bricklaying gang #1.

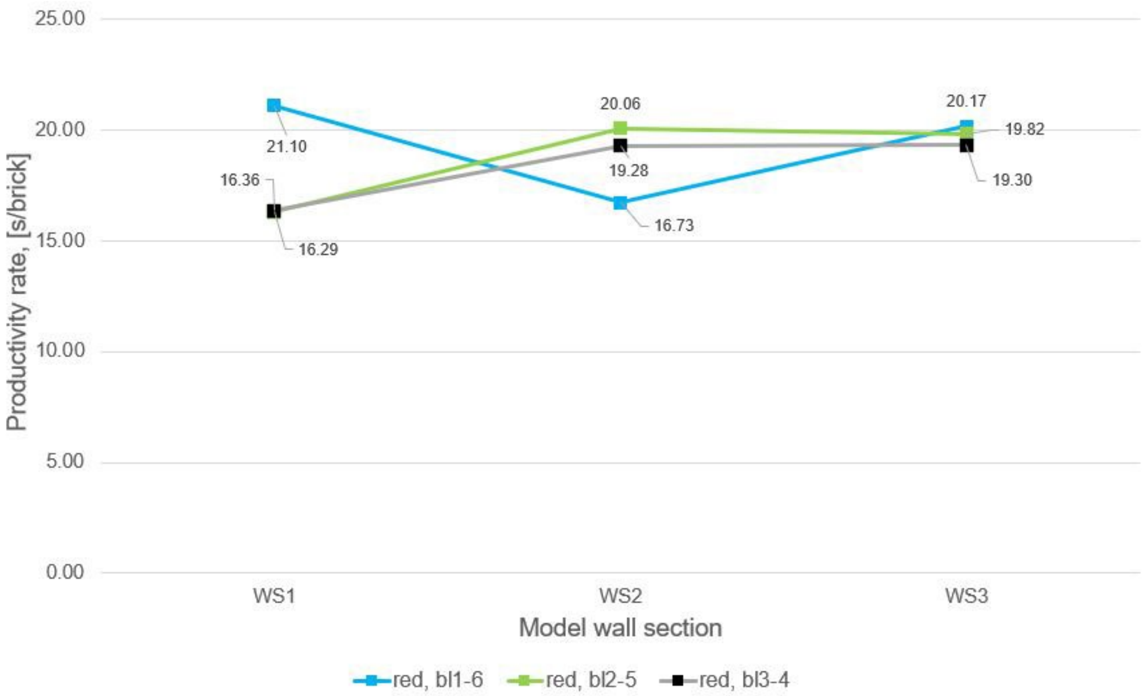


Figure 8.5 Mean productivity rates per model wall section for each model bricklaying gang for red bricks

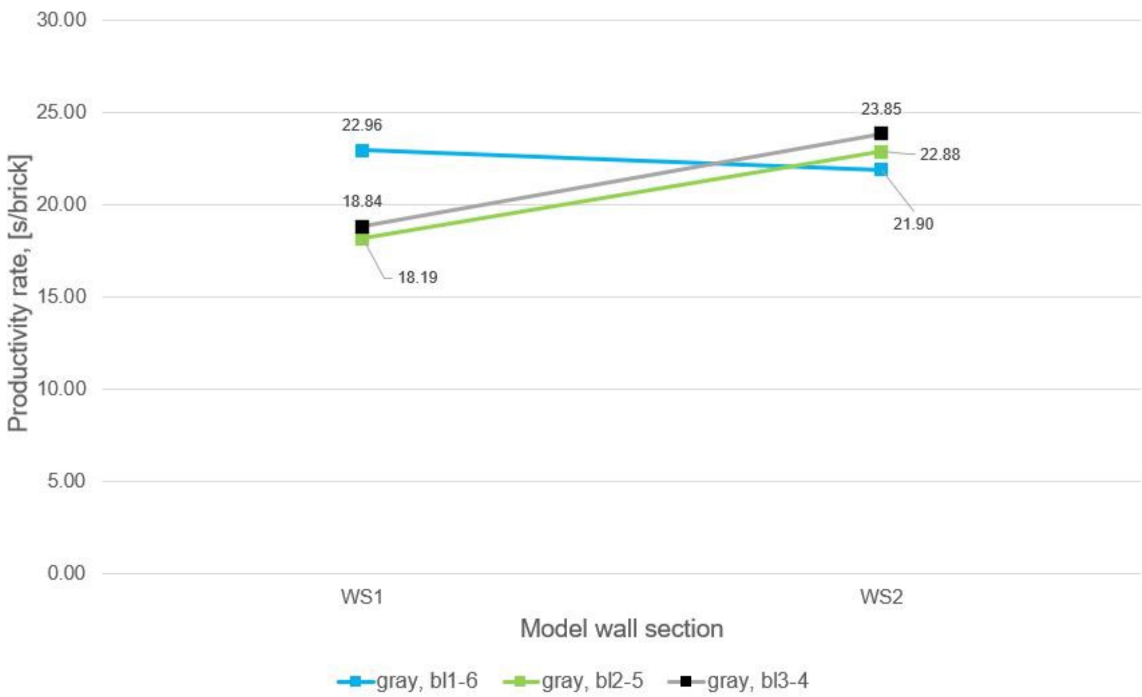


Figure 8.6 Mean productivity rates per model wall section for each model bricklaying gang for gray bricks

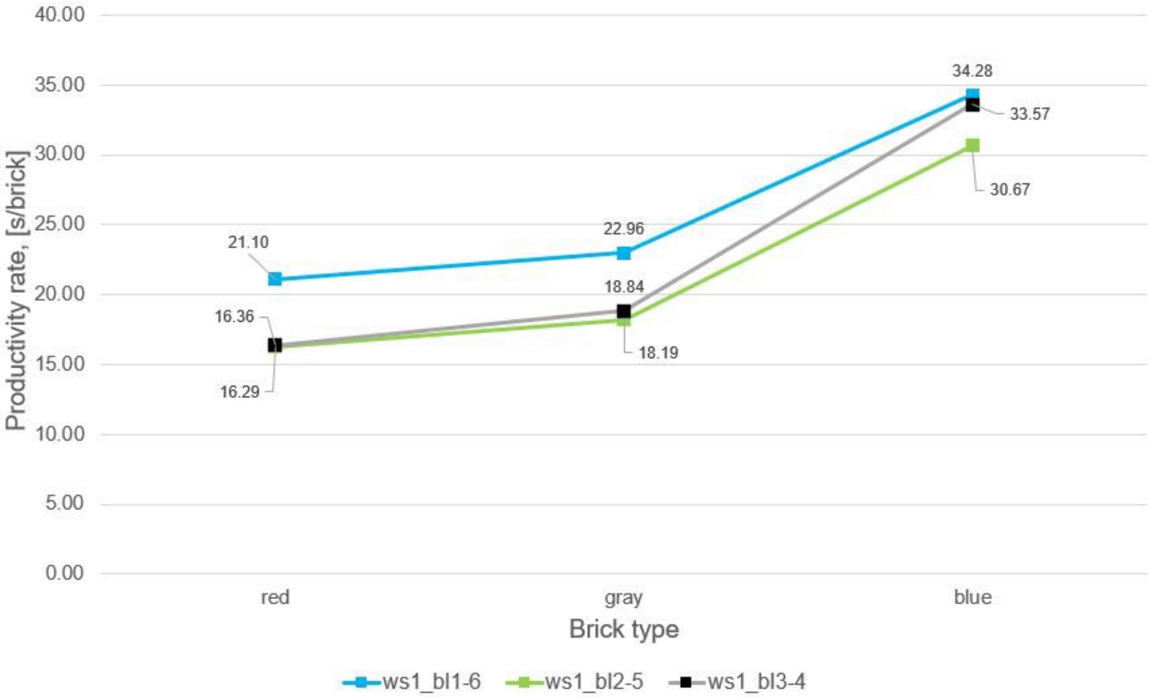


Figure 8.7 Mean productivity rates per brick type for each model bricklaying gang for model wall section #1

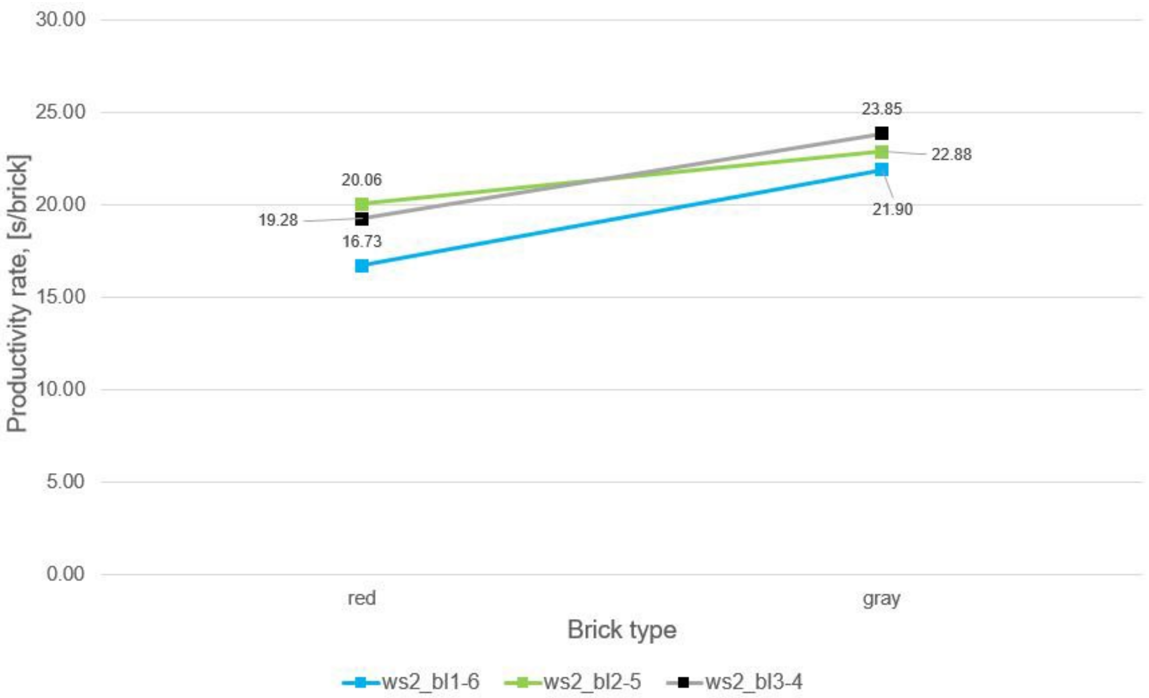


Figure 8.8 Mean productivity rates per brick type for each model bricklaying gang for model wall section #2

8.2.2 Analysis of the output of the second batch of runs

8.2.2.1 Descriptive statistics and factors analysed

As explained in Section 7.5.2, the DES model component was run 20 times for each bricklaying gang composition-brick type-model wall section configuration. The activity duration of the jointing task was determined by the brick type and model wall section combination, while the duration of the laying bricks activity was calculated based on the output of the ANN model component, where the model bricklayer, brick type and course difficulty characteristics had been entered. The DES model component provided the project duration, which then needed to be divided by the total number of bricks (for the 100 wall sections) used for the built wall sections for the comparison of the different configurations. This way the productivity rates were given in seconds/brick dimension. The descriptive statistics for these productivity rates can be seen in Table 8.11 and the histogram in Figure 8.9.

	Productivity Rate
Number of data points	240
Minimum [s/brick]	3.88
Maximum [s/brick]	10.30
Mean [s/brick]	5.840
Standard Deviation [s/brick]	1.254
Variance [$(s/brick)^2$]	1.573
Skewness	0.908
Standard Error of Skewness	0.157
Kurtosis	0.322
Standard Error of Kurtosis	0.313

Table 8.11 Descriptive statistics for productivity rate

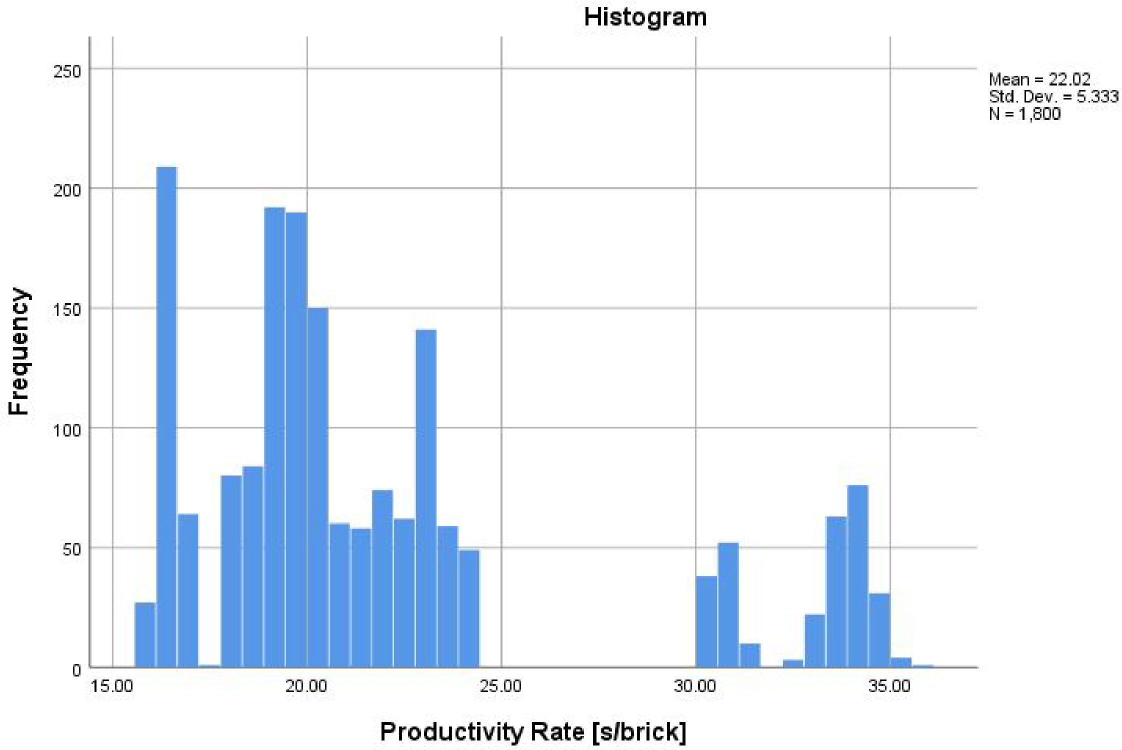


Figure 8.9 Histogram of productivity rate

Table 8.12 contains the list of the factors with their scales explained. Moreover, it shows the abbreviations used later in this chapter. For example, BT1 stands for red bricks. The bricklaying composition is further explained in Table 8.13 using the abbreviations for the model bricklayers introduced in Section 7.3.1.

Factor/Scale	**1**	**2**	**3**
Bricklaying gang composition (BLC)	Mixed (BLC1)	Straight (BLC2)	-
Model wall section (WS)	Model wall section #1 (WS1)	Model wall section #2 (WS2)	Model wall section #3 (WS3)
Brick type (BT)	Red (BT1)	Gray (BT2)	Blue (BT3)

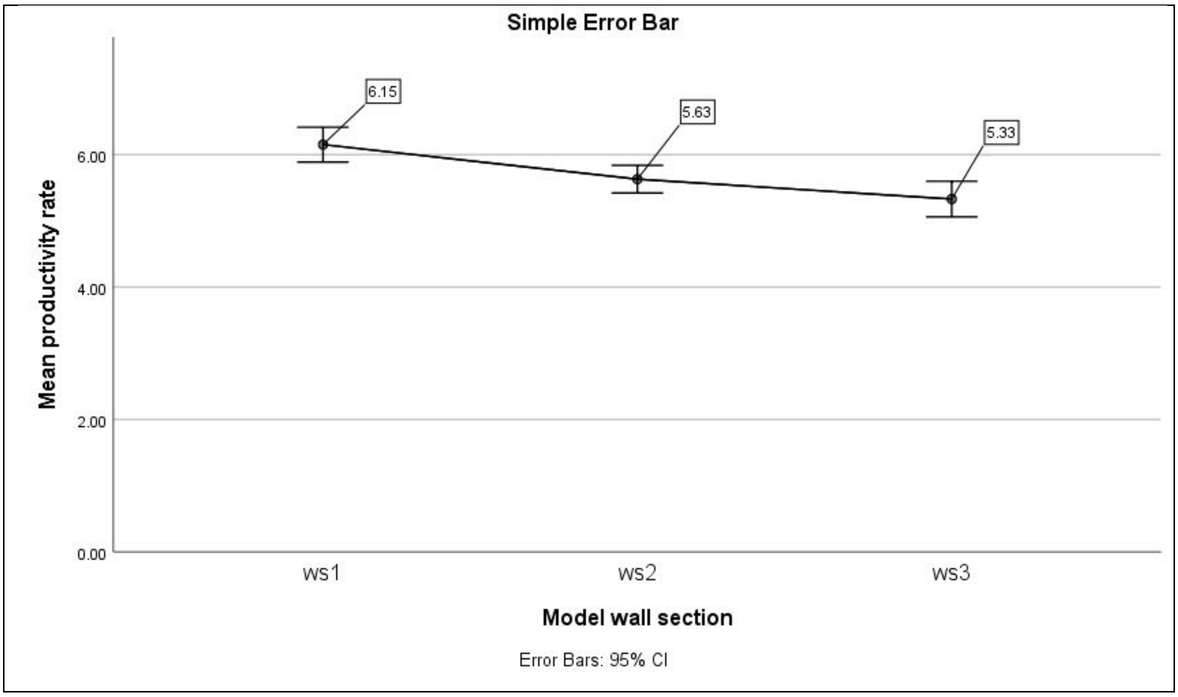
Table 8.12 Factors and their scales

	Mixed	**Straight**
1	BL1+BL6	BL1+BL1
2	BL1+BL6	BL2+BL2
3	BL2+BL5	BL3+BL3
4	BL2+BL5	BL4+BL4
5	BL3+BL4	BL5+BL5
6	BL3+BL4	BL6+BL6

Table 8.13 Mixed and straight pairings of bricklayers

8.2.2.2 Error bars

The error bars showing the 95% confidence intervals for the different groups of each factor can be seen in Figure 8.10. The mean productivity rate values in s/brick for every category are labelled. Due to the chosen dimension, the higher the value, the slower the works are performed. The following tests showed whether the differences between the categories were significant. Looking at the depicted means in the graphs below, trends can be observed. For example, in the case of brick type, blue bricks are laid slower than gray ones, and walls of red ones are the fastest to build. This is in line with the previously drawn conclusions. The graph of the bricklaying gang composition suggests that mixed gangs work faster. However, it is worth noting that these only show the means when the grouping is done for only one factor. For instance, the graph of the model wall sections suggests that the construction is quicker for the supposedly more difficult wall sections, that the more complex it is, the faster it can be built. This is most likely because the more difficult brick types are only used for the easier model wall sections in the model project.



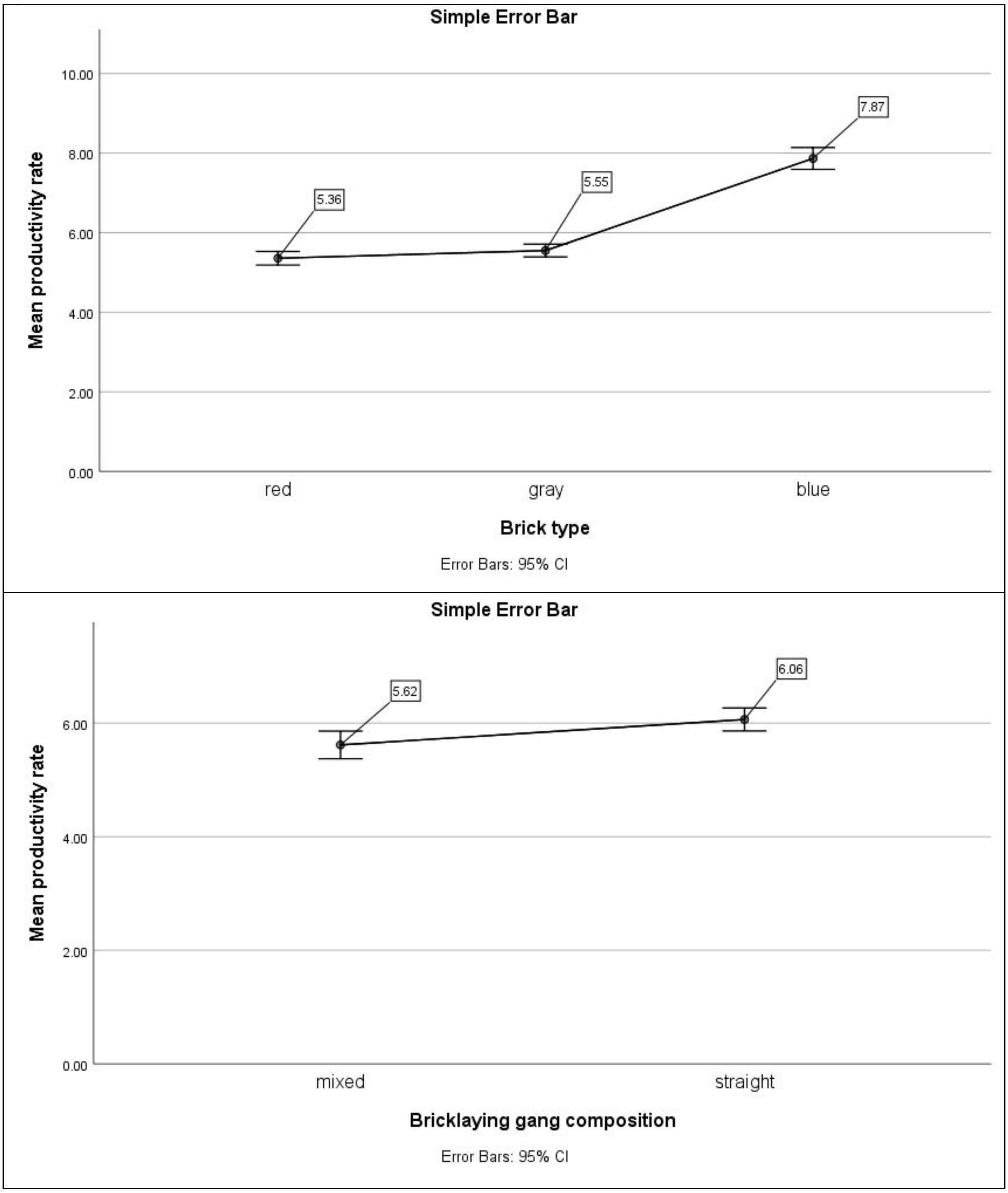


Figure 8.10 Error bars

8.2.2.3 Normality and homogeneity of variance

To select the appropriate test, it needed to be determined whether the variables followed a normal distribution, and their variances were homogenous between the categories of the factors. These assumptions of normality and homogeneity need to be met, in the case of parametric tests, for the F statistic, the output of the tests, to be reliable.

The productivity rates at every level of each variable were checked for normality because for the tests, this is what matters, and not the overall normality. The analyses included running the Kolmogorov-Smirnov and Shapiro-Wilk tests. The tests showed that some groups followed a normal distribution, while others did not. Table 8.14 summarises the results of the normality tests.

Factor	Cat.	N	Kolmogorov-Smirnov		Shapiro-Wilk		Normal?
			D	Sig.	D	Sig.	
WS	WS1	120	0.106	0.002	0.945	0.000	no
	WS2	80	0.119	0.007	0.954	0.006	no
	WS3	40	0.164	0.009	0.932	0.019	no
BT	BT1	120	0.132	0.000	0.931	0.000	no
	BT2	80	0.086	0.200	0.980	0.252	yes
	BT3	40	0.091	0.200	0.974	0.483	yes
BLC	BLC1	120	0.215	0.000	0.834	0.000	no
	BLC2	120	0.058	0.200	0.981	0.082	yes

Table 8.14 Results of the normality tests (D: test statistic, Cat.: category, gray background: normal distribution)

Besides normality, the homogeneity of variance was also checked by using Levene's test. Based on the test, it can be concluded that the variances are significantly different in the case of model wall section and brick type. The results are included in Table 8.15.

Factor	F	df_1	df_2	Sig.	Homogenous?
WS	18.455	2	237	0.000	no
BT	3.759	2	237	0.025	no
BLC	0.701	1	238	0.403	yes

Table 8.15 Results of Levene's test (F: Levene test statistic, gray background: homogeneity of variance)

The results of the normality and Levene's tests show that while the scores of some categories follow a normal distribution, and the variances of the groups in some factors are homogenous, others are non-normal and heterogeneous. Due to this, both parametric and non-parametric tests were performed to determine whether the productivity rate is affected by the factors. In the case of both types of tests, the categories within one factor were compared to each other.

8.2.2.4 Parametric tests

From the parametric tests, ANOVA is used to determine whether the selected factors have an influence on the dependent variable, i.e., the productivity rate. It is a parametric test; therefore, it assumes a normal distribution. Table 8.16 summarises the main results of the tests. If the variances of the categories are significantly different from each other, Welch's F has to be checked. If this is significant, that means that the factor influences the dependent variable, which is now the productivity rate. This is the case for model wall section and brick type. Table 8.18 contains the results of Welch's test. The effect size was calculated according to (2) (Horn, 2006). The effects were determined based on Table 8.17. The implications of the Brown-Forsythe test being significant are the same as that of Welch's F being significant. Table 8.19 contains the results for this test. The effect sizes were calculated according to (2) and the effects were determined based on Table 8.17. The Brown-Forsythe test gave the same results as Welch's.

Factor	Variances	ANOVA/Robust tests	Significant contrasts	Significant post-hoc tests
WS	significantly different	Welch's: significant Brown-Forsythe: significant	▪ WS1 vs. WS2&WS3 ▪ WS3 vs. WS1&WS2 ▪ WS1 vs. WS2	▪ WS1 vs. WS2 ▪ WS1 vs. WS3
BT	significantly different	Welch's: significant Brown-Forsythe: significant	▪ BT1 vs. BT2&BT3 ▪ BT2 vs. BT3 ▪ BT3 vs. BT1&BT2	▪ BT1 vs. BT3 ▪ BT2 vs. BT3
BLC	not significantly different	ANOVA: significant		

Table 8.16 Parametric test results

$$\omega^2 = \frac{df_1 * (F-1)}{df_1 * (F-1) + N} \tag{2}$$

where F: Welch's/Brown-Forsythe F, N: sample size.

Effect size (ω^2)	Effect
> 0.01	small
> 0.06	medium
> 0.14	large

Table 8.17 Effect sizes

Factor	Welch's F	df_1	df_2	Sig.	Effect size	Effect
WS	9.796	2	123.071	0.000	0.125	medium
BT	131.958	2	106.229	0.000	0.680	large

Table 8.18 Results of Welch's test

Factor	Brown-Forsythe F	df_1	df_2	Sig.	Effect size	Effect
WS	11.438	2	220.333	0.000	0.145	large
BT	140.599	2	153.857	0.000	0.694	large

Table 8.19 Results of Brown-Forsythe's test

In the case of the variances being homogenous, the ANOVA table has to be looked at. This was the case for bricklaying gang composition. The test was significant. The results can be seen in Table 8.20. The effect size was calculated based on (3), and the effect was determined according to Table 8.17.

$$\omega^2 = \frac{SS_M - df_M * MS_R}{SS_T + MS_R} \quad (3)$$

where SS_M: between group effect (sum of squares model), df_M: degrees of freedom for the effect, MS_R: residual mean squared error, SS_T: total amount of variance in the data (sum of squares total).

Factor	F-ratio	Sig.	SS_M	SS_T	MS_R	df_M	Effect size	Effect
BLC	7.886	0.005	12.060	376.018	1.529	1	0.0279	small

Table 8.20 Results of ANOVA

Table 8.21 shows the main ANOVA summary table for bricklaying gang composition. The combined between group effect is the overall effect due to the model, while the within groups effect is the unsystematic variation in the data existing due to individual differences between the groups. Since the F-ratio value corresponding to the former is significant, bricklaying gang composition has a significant effect on the productivity rate. The F-ratio of the linear term is significant suggesting a linear trend.

Bricklaying gang composition			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		12.060	1	12.060	7.886	0.005
	Linear Term	Contrast	12.060	1	12.060	7.886	0.005
Within Groups			363.958	238	1.529		
Total			376.018	239			

Table 8.21 ANOVA results for bricklaying gang composition

Since the previous tests only show that the given factor has some effect on the dependent variable, planned contrasts and post-hoc tests were used to see where the differences lie, in the case of the factors with three categories. Table 8.22 summarises the orthogonal contrasts tested for the factors. First, the lowest score was selected as a baseline, and the other two categories were compared to this. Then the second lowest score was compared to the lowest score. After this, another set of comparisons were performed. This time the highest score was chosen as the baseline and compared to the lower scores. Then the middle one was compared to the lowest score. The significant contrasts are listed in Table 8.24.

		I	II		I	II
WS, BT	**1**	-2	0		1	-1
	2	1	-1		1	1
	3	1	1		-2	0

Table 8.22 Contrasts for the model wall section and brick type variables

The results for those contrasts that were significant are shown in Table 8.24. It also lists the effect sizes, which were calculated according to (4), while the effects were determined based on Table 8.23.

$$r = \sqrt{\frac{t^2}{t^2 + df}} \tag{4}$$

Effect size (r)	Effect
> 0.1	small
> 0.3	medium
> 0.5	large

Table 8.23 Effect sizes

Comparisons	t	Sig.	2-tailed/ 1-tailed	df	Effect size	Effect
WS1 vs. WS2&WS3	-4.258	0.000	2-tailed	191.391	0.2942	small
WS3 vs. WS1&WS2	3.56	0.001	2-tailed	74.727	0.3808	medium
WS1 vs. WS2	-3.079	0.002	2-tailed	197.774	0.2139	small
BT1 vs. BT2&BT3	11.52	0.000	2-tailed	179.216	0.6523	large
BT2 vs. BT3	14.634	0.000	2-tailed	67.157	0.8725	large
BT3 vs. BT1&BT2	-16.254	0.000	2-tailed	54.744	0.9101	large

Table 8.24 Results of the significant contrasts

For post-hoc tests, in the case of homogenous variances, Hochberg's GT2 and Gabriel's procedures were selected as they can deal with unequal sample sizes. The Games-Howell procedure was chosen for heterogeneous variances because that can also handle different sample sizes. The significant tests are listed in Table 8.16. These results are in line with the significant contrasts.

8.2.2.5 Non-parametric tests

The Kruskal-Wallis test, the non-parametric equivalent of the one-way independent ANOVA, was used to see the differences between the categories. If it is significant, the given factor significantly affects the dependent variable. In this case, all three factors were found to significantly affect the productivity rate. The details are shown in Table 8.25.

Factor	Kruskal-Wallis			Jonckheere-Terpstra		
	H	df	Sig.	z	Sig.	order
WS	10.754	2	0.005	-3.313	0.001	descending
BT	92.731	2	0.000	8.363	0.000	ascending
BLC	16.283	1	0.000	4.035	0.000	ascending

Table 8.25 Results of the Kruskal-Wallis and Jonckheere-Terpstra tests (H: Kruskal-Wallis test statistic, z: standardised Jonckheere-Terpstra test statistic)

The Kruskal-Wallis test can determine if the factor has an effect on the dependent variable; however, it cannot show trends. Jonckheere-Terpstra tests were performed to determine whether the categories' order is meaningful. The sign of the test statistic indicates an ascending, in the case of a positive number, or a descending order of medians, in the case of a negative one. For example, in the case of brick type, the medians of the groups are in an ascending order from BT1 (red), through BT2 (gray) to BT3 (blue), the productivity significantly increases. Bricklaying gang composition also shows an ascending order from BLC1 (mixed) to BLC2 (straight). The results of this test can be seen in Table 8.25.

With the significant Kruskal-Wallis tests, pairwise comparisons were also performed. The details of the significant ones can be seen in Table 8.26. The significance column contains the adjusted significance values, which are determined based on the Bonferroni correction. To minimise the Type I errors, the scores' significance values were multiplied by the number of possible comparisons for each factor. For instance, in the case of brick type, there were three possible comparisons (BT1vBT2, BT1vBT3, BT2vBT3); therefore, the original significance value was multiplied by 3. Then these corrected significance values were compared to the 0.05 significance level. The effect size was calculated according to (1). The effect was determined based on Table 8.9.

Contrast	**2-tailed/ 1-tailed**	**z**	**Sig.**	**N**	**Effect size**	**Effect**
WS1vWS3	2-tailed	3.136	0.005	160	0.248	small
BT1vBT3	2-tailed	-9.563	0.000	160	-0.756	large
BT2vBT3	2-tailed	-7.560	0.000	120	-0.690	large

Table 8.26 Results of the pairwise comparisons (z: standardised test statistic, N: group size)

According to Table 8.26, the productivity rate for building with blue bricks is significantly higher (meaning that construction is slower) than that of the other two materials. Based on the non-parametric tests performed, it can be concluded that all three factors significantly affect the productivity rate.

8.2.2.6 Mean productivity rates per factor

During the simulation runs in this batch – on average – equal amounts of wall sections were built by the bricklaying gangs listed in Table 8.13. The mean productivity rates for the two bricklaying gang composition options in the case of the different brick types and model wall sections are depicted in Figures 8.11 through 8.14. It can be seen that the gangs with mixed composition worked faster in almost all of the cases. The only exceptions are model wall section #1 built of either gray or blue bricks (see Figure 8.11). However, in the case of the former, the difference is only approximately 5%. In the case of red bricks, regardless of the difficulty of the wall section, mixed bricklaying gangs may be recommended (see Figure 8.13). The same is true for model wall section #2 built of gray bricks (see Figure 8.12).

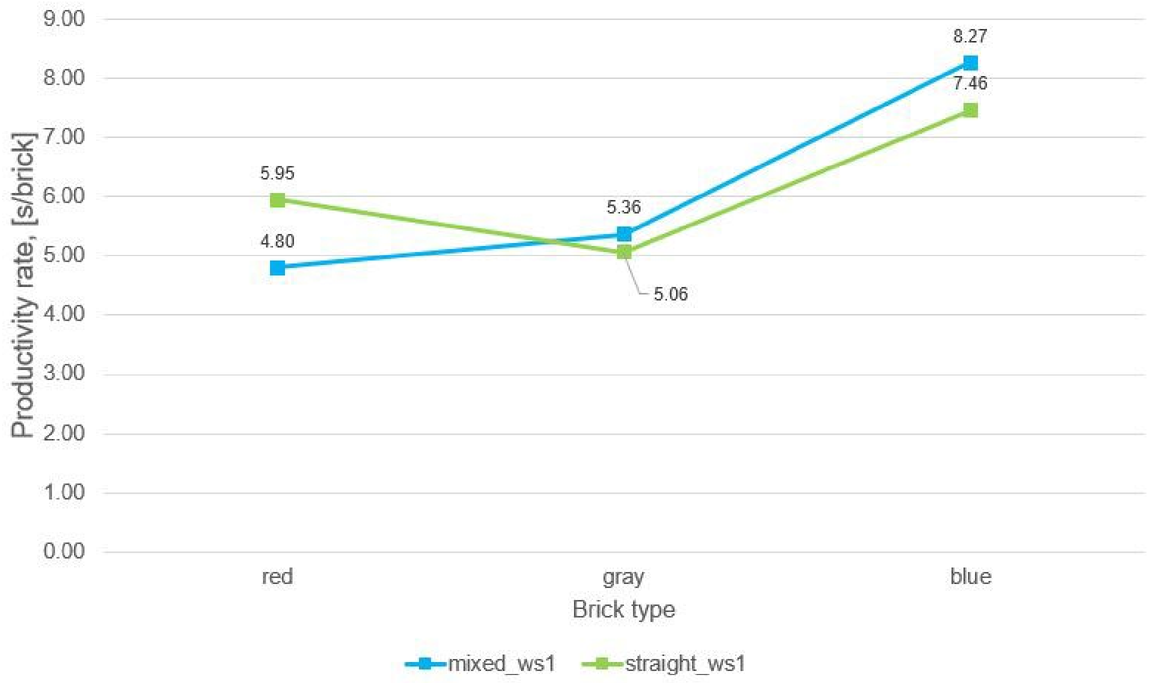


Figure 8.11 Mean productivity rate per brick type for each bricklaying gang composition for model wall section #1

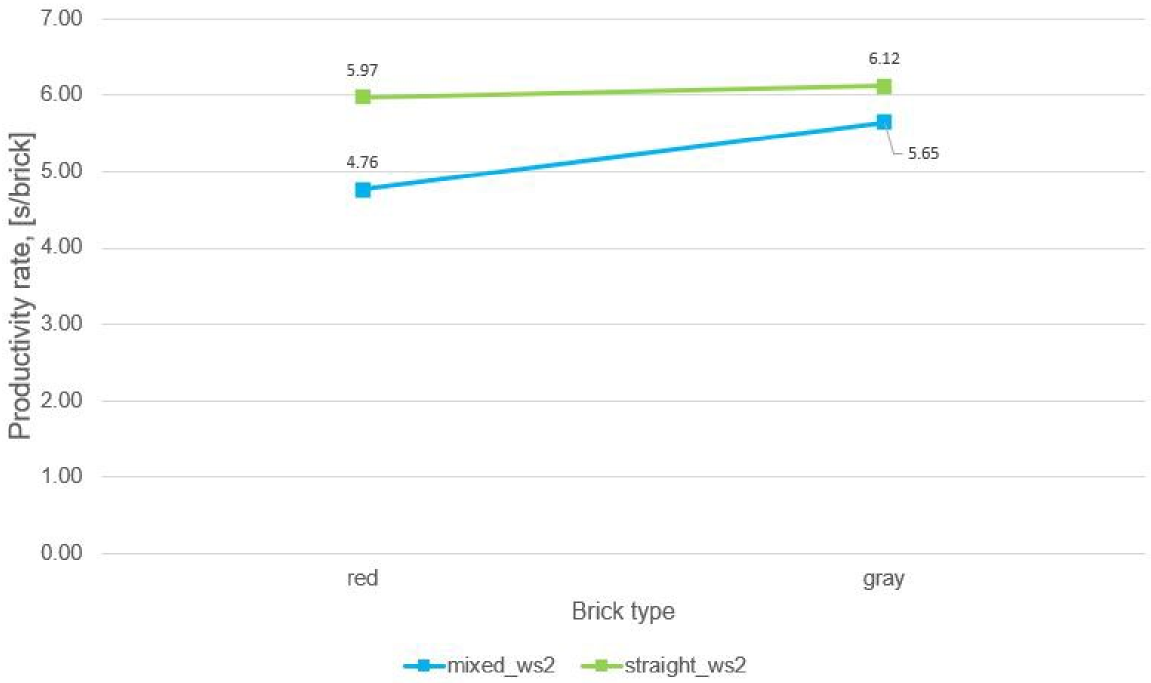


Figure 8.12 Mean productivity rate per brick type for each bricklaying gang composition for model wall section #2

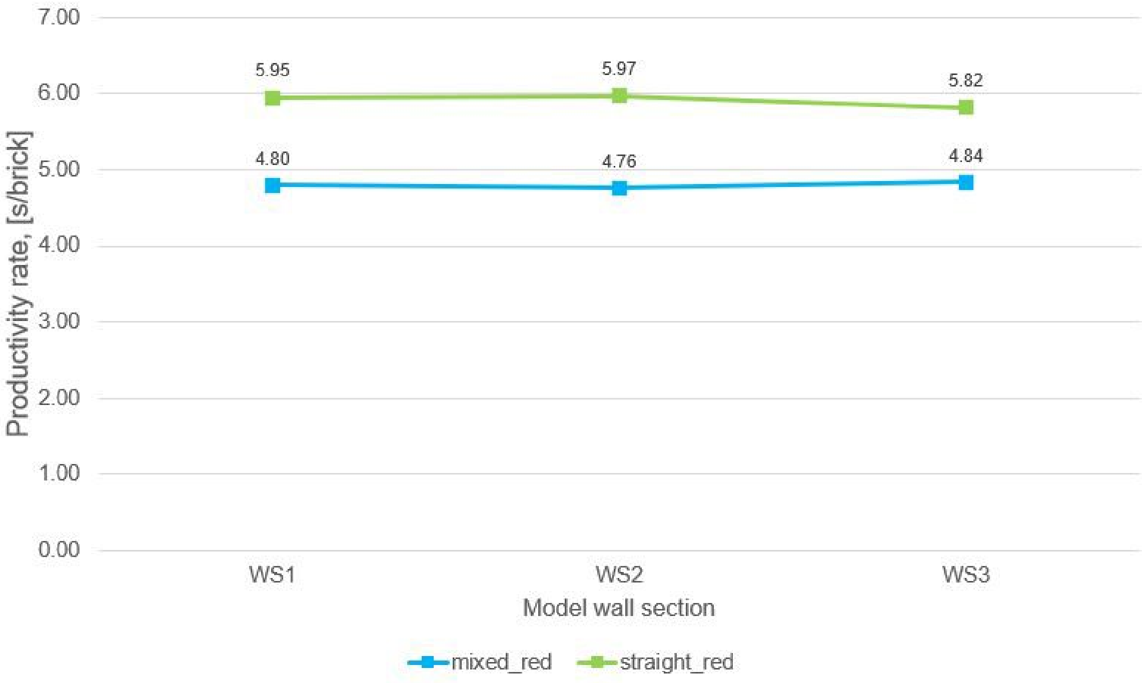


Figure 8.13 Mean productivity rate per model wall section for each bricklaying gang composition for red bricks

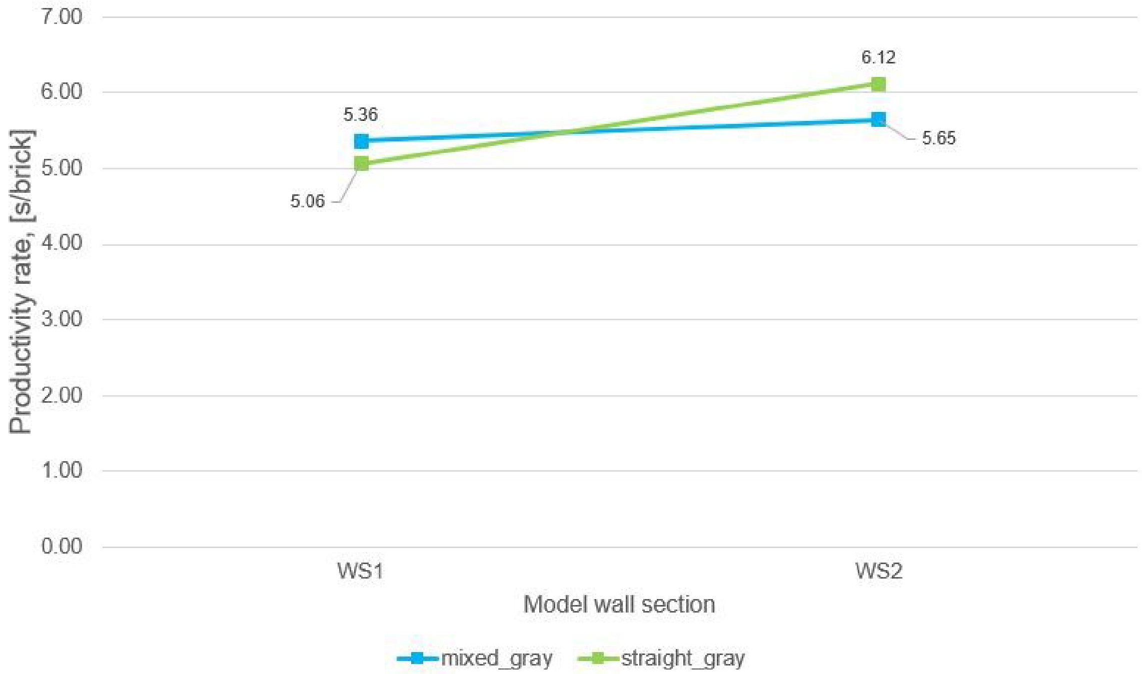


Figure 8.14 Mean productivity rate per model wall section for each bricklaying gang composition for gray bricks

8.3 Application of the developed model

As detailed in Chapters 4, 5, and 7 and shown in Figure 8.15, the developed model has two components: an ANN and a DES part. The artificial neural networks were trained using the collected data. As explained in Section 7.4, in the next step, the ANN model component was used to provide the productivity rates for model bricklayer-model wall section combinations. These output values were used to calculate the productivity rates of model bricklaying gangs, which then – combined with the model wall section data – became the input for the DES model component as the task duration of the activity laying bricks. The output of this part of the model provided the process duration, in the case of all model bricklaying gangs and model wall sections. These could then be compared to each other and the conclusions as to the most optimal labour allocation options could be drawn. This was shown in this chapter.

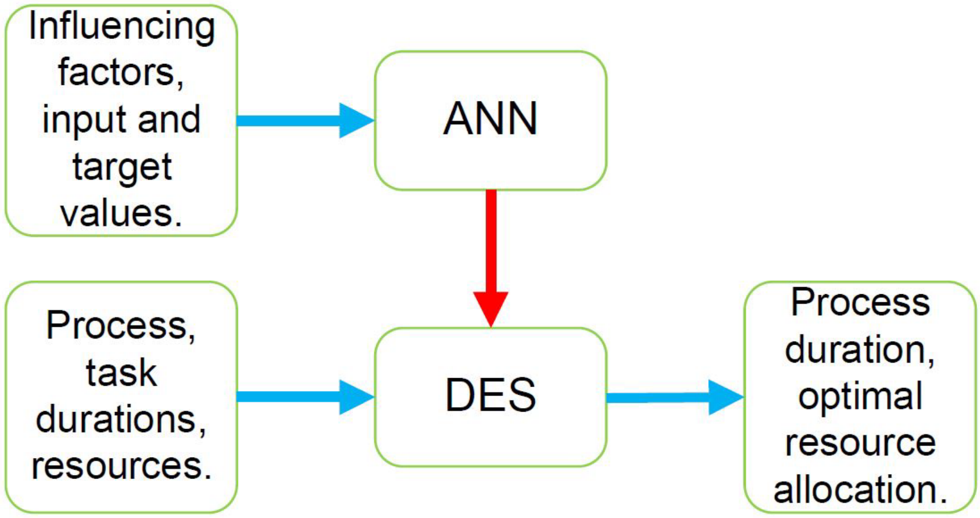


Figure 8.15 The DES-ANN hybrid model

The same way, instead of using model bricklayers, bricklaying gangs, and wall sections, data of actual bricklayers and wall sections can be input into the ANN model component to obtain the productivity rates. Possible bricklaying gangs can be formed from the bricklayers, and their productivity rates calculated. These values can then be fed into the DES model component to get the process durations and to check the resource allocation options. With the help of the model, it can be determined which the most efficient bricklaying gangs are and which bricklaying gangs should be allocated to which wall sections in order to get the shortest process duration and shortest overall project duration.

This model can be improved by training the ANN model component with more real-life data to make the output productivity rates more accurate and the model's generalisation performance better. It is also possible to modify the model to fit another construction operation, such as block laying. For this, the process defined in the DES model component needs to be changed. In addition to that, the ANN model component needs to be trained with a dataset collected by observing the given operation. Furthermore, different factors can be added to or instead of the ones selected for this study.

8.4 Chapter summary

The first part of this chapter summarised the results of the sensitivity analysis of the ANN model component and the statistical analyses. These were performed to examine the effects of the selected factors on the productivity rate. Based on these, experience, course difficulty, and brick type seemed to be the most important, significantly affecting the productivity rate. In the case of experience, the relationship is positive, meaning that as experience increases, the productivity rate increases, as well. In the case of the wall-related factors, the relationship is inverse, that is the productivity rate decreases as course difficulty and brick type (essentially brick difficulty) increases. The second part of the chapter presented the analysis of the output of the simulation runs. In the first batch of runs, the model bricklaying gangs were assigned to the tasks one at a time, and the process durations were analysed and compared. In the case of each model wall section, a different bricklaying gang was most productive. However, generally, model bricklaying gang #1 tended to be the slowest, while the performance of the other two model bricklaying gangs tended to be closer to each other, with bricklaying gang #2 doing slightly better. Regardless of the wall section and the bricklaying gang, construction time increased from red bricks to gray bricks to blue bricks. In the second batch of simulation runs, all model bricklaying gangs were assigned to the tasks at one time, and pairs of the same model bricklayers the next time. The process durations were analysed and compared. Gangs with mixed composition tended to work faster in almost all cases. The final section of the chapter discussed how the model can be used and further developed. Chapter 9 will summarise the conclusions that can be drawn from the analyses.

CHAPTER 9

CONCLUSIONS

9.1 Introduction

The construction industry plays a significant part in the UK's economy. When the construction-related businesses are also included, its contribution is approximately 12% of the GDP (Green, 2020). Therefore, construction productivity has always been an important topic, and hence subject of academic, industrial, and governmental research, as well. While the number of construction projects is growing, the supply of skilled labour is decreasing owing to the aging workforce and the low level of new entry (Brooks and McIlwaine, 2021). Therefore, it is important to better understand the productivity of labour-intensive works in order to be able to manage skilled labour appropriately and better plan future projects.

9.2 Review of research aim and objectives

Per Chapter 1, the aim of the research project was to provide a better understanding of the bricklaying process and how it can be modelled, descriptively and normatively, to find a modelling approach that allows for a better examination of the effects of various factors on bricklaying productivity. To achieve this aim, the following objectives were set:

1. To explore how construction productivity can be modelled. This entailed examining various methods used on different levels of productivity and selecting the most suitable modelling approach that fit the aim of the study.
2. To study bricklaying works, bricklayers' characteristics, and gang composition. This included taking time measurements and observations so as to gather knowledge on the workflow of the operation, various materials, different wall types, bricklayers, and resource allocation. This was necessary for determining the building blocks of the model and assembling the data table fed into the model.
3. To investigate the factors influencing construction labour productivity. This entailed the selection of the most relevant factors in the planning phase of construction projects, and brickwork, in particular.
4. To create the model using the selected method including the chosen factors.
5. To analyse how the selected factors affect productivity. This was achieved with the help of the model and statistical analyses.
6. To test the model by running it with model project data. This included creating model wall sections, bricklayers, and bricklaying gangs. This enabled testing the resource allocation implications of bricklaying gang compositions.

9.2.1 Objective #1: To explore how construction productivity can be modelled

Productivity can be measured and analysed at different levels. One possibility is to differentiate between activity, project, and industry levels (Ayele and Robinson Fayek, 2018). This research project focused on the activity level, which determined the measurement of productivity and the choice of methods. To measure efficiency and productivity work sampling, five-minute rating, and time study can be performed. The latter was selected for collecting data as more information can be gathered through that than by the other two mentioned options. To study the effects of various factors on productivity, use can be made of statistical analysis, artificial intelligence, simulation, fuzzy logic, genetic algorithms, expert systems, or – at the industry level – multi-criteria decision analysis methods. All these methods were introduced, and examples were shown for their application in Chapter 2. Machine learning (a sub-field of artificial intelligence) and simulation were discussed in more detail in this chapter as these were chosen for modelling in this research.

Artificial neural networks (ANN), a machine learning approach, were selected for one component of the model because they can learn from the input data, even if the dataset is imperfect, and make predictions – in this case, for productivity – for new input data (Flood and Kartam, 1994a; Di Franco and Santurro, 2020). ANNs are capable of handling the complexity and uncertainty inherent to construction problems (Chao and Skibniewski, 1994; Di Franco and Santurro, 2020).

For the other component of the model, a simulation method was chosen because it helps model a system and experiment on the system (by changing its parameters), which allows for generating multiple scenarios and make generalisations to predict performance (White and Ingalls, 2017). Out of the three basic simulation methods – discrete-event simulation, system dynamics, and agent-based modelling – discrete-event simulation (DES) was used, which is suitable for modelling a construction process, providing the process duration and information on resource usage and allocation.

Creating hybrid models is beneficial because by combining the methods, their advantages are also combined, while their shortcomings can be balanced out. Chapter 2 presented numerous examples for hybrid models, including two DES-ANN hybrids (Chao and Skibniewski, 1994; Song and AbouRizk, 2008).

9.2.2 Objective #2: To study bricklaying works and bricklayers

For modelling bricklaying works, it was necessary to collect information on bricklaying operations and bricklayers. This was achieved in multiple ways. The most prominent one was through structured observations. These took place on two construction sites in North East England from mid-November 2018 to mid-June 2019. On both sites, cavity walls were constructed. On one site this consisted of a block inner leaf and a perforated, Staffordshire blue engineering brick outer leaf, while on the other steel framing system was used, and two buildings had a red brick façade of stock bricks with a single frogging, and for the other two buildings, gray, solid, concrete bricks were laid for the outer leaf. Three different masonry sub-contractors worked with the three different materials; therefore, altogether 21 bricklayers were observed.

Over the course of the site visits, net time measurements were taken of the laid courses with noting the bricklayer(s), the number of bricks laid, and the exact course (building, floor, number of the course) constructed, and the date. These pieces of information were used to put together the data table needed for modelling. Besides the measurements, the process of bricklaying was also observed because the steps had to be determined for the sequence defined in the simulation model. This was described in detail in Section 4.2. In addition, the site notes included remarks on the similarities and differences of working with different materials and the various bricklayers, and also of the gang compositions.

Apart from structured observations, semi-structured interviews with experts were conducted. The questions were mostly open-ended and were divided into three categories: process, wall, and bricklayers. The responses were used to better understand these topics. For example, the ones in the process group helped finalise and verify the workflow in the DES model component.

All the above were explained in more detail in Chapter 3, while the literature review in Chapter 2 also had a section (2.6) dedicated to bricklaying works giving an overview of the published bricklaying studies.

9.2.3 Objective #3: To investigate the factors influencing productivity

A great number of productivity influencing factors can be identified, and in studies where the aim is to present a collection, numerous factors are included. These can be compiled for various levels of productivity, countries, or based on the point of view of different construction project stakeholders. Section 2.2 gave an overview of studies resulting in a comprehensive list of factors.

When modelling specific construction works, having too many factors might render the model useless; therefore, it is important to include a smaller set of factors, and only known variables, for which data collection is possible (Horner and Talhouni, 1995; Graham and Smith, 2004). In Section 2.6, which introduced the research bricklaying productivity, the factors included in the models were also listed. Table 2.4 summarised them in five categories: design, gang, management, site-related, and external factors.

Since the aim of this research project was to aid pre-construction planning, the factors chosen needed to be ones that are known in advance. In this vein, design and gang-related factors were selected to be included in the model. Numerous studies identified skills and experience among the most important influencing factors. Therefore, these were chosen from the gang-related group. Skills were further broken down into four factors as this further categorisation allowed exploring relevant categorical and hierarchical skills with more finesse: quality, perceived speed, knowledge, and independence. In some studies, design complexity was also among the significant ones. In this research project, complexity was expressed as course difficulty and brick type, with the latter expressing a difficulty ranking, as well. All seven factors (quality, perceived speed, knowledge, independence, course difficulty, brick type) were ordinal variables and could take up values of 1, 2, or 3. The selection of the factors was also informed by the observations and interviews and was explained in more detail together with their scale in Section 4.1.

For the data table, the values of all seven factors were needed. The values of the wall-related factors were assigned based on the observations, while the values of the worker-related factors were the results of the evaluation of the bricklayers by their supervisors, which was explained in Section 3.5.

9.2.4 Objective #4: To create the model

The model developed is hybrid, it consists of two components: an artificial neural network and a discrete-event simulation part. Figure 9.1 shows the structure of the model.

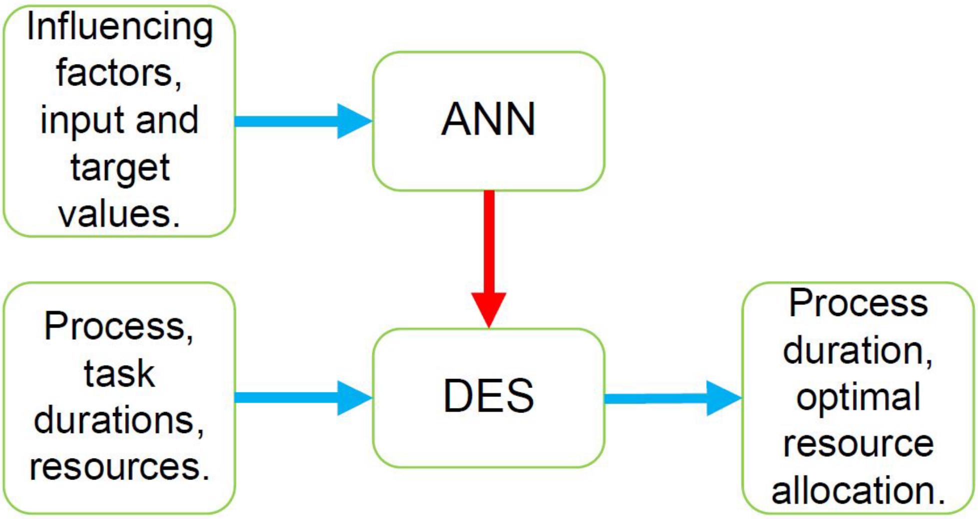


Figure 9.1 The hybrid DES-ANN model structure

The ANN component of the model was built based on the framework described in Section 5.2. Hundreds of feedforward networks were defined to find the best performing ones. Due to having selected seven influencing factors according to objective #3, all the networks had seven input neurons, and one output neuron for the productivity rate. The number of hidden neurons ranged from 5 to 20, which were in either one or two hidden layers. Six training algorithms were chosen for the backpropagation: Levenberg-Marquardt, Bayesian Regularisation, gradient descent with adaptive learning rate backpropagation, gradient descent with momentum and adaptive learning rate backpropagation, Broyden-Fletcher-

Goldfarb-Shanno quasi-Newton backpropagation, and scaled conjugate gradient algorithms. As for the activation functions, log-sigmoid and tangent sigmoid transfer functions were selected for the first or – in the case of two hidden layers – the first two layers, and linear function for the final layer. The correlation coefficient, the mean squared error, and the mean absolute percentage error were the chosen performance measures. These values were checked for all the created networks.

The validation of the model component was achieved through 10-fold validation. The data table was divided into 10 folds, i.e., 10 equal sets, which meant that at any time, 9 folds were used for training, and 1 for testing the network. Then the averages of the performance measures of the best networks in each fold were calculated. After this first round, it was found that the mean absolute percentage error was higher than 20%, which was not ideal. Therefore, six datapoints were removed from the data table, and again hundreds of networks were created as described above. The best performing networks were shown in Table 5.5. The final three networks were listed in Table 5.6.

The DES component of the model was created by using the framework presented in Section 7.2. The two parts of the model make up a sequential structure, where the output of the first component becomes the input of the second one. This is called the interaction point, and the interacting variable is the productivity rate, which is calculated by the ANN part, and is used as the task duration of the laying bricks activity in the DES component. Six model bricklayers and six model wall sections were created, and the productivity rates were determined by the ANN component for all possible combinations. Subsequently, model bricklaying gangs were defined, the net task durations were calculated, and these values were fed into the DES component. This was explained in detail in Section 7.4. The process modelled with DES was determined based on objective #2. The task durations for the other activities in the workflow were calculated based on time measurements taken during the observations. Finally, model bricklaying gangs and labourers were assigned to the tasks, as well. Section 7.3 described the details.

9.2.5 Objective #5: To analyse the effect of the factors on productivity

The effect of the factors on the productivity rate were tested in two ways. One was to do the sensitivity analysis of the ANN model component. This meant that the value of the chosen factor was changed between 1 and 3 by 0.1 increments, while the values of the other factors were kept at their mean values. This was done in the case of the three best performing networks. Section 5.5 provided the details.

Statistical analyses were also performed on the data table. As the normality and homogeneity tests showed that some groups of factors followed a normal distribution, while others were non-normal, and that in some cases the variances were homogeneous, while in others they were heterogeneous, both parametric (ANOVA, Welch's, Brown-Forsythe's) and non-parametric tests (Kruskal-Wallis, Jonckheere-Terpstra) were used to determine which factors had significant effects on the productivity rate. In addition, simple and multiple regression analyses were conducted to examine the relationship between the factors and the productivity rate. The results of the statistical analysis were documented in Chapter 6, while Section 8.1 summarised and compared the outcome of the sensitivity analysis of the ANN model component and the statistical analysis.

9.2.6 Objective #6: To test the model

The output (net process durations) of two batches of simulation runs were recorded and analysed. In the first one, the model bricklaying gangs were assigned to the tasks one at a time, and the process durations were analysed and compared to each other to note the similarities and differences for the three brick types and model wall sections. The preparation for the tests were explained in Section 7.5.1, while the results of the runs were shown in Section 8.2.1.

In the second batch of simulation runs, all model bricklaying gangs were assigned to the tasks at one time, and pairs of the same model bricklayers the next time. The process durations were analysed and compared to each other to note the similarities and differences for the three brick types and model wall sections. The preparation for the tests were explained in Section 7.5.2, while the results of the runs were shown in Section 8.2.2.

9.3 Contributions to knowledge

The hybrid DES-ANN model (see Figure 9.1) presented in this study was developed to better estimate the bricklaying process duration in the planning phase of a project, taking worker and wall-related factors into consideration. In addition, the model is capable of testing resource allocation options to find the optimal one. Only two other similar hybrid models were found in the literature. The main difference is that in Chao and Skibniewski's (1994), the model worked the other way round, they applied DES to generate activity durations for the ANN model component. The basic idea of Song and AbouRizk's model (2008) was similar in that the ANN model component helped in estimating the activity durations in the DES part; however, that was developed specifically for steel fabrication operations; therefore, the overall modelling framework was different. This DES-ANN model was created for labour-intensive construction operations, where the labour resource is especially important. While in this thesis its application is for bricklaying works and a certain set of factors that influence productivity was considered, by following the same steps different factors or different operations can be modelled.

As part of this research project, with the help of the developed model and extensive statistical analyses, the effects of the chosen factors on productivity were examined. Worker characteristics (quality, perceived speed, knowledge, independence, experience) and wall-related factors (course difficulty, brick type) were selected as the values of these can be known in the planning phase of projects. Among the studies on bricklaying productivity, experience and/or skills were included in Karthik and Kameswara Rao's (2019), Gerek et al.'s (2015), and Aswed's (2016) research. In the case of the first, skills and experience were found to be the most important influencing factors, while in the case of the other two, design-related factors topped the lists. These two factors appeared in the top few factors in other productivity studies, as well (Alaghbari *et al.*, 2019; Hamza *et al.*, 2019). Experience was also found to be the most important out of the selected worker-related factors in this research. Productivity rate showed a steady increase as experience increased, meaning that more experienced bricklayers worked faster.

Even if skills were included in some models, they were rarely defined. Only two models, Olomolaiye's (1988) and Florez's (2017), defined skills. However, their definitions were different from the four factors used in this study. By considering four factors, relevant categorical and hierarchical skills were explored and with more finesse than the previous two models.

Independence was found to make a significant contribution to the multiple regression models, meaning that it significantly predicts the productivity rate. With the increase of independence, the productivity rate also increased according to both the multiple regression analysis and the sensitivity analysis of the ANN model. Based on Brown-Forsythe's test and one multiple regression analysis, perceived speed was also found to be a significant factor. However, the trends showed by the results varied. This might be due to the difference between the supervisors' subjective evaluation and the objective time measurements. Quality and knowledge were not significant in any of the tests. It is worth noting that productivity rate showed an increase with increasing quality. This is, perhaps, a surprising discovery, taking into account that high-quality work may require more time. One explanation for this result might be (suggested by the interviews and the supervisors' evaluation) that more experienced bricklayers produce better quality work, and they also tend to work faster. However, the data were not enough to make definite conclusions. Both wall-related factors (course difficulty, brick type) were found to be significant in all statistical analyses performed. From the results and the sensitivity analysis of the ANN model component, as these factors increase, the productivity rate decreases. The values of both factors were defined to reflect increasing difficulty, and the results confirmed this. (More detailed results can be found in Chapters 5 and 6.)

The effects of the choice of bricklaying gang and bricklaying gang composition on productivity were also examined with the help of the DES model component. In the case of the former, the simulation was run for all model bricklaying gang-model wall section-brick type combination. Non-parametric statistical tests showed all these factors to be significant. The model wall section and brick type factors used in the analyses, reflected increasing difficulty, and the results confirmed the decreasing productivity. In the case of each model wall section, a different bricklaying gang was most productive. As a practical application, this result has the potential to benefit personnel on site when assigning gangs to wall sections. A gang might be more suitable for a specific wall than another gang. In addition, the gang consisting of the least and most experienced bricklayers tended to be the slowest; therefore, as an application of this finding, to enhance productivity, having more balanced gangs might be beneficial, that is pairing bricklayers with more similar attributes. In the second batch of simulation runs, all bricklaying gang composition-brick type-model wall section combinations were tested. In this case, both parametric and non-parametric statistical analysis showed all factors to be significant. Here the question was whether – on the project as a whole – having mixed bricklaying gangs or gangs comprised of bricklayers with the same skills and experience led to shorter process duration. In all cases, except for the blue bricks, mixed bricklaying gangs produced better results. Therefore, the allocation of mixed bricklaying gangs might be beneficial overall to enhance productivity. Note that walls of blue bricks require special considerations. (More detailed results can be found in Chapter 8.)

The frameworks developed for the two model components are also contributions of this research project. These can be used individually or in combination. The steps for developing an ANN model can be found in Section 5.2. This includes all the necessary considerations from the network architecture to the training algorithms. The simulation framework described in Section 7.2 helps selecting the most suitable simulation method or hybrid simulation approach with the most appropriate structure and interaction point(s).

Finally, if further research validates the findings of this work, as a practical application, the results of this study have the potential to benefit bricklaying construction companies in improving task productivity with strategies that can be controlled by the supervisors on site. For instance, the difficulty of the wall section needs to be taken into consideration when assigning a gang for its construction and having mixed bricklaying gangs can be beneficial.

9.4 Limitations of research

The findings of this research project should be considered in light of its limitations.

One set of limitations are in connection with the data collection and the number of datapoints. First, selecting projects to observe was challenging. Due to time and financial constraints, these projects needed to be in North East England. The projects also needed to have considerable masonry packages that were realised in the period allocated for data collection. In addition, the contractor companies had to be willing to authorise observations taking place on the construction site. Furthermore, scheduling the visits was also difficult, made even more complicated due to occasional material shortages and equipment breakdown on site. With more resources, including more observers, time, and the possibility to travel further, more visits could have been made and more projects could have been observed. However, owing to the issues mentioned above, probability sampling of projects and bricklayers would not have likely occurred even in this case. As artificial neural networks can learn more from more data, having a larger data table would have helped the model's accuracy and generalisation performance. A third project with a similar structure (cavity wall) and materials would have been beneficial for further testing and validating the DES component. More materials, structures, and bricklayers could have been observed allowing for the introduction of more factors, or further exploring the current ones.

This leads to the next set of limitations: the selected factors. When choosing the number of factors that influence productivity, it was important not to choose too many as that could have made the model needlessly complex and inconvenient to use. However, it should be noted that differences in productivity can be caused by omitting factors. In addition, the values of the worker-related factors – with the exception of experience, where the categories were defined based on the years spent working in construction – were determined by the bricklayers' supervisors. This was unavoidable considering the choice of factors, which also means that the results are very much dependent on the supervisors' subjective opinions. Perhaps, measuring these worker-related factors requires more than the opinion of the supervisors, even though the evaluation of the bricklayers was based on the supervisors' probably careful and long-time observations of the bricklayers. The fact that the worker-related factors used in this study were greatly subjective (purposefully selected), yet seem to be useful, should prompt studies where more objective ways of measuring quality, knowledge, and independence of workers are investigated.

Another issue in connection with the number of observations is that since the activity laying bricks is the most important in the workflow, few time measurements were made for the other activities. In the case of a blue brick wall section, the jointing task takes almost as much time as the laying of the courses. Therefore, more observations could have been made of the jointing task. In addition, the task duration should have been differentiated by bricklayers.

9.5 Directions for future work

Following on from the limitations of the research, the study can be continued in multiple ways. First, further observations can be conducted. Observations of the same structure and materials can be used to train the ANN model component with more input data, thus making predictions more accurate, and the model's generalisation performance better. In addition, the DES component would also benefit from running it with real-life project data.

During the site visits to the first projects, the construction of blockwork was also observed. These observations, together with further time measurements, could be used to draw conclusions about bricklayers working with blocks and compare these to brickwork.

Additional observations and interviews with experts could reveal more factors to be included in the model. Especially worker-related ones would be beneficial as those are often overlooked by studies. This would require defining metrics and gathering subjective data with appropriate tests.

The model might also benefit from the application of fuzzy logic (FL), which was listed as one of the approaches used in productivity studies in Chapter 2. FL is capable of modelling uncertainty and is helpful when the variables are expressed in linguistic terms, rather than crisp values. Therefore, FL could be part of the ANN model component, thus making it a neurofuzzy model, where FL is used to input the supervisors' evaluation of the bricklayers into the model. Furthermore, future research, with a large enough dataset, could use more powerful and more data-intensive machine learning algorithms, such as enhanced probabilistic neural networks, finite element machine for fast learning, and dynamic ensemble learning algorithm.

In the DES model component, triangular and beta distribution functions were applied for the task durations. However, other distribution functions could also be considered.

Finally, the same way this model was created, using the frameworks, models of other construction operations could also be modelled. Due to the skill shortage, examining labour-intensive works would be the most beneficial.

9.6 Chapter summary

This chapter began with reviewing the research aims and objectives set at the start of the research project. It was briefly described how each of the objectives, and – with the help of these objectives – ultimately, the research aim was achieved. The next section presented the research project's contribution to knowledge with implications to both theory and practice. The limitations of the research were also discussed. The last section showed how this research can be continued in the future.

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APPENDIX A

PUBLISHED PAPERS (IN CHRONOLOGICAL ORDER)

Paper #1 (conference paper)

A Framework for Modelling Masonry Construction Using Hybrid Simulation Approaches

Orsolya Bokor, Laura Florez, Allan Osborne, Barry J. Gledson

Labour is a crucial resource for construction projects. More risks are associated with this than with other resources, such as materials and equipment. Contractors need tools to make more precise estimations concerning labour productivity that will allow them to minimise these risks and manage labour resources in the most efficient way possible. To achieve this, use can be made of construction simulation techniques, however, depending on the complexity of the problem, applying a single simulation approach might not be enough to appropriately model construction. Hybrid simulation approaches seem to be suitable because they combine the advantages of their components to reflect the dynamic nature of construction processes better and consider the number of uncertainties. Hybrid approaches can combine traditional discrete-event simulation (DES), agent-based modelling (ABM) or system dynamics (SD) with each other or with, for example, fuzzy logic (FL) to better capture the factors influencing productivity. To address these issues, a framework for modelling a masonry construction process that uses hybrid simulation is presented. Because masonry works are one of the most labour-intensive construction processes, and skilled labour resources are scarce, the use of such a framework would help contractors to make more realistic schedules based on accurate labour productivity estimation; thus, enabling them to utilise their resources more efficiently.

Keywords: agent-based modelling, discrete-event simulation, fuzzy logic, hybrid simulation, masonry, productivity, scheduling, system dynamics.

Citation: Bokor, O., Florez, L., Osborne, A. and Gledson, B. J. (2018) 'A Framework for Modelling Masonry Construction Using Hybrid Simulation Approaches', in Skibniewski, M. J. and Hajdu, M. (eds) *Proceedings of the Creative Construction Conference 2018*. Ljubljana, Slovenia: Diamond Congress Ltd., pp. 732–738. doi: https://doi.org/10.3311/CCC2018-096

Paper #2 (journal paper)

Overview of Construction Simulation Approaches to Model Construction Processes

Orsolya Bokor, Laura Florez, Allan Osborne, Barry J. Gledson

Construction simulation is a versatile technique with numerous applications. The basic simulation methods are discrete-event simulation (DES), agent-based modeling (ABM), and system dynamics (SD). Depending on the complexity of the problem, using a basic simulation method might not be enough to model construction works appropriately; hybrid approaches are needed. These are combinations of basic methods, or pairings with other techniques, such as fuzzy logic (FL) and neural networks (NNs). This paper presents a framework for applying simulation for problems within the field of construction. It describes DES, SD, and ABM, in addition to presenting how hybrid approaches are most useful in being able to reflect the dynamic nature of construction processes and capture complicated behavior, uncertainties, and dependencies. The examples show the application of the framework for masonry works and how it could be used for obtaining better productivity estimates. Several structures of hybrid simulation are presented alongside their inputs, outputs, and interaction points, which provide a practical reference for researchers on how to implement simulation to model construction systems of labor-intensive activities and lays the groundwork for applications in other construction-related activities.

Keywords: agent-based modelling, discrete-event simulation, fuzzy logic, hybrid simulation, masonry, scheduling, system dynamics.

Citation: Bokor, O., Florez, L., Osborne, A. and Gledson, B. J. (2019) 'Overview of construction simulation approaches to model construction processes', *Organization, Technology and Management in Construction*, 11, pp. 1853–1861. doi: https://doi.org/10.2478/otmcj-2018-0018

Paper #3 (conference paper)

Input for Hybrid Simulation Modelling Construction Operations

Orsolya Bokor, Laura Florez, Barry Gledson, Allan Osborne

Good pre-construction planning efforts are a vital part of the effective management and delivery of construction projects. In order to prepare more accurate schedules and cost calculations, realistic productivity rates to improve precision are needed. The use of simulation for modelling the elements of construction processes can assist with this aspiration. The application of hybrid simulation approaches is particularly appropriate as they can capture complicated behaviour, uncertainties, and dependencies. This paper discusses the use of one such approach combining discrete-event simulation (DES) and system dynamics (SD) to determine more accurate productivity rates. The DES component models the operations with the workflow of the tasks performed. Its input consists of the task elements with their durations and resource information. The factors that influence the productivity rates are taken into account with the help of the SD component. Input for this part of the model includes the factors as well as considerations of their interrelationships and effects. In this work, a case study of such input data for masonry works – for brick- and blockwork – is presented. It shows the input data and its integration in the DES-SD approach for modellers to determine more realistic productivity rates.

Keywords: discrete-event simulation; labour; masonry; modelling; productivity; simulation; system dynamics.

Citation: Bokor, O., Florez, L., Gledson, B. and Osborne, A. (2019) 'Input for hybrid simulation modelling construction operations', in Skibniewski, M. J. and Hajdu, M. (eds) *Proceedings of the Creative Construction Conference 2019*. Budapest, Hungary: Diamond Congress Ltd., pp. 571–577. doi: https://doi.org/10.3311/CCC2019-078

Paper #4 (conference paper)

Using Artificial Neural Networks to Model Bricklaying Productivity

Orsolya Bokor, Laura Florez-Perez, Giovanni Pesce, Nima Gerami Seresht

The pre-planning phase prior to construction is crucial for ensuring an effective and efficient project delivery. Realistic productivity rates forecasted during pre-planning are essential for accurate schedules, cost calculation, and resource allocation. To obtain such productivity rates, the relationships between various factors and productivity need to be understood. Artificial neural networks (ANNs) are suitable for modelling these complex interactions typical of construction activities, and can be used to assist project managers to produce suitable solutions for estimating productivity. This paper presents the steps of determining the network configurations of an ANN model for bricklaying productivity.

Keywords: artificial neural networks; bricklaying; construction; labour productivity; scheduling.

Citation: Bokor, O., Florez-Perez, L., Pesce, G. and Gerami Seresht, N. (2021) 'Using Artificial Neural Networks to Model Bricklaying Productivity', in *Proceedings of 2021 European Conference on Computing in Construction*. European Council on Computing in Construction, pp. 52–58. doi: https://doi.org/10.35490/EC3.2021.155

APPENDIX B. INTERVIEW QUESTIONS

PROCESS

- Describe the process of building a brick/block wall (tasks, required resources). Is it different for different purposes (external, internal, façade)?
- Is the process different in different regions of UK? Of Europe? Elsewhere? Is there a standard? British? European? (Or just for design (EC)? Maybe for quality check for finished walls?)
- Has the process changed over time?
- What are the tools called? (esp. the ones used for raking, pointing, profiles for the line, and supports)

WALLS

- What makes a wall difficult to construct? Categories:

1	no opening, only half-cuts
2	few openings, more cuts, movement joint
3	many openings, many cuts (measured individually), movement joints
4	curved walls, not perpendicular corners

Characteristics: cuts, openings, corners, movement joints, bond, pattern, pointing type,

- How is it different for different materials?
- Does the size of the units matter? E.g., is it different to place ½ or 1 brick? (duration-wise)
- Does the size of the wall matter? (long or short, high or standard height, ground floor or higher up)
- Do students learn different bonds, curved walls, decorations?

BRICKLAYERS (do they use the term mason?)

- What are the most important skills of a bricklayer?
- What are the most important characteristics of a bricklayer? Probes: characteristics: quality, speed, knowledge, independence, training, experience?
- Do these affect productivity? Which ones? How?
- What is the standard capacity of bricklayers?
- How are students assessed? Is it the same at other colleges? Probes: Does time matter? Or just quality?
- What is the usual composition of squads?
- How many bricklayers usually work on a given section? How do they divide work?
- What is the difference between level 1, 2, and 3 of bricklaying courses? Can they work on site after first?
- Will robots be used instead of people?