A Decision Support System for Integrated Design of Hybrid Renewable Energy System

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A Decision Support System for Integrated Design of Hybrid Renewable Energy System

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Abstract

While large-scale wind farms and solar power stations have been used widely as supplement to the nuclear, fossil fuels, hydro and geothermal power generation, at smaller scales these resources are not reliable to be used independently and may result in load rejection or an over-size design which is not cost effective. A possible solution to solve this issue is using them as a parts of a hybrid power system. Complexity in design and analysis of hybrid renewable energy systems (HRES) has attracted the attention of many researchers to find better solutions by using various optimisation methods. Majority of the reported researches on optimal sizing of HRES in the literature are either only considering one objective to the optimisation problem or if more than one objective is considered the effect of uncertainties are ignored.

This dissertation work investigates deterministic and stochastic approach in design of HRES. In deterministic approach it shows how adding a battery bank to a grid-connected HRES might result in more cost effective design depending on different grid electricity prices. This work also investigates the reliability of HRES designed by conventional deterministic design approach and shows the weakness of common reliability analysis. To perform the stochastic approach the renewable resources variation are modelled using time series analysis and statistical analysis of their available historical meteorological data and the results are compared in his work. Chance constrained programming (CCP) approach is used to design a standalone HRES and it is shown that the common CCP approach which solves the problem based on the assumption on the joint distribution of the uncertain variables limits the design space of problem. This work then proposes a new method to solve CCP to improve the size of design space. This dissertation comprises multi-objective optimisation method based on Non-dominated Sorting Genetic Algorithm (NSGA-II) with an innovative method to use CCP as a tool in estimating the expected value of the objective function instead of Monte-Carlo simulation to decrease the computational time.

To my Father

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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 contribution from work of others.

Name: Azadeh Kamjoo

Signature:

Date:

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Azadeh Kamjoo
Newcastle upon Tyne

Nomenclature and Abbreviations

α	confidence level
Δ_t	the time step (one hour in this study)
η_{PV}	efficiency of the PV array and corresponding converters
η_{Bat}	battery efficiency
μ	Mean
δ	standard deviation
ρ	air density (1.225 Kg/m^3)
A_{PV}	PV panel area (m^2)
A_{WT}	wind turbine rotor disk area (m^2)
C_0	total constant cost including the cost of installation of the wind turbine and PV panels ($)
C_{Bat}	nominal battery bank capacity (Ah)
C_{IC}	the total cost of the system($)
$C_{O\&M}$	present value of maintenance cost ($)
C_{rep}	the present value of replacement cost ($)
$C_{Unit,Bat}$	unit Cost of battery bank ($/Ah)
$C_{Unit,PV}$	unit Cost of PV panel ($/m^2)
$C_{Unit,WT}$	unit cost of the wind turbine($/m^2)
C_p	wind turbine power coefficient,
F^{-1}	inverse of the joint cumulative distribution function
I	horizontal solar irradiance in (W/m^2)
I_{Bat}	battery current (A)
k_d	annual real interest rate (%)

L_p	system life period (years)
N_{Bat}	total number of batteries
N_{rep}	number of replacements of the battery over the system life period
P_{Bat}	battery bank available power (W)
P_{PV}	the PV array output power (W)
P_{WT}	wind turbine power (W)
$P_{PV,Nom}$	PV panel nominal power (W)
SOC	state of the charge of the battery
TC	the total cost of the system ($)
V_{Bat}	battery voltage (V)
Z_α	inverse of the cumulative normal probability distribution
$ARMA$	auto-regressive moving average
DOD	depth of discharge
$DPSP$	deficiency of power supply probability
GA	genetic algorithm
$HRES$	hybrid renewable energy systems
$LPSP$	loss of power supply probability
MSE	mean squared error
$NSGA-II$	non-dominated sorting genetic algorithm
PSO	particle swarm optimisation
RSM	response surface methodology
SA	simulated annealing
TS	Time Series

1 Introduction

1.1 Need for Renewable Energy

A great part of energy supply of the today world is provided from conventional energy resources. These energy resources are finite and fast depleting and are provided at a very high cost [1]. At the same time the energy demand around the world is increasing exponentially and conventional energy resources would not be able to supply it for long. In addition to high cost and the limitations in supply resources of conventional energy resources, their negative impact on environment and global warming have attracted the attention to other alternative power sources those are environmental friendly, reliable and cost effective. Renewable resources appear to be one of the most sustainable energy resources available. Wind energy, solar energy, biomass, hydropower, ocean tidal and wave energy are examples of renewable energy resources. Renewable energy sources can particularly be the best electricity provider in small scale applications such as street lighting, household electricity and also energy supply for remote places and islands [2-4]. Using renewable energy resources can decrease the cost of transmission and transformational costs although common drawback of using renewable resources is constant challenge with their unpredictable nature which is completely dependent on climate changes and may result in load rejection at some points [5]. A possible solution to solve this issue is using them as a parts of a hybrid power system.

1.2 Hybrid Renewable Energy Systems

Hybrid renewable energy systems (HRES) combine two or more renewable energy sources to generate power [6-8] such that each of them can cover the weakness of another one in load demand coverage and the power generation system can provide continuous power supply in various weather statuses and potentially improves the system efficiency and reliability of power supply [9-11]. Obviously the combination of different renewable resources needs to be adapted based on the conditions of each specified location.

The hybrid power systems can be designed as the stand-alone or grid-connected systems. Many parameters such as attainable power from grid, cost of providing power from grid and individual meteorological characteristic of the desired site. The grid-connected systems are designed in the way that they are able to cover their local demand and depending on the grid capacity, the excess produced power can be sold to the grid to be transferred to other places of demand. Additionally in case of power shortage in the production of renewable resources the remaining required power can be provided by grid thus these systems do not require a separate storage system to maintain the reliability because the grid will perform as an infinite backup system.
On the other hand, stand-alone hybrid renewable systems are the most promising solution to bring electricity to remote places. However since there is no grid connection available for these systems they require to have a backup or auxiliary unit such as battery banks or conventional diesel generators for assistance in maintaining the reliability.

In both grid connected or stand-alone cases, investment costs of providing electricity from renewable sources and reliability of the designed system are usually problems with main importance in long term planning of energy systems and as a result selecting the best renewable energy resource; optimal solution among different possible combination of renewable energy sources is important. Depending on the number of objectives a single-objective or multi-objective problem is defined to find the optimal solution or a set of trade-off solutions in design of HRES for decision making.

1.3 Design Decision Support System

As mentioned before hybrid renewable energy systems have been proved as a viable solution to bring electricity to remote places where it is expensive or impossible to extend the grid. Considering that the renewable power generators are reliant on the climate conditions which makes them inherently intermittent, the fact that these systems either need to be able to provide electricity without the support of grid connection and maintain the certain reliability if stand-alone or the cost-effectiveness of produced power for grid-connected systems, can sometimes result in overdesign of these systems or the outcome may become less efficient economically. The goal of providing electricity from combining renewable resources at a reasonable cost and reliability, optimal design of HRES in terms of operation and combination of the components is essential[12] . Complexity in design and analysis of hybrid renewable energy systems has attracted the attention of many researchers to find better solutions in the design of HRES, which mostly are focused on cost reduction and efficiency improvement of these systems [13].

In the design process there are often more than one alternative for each design component and there are many design possibilities to be considered and evaluated. This is the main reason for optimisation process and providing quantitative assessment of different design solution to support and facilitate the decision making process [14-16]. Decision making problems can be categorized to two classes based on the number of objective functions that are involved in the problem; single objective and multi-objective. In a single objective problem the aim is to identify the best solution corresponding to minimising or maximising a single objective function. However many real world decision making processes involve more than one objective function at the same time like minimising cost and maximising the reliability. Clearly this category of problems does not have a single solution achieving contradicting objectives. That is why multi-objective problems do not have a single optimal solution but they have a set of compromised solutions between different objective functions known as Pareto sets. Providing a set of solutions to an optimisation problem introduces three major advantages [17] a wider set of solutions are identified; selecting between different alternatives enquires the necessity of an analyst to produce different solutions and the decision maker to evaluate the solutions provided by the analyst and make decisions; models of a problem would be more realistic by considering several objectives. However, multi objective problems can be changed to a single objective problem by integrating multiple objectives in one or by considering an objective as main objective and the rest as design constraints. However in this approach the analyst makes most of the decisions by deciding the weight that each of the multiple objectives would have in the integrated single objective or by the level of compromise he defines for the design objectives as constraints. This approach would take away the evaluation and deciding between different alternatives from the decision maker. On the other hand the interaction between different objectives yields to a set of design candidates known as Pareto-optimal solutions. The main characteristic of Pareto set members is that they are not dominated by other solutions, meaning that it is not possible to improve on one objective without worsening another objective function.

In optimal design of HRES several objectives need to be optimised, most of them contradicting (e.g. cost & reliability), therefore in design of HRES a multi-objective optimisation approach should be followed. However selection among design candidates is subjective and depends on decision maker's judgement, which in turn depends on his knowledge, background. A Design Decision Support System (DDSS) is required to help decision makers to choose among different design alternatives. This is achievable by taking into account all the technical & economic considerations and providing the user with facilities like sorting, filtering, and visual figures to compare and finally select the more suitable design.

1.4 Optimal Sizing of HRES

Designing a power generation plant is very important from economic, environmental and quality of production point of view. Considering the worldwide increase in energy demand, increasing the capacity of existing grid networks or adding new micro grids has become a problem of interest in many aspects. The unavoidable discontinuity in the generation of power production systems with a single renewable resource has caused design of HRES more popular in the recent years. Despite of the number of research reported in design of HRES, the majority of them are considering a single objective. Garcia and Weisser [18] compared two models to determine the optimal size of wind-diesel power system with hydrogen storage in a grid-connected system. Both models are designed with considering either the cost or reliability as the main objective. Design of HRES for remote place makes the system availability the main objective rather than the cost. In this case finding the proper storage system is also considered to maintain desired availability. Balamurugan et al. [19] optimised a hybrid power system of wind, biomass, solar photovoltaic with battery bank storage considering availability as the main objective. The hybrid energy system is sized considering a suitable storage system to provide the power at periods when there is no solar power available or during minimum wind speed periods.

As mentioned two important contradictory objective functions in optimal sizing of HRES are usually cost and reliability and since these objectives are contradicting a single optimal solution cannot be found with minimum cost and maximum reliability and multi-objective optimisation should be performed to find the trade-off set; Pareto set of the solutions. Many studies have been reported in multi-objective optimisation of HRES considering different objection functions, using various optimisation techniques. Katsigiannis [20] used a multi-objective algorithm to minimise the cost of produced power of the system and total green house gas emission during the system. Kaabeche, Belhamel and Ibtiouen [21] recommended an optimisation model based on iterative technique to optimise the size of hybrid wind/photovoltaic system combining with a battery bank minimising het deficiency of power supply and levelised unit electricity cost. However, despite the claim of considering more than one objective in design of HRES in mentioned studies, they are in fact single objective, as either objectives are not contradicting or all-but-one are treated as constraints.

1.5 Optimisation Methods

This section briefly explains some of the optimisation methods used in design of HRES.

1.5.1 Particle swarm optimisation

Particle swarm optimisation (PSO) is a population-based stochastic optimisation technique in evolutionary computation. This technique was developed in 1995 by Kennedy and Eberhart and is based on movement of swarms, looking for food. Each potential solution to the optimisation problem is called a particle and the co-ordinates of each particle are defined by its velocity vector and its position. Initially each particle is flown through the search space at a random velocity. Assuming that the population have good knowledge about other particles and their own position, at each iteration the particles examine the search area, modify their velocity and move towards the best solution among them. Since all the particles in the population follow the same approach at each iteration a group movement toward the optimum solution is reached. The process continues until the constraint on the maximum iteration is reached.

The implementation of PSO is based on simple equations and thus the process time is short and efficient however since the movement of the particles in three directions coordinates with the number of design variables, where there are more than three design variables it would be more suitable to use another optimisation technique. Mahor et al. [22] applied particle swarm optimisation to solve same problem concluding that the proposed PSO method had better performance comparing to the conventional optimisation techniques. Kaviani et al. [23] used a PSO to optimise a hybrid photovoltaic-wind-fuel cell generation system minimising the annual cost of the hybrid system providing desired reliability in maintain the load demand. More samples in use of PSO can be addressed in [24-26].

1.5.2 Simulated annealing

The simulated annealing (SA) process is a general optimisation technique which was first introduced by Kirkpatrick et al [27]. At each iteration of the SA process, a candidate move is selected randomly and this move is evaluated. If the move leads to a better solution which means the new solution has better fitness value then the move is accepted otherwise it might be rejected with a probability that depends on the difference between its fitness value and the best fitness value. The annealing process based on decreasing the temperature allows wider search area by choosing faster temperature decrement at the start of the iteration process and slower temperature decrement to reach the local search in the next iterations. The cooling schedule procedure is the main structure of the SA method. SA method has not been very popular in the design of HRES. Giannakoudis et al. [28] performed an optimisation method based on SA to design and operate a hybrid power generation system that includes wind turbine, photo voltaic panels, , hydrogen storage tanks, a compressor, a fuel cell and a diesel generator.[29-31] can be referred as they have also worked based on SA.

1.5.3 GA

Genetic Algorithm (GA) is developed based on biological principles of genetics. GA was first introduced by Holland [32] and has been widely used in solving optimisation problems in variety of real world problems in different research areas. Following the biological process, such as crossover, and mutation in the optimisation process, GA is capable of solving complex real world problems [33]. The algorithm starts by creating a “Population” of “chromosomes” which are randomly generated and each can be possible solution to the optimisation problem. Each “Chromosome” is measured against the value of the objective function and assigned a value of “Fitness” and the least favourable chromosomes in terms of fitness would be discarded. At each generation the chromosomes are sorted and some are selected as the parents to “Crossover” and form offspring. The offspring might replace the parents in case they have better characteristics; better fitness value. Another important biological operator in genetic algorithm is “Mutation”. At each generation a number of chromosomes undergo mutation in which essentially a random section of chromosome is changed to generate a different chromosome. The process of implementing crossover, mutation operators and selection on chromosomes are iterated until the population is converged and the optimal solution is found or the maximum number of generation is reached. The main advantage of the GA is that it can easily jump out of a local optima and reach the global optima. Unlike PSO method GA does not put any limit on the number of design variables however it might be more challenging to implement the GA code.

Genetic algorithm may not always be the quickest way to find the optimum solution, when it comes to complex problems with many constraints; it is a very effective method to solve the problem. Overall advantages that GA has over other optimisation methods have attracted many researchers to use GA in reported researched in design of HRES [34-40]. Ould et al. [41] proposed a real multi-objective GA in optimal sizing of a hybrid wind-solar-battery system with the objective of minimising the yearly cost system and the loss of power supply probability. However the effect of uncertainties in renewable resources is ignored in this research. Yang et al. [42]proposed optimal sizing method based on GA technique using the Typical Meteorological Year data. This proposed optimisation model calculates the system optimum configuration which is able of achieving the desired LPSP with minimum Annualized Cost of System.

The genetic algorithm follows below steps.

Generate initial population

As described the population consists of a number of members, chromosomes that each have the possibility to be a solution to the optimisation problem. A chromosome is made up by the design variables.

The initial population is generated randomly by selecting a random value for each design variable between defined bounds using below equation.

$$v = v_l + (v_h - v_l).\delta \tag{1.1}$$

where v would be the random value of the design variable, δ a randomly generated number between 0 and 1. v_l , v_h are the lower and higher bound of the design variable respectively.

Crossover

Crossover is the main genetic operator in the genetic algorithm. This operator operates on a pair of chromosomes, combines parts of the parent chromosomes features to produce offspring. To perform this operator two individuals are randomly selected from sampling pool. The number of individuals undergoing the crossover is determined by crossover probability p_c . A high crossover probability allows exploration on more solution space which reduces the chance of convergence of the algorithm to a local optimum. Although choosing a very high crossover probability would increase the computation time in exploring unpromising regions of solution space [43].

a)N-point crossover: This form of crossover is the simplest form of crossover. According to it, based on the number of cut points the parents are divided to the different segments those would be exchanged to form new individuals (children). The number of cut point can be chosen randomly however it cannot exceed the number of control variables.

b)Uniform crossover: in this method each gene of the child would be randomly selected between the respective genes of the parents. The genes of both parents would have equal chance to be selected as genes of the child.

c)Arithmetical crossover: This type of crossover is defined as a linear combination of vectors and is very useful in real representation. Below equations represent the arithmetical crossover:

$$child_1 = \omega.Parent_1 + (1-\omega)Parent_2 \tag{1.2}$$

$$child_2 = \omega.Parent_2 + (1-\omega)Parent_1 \tag{1.3}$$

where ω is a random number between 0 and 1.

d)Blend crossover: This type of crossover is the most common form of recombination and is the general form of arithmetical crossover. It can be expressed using below equations.

$$child_1 = \xi.Parent_1 + (1-\xi)Parent_2 \tag{1.4}$$

$$child_2 = (1-\xi).Parent_1 + \xi Parent_2 \tag{1.5}$$

and ξ is determined as:

$$\xi = (1+2\varepsilon)u - \varepsilon \tag{1.6}$$

where u is a random number generated for each gene with uniform distribution in the interval of 0 and 1. Parameter ε is chosen as a once for all the genes and its value changes between 0 and 1.

If ε is set as 0 the blend crossover would work as arithmetical crossover.

<u>Mutation</u>

Unlike crossover the mutation operator aims in producing new individual from only one parent. By making spontaneous changes to the structure of chromosome the mutation operator introduces new solution to the optimisation problem. A simple way to implement the mutation operator would be to alter one or two genes in the chromosome. Every gene in the structure of the parent chromosome has equal chance to be mutated. This operator serves the GA by introducing new genes to the set of solution that might have been lost through the selection process or have not been presented in the initial population. Similar to crossover probability, mutation probability defines the percentage of the population that would undergo the mutation. However choosing a proper value for mutation rate is very important as if it is very low many new genes that might be useful would not be introduced to the solutions and if it is very high the offspring would lose their resemblance to their parents and the algorithm would lose the ability of learning from the past of the search.

Selection

In Holland's original GA [32] selection was referred to choosing parents to recombination and in that method the parents where always been replaced by their produced offspring despite of the possibility that offspring might be less fitter than the parents. With this strategy might result in losing some fitter chromosomes [43]. Although the term Selection is also used to form new generation [44]. Generally selection is implemented two times in genetic algorithms: selection for reproduction and selection for next generation.

a)Selection for reproduction

This kind of selection is performed to choose the chromosomes within the current population those would be taken to reproduction. There are three selection methods; roulette wheel, rank based and tournament selection and all of them use the chromosomes fitness values to perform the selection process. The selected individuals would be added to a sampling pool.

- Roulette-wheel selection

This selection method is a proportionate selection based on the fitness value. All the individuals of the population would have the chance of being selected. This method is emphasized to the fitter individuals in the population and the individuals with lower fitness value would have slimmer chance to be selected. At the population with n_{pop} chromosomes, each individual of x_i with the fitness of $fitness(x_i)$ is assigned a probability of selection which is calculated as:

$$\Pr(i) = \frac{fitness(x_i)}{\sum_{i=1}^{n_{pop}} fitness(x_i)} \qquad (1.7)$$

In this method the chance of an individual being selected is proportional to the value of its probability of selection. The advantage of this method is that it does not discard any of the chromosomes in the selection process and gives the chance however the chromosomes with higher fitness value would occupy bigger segment in the wheel and would have higher chance of being selected. This might cause the diversity of the population to decrease and the algorithm to converge to a local optima point. A sample procedure of implementing roulette-wheel selection is shown below:

While sampling pool is full
Number=Random number (0, 1)
For each member in population
If Number>Fitness (member) select member
End for
End

❖ Rank-based selection

Rank-based selection is another form of proportionate selection. In this method the rank of the chromosomes is used to calculate the selection probability. This method gives higher chance to the individuals with lower fitness to be chosen and participate in reproduction process which could help to prevent the algorithm from premature convergence.

To implement the ranking-based selection the chromosomes in the population are first sorted in ascending order based on their fitness value so that the chromosome with lowest fitness value would be the first in order and would be assigned the rank of 0 and the last chromosome on the list with the highest value of fitness would have the rank of $n_{pop} - 1$.

Generally, there are different approaches for calculating selection probabilities, using different type of ranking; Linear ranking and Square ranking and in both of them the selective pressure β is used to calculate the selection probability [45].

- Linear ranking: in this method the value of the selection probability each individual x_i is proportional to the value of its rank.

$$\Pr_{lin-rank}(x_i) = \frac{\alpha + [rank(x_i)/(n_{pop} - 1)](\beta - \alpha)}{n_{pop}} \tag{1.8}$$

In this equation the value of the selective pressure β presents the expected number of the offspring to be allocated to the individual with the highest rank and the α presents the expected number of the offspring to be allocated to the individual with the lowest rank. The value of β changes $1 \le \beta \le 2$ and $\alpha = 2 - \beta$. When $\beta = 1$, all individuals in the population would get similar chance to be selected and if $\beta = 2$ the individuals with higher rank would obtain higher selection probability comparing to lower ranks.

- Square ranking: in this method the selection probability is calculated based on the square of the rank.

$$\Pr_{sq-rank}(x_i) = \frac{\alpha + [rank^2(x_i)/(n_{pop} - 1)^2](\beta - \alpha)}{c} \tag{1.9}$$

Similar to linear ranking the value of β changes $1 \leq \beta \leq 2$ however here the value of α is arbitrary choosing in the boundaries $0 < \alpha < \beta$. Normalization factor c is calculated as:

$$c = (\beta - \alpha) n_{pop} (2n_{pop} - 1) / 6(n_{pop} - 1) + n_{pop} \alpha \tag{1.10}$$

In both linear and square ranking methods, after calculating the selection probability the sampling process to choose individuals is done using roulette-wheel selection.

- Tournament selection

The selection in this method is based on the fitness function. A q number of individuals of the population are selected randomly to form a tournament and among them the individual with the highest fitness value would be selected as the winner of the tournament and would be added to the sampling pool for reproduction. The size of the tournament q can vary from 2 to the population size n_{pop} however the default number would be 2. The larger the tournament size gets the more biased the selection would become. The tournament selection is repeated until the sampling pool is full.

b)Selection for replacement

Selection for replacement is performed after implementing the genetic operators; crossover and mutation on the individuals in the sampling pool that are selected for reproduction process. There are different approaches for selecting the individuals to form the new population. A method that keeps the elitism in the selection is done by adding the offspring to the existing population to make sure the first m individuals with high fitness values are not missed. The $n_{pop} - m$ individuals can be chosen randomly to keep the diversity in the next population.

1.5.4 NSGA-II

As the GA method has been proved to be a popular and effective method in solving multi-objective optimisation problems, the non-dominated sorting genetic algorithm (NSGA-II) [46] is a method of performing multi-objective evolutionary algorithms (MOEA) in which the best individuals of the population would be given the opportunity to be directly transferred to the next generation by an elite-preserving operator. By doing this a good solution found in any generation is never removed from the population unless a better solution is found.

The non-dominated sorting genetic algorithm (NSGA-II) improves the performance of GA by reducing the computational complexity and introducing elitism. The elitism favours the best individuals in the population so wherever the superior individuals are produced the elitism ensures that they would remain within the next population. Therefore a good individual would never be removed unless it is dominated by a better solution. This technique improves the convergence of GA [46] in single objective problem to the global optima and in multiple objective to the Pareto set. In a single objective problem the best solution would be identified by the value of its fitness which would be highest among the individuals. However since in multi-objective problem there is more than one objective function, sometimes conflicting, there would not be a single prominent solution as the optimum solution. In these types of problems solutions can be classified based on their non-dominance rank comparing to the other individuals in the population. There would be more than one non-dominated solution in each non-dominant set. Although the presence of elitism would improve the performance of multi-objective GA, the level of elitism should be defined very carefully otherwise it may decrease the diversity in the solutions [47]. NSGA-II provides an effective method in considering elitism while it guaranties the required diversity. It also proposes a better sorting algorithm in optimisation process. The initial population is produced similar to usual GA, however before commencing implementation of GA operators, Cross over and Mutation; the population individuals are first sorted based on non-domination into different fronts.

Non-dominated sort

The individuals of population are sorted based on non-domination sort. If an individual have objective function values not worse than the other and at least one of its objective function values is better, it would be called the dominate individual. With that definition, the first front members are non-dominant set in current population and the second front members are dominated only by the first front individuals and so on. A rank is assigned to the individuals based on the front they belong, for instance the individuals in first front would be ranked as 1 and so on. The sorting algorithm follows below steps [46]:

❖ For each individual p in the main population P:

- Initialise $S_p = \Phi$. This set would contain the dominated individuals by p.
- Initialise $n_p = 0$ which would be the number of the individuals dominating p.
- For each individual q in P
    - If p dominated q then $S_p = S_p \cup \{q\}$
    - Else if q dominated p then $n_p = n_p + 1$
- If $n_p = 0$ then p belongs to first front; $F_1 = F_1 \cup \{p\}$ and set the rank of p to 1.

❖ Initialise the front counter to one; $i = 1$.

❖ While the i^{th} front is not empty; following is carried out

- $Q = \Phi$. This set is defined to sort the individuals for $(i+1)^{th}$ front.
- For each individual p in front F_i
    - For each individual q in front S_p
        - Decrement the domination count for individual q; $n_q = n_q - 1$
        - If $n_q = 0$ then none of the individuals in subsequent front dominates q. Set the $q_{rank} = i + 1$ and $Q = Q \cup \{q\}$
- Increase the front counter by one $i = i + 1$.

- $F_i = Q$.

Following the above algorithm; at each generation individuals are assigned to different fronts based on their domination by other individuals.

Crowding distance

In addition to the fitness value each individual has another parameter called the crowding distance. Crowding distance is a measure which is calculated for individuals in the same front to show how close they are to each other. Larger average value of crowding distance shows better diversity in the population. The crowding distance is calculated following below algorithm:

❖ For each front F_i with the individual numbers of n

- Initialise the initial value of crowding distance to zero for all individuals. As an example $F_i(d_j) = 0$ means the crowding distance of j^{th} individual in front F_i is set to zero.
- For each objective function m
  - Sort the individuals in front F_i based on the objective function m ; i.e. $I = sort(F_i, m)$
  - Assign the infinite distance to the boundary individuals in F_i . This means these individuals are always selected.
  - For $k = 2$ to $(n-1)$

$$I(d_k) = I(d_k) + \frac{I(k+1).m - I(k-1).m}{f_m^{\max} - f_m^{\min}} \qquad (1.11)$$

where $I(k).m$ is the value of the m^{th} objective function of the k^{th} individual in I .

Selection process

Once the individual are ranked and their crowding distance is calculated the selection process is carried out to select the parent chromosomes for evolution process. To do the selection a binary tournament selection is employed. In a binary tournament selection process two randomly selected individuals are compared in terms of their fitness and the individual with better fitness is selected as a parent. Tournament selection is carried out until the pool size is filled where pool size is the number of parents to be selected. Selection is based on rank and if individuals with same rank are encountered, crowding distance is compared. A lower rank and higher crowding distance is the selection criteria.

Recombination and Selection

After implementing the crossover and mutation operators on the selected parents, the offspring are added to the current generation and the next generation individuals are selected. As selection is performed on a population consisting previous and new individuals, it is assured that all the best solutions are always contained. The process of non-domination sorting, crowding distance calculation, and selection is continued until the population individuals contain the first front individuals or when the maximum number of generations is reached.

Katsigiannis [20] used NSGA-II to design a small stand-alone hybrid power system that contained both renewable and conventional diesel generator with the objectives of minimising the energy cost of the system and total greenhouse gas emission during life time of the system.

1.5.5 Other optimisation methods reported in literature

There are several other optimisation methods reported in the literature in design of HRES. Agustín and Dufo-López introduced an evolutionary algorithms for the optimal design and determination of control strategy of a hybrid system consisting of a wind-photovoltaic–diesel–batteries–hydrogen system [48]. Bernal-Agustín and

Dufo-López [49] put effort in analysing the main reported research strategies on optimisation of hybrid systems consisting battery energy storage. The results showed that the EA has the ability to maintain satisfactory results within low computational time. Based on their previous researches, Bernal-Agustín et al.[50] applied the MOEA to the multi-objective optimal design of stand-alone hybrid wind-photovoltaic–wind–diesel system minimising the total pollutant emissions and the total cost during its life time of the system. These authors later proposed a three-objective optimisation method based on MOEA adding minimum amount of unmet demand as the new objective to the previous problem [51] . Diaf et al. [52]analysed the optimum configuration of a stand-alone hybrid wind-photovoltaic system that provides the energy demand of a typical remote consumer with the minimum levelised cost of energy. The search method was used to analyse different combinations and running several simulations.

Montoya et al. [53] proposed a multi-objective MOEA to minimise voltage variations and power losses in power networks. Ekren et al [54]used Response Surface Methodology (RSM) which is a collection of statistical and mathematical methods which relies on optimisation of response surface with design parameters. In the study the output performance measure is a hybrid system cost and the design parameters are PV size, wind turbine rotor swept area and the battery capacity.

1.6 Available Software Tools for Sizing HRES

In addition to the different optimisation techniques used in optimal sizing of HRES, there are many software tools developed to use in this area such as iHOGA, COMPOSE, HYBRID2, SOMES, Dymola/Modelica, TRNSYS, iGRHYSO, RAPSIM …. Some of this software which is commercially available is explained here.

HOMER

HOMER is one of the most famous and popular program which is developed by National Renewable Energy Laboratory (NREL). HOMER is widely used in prefeasibility studies and optimisation of hybrid systems. To start the design process, the software requires inputs such as resources data, component type, storage requirements, economical constraints and efficiency. Homer gives the option of choosing the components among wind turbine, photovoltaic panels, hydro, batteries, diesel, and fuel cells and is able to evaluate suitable options based on cost and available resources [55]. This software is widely used in reported literature in optimal design of hybrid renewable energy systems [56-62]. However it only allows single objective optimisation to minimise the cost and multi-objective problems cannot be formulated in HOMER and it does not consider the effect of DOD of the battery which has a significant role in lifetime of the battery bank.

iHOGA

Improved Hybrid Optimisation by Genetic Algorithm (iHOGA) developed by university of Zaragoza, Spain is able to perform the single or multi objective optimisation with a low computational time using GA. The free version of the software can only be used for training purposes and not for the project with the limitations on the total average daily load and probability analysis.

COMPOSE

Compare Options for Sustainable Energy, COMPOSE is developed by Aalborg university in Denmark and is a techno economical that can be used in to assess how the energy systems can support intermittency while offering a realistic evaluation of cost and benefits under uncertainty. The software is free to download however a three day training is required [63]

HYBRID2

HYBRID2 is developed by Renewable Energy Research Laboratory (RERL) of the University of Massachusetts with the support of NREL [64] HYBRID2 uses statistical methods to analyse the inter step variations . It allows the user to run simulations and do the economic evaluation. The software has limited parameters and is not flexible however it has a library with variety of resource data files.

SOMES

This software has been developed by Utrecht University, Netherlands in 1987 and it is able to simulate the average electricity production of renewable energy systems and perform the optimisation to find the lowest electricity cost.

Dymola/Modelica

Fraunhofer Institute for Solar Energy used Dymola/Modelica to model the hybrid systems consisting of wind turbine, PV panel, Fuel cells and batteries with the input of weather data to evaluate the lifecycle cost and levelised cost of the produced energy.

TRNSYS

Transient Energy System Simulation Program (TRNSYS) was initially developed in 1975 jointly by University of Wisconsin and University of Colorado for thermal systems but over the years is has been upgraded to a hybrid simulator. Although TRNSYS does not have optimisation tool it is a powerful simulation tool. The software is not free to use.

iGRHYSO

Improved Grid-connected Renewable Hybrid Systems Optimisation (iGRHYSO) is an optimisation tool for grid-connected systems and is able to consider the effect of the temperature rise on PV panel output and also can analyse the output power of the wind turbine.

RAPSIM

Remote Area Power Simulator (RAPSIM) was developed by University Energy Research Institute, Australia in 1996. This software is a simulator for hybrid systems consisting of wind turbine, PV panel, and diesel generator and battery bank. It is not clear if there are any updated versions of the software developed in 1997.

It should be noted that most of these software are only simulators and are not able to solve the optimisation problem and those which have the optimisation ability either ignore the effect of uncertainties in resources (follow deterministic design approach) or as COMPOSE software does; they only enable the user to specify uncertainty ranges for example for wind production which is not a realistic design approach.

1.7 Deterministic and Stochastic Design Approaches

The performance of a HRES depends on proper design and sizing of its components. Generally there are two design approaches in design of HRES: deterministic and stochastic.

1.7.1 Determinstic design approach and problem formulation

In deterministic approach all the system parameters are deterministic values and their variation through the time is assumed to be known and there are no uncertainties involved. The system is designed based on the average values of meteorological data and load demand for each step of the design period. To maintain the system reliability a factor of safety is usually added to the average values or the system is designed based on the worst case scenario, for example the system is designed based on the month with minimum renewable resources and maximum load demand, or the battery bank is sized based on two or three days of non-availability of renewable resources called as days of autonomy.[21, 65]

As mentioned before, in a deterministic design approach all the input data are average values and the system is designed based on worst case scenario. The renewable power generators are highly vulnerable to external environmental variations which directly affect their performance in terms of maintaining the desired reliability. To overcome this issue, the battery bank is usually sized based on worst case scenario which is unavailability of renewable resources for several days known as days of autonomy, usually two or three days. The size of other components of HRES is then determined by solving a single objective optimisation problem with the objective of minimising the system total cost using average values for wind speed, solar irradiance and load demand. Each design candidate is evaluated throughout the design period; whole year; and would consider as feasible solution if it complies with reliability constraint. The feasible solution with minimum total cost would be then introduced as the optimum solution. Although the assumption of nonexistence of renewable resources for two or three days seems unlikely to happen and sizing the battery bank.

Deterministic design approch problem formulation:

The single-objective optimisation problem of HRES design can be defined as:

$$\min_{A_{WT}, A_{PV}, N_{Bat}} \{C_{IC} + C_{O\&M} + C_{\mathrm{Re}\,placement}\} \tag{1.12}$$

s.t.

$$DPSP < \alpha \tag{1.13}$$

$$SOC \geq SOC_{\min} \tag{1.14}$$

$$SOC_{t+1} = f_1(SOC_t, A_{WT}, A_{PV}, Demand) \tag{1.15}$$

where

$$C_{IC} = f_2(A_{WT}, A_{PV}, N_{Bat}) \tag{1.16}$$

$$C_{O\&M} = f_3(A_{WT}, A_{PV}, N_{Bat}) \tag{1.17}$$

$$C_{replacement} = f_4(A_{WT}, A_{PV}, N_{Bat}) \tag{1.18}$$

1.7.2 Stochastic design approach

In stochastic design approach, one or more than one design variables are involving uncertainties, here the wind speed and solar irradiance as a result the power generated by these resources are random values. Considering the uncertainties during the design process can result in more reliable design output. However in this design method the main challenge would be modelling the uncertainties in the most accurate way. The first step in stochastic design approach is to find the best suited model for uncertain variables

Modelling uncertainties:

Here two different approaches in modelling uncertainties are discussed.

a) Time series analysis, Auto Regressive Moving Average models

Time series analysis could be a viable method to model the uncertainties with unknown variations. The special feature of time series analysis is the fact that successive observations are not usually independent. Most time series are stochastic and there would not be the possibility of exact prediction so the accuracy of future values is conditioned by the knowledge of past values. Having sufficient historical data on wind speed and solar radiation values in desired location, an Auto Regressive Moving Average (ARMA) model can be fitted to the historical data of wind speed and solar irradiance data to be used as the random generator in performance evaluation of HRES design candidates.

The ARMA model is usually fitted to correlated time series data and is a way in predicting the future value of time series. This model has two parts; autoregressive (AR) and moving average (MA). The mathematical formulation of ARMA is:

$$y_t + a_1 y_{t-1} + a_2 y_{t-2} + ... + a_p y_{t-p} = \varepsilon_t + c_1 \varepsilon_{t-1} + ... + c_q \varepsilon_{t-q} \tag{1.19}$$

where p and q are ARMA model orders, $a_1,..., a_p$ are the autoregressive parameters, $c_1,....c_q$ are the moving average parameters and $\varepsilon_t ,..., \varepsilon_{t-q}$ are random variables with mean value of zero and standard deviation of δ.

The ARMA model orders and parameters are estimated as follow:

❖ **Transformation of the historical data**

Transformation of input data is performed if required in order to stabilize the variance and make the data more normally distributed. To check the necessity the transformation the skewness of the data set can be used as a measure of normality.
Skewness is a measure of asymmetry of the data around the sample mean and is defined as the third standardised moment and is calculated as:

$$s = \frac{E(x-\mu)^3}{\delta^3} \tag{1.20}$$

where μ is the mean value of x, δ is the standard deviation of x, and $E(t)$ represents the expected value of quantity of t. The negative value of skewness means the data are spread out more to the left of the mean and if the data are more spread out more to the right of the mean the value of the skewness would be positive. The skewness of the normal distribution is zero. There are various methods to transform the data set to Gaussian form.

❖ **Power Transformation**

Brown [66] introduced a method to transform the Weibull distribution into Gaussian form as :

$$U_{T(t)} = U_{(t)}^m \text{ with } t = 1,2,..., n \tag{1.21}$$

where $U_{(t)}$ is the original data set and $U_{T(t)}$ is the transformed time series with Gaussian PDF, and m is the power transformation. Dubey [67] showed that Weibull PDF is very similar to Gaussian PDF for the values of Weibull distribution shape factor; k between 3.26 and 3.6. Lujano-Rojas et al [68] varied the value of m between $k/3.6$ to $k/3.26$ in order to find the best power transformation value, resulting in the closest PDF to the Gaussian by calculation the coefficient of skewness for each data set. Coefficient of skewness of the data as is calculated by [69]:

$$SK = \frac{Q_3 + Q_1 - 2Q_2}{Q_3 - Q_1} \tag{1.22}$$

where $Q_1 = A^{-1}(0.25)$, $Q_2 = A^{-1}(0.5)$ and $Q_3 = A^{-1}(0.75)$ are first, second and third quantiles respectively. A^{-1} is the inverse of the Cumulative Distribution Function (CDF) of the data set.

This method can only be performed on wind speed data as the solar irradiance does not follow a Weibull PDF.

- **Box-Cox transformation**

Another method of transformation is Box-Cox transformation that transforms non-normally distributed data to a set of data that has approximately normal distribution.
If λ is not zero:

$$data(\lambda) = \frac{data^{\lambda} - 1}{\lambda} \tag{1.23}$$

if λ is zero:

$$data(\lambda) = \log(data) \tag{1.24}$$

To find the best form of transformation in this study, the results of performing Power transformation and Box Cox transformation and the original data set of wind speed are compared in terms of the value of skewness and the series with the closest value to zero of skewness is chosen. For solar irradiance the result of Box cox transformation is compared to the original data and the series with the absolute value of skewness closer to zero is selected.

- **Dickey-Fuller test**

To evaluate the stationarity of the data the Augmented Dickey Fuller test is used [70, 71]. This test checks whether a unit root is present in autoregressive model.

$$y_t = \varphi y_{t-1} + \xi_t \tag{1.25}$$

where y_t is the variable of interest; φ is a coefficient and ξ_t is the error term. A unit root is present if φ is 1. In case of the presence of unit root in the model the data would be non-stationary and needs to transform to a stationary data set by performing de-trending process. The non-stationary data can be transformed to stationary by.

- Fitting a smooth curve to the existing trend.
- Differentiate the curve until the remaining trend is negligible.

- **Order of ARMA model**

The method for estimation of order of ARMA model was first introduced by Box and Jerkins [72] which was based on judging the orders by visual appearance of autocorrelation function (acf) and partial autocorrelation function (pacf) plots. However, identifying the ARMA models orders by this method is very difficult and requires a lot of experience even for simplest models.

Another method in ARMA model order identification is based on fitting a set of trial candidate models and computing the goodness of fit of the models. The goodness of fit of the models can be computed by Akaike Information Criterion (AIC) and Final Prediction Error (FPE) [73]. The goodness of the fitted model is measured by evaluation the models residuals.

$$AIC = \log\left[V\left(1+\frac{2n}{N}\right)\right] \tag{1.26}$$

$$FPE = V\frac{1+n/N}{1-n/N} \tag{1.27}$$

where V is the variance of model residuals N is the length of the time series and $n = p+q$ is the number of estimated parameters in ARMA model. The model with lowest FPE and AIC value is then selected as the model of best fit.

- **Ljung-Box Test**

If a good model is chosen and effectively describes the original data, it is expected that the residuals to be random or uncorrelated because if the residuals are correlated the prediction error would increase by time. Ljung-Box Test [74] is used to examine the existence of correlation between the fitted ARMA model residuals[75]. If the model is appropriate, then Q should be approximately distributed as χ^2 with $m-p-q$ degrees of freedom.

$$Q = N(N+2)\sum_{k=1}^{m}\frac{r_k^2}{N-k} \tag{1.28}$$

where N is the time series size, r_k is the correlation if residuals at lag k. The null hypothesis is rejected if Q is higher than chi-square distribution $\chi^2_\alpha(m-p-q)$.

❖ **Simulation and back-transformation**

The data is simulated using fitted ARMA model and then back transformed to its original scale [76].

Using this method an Auto Regressive Moving Average (ARMA) model is fitted to the historical data of wind speed and solar irradiance data which can be used as the random generator in performance evaluation of HRES design candidates.
The results obtained using this method is discussed in chapter 5.

b) Fitting the historical data to known distributions

One of common approaches is fitting the uncertainties to known distributions such as Weibull or Beta distributions [77].
The performance of this method in modelling wind speed and solar irradiance are compared to the output of performing time series analysis in chapter 6.

<u>Stochastic design approch problem formulation:</u>

Using either of discussed methods in modelling uncertainties in stochastic design of HRES two approaches are followed in this work.

Stochastic design, approach 1 problem formulation

In this approach the wind speed and solar irradiance variations are modelled with ARMA model. Using Monte-Carlo simulation the design candidates are evaluated in terms of reliability and the optimum solution with minimum cost is obtained. The optimisation problem is defined as:

$$\min_{A_{WT},A_{PV},N_{Bat}} imize \{C_{IC} + C_{O\&M} + C_{\mathrm{Re}\,placement}\} \tag{1.29}$$

s.t.

$$E[DPSP] \le \alpha \tag{1.30}$$

$$SOC \ge SOC_{\min} \tag{1.31}$$

$$SOC_{t+1} = f_1(SOC_t, A_{WT}, A_{PV}, Demand) \tag{1.32}$$

where

$$C_{IC} = f_2(A_{WT}, A_{PV}, N_{Bat}) \tag{1.33}$$

$$C_{O\&M} = f_3(A_{WT}, A_{PV}, N_{Bat}) \tag{1.34}$$

$$C_{replacement} = f_4(A_{WT}, A_{PV}, N_{Bat}) \tag{1.35}$$

where $E[DPSP]$ is the expected value of DPS.

The results obtained by using this method are discussed in chapter 5.

Stochastic design, approach 2 problem formulation

By replacing the expected value of the DPSP with the probability of deficiency in generated power, the optimisation problem would change to an optimisation problem with probabilistic constraint which can be solved by using chance-constrained programming. Chance constrained programming is been used in various fields of engineering where there is uncertainties involved.

In this approach the wind speed and solar irradiance variations are fit to known distribution and chance constrained programming is used to obtain the optimum solution. Here the generated power by wind turbine and PV panel are dependent random variables following known distributions and the power of battery bank is dependent random variable. Here the optimisation problem is defined as:

$$\min_{A_{WT},A_{PV},N_{Bat}} \{C_{IC} + C_{O\&M} + C_{\mathrm{Re}\,placement}\} \tag{1.36}$$

s.t.

$$Pr(\sum P_t \geq Demand_t) \geq \alpha \tag{1.37}$$

$$P_t = P_{WT_t} + P_{PV\,t} + P_{Bat\,t} \tag{1.38}$$

$$SOC \geq SOC_{min} \tag{1.39}$$

$$SOC_{t+1} = f_1(SOC_t, A_{WT}, A_{PV}, Demand) \tag{1.40}$$

where

$$C_{IC} = f_2(A_{WT}, A_{PV}, N_{Bat}) \tag{1.41}$$

$$C_{O\&M} = f_3(A_{WT}, A_{PV}, N_{Bat}) \tag{1.42}$$

$$C_{replacement} = f_4(A_{WT}, A_{PV}, N_{Bat}) \tag{1.43}$$

Chance constrained programming

Various optimisation problems in design and planning areas need to deal with constraints involving random parameters, which are required to be satisfied within a pre-defined probability. Mathematical formulation for designing reliability constrained optimisation problems lead to chance constrained programming or probabilistic programming. Chance Constrained Programming (CCP) was first introduced by Charnes and Cooper [78] in 1959and later Miller and Wagner [79] and Prekopa [80] introduced chance constrained programming for multivariate variables. The main feature of CCP is that this method uses an effective way of modelling uncertainty in optimisation problems in which the inequality constraints are satisfied with a probability which is defined at the beginning of the process. The predefined probability ensures a certain level of reliability [81]. Due to its high performance in the solving the problems with high level of uncertainty, CCP is been widely used to model reliability of technical and economic problems real time optimization [82]. The general form of a chance constrained problem can be formulated as:

$$\min\ f(x, \xi) \tag{1.44}$$

s.t.

$$\Pr(G(x,\xi) \le 0) \ge \alpha \tag{1.45}$$

where $f(y,\xi)$ is the objective function which contains random variables, y represents the vector of decision variables, ξ represents the vector of k random variables with given cumulative density functions that $F_{\xi_j}(z) = \Pr(\xi_j \le z),\ j = 1,...,k$ and $g_r, r = 1,...,k$ represents set of constraints involved with random variables. The chance constrained method programming demands that the joint probability of k individual constraints to be satisfied with a given probability level [83] of α. There might be some deterministic constraints in the problem which are shown with p_i.

To solve the chance constrained problem if the $g_j(y,\xi)$ can be expressed linearly in the form of $g_j(y,\xi) = \sum_i T_{ji} y_i - \xi_j,\ j = 1,....,k$ it can be shown that each of individual chance constraints can be re-written as:

$$\sum T_{ji} y_i \ge E(\xi_j) + \sqrt{Var(\xi_j)} Z_\alpha \tag{1.46}$$

$$Z_\alpha = \Phi^{-1}\left(1 - \frac{1-\alpha}{k}\right) \tag{1.47}$$

where $E()$ and $Var()$ are the expected value and variance of the random variable and the standard normal cumulative density function is shown by $\Phi()$.

This method has been used for optimal sizing of HRES in the desired site and the results are presented in chapter 6.

1.8 Scope of thesis and contribution to the knowledge

This thesis will focus on the different design approaches in optimal sizing of HRES.

Following a deterministic design approach:

- an economic analysis on optimal sizing of a grid-connected HRES shows that based on grid electricity price; considering a small storage, battery bank, to supply the deficit of produced power in renewable resources may prove to be more cost effective than conventional method of buying from grid.

- it is shown that although the HRES components might be sized based on worst case scenario, the system might not be able to perform satisfactory if only the overall performance of the system is considered without a detailed study on the time and period of blackout occurrence although its overall reliability measure might meet the design constraint.

In order to maintain a high performance HRES which is cost effective, green, and durable and with good output quality, instead of deterministic design approach which is traditionally used in design of HRES, different stochastic design approaches are proposed. The effect of uncertainties in the renewable resources during the design are considered by

- time series analysis which is performed on historical data of wind speed and solar irradiance and fitted ARMA models to each hour of a typical day of each month of the year is used to as the random data generator in Monte Carlo simulation for a realistic design output.
- through a case study it is shown that the choice of modelling method for the wind speed and solar irradiance should be done by comparing the statistical characteristic of different approaches; fitting an ARMA model to using the known distributions; and it is completely dependent on the location of the desired site.
- through a comparison between common method of chance constrained programming with the assumption of the random variables following a bi-variant Gaussian distribution and the novel proposed method that solves the chance constrained problem based on calculating the joint CDF of the unknown joint distribution of the random variables, it is shown that the common method is limiting the feasible region of solutions and results in a more conservative and naturally less cost effective optimum solution.

Majority of the reported researches on optimal sizing of HRES in the literature are either single-objective optimisation or if more than one objective is considered the effect of uncertainties are ignored. In this thesis

- a multi-objective optimisation based on NSGA-II is proposed that considers the uncertainties with a novel method based on chance constrained programing instead of Monte Carlo simulation in estimation of the expected value of the hourly wind speed and solar irradiance data. It is shown that the proposed method improves the computational time while maintaining the acceptable performance.The optimisation algorithm, time series analysis, chance constrained programming and the presented analysis have all been developed by the author using MATLAB software.

In order to present the performance of proposed methods in this project a concept configuration of HRES is considered which is shown in Figure 1-1. Figure 1-2 shows a load profile which is a typical load profile, adopted based on the load profile presented in [84] to suit the case study. The specifications of the components are presented in Table 1-1 [21].

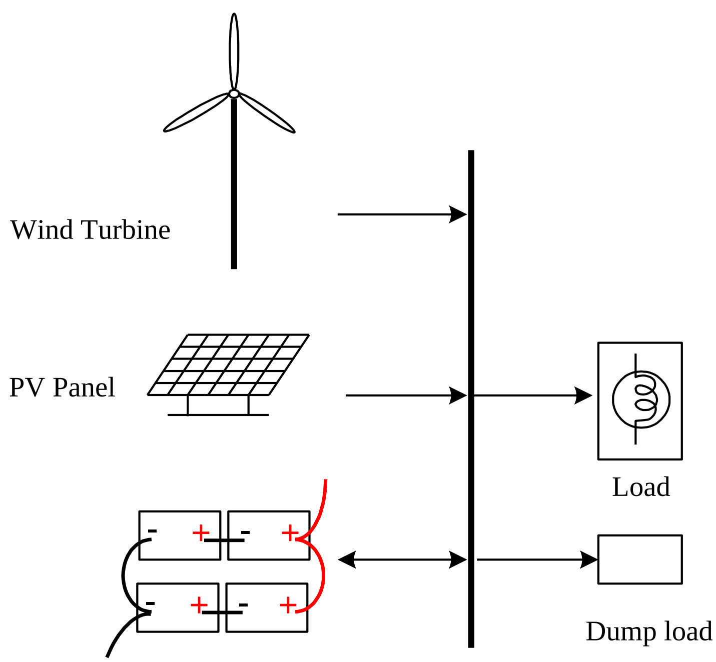


Figure 1-1 Concept diagram of HRES

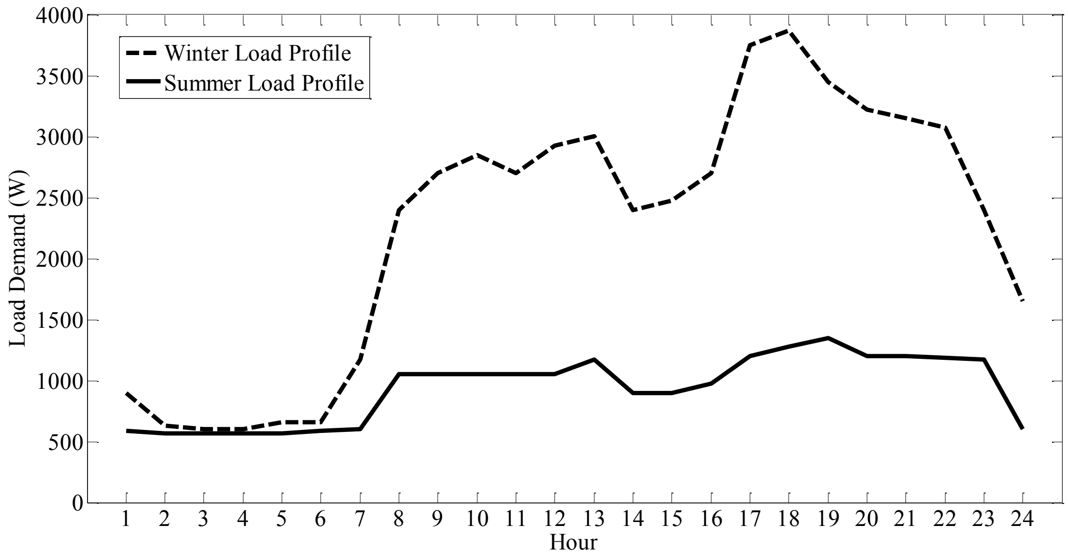


Figure 1-2 Summer and winter load profiles

Table 1-1 Components design parameters

	Efficiency (%)	Lifetime (year)	Initial Cost	O&M Cost	Interest Rate(%)	Inflation rate (%)	Feed-in Tariff (c/kWh)
PV panel	12.3	25	600 ($/m2)	1% of price	8	4	27
WT		20	700 ($/m2)	3% of price	8	4	44
Battery Bank	90	8	1.5 ($/Ah)	1% of price	8	4	-

1

1.9 Structure of this thesis

Chapter 2 provides the mathematical models of the components considered in Figure 1-1. The economic cost and income modelling for stand-alone and grid-connected HRES are presented in this chapter. Chapter 3 investigates the cost effectiveness of adding a battery bank to grid-connected HRES to maintain shortage of produced power by renewable resources comparing to buying the electricity from grid through a deterministic design approach. Chapter 4 is dedicated to analysis of reliability of output power supply in deterministic design approach and it is shown that a more detailed analysis is required to ensure the reliability constraint is met in deterministic approach. Next chapters are dedicated to stochastic design approach and different design methods in modelling uncertainties are investigated and improved. Following stochastic design approach the historical weather data are modelled using time series analysis and used to design a HRES for desired site. The methodology and results are presented in Chapter 5. Chapter 6 compares the results of conventional approach in solving chance constrained problems which is based on the assumption of considering the Gaussian distribution to present the randomness of uncertain variables with a proposed method which solves the chance constrained problem considering the joint distribution of random variables as unknown. Chapter 7 performs a multi-objective optimisation based on NSGA-II with a novel method in integrating the uncertainties in design based on chance constrained programming. Chapter 8 concludes the thesis with several remarks of the finished project along with future research directions.

2 Modelling

2.1 HRES components

The HRES design is crucially dependent on the performance of its individual components. In order to analyse the overall system performance the individual components need to be modelled first. Different mathematical models are proposed by researchers to estimate the output power of wind turbine, photovoltaic panel and batteries. The models implemented in this study are chosen with consideration of giving a realistic estimation of the output of each system without being too complicated with details.

2.1.1 Wind Turbines

Wind energy has been a popular alternative power source in recent years and many researches have been done to demonstrate the potential of this renewable power source around the world [85]. Although the power production from wind energy is challenging due to its dependency to weather conditions studies show that wind is a periodical phenomenon for large geographical areas [86]. However wind energy may not be available everywhere because of low wind speed, it can be an attractive and economically viable energy resource in many locations around the world. A wind turbine converts available power in the wind into electricity. The capacity of wind turbines varies from a few watts which can be used in residential and commercial application to Megawatts in wind plants. Nowadays, wind turbines are categorized to horizontal-axis wind turbines (HAWT) and vertical-axis wind turbines (VAWT). The shaft and electrical generator are located on top of the tower of HAWT and the turbine is pointed to the wind direction, where the main rotor of the VAWT is set vertically and is not pointed to the wind. Although the VAWT have a simple installation and control, since they cannot produce as much power of HAWT, they are not as favourable as HAWT so the majority of installed HAWTs today are from the HAWT type. Figure 2-1 presents a two configuration of wind turbine.

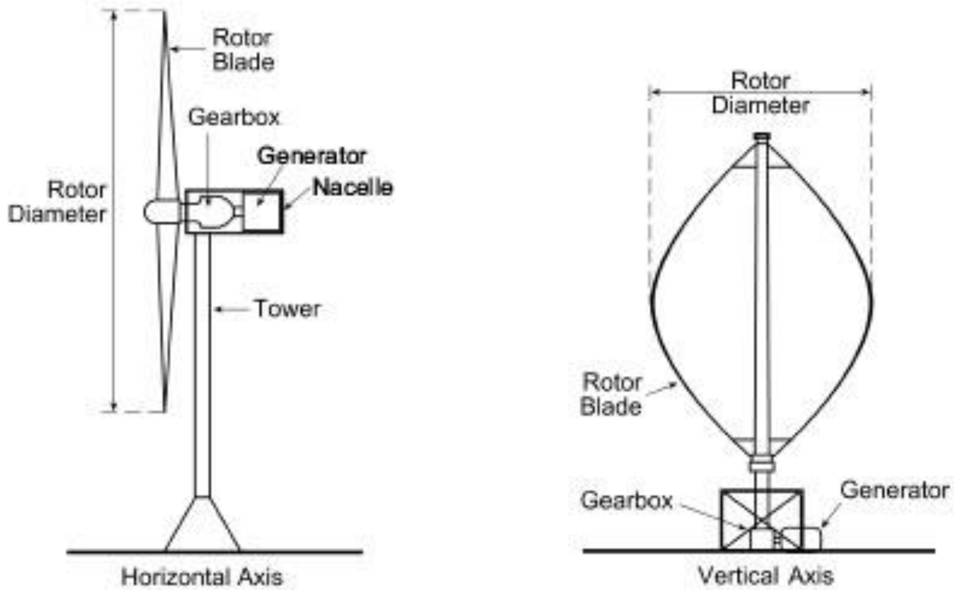


Figure 2-1 Wind Turbine Configurations

Design of wind turbines contains determining the number and size of blades, the rotor diameter, material, chord size, height of the tower, gear box and etc. The height of the tower and the rotor size are both depending of the diameter of the rotor. And the parameters such as aerodynamic efficiency, cost and noise have an essential role in determining the number of the blades. The today market is dominated by two-blade and three-blade wind turbines. Although the two blade has lighter weight and it is easier to install, since the three-blade design increases the efficiency by 5-10% and smoother output power however they have higher cost and weight. Considering other parameters such as control system and gear box the optimum designs with high-efficiency and minimum cost is chosen by designer of the wind turbines.

2.1.2 Wind Turbine Model

The wind power generated by a wind turbine can be represented by:

$$P_{WT} = \frac{1}{2}\rho C_p V_w^3 A_{WT} \tag{2.1}$$

where P_{WT} is the wind turbine output power in W, $\rho = 1.225 kg/m^3$ is the air density, C_p is the wind turbine power coefficient, A_{WT} is the rotor disk area in m^2 and V_w is the hourly average wind velocity in m/s at the hub elevation.

The wind speed varies with the height and the wind data measurement equipment is installed at different heights so it is crucial to calculate the wind speed at the wind turbine hub. The wind speed V_w at the hub height can be calculated as:

$$V_w = V_{ref} \frac{\ln\left(z_{hub} / z_0 \right)}{\ln\left(z_{ref} / z_0 \right)} \tag{2.2}$$

where z_{hub} is the hub height; V_{ref} is the wind speed at the reference height z_{ref} and z_0 is the surface roughness length in m. Wind speed at any given height of the tower can be found if the surface roughness and wind measurements at different height are available. The value of z_0 in logarithmic law for open farm is assumed as 0.03.

The power coefficient depends on the wind turbine characteristics and varies with the wind speed. In this study, the power curve of the different wind turbines are used to calculate the corresponding Cp value to different wind speeds. Using the least square method a mathematical model is fitted to the points to model the C_P value variation at different wind speeds as:

$$C_P = C_1 v^q + C_2 v^{q-1} + \cdots + C_q v + C_{q+1} \tag{2.3}$$

A least-square problem is a category of optimisation problem which does not include constraints. The objective of this optimisation problem is to minimise the sums of squares of the form $a_i^T x - b_i$ [87]. The optimisation problem can be written as

$$\min \ f(x) = \sum_{i=1}^{k} (a_i^T x - b_i)^2 \tag{2.4}$$

where $A \in \Re^{k \times n}$, a_i^T are the rows of A and the vectors $x \in \Re^n$ is the optimisation variables. The optimisation problem 2.4 can be solved by solving a set of linear equations.

$$(A^T A)x = A^T b \tag{2.5}$$

And from 2.5 we would have

$$x = (A^T A)^{-1} A^T b \tag{2.6}$$

Using least square curve fitting to extract the best fitted curve to the observed Cp vs. v_w for the n_{WT} observed wind turbines and n_v wind speeds that the Cp values are known the elements of for a polynomial of the order of q Equation 2.6 can be written as:

$$x = [C]_{(q+1)\times 1} \tag{2.7}$$

$$A = \begin{bmatrix} \begin{bmatrix} v_1^q & \cdots & v_1^0 \\ \vdots & \cdots & \vdots \\ v_1^q & \cdots & v_1^0 \end{bmatrix}_{n_{WT}\times(q+1)} \\ \vdots \\ \vdots \\ \begin{bmatrix} v_{n_v}^q & \cdots & v_{n_v}^0 \\ \vdots & \cdots & \vdots \\ v_{n_v}^q & \cdots & v_{n_v}^0 \end{bmatrix}_{n_{WT}\times(q+1)} \end{bmatrix}_{n_v n_{WT}\times(q+1)} \tag{2.8}$$

$$B = \begin{bmatrix} \begin{bmatrix} c_{P_{1,1}} \\ \vdots \\ c_{P_{n_{WT},1}} \end{bmatrix}_{n_{WT}\times 1} \\ \vdots \\ \vdots \\ \begin{bmatrix} c_{P_{1,n_v}} \\ \vdots \\ c_{P_{n_{WT},n_v}} \end{bmatrix}_{n_{WT}\times 1} \end{bmatrix}_{n_{WT} n_v \times 1} \tag{2.9}$$

Using the curve fitting tool in MATLAB software a polynomial is fitted to extract a generic Cp equation to be used in the calculations.

Following described method on the data of different wind turbines in the range of $1kW$ to $15kW$; Figure 2-2; applied to the case study used in this project the C_P variation is modelled by:

$$\begin{aligned} C_p &= 3.646\mathrm{e}^{-7} v_w{}^6 - 2.95\mathrm{e}^{-5} v_w{}^5 + 0.9088\,e^{-3} v_w{}^4 - 0.01295\, v_w{}^3 + \\ &+ 0.07874\, v_w{}^2 - 0.11\, v_w - 0.001027 \end{aligned} \tag{2.10}$$

2.1.3 Photovoltaic Panels

Solar energy is one of the most significant energy resources available to be used in producing the increasing power demand of the world. Solar energy can be used in solar thermal systems which convert the solar energy into required thermal energy

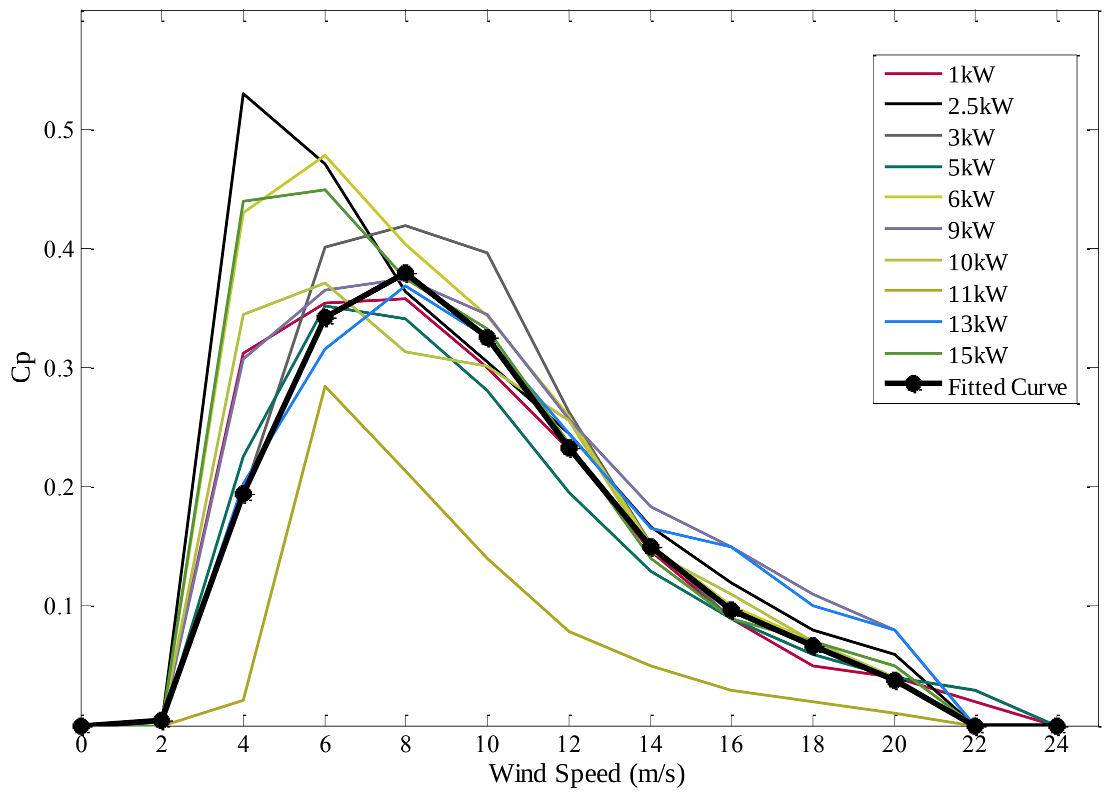


Figure 2-2 Cp curves of different wind turbines in the range of $1kW$ to $15kW$

form or they can be used in photovoltaic systems that convert the solar energy to electricity. Among these two main uses of solar energy, converting to electricity is the interest of this study. The efficiency of the photovoltaic panels has improved significantly from 4% for first model which was developed in 1954 by Chaplin, Fuller and Pearson to over 40% recently [88].

The semiconductors in structure of photovoltaic panels produce electricity by absorbing the solar irradiation coming through them. Solar cells consist of large-area semiconductor diode [89]. The p-n junction is created by adding impurity to the semiconductor crystal. Since there are four electrons required to fit an atom to the crystal structure if the impurities are phosphorus-atoms with five outer electrons, four would be used to fit to the crystal structure and one would remain free. In this case there would be a region with majority of free negative charge which is called n-region. On the other if the impurities are from boron atoms with three electrons, one electron would be missing. The missing electron is considered as a hole and the region is called p-region. Due to the charge differences at the frontier of two regions, the electrons move to p-region and holes in to n-region until a neutral junction is produced, called as space-charge-region.

The solar radiation falling into the semiconductor produces electron-hole pairs. These pairs diffuse into space-charge-region where they are divided by the electric field between n-region and p-region. If a resistor is connected between the two regions the electrical power starts flowing. Figure 2-3 shows the principle of power generation in photovoltaic panels.

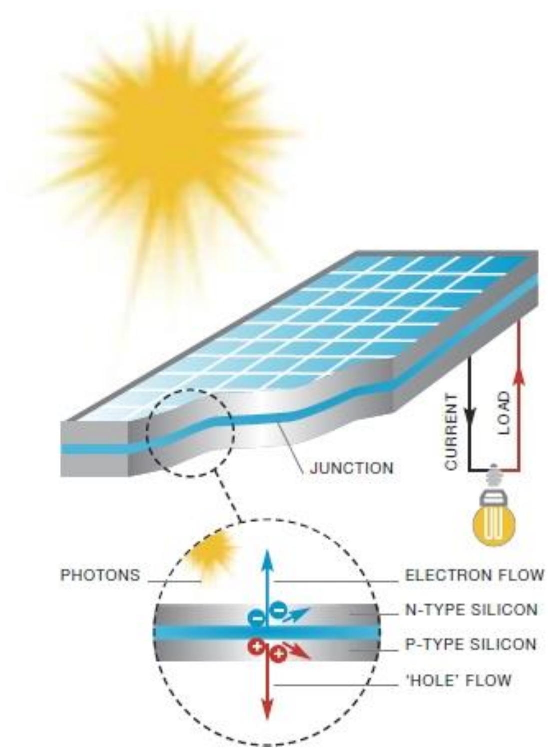


Figure 2-3 Principles of PV energy conversion

2.1.4 Photovoltaic(PV) Panel Model

The PV array model used in this study is given by:

$$P_{PV} = IA_{PV}\eta_{PV} \tag{2.11}$$

where P_{PV} is the PV array output power in W, I is the horizontal solar irradiance in W/m^2, A_{PV} is the PV panel area in m^2 and η_{PV} is the efficiency of the PV array and is calculated as [11]. Although the total solar irradiation of depends on position of the sun that varies from month to month, instead of estimating the amount of total solar radiation with the deterministic method which use the direct normal and diffuse solar radiations, in this study the historical data which is actually measured is used in stochastic approaches to implement the factor of uncertainty in estimating the solar power in the desired site.

The effect of the temperature on the efficiency of the PV panel is considered using:

$$\eta_{PV} = \eta_r\left[1 - \beta(T_c - T_r)\right] \tag{2.12}$$

where η_r is the module reference efficiency, β is the array efficiency temperature coefficient, T_r is the reference temperature for the cell efficiency and T_c is the monthly average cell temperature [90] and can be calculated as follows:

$$T_c = T_a + \frac{\alpha\tau}{U_L} I \tag{2.13}$$

where T_a is the instantaneous ambient temperature,

$$\frac{\alpha\tau}{U_L} = I_{T,NOCT} \Big/ (NOCT - T_{a,NOCT}) \tag{2.14}$$

$NOCT$ is normal operating cell temperature, $T_{a,NOCT} = 20°C$ and $I_{T,NOCT} = 800W/m^2$, for a wind speed of $1m/s$.

2.1.5 Storage System

Energy storage system has an important role in maintaining energy balance in HRES production and load demand. As it enables the system to store the excessed energy when the production is high and demand is low for example during the day and use it at times when there is deficit of supply. Different type of energy storages can be used in HRES such as Compressed Air Energy Storage, Hydrogen Fuel cells and Batteries. Among them batteries are more popular in HRES as they do not enquire any auxiliary systems to be run in conjunction to them and they offer best technology for required reliability and efficiency and cost in HRES.

Batteries are available in variety of types such as Lithium Ion (LiIon), Sodium Sulphor (NaS), Nickel Cadmium (NiCd) and Lead Acid batteries. LiIon batteries have the characteristic of high efficiency and lifespan at high depths of discharge however they are currently too expensive. NaS batteries have temperature constraint for their optimal use and NiCd batteries have high rate of self-discharge which make them less ideal for use in HRES. So far Lead Acid batteries have been the most popular type of storage in HRES [91, 92].

2.1.6 Battery bank Model

Common drawback of using renewable resources is their unpredictable nature which is completely dependent on weather conditions and may result in load rejection at some points. In standalone HRES, the balance between demand and generation is obtained by an auxiliary power source such as a diesel generator or a battery bank. The battery used in this study is a lead acid battery. The selection of an appropriate size of a battery bank requires complete analysis on the charge and discharge process of the battery which depends on the load profile and the output of wind turbine and

PV panels. The property of the battery related to the performance of HRES is the state of charge (SOC) of the battery at each analysis time step. SOC is simulated during the charging process as [93]:

$$\mathrm{SOC}_{t+1} = \mathrm{SOC}_t(1-\delta_t) + \frac{\mathrm{I}_{\mathrm{Bat}\,t}\Delta \mathrm{t}\,\eta_{\mathrm{C}}}{\mathrm{c}_{\mathrm{Bat}}} \tag{2.15}$$

where, $\delta(t)$ is the hourly self-discharge rate (an average value of 0.02% is used in this study). Δt is the time step for calculating the SOC (in this study, Δt is equal to one hour). c_{Bat} is the nominal battery bank capacity in Ah and η_C is the charge efficiency factor. The battery current I_{Bat} can be calculated as:

$$I_{Bat_t} = \frac{P_{PV_t} + P_{WT_t} - P_{load_t}}{V_{Bat}} \tag{2.16}$$

where, V_{Bat} is the battery voltage.

During the discharge, SOC is calculated as [93]:

$$SOC_{t+1} = SOC_t(1-\delta_t) - \frac{I_{Bat\,t}\Delta t}{c_{Bat}} \tag{2.17}$$

in which

$$I_{Bat_t} = \frac{P_{load_t} - P_{PV_t} - P_{WT_t}}{V} \tag{2.18}$$

Charge and discharge processes are subjected to the following constraints:

$$SOC_{\min} = 1 - DOD_{\max} \tag{2.19}$$

where $DOD_{\max}$ is the maximum depth of discharge of the battery.

$$SOC_{\min} \leq SOC_t \leq SOC_{\max} \tag{2.20}$$

and

$$I_{bat,\max}(t) = \max\left\{0, \min\left[\begin{array}{l} I_{\max}, C_{bat}(c(SOC_{\max} - SOC(t)) + \\ + \dfrac{(SOC(t) - SOC_{\min})(1-c)}{\Delta t} \end{array}\right]\right\} \tag{2.21}$$

The constant c is considered 1 if battery is charging and 0 if the battery is discharging.

2.1.7 Battery lifetime

Lifetime of the battery is limited by two independent factors, the battery's float and the life battery's cycle life. The battery's float life is the maximum duration that the battery will last before being replaced even if it has not been used at all. Dispatch strategy has direct effect on battery's lifetime, and by each charge and discharge cycle some depletion happens in battery. Ashari et al. [26] used equivalent full cycles (EFC) for measuring battery's lifetime taking in to account the depth of discharge in each charge and discharge cycle.

$$EFC = No\_of\_cycles|_{DOD} DOD \tag{2.22}$$

where EFC is the Equivalent Full Cycles, DOD is Depth of Discharge and $No\_of\_cycles|_{DOD}$ is number of charge–discharge cycles at the given DOD.

An average EFC_{av} is calculated and after all the equivalent cycles the battery needs to be replaced.

In this study the best fitted curve which is obtained based on to Ashari et al [94] data is employed to reach more precision in battery's EFC calculation, Figure 2-4. In each individual discharge and charge's cycle battery's equivalent No. of cycle is calculated first and the total EFC of the battery is then calculated. When the EFC reached to battery's maximum number of cycles specified by the manufacturer the battery needs to be replaced.

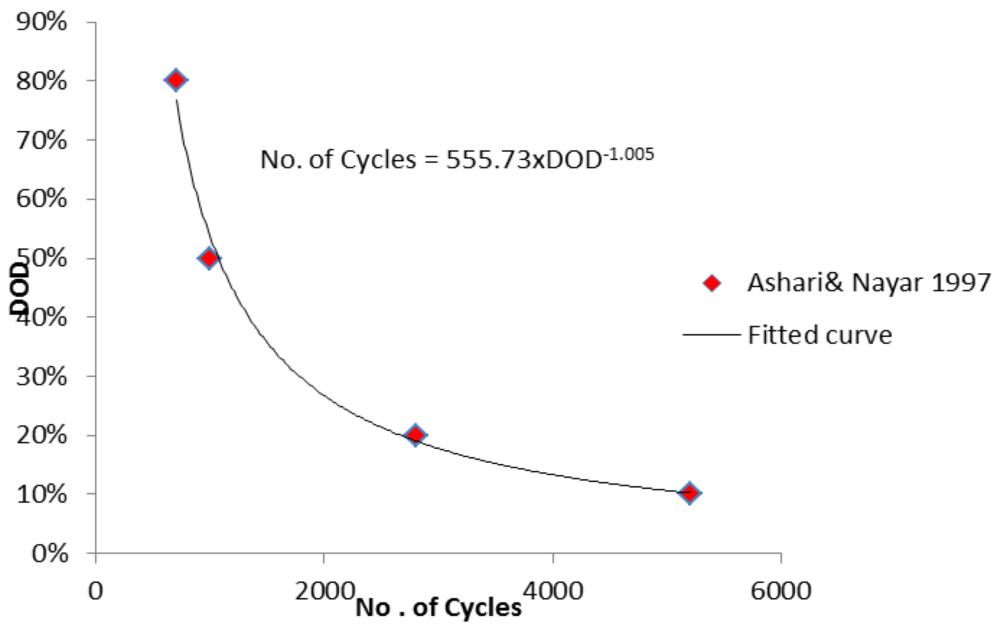


Figure 2-4 Battery's lifetime vs. DOD

So the battery needs to be replaced either because of the use or its age depending on which of them reached to its limits faster.

2.1.8 Economic Analysis

Economic analysis has a leading role in size optimisation of HRES to result in a reasonably profitable investment. Based on the HRES components and also if the HRES is grid connected or stand-alone, all or some of below mathematical models are used in economic analysis of design candidate.

2.1.9 Income Modelling

a) Income of feed-in tariff

In some countries based on the amount of the power HRES generates and used domestically, the owner receives some income, called as feed-in tariff which is calculated with:

$$I_{FIT} = L_P(FIT_{WT}P_{WT,load} + FIT_{PV}P_{PV,load}) \tag{2.23}$$

where FIT_{WT} and FIT_{PV} are feed-in tariff of wind turbine and PV panels respectively . $P_{WT,load}$ and $P_{PV,load}$ are the wind turbine and PV panels' production which is used domestically.

b) Income of selling to grid

In case that the HRES is connected to the grid and there is the capacity in the grid to buy the electricity from micro girds, the excess of generated power can be sold to the grid and the income can be calculated by:

$$I_{Sell,grid} = L_P T_{sell,grid}(P_{WTt,excess} + P_{PV,excess}) \tag{2.24}$$

where $T_{sell,grid}$ is tariff of selling unit power to the grid. $P_{WT,excess}$ and $P_{PV,excess}$ are excess power of wind turbine and PV panel which are calculated after load satisfaction and charging the battery (if existed).

2.1.10 Cost Modelling

Economic analysis is an important factor to consider in size optimisation of HRES in order to achieve a reasonably profitable investment. In this study the total cost of the system TC (of the design candidates) is calculated as the economical measure taking into account the initial capital cost (C_{IC}), replacement cost ($C_{replacement}$) and present value of maintenance cost ($C_{O\&M}$). That is:

$$TC = C_{IC} + C_{replacement} + C_{O\&M} \tag{2.25}$$

a) Initial Capital Cost

The initial capital cost consists of the cost of components and their installation cost.

$$C_{IC} = \left(A_{PV} C_{Unit,PV}\right) + \left(A_{WT} C_{Unit,WT}\right) + (N_{Bat} c_{Bat} C_{Unit,Bat}) + C_0 \tag{2.26}$$

A_{PV} and $C_{Unit,PV}$ are the total PV Area m^2 and unit cost $\$/m^2$ of the PV array, respectively. A_{WT} and $C_{Unit,WT}$ are the total rotor disk area and unit cost of the wind turbine, respectively. N_{Bat}, c_{Bat} and $C_{Unit,Bat}$ are the total number, nominal capacity Ah and the unit cost $\$/Ah$ of the battery bank, respectively. C_0 is the total installation constant cost including the cost of installation of the wind turbine and PV panels and is considered to be 20% of the component cost of the wind turbine and 40% of the component cost of the PV system [21].

b) The Present Value of Replacement Cost

In this study the only component which needs to be replaced during life time of the HRES is assumed to be the battery bank so this cost is only calculated when the battery bank exists in the configuration.

The replacement cost of the battery bank can be calculated as [21]:

$$C_{replacement} = N_{Bat} c_{Bat} C_{\text{Unit,Bat}} \sum_{i=1}^{N_{rep}} \left[\frac{1+f}{1+k_d} \right]^{N_i / N_{rep} + 1} \tag{2.27}$$

where N_{Bat}, c_{Bat} and $C_{Unit,Bat}$ are the total number, nominal capacity and the unit cost of the battery bank, respectively.

N_{rep} is the number of replacements over the system life span, f inflation rate; k_d annual real interest rate. The value of N_{rep} is calculated based on the number of charge and discharge cycles; EFC.

c) The Present Value of Operation and maintenance Cost

The present value of operation and maintenance cost of the hybrid system is expressed as[21]:

$$C_{O\&M,HRES} = \begin{cases} C_{(O\&M)_0} \left(\frac{1+f}{k_d - f} \right) \left[1 - \left(\frac{1+f}{1+k_d} \right)^Y \right], & k_d \neq f \\ C_{(O\&M)_0} Y, & k_d = f \end{cases} \tag{2.28}$$

where Y is the system life span in years, $C_{(O\&M)_0}$ is the operation and maintenance cost in the first year.

$C_{(O\&M)_0}$ can be given as a fraction (k) of the initial capital cost C_{IC} as:

$$C_{(O\&M)0} = kC_{IC} \tag{2.29}$$

The value of k is assumed to be 1% for the PV system, 3% for wind turbine and 1% for battery bank [21].

d) The present value of buying electricity from grid

In grid-connected HRES, grid can provide the shortage of the power to satisfy the demand the cost of maintaining the power shortage from grid can be calculated by:

$$C_{buy,grid} = \begin{cases} L_p \left(LCE_{offpeak,grid} P_{shortage,offpeak} + LCE_{peak,grid} P_{shortage,peak} \right) & (a) \\ L_p \left(LCE_{offpeak,grid} P_{shortage,offpeak} \right) & (b) \end{cases} \tag{2.30}$$

L_p system life period in years

(a) if there is no battery bank

(b) when there is battery bank

3 Optimal sizing of grid-connected hybrid wind-PV systems with battery bank

3.1 Introduction

Conventionally a battery bank is used as the backup system in standalone Hybrid Renewable Energy Systems (HRES) while in grid-connected systems the grid performs as the backup during power shortage periods. For the latter, different prices of electricity during peak and off-peak hours raises a question about the cost effectiveness of using the grid as a backup. Adding a small storage system to maintain the shortage of electricity produced by renewable resources at peak hours may prove to be more cost effective backup. This chapter focuses on the design of an optimised grid connected small-scale HRES, incorporating a battery bank to store electricity during off-peak periods and uses this storage to support the HRES during peak demands. This system is intended to be cost effective (taking into consideration the Feed-In-Tariff) and make building self-sufficient with regard to energy use.
The performance of the proposed design method is evaluated based on a case study for a typical household in UK.

Increase in energy demand has made the renewable resources more attractive. Common drawback of using renewable resources is constant challenge with their unpredictable nature which is completely dependent on climate changes and may result in load rejection at some points. Conventionally the balance between demand and HRES is obtained by grid in grid-connected systems and overproduction is sent into the grid. In these systems, the grid performs as the storage system with infinite capacity which makes the HRES reliable at any time. However different grid electricity prices in peak and off-peak hours could become an economical challenge in maintaining power shortage in peak hours from the grid. In this chapter a new method in design of HRES is introduced by adding a small battery storage system to cover the power shortage during peak hours.

Normally battery bank is used as a backup in standalone systems. Bernal-Agustín and Dufo-López [48, 49] put their effort in analysing the main strategies in optimisation of hybrid systems with battery bank as storage. Balamurugan et al. [19] proposed a hybrid energy system consisting of biomass, wind, solar photovoltaic and battery to deliver energy at optimum availability, considering proper energy storage to meet the peak load demand during low or no solar radiation periods or during low wind periods. Ould Bilal et al. [41] & Yang [93] & Kaabeche [21] proposed methods for sizing a hybrid solar–wind-battery system with the aim of minimising cost system with maximum reliability.

Recently some research has been carried out in which the hybrid system is grid-connected but still includes a battery bank as storage. Castillo-Cagigal et al [95] developed a prototype of a self-sufficient solar house equipped with grid connection, PV generation, lead–acid batteries, controllable appliances and smart metering. Mudler [96] proposed a method to determine the optimal storage size for grid-connected dwelling with PV panels. Particularly increase in grid electricity prices for example in peak hours will change the status of complete dependency on grid during shortage times.

The presented study addresses the optimisation of a grid-connected HRES based on wind and solar energy considering different grid electricity prices with a storage system to cover the power shortages during peak hours.

3.2 Economic analysis

Economic analysis has a leading role in size optimisation of HRES to result in a reasonably profitable investment. In this study the Return On Investment (ROI) of the design candidates is calculated as the economical measure which is calculated using:

$$ROI = \frac{TI - TC}{TC} \times 100 \tag{3.1}$$

TI, the total income of the system takes into account the present value of feed-in tariff income I_{FIT} and present value of selling excess electricity to the grid $I_{Sell,grid}$.

$$TI = I_{FIT} + I_{Sell,grid} \tag{3.2}$$

TC, the total cost of the system takes into account the initial capital cost C_{IC}, the present value of replacement cost C_{rep} and present value of maintenance cost $C_{O\&M}$ and present value of buying electricity from grid $C_{buy,grid}$.

$$TC = C_{IC} + C_{rep} + C_{O\&M} + C_{buy,grid} \tag{3.3}$$

3.3 Problem formulation & design scenarios

The objective is to find the optimum configuration of a grid-connected HRES with maximum ROI while satisfying the load demand. The optimisation problem can be formulated as:

$$\max ROI = \frac{TI - TC}{TC} \times 100 \tag{3.4}$$

In this chapter the wind turbine/PV system sizing optimisation is performed following a deterministic design approach. The averages hourly of weather data and load profile are used as inputs of the design. The power from each resource is calculated at each time step (every hour) based on the capacity of power generator. The overall performance of each design candidate configuration is simulated during the entire year.

In sizing of HRES components, two design scenarios are followed.

Scenario 1: Considering grid as the backup system in peak and off-peak hours and selling excess of produced electricity to the grid. The total power of HRES is calculated with below equation:

$$P_{Total,HRES} = \begin{cases} P_{WT} + P_{PV} & (a) \\ P_{WT} + P_{PV} + P_{grid} & (b) \end{cases} \tag{3.5}$$

(a) if total power generated by wind turbine and PV is sufficient to cover the load demand.

(b) if P_{WT} and P_{PV} is not sufficient to cover the load demand.

Scenario 2: Considering grid as the backup system in off-peak hours and battery bank for peak hours.

The flow of excess power in this scenario is toward the battery bank if the battery is not fully charged and in case that the battery is fully charged then the excess will be sent to the grid.

To size the battery bank the amounts of excess energy and the peak hour power shortage of each individual day is calculated and based on that data the battery bank is sized. The battery is sized based on the worst day data using Equation 3.6.

$$N_{Bat} = \frac{P_{shortage}\Delta t}{V_{Bat} DOD_{\max} C_{Bat}} \tag{3.6}$$

where $Load$ is maximum daily load (Wh); S_D is the number of autonomy or storage days in this study considered as 3days; V_{Bat} is the battery bank voltage in (V); $DOD_{\max}$ is the maximum depth of discharge and η_{Bat} is the battery efficiency.

The performance of whole system is then simulated with equation:

$$P_{Total\_HRES} = \begin{cases} P_{WT} + P_{PV}, & (a) \\ P_{WT} + P_{PV} + \begin{cases} P_{grid} \\ P_{Bat} \end{cases} & \begin{matrix} (b) \\ (c) \end{matrix} \end{cases} \quad (3.7)$$

(a) if total power generated by wind turbine and PV is sufficient to cover the load demand otherwise

(b) where P_{WT} and P_{PV} is not sufficient during off-peak hours

(c) where P_{WT} and P_{PV} is not sufficient during peak hours and state of charge the battery :

$$SOC \geq SOC_{\min} \quad (3.8)$$

Feasible solutions of scenario 2 are compared with scenario 1 solutions and the most satisfactory solution is then selected.

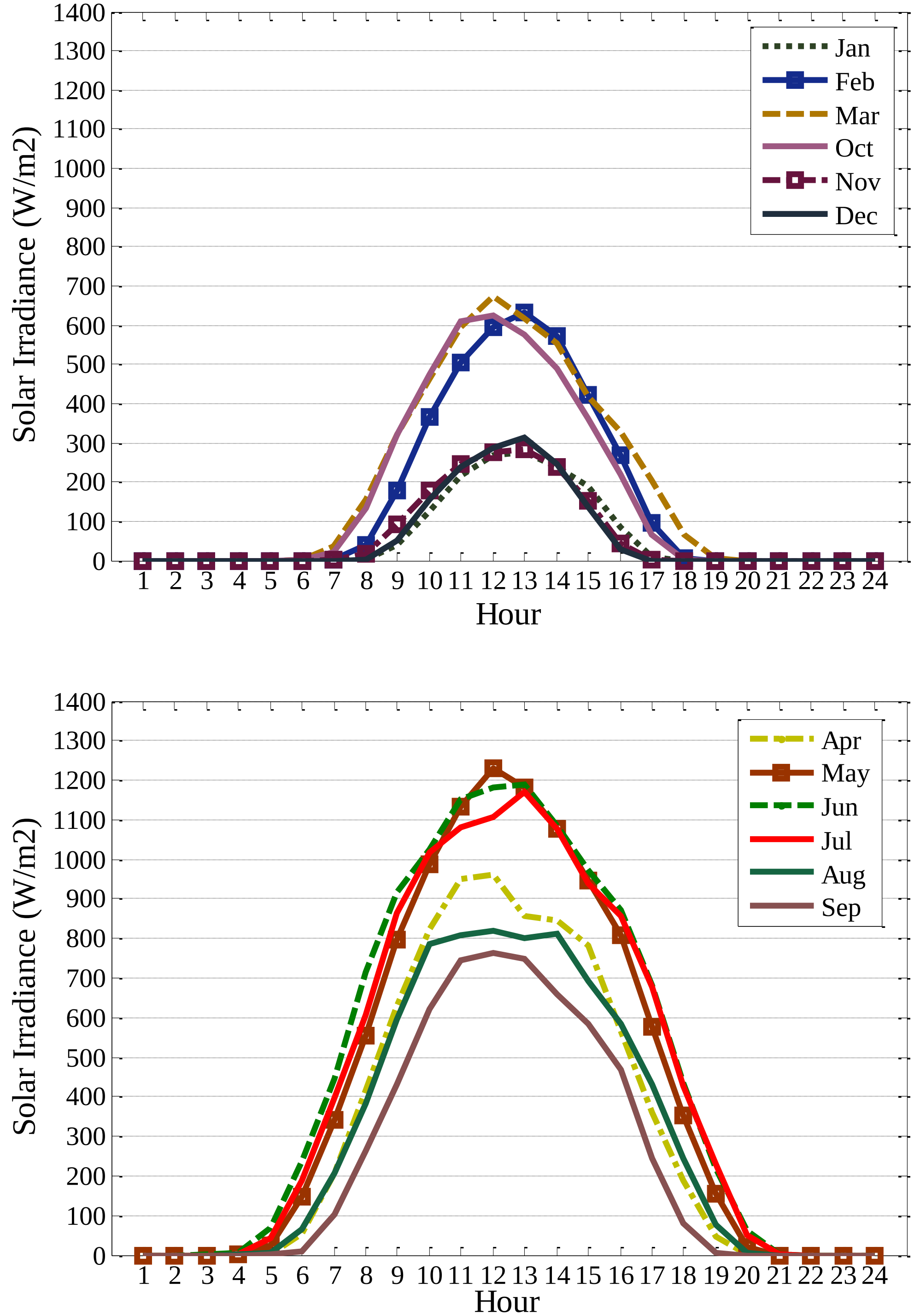


Figure 3-1 Average Hourly Solar Irradiance:

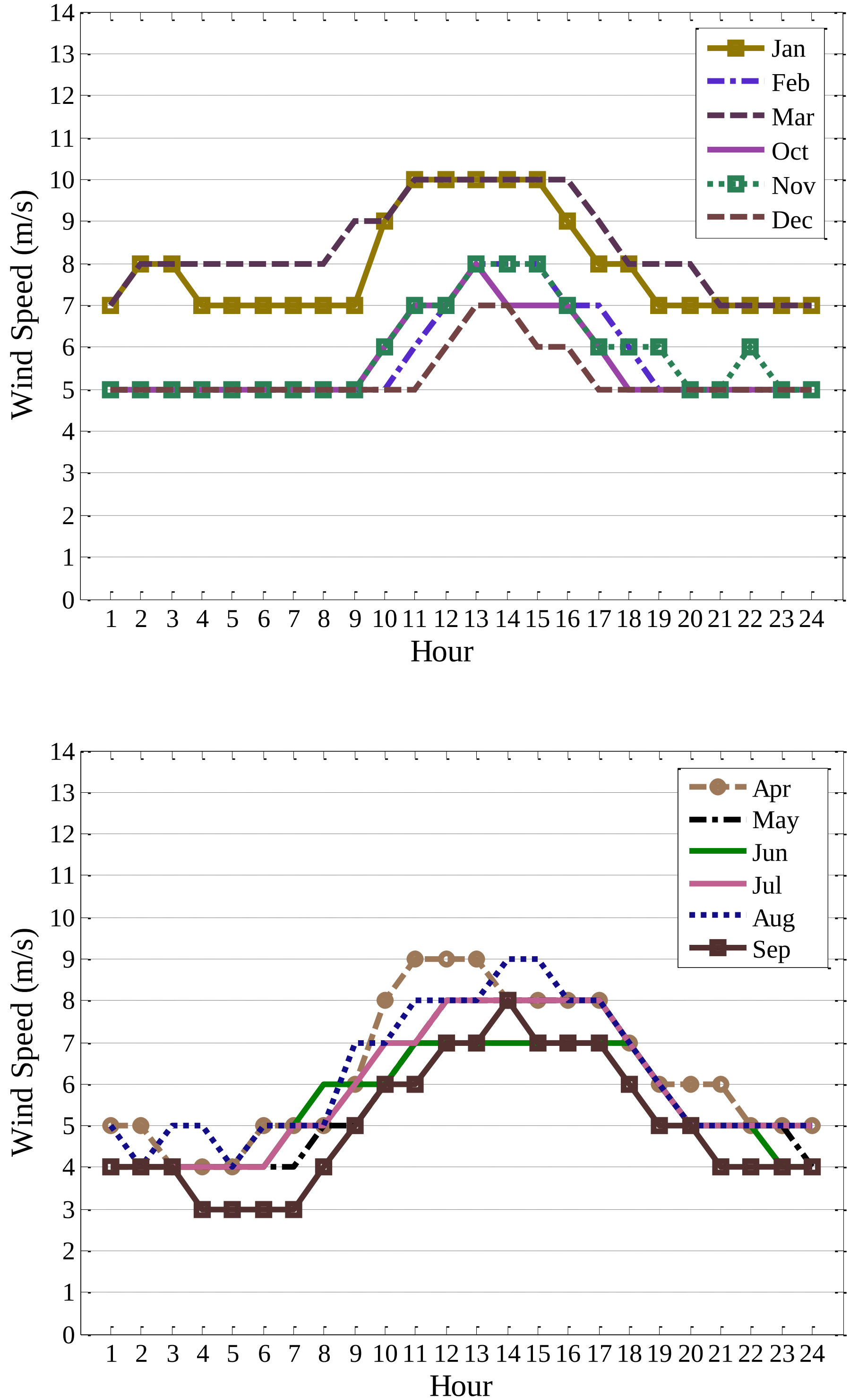


Figure 3-2 Average Hourly Wind Speed

3.4 Case study

The proposed methodology is used to design a grid-connected HRES for a household in Kent; UK. Inputs of the design are typical summer and winter load profiles presented in Figure 1-2 and hourly average of wind speed and solar irradiance data for 12 months of the year which are presented in Figure 3-1 and Figure 3-2.

Technical and economical characteristics of the system components and grid prices are given in Table 1-1 & Table 3-2.

As can be seen in Table 3-2 , the grid electricity has similar price during peak and off-peak hours in the UK [97]. Therefore in this study the system is designed under different assumptions for the peak hour's price. Comparing the results comparison the peak hour rate at which adding a storage system to cover the power shortage would be more cost effective than buying the required electricity from grid will be obtained.

Table 3-1 The battery bank specification

	Nomial Capacity (Ah)	Nominal Voltage (V)	DOD (%)	Number of Cycles
Battery Bank	40	24	90	535

Table 3-2 Grid electricity process in UK

Grid	Off-peak price (c/kWh)	Peak price (c/kWh)
First 900kWh	29	NA
Consumptions after first 900kWh	17	NA
Selling electricity to grid (c/kWh)	5	5

3.5 Results

The results of design process for 10 assumptions for the peak hour price are presented in Table 3-3.

As expected the optimum size for PV is calculated as zero in all optimum solutions due to the fact that wind is dominant in the site under study. The further investigations showed that the configurations with PV arrays did not deliver the best performance considering the dramatic increase they make to the total cost of the system. Figure 3-3 has a more detail look on the effect of adding PV panel on a sample for wind turbine with overall share of 45% in load satisfaction. It can be seen that by increasing the area of PV arrays from zero to 400 m^2 the HRES performance increases by 25% in the load demand satisfaction while the total cost of system increases dramatically.

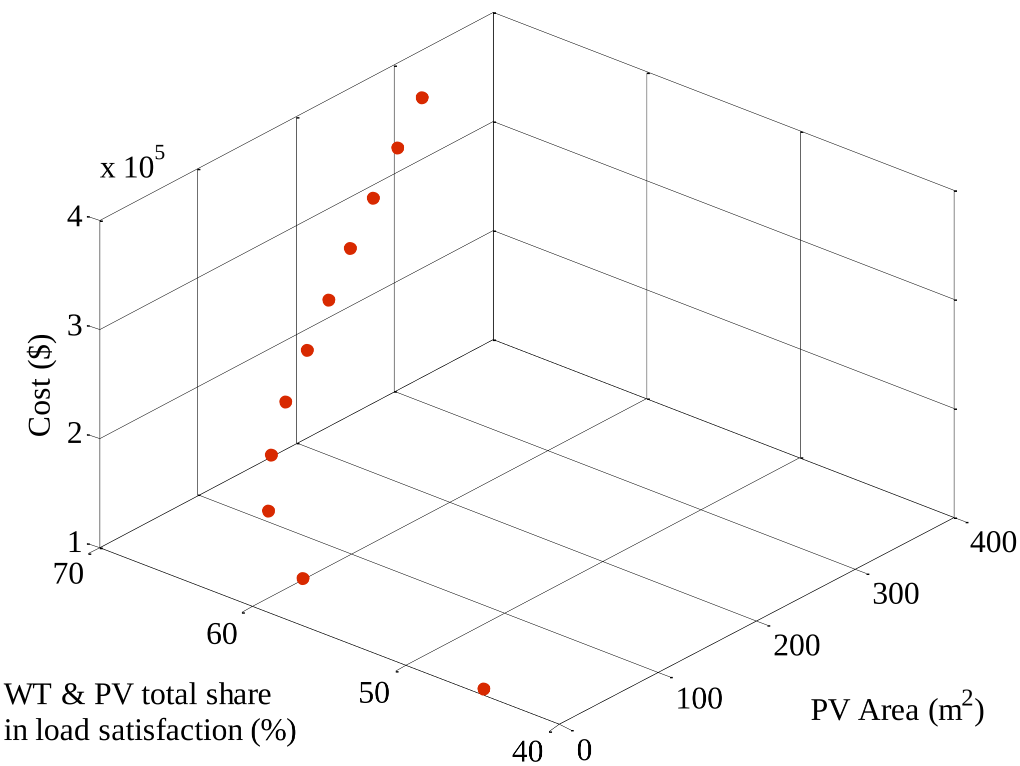


Figure 3-3 PV Area vs. HRES Performance and Cost

Figure 3-4 demonstrates share of each power source when the peak hour price rate increases from 1.1 to 3 times of off-peak prices. It is shown that if the price of peak hours increases by 2.3 times or more than the off-peak price, then the optimum configuration contains the battery bank.

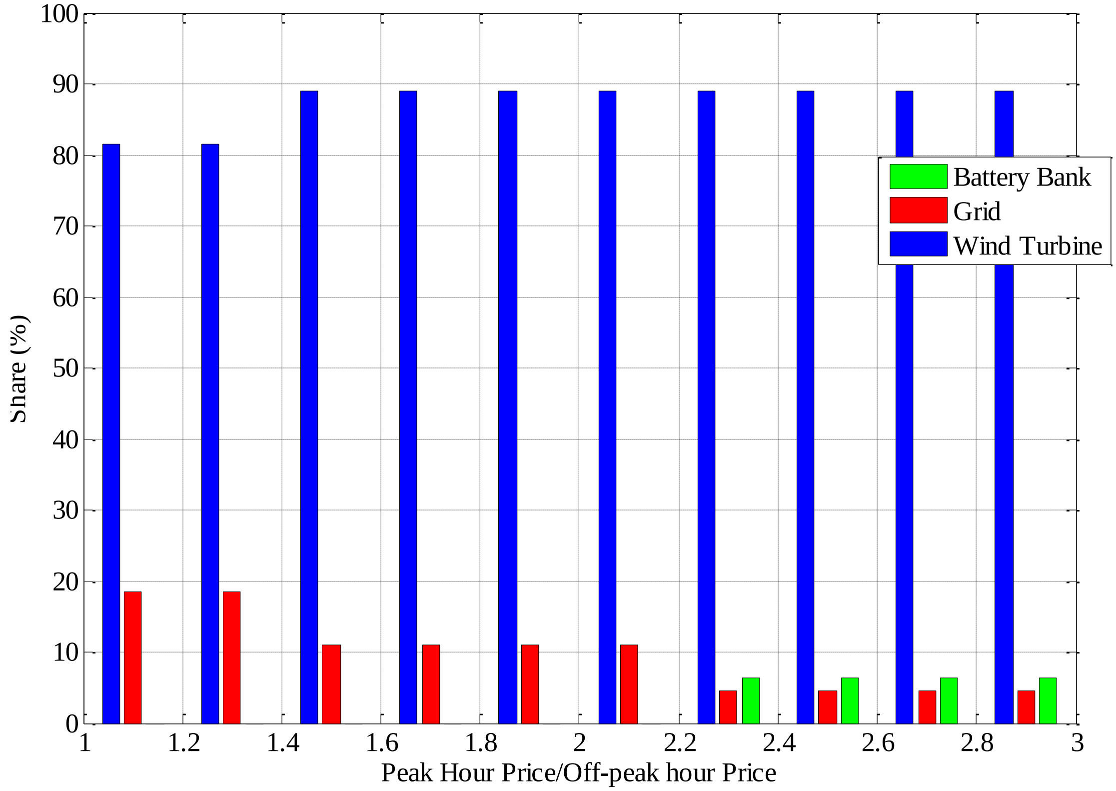


Figure 3-4 share vs. Peak Hour Price Rate

From result data in Table 3-3 the peak hour prices can be divided into three categories:

1-Peak Prices<= 1.3Off-peak hours

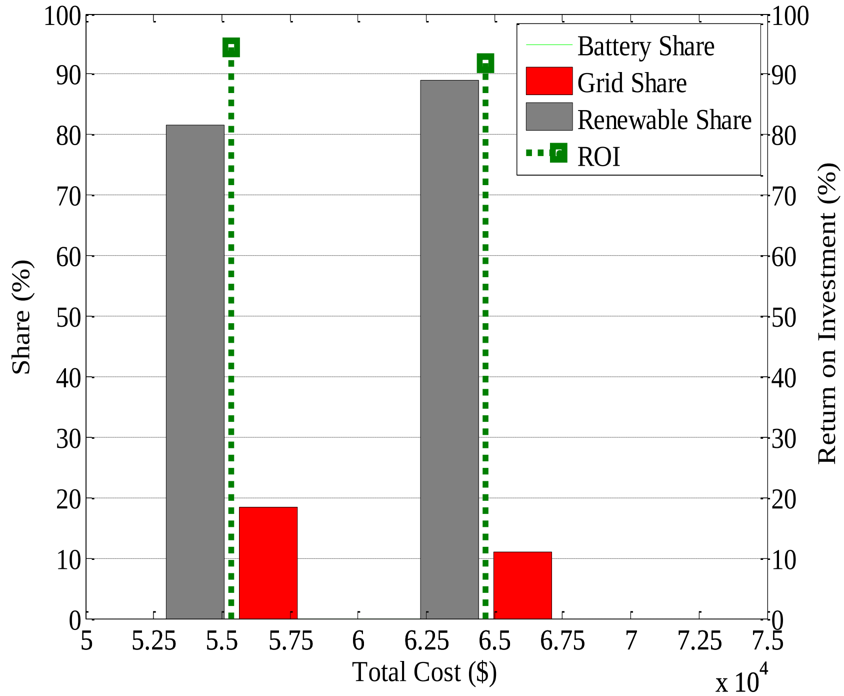
2-1.3<Peak Prices< 2.3Off-peak hours

3-Peak Prices>= 2.3Off-peak hours

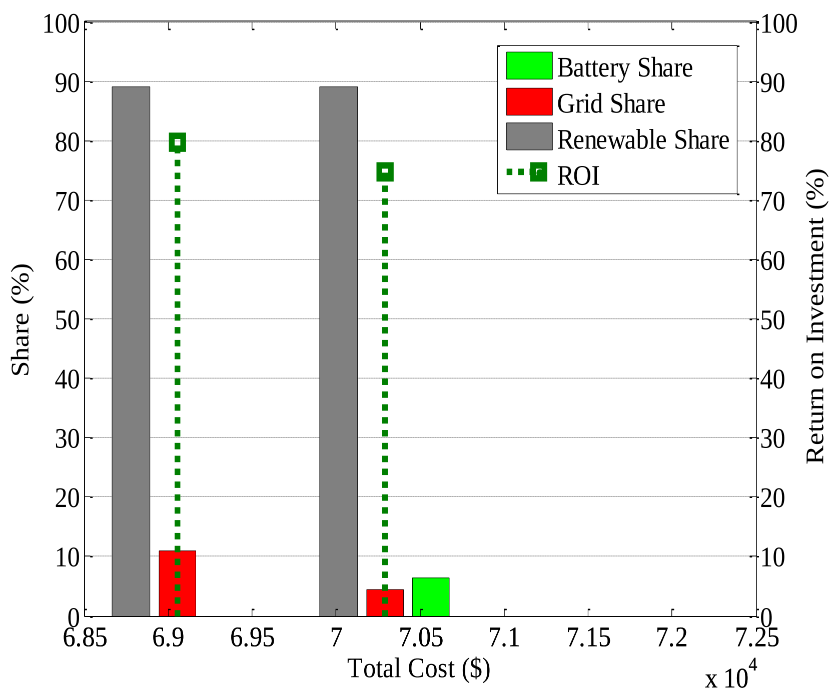
Table 3-3 Optimum configuration of each price rate

Peak price/Off-peak price	WT Rotor Disk Area (m2)	PV Panel Area(m2)	Number of Batteries	Grid Supply for Peak hour
1.1	28.27	0	0	Yes
1.3	28.27	0	0	Yes
1.5	40.72	0	0	Yes
1.7	40.72	0	0	Yes
1.9	40.72	0	0	Yes
2.1	40.72	0	0	Yes
2.3	40.72	0	32	No
2.5	40.72	0	32	No
2.7	40.72	0	32	No
2.9	40.72	0	32	No

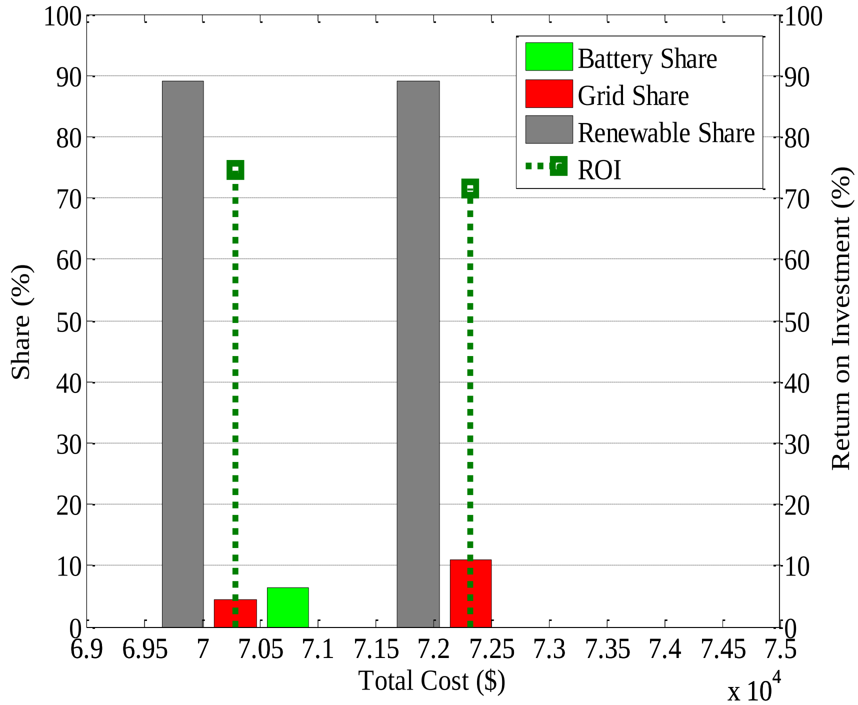
Figure 3-5 compares the price and the share of each power resource for a sample rate in each of three above categories. The figure shows that at rates less than 1.5 there is no justification to add the battery bank. By comparing two best solutions of Figure 3-5 (1) it is observed that the configuration with less share of HRES have less total cost comparing to next configuration which actually has more HRES share in load satisfaction. As the peak hour price increases to 1.5 times the off-peak hour the configuration with batteries appear as the second best options yet not the best one Figure 3-5 (2). And eventually the configuration with the battery bank becomes the optimum configuration when the peak hour price reaches to 2.3 times more than the off-peak hour price Figure 3-5(3).



(1) Peak price=1.1 Off-peak



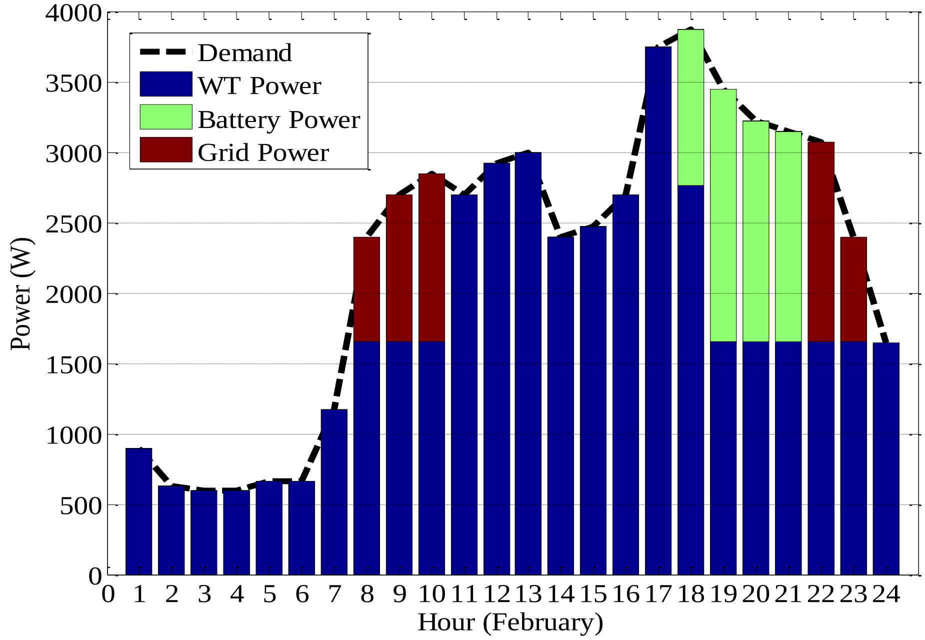
(2) Peak price=1.9 Off-peak

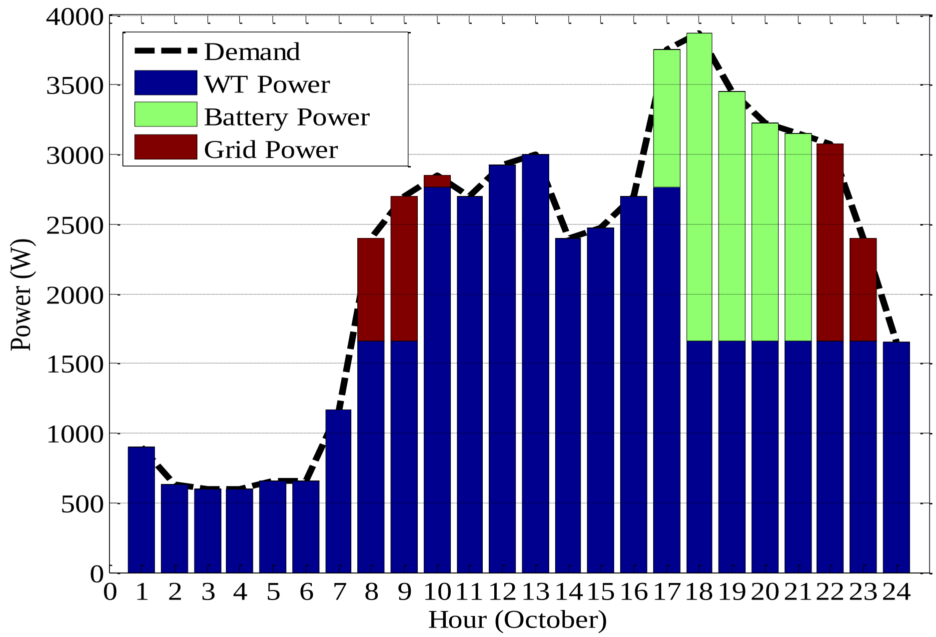


(3) Peak price=2.3 Off-peak

Figure 3-5 comparison between two best solutions of three different Peak prices

Figure 3-6 shows the detail of produced power and demand of the months in which the battery bank is used. Apparently the battery bank is used in four months of the year in which the wind speed is low. In other months either the wind turbine produces sufficient power or the shortage occurs in off-peak hours and the shortage is maintained from the grid.


4000
3500
3000
2500
2000
1500
1000
500
0
Power (W)
Demand
WT Power
Battery Power
Grid Power
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour (February)


4000
3500
3000
2500
2000
1500
1000
500
0
Power (W)
Demand
WT Power
Battery Power
Grid Power
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour (October)

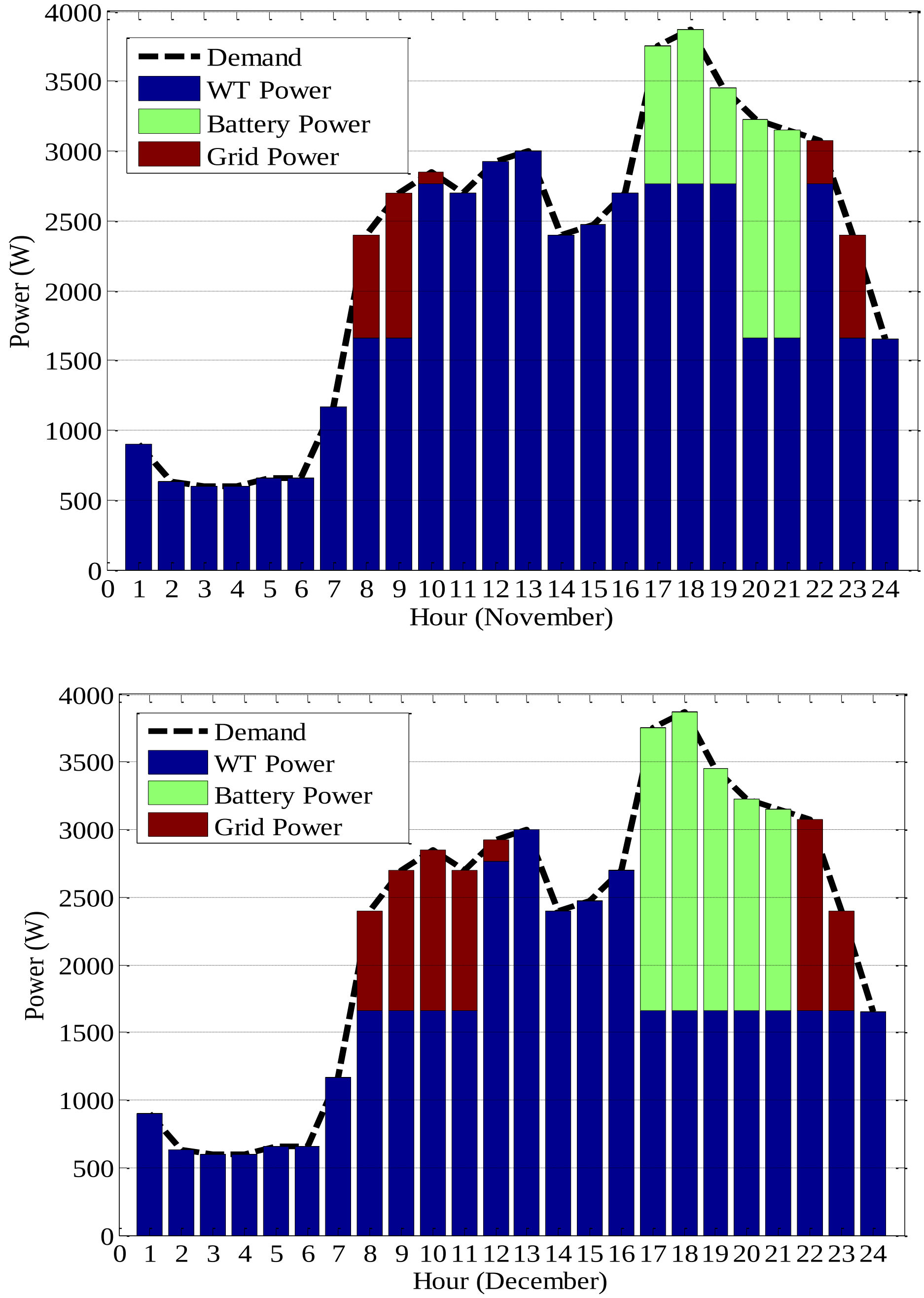


Figure 3-6 The produced power of each source for typical months

3.6 Summary

New concepts in buying electricity from grid such as different prices at different hours requires development of new design methods in grid-connected HRES those conventionally rely on grid to obtain their required electricity during the shortage hours. The method proposed in this study is based on investigating the possibility of adding a small storage system to cover the electricity shortage during peak hours. The proposed method takes into account adding battery bank to conventional grid-connected HRES configuration as an option to overcome the consequences of different electricity prices. The outcome of the design would be more profitable and at the same time the owner would be less dependent on the grid. The system configurations are evaluated in terms of power production and economical aspects. The amount of electricity bought from the grid is added as an economic factor to the design of the HRES

4 Reliability of Deterministic Design Approach

4.1 Introduction

In the deterministic approach, all design inputs and variables are considered as known variables without any randomness or uncertainties involved in design variables during system design and analysis. Common deterministic approaches use mean values as inputs of the systems. In most of the studies reported on the deterministic design approach of HRES, the hourly average values of solar radiation, wind speed and power demand are used as the design inputs [37, 98, 99]. To ensure the system reliability, the system is designed based on worst case scenarios (for example the system is designed based on the month with least available renewable resources) [100] or a margin of safety is usually considered. It is also shown in [101] that in the context of multi-objective optimisation with conflicting objectives of cost and reliability, for each design problem, there exists an optimum margin of safety that can be used to produce a Pareto solution. Following the deterministic design approach, different methods in optimal sizing of HRES have been considered based on different reliability objectives. Balamurugan et al. [19] proposed a hybrid energy system consisting of biomass, wind, photovoltaic and battery to deliver maximum renewable energy by considering appropriate energy storage to meet peak demand during periods of low (or no) solar radiation or wind. Diaf et al. [102] analysed the optimum configuration of a standalone hybrid photovoltaic-wind system that guarantees the energy autonomy of a typical remote consumer with the lowest LCOE. Yang et al. [42] proposed an optimal sizing method based on Generic Algorithm (GA) technique using a typical meteorological year data. The proposed optimisation model calculates the system optimum configuration which is capable of achieving the desired loss of power supply probability (LPSP) with minimum Annualized Cost of System. Deterministic approaches are widely used in design of HRES, though they rely on many uncertain parameters which have direct effects on the performance of the designed HRES. Unrealistic estimation of the uncertainties may lead to violation of system design constraints such as lower reliability. On the other hand overestimation in the effect of uncertainties in the output of the HRES may yield in high maintenance costs and [103] shows that calculated costs via a deterministic approach deviate from the cost obtained by Monte Carlo simulation even without having uncertainty in cost modelling. Normally obtaining a desired reliability level is considered during design of a standalone HRES by sizing the battery bank based on worst case scenario which is non-availability of renewable resources for several days called as days of autonomy. Conventional reliability measurement methods take into account the overall performance of the system and do not focus on the time and period of blackout occurrence.

This chapter focuses on the reliability measures during the design of HRES and shows the weakness of traditional design method of HRES in maintaining a satisfactory power generation system even though the overall desired reliability criteria is been satisfied. The concept block diagram of the designed system in this study is presented in Figure 1-1. The power supply from wind turbine and PV panels to the load, the battery bank and dump load follows the priority of first load; second the battery bank and last the dump load. When the total output of wind turbine and PV panels is more than load demand and the battery is not fully charged the excess energy is used to charge the battery and in case that wind turbine and PV panel output is not enough to cover the load demand the battery will maintain the power shortage.

4.2 Problem formulation and design methodology

The objective is to find the optimum configuration of a standalone HRES with minimum total cost while satisfying the load demand at the desired reliability level.
The input data would be average hourly or monthly meteorological data of wind speed and solar irradiance of the desired site along with the average hourly load demand. Here $DPSP$, the deficiency of power supply probability is chosen as the reliability assessment criterion and any configuration of hybrid system which satisfies above constraint is considered as feasible solution.

Here the wind turbine/PV system sizing optimisation is performed following a deterministic design approach based on exhaustive search. The averages hourly of weather data and load profile are used as inputs of the design. The power from each resource is calculated at each time step (every hour) based on the capacity of power generator.

Conventionally the battery bank is sized prior to wind turbine and PV panels' sizing. The size of the battery bank is determined to meet the load demand during autonomy days, two or three days a year [11]. Following equation estimates the battery bank size with consideration of maximum depth of discharge, rated battery capacity and battery life using Equation 3.6.

The performance of whole system is then simulated with :

$$P_{Total\_HRES} = \begin{cases} P_{WT} + P_{PV}, & (a) \\ P_{WT} + P_{PV} + P_{Bat} & (b) \end{cases} \tag{4.1}$$

(a) if total power generated by wind turbine and PV is sufficient to cover the load demand otherwise

(b) where P_{WT} and P_{PV} is not sufficient

and state of charge the battery :

$$SOC \geq SOC_{\min} \tag{4.2}$$

The reliability of each design candidate can be measured with Equation 4.3 [104]:

$$DPSP = \frac{\sum_{i=1}^{8760} DPS_i}{\sum_{i=1}^{8760} P_{load_i}} \tag{4.3}$$

where DPS is amount of deficiency in power supply at each hour.

4.3 Case study

The conventional design method is used to design a grid-connected HRES for a household in Kent, UK. Inputs of the design are typical summer and winter load profiles Figure 1-2 and hourly average of wind speed and solar irradiance data for 12 months of the year which are presented in Figure 4-1 & Figure 4-2 .

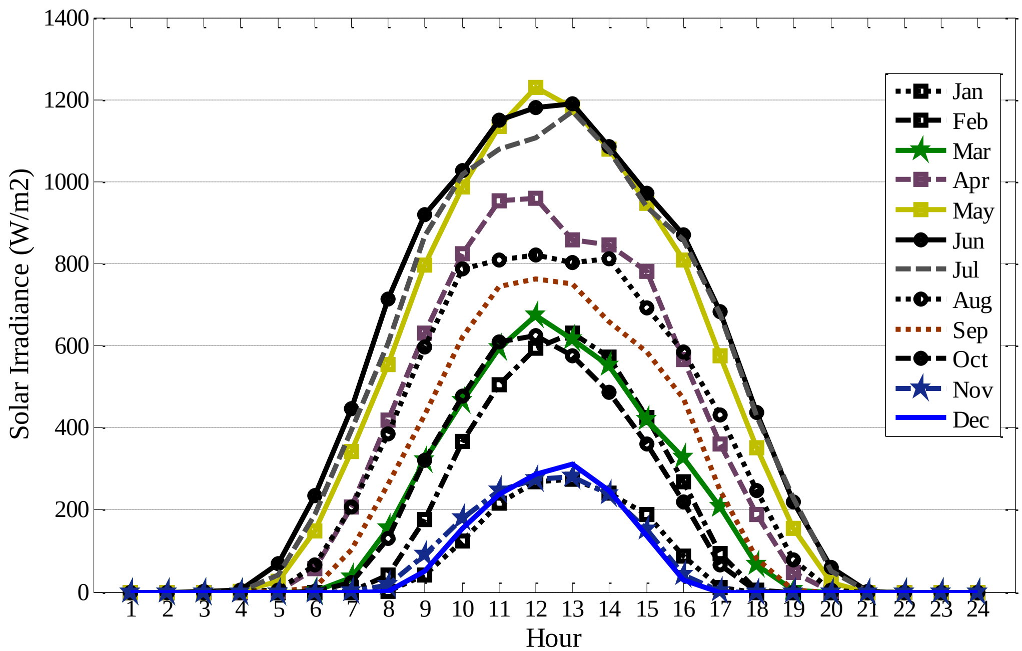


Figure 4-1 Average Hourly Solar Irradiance

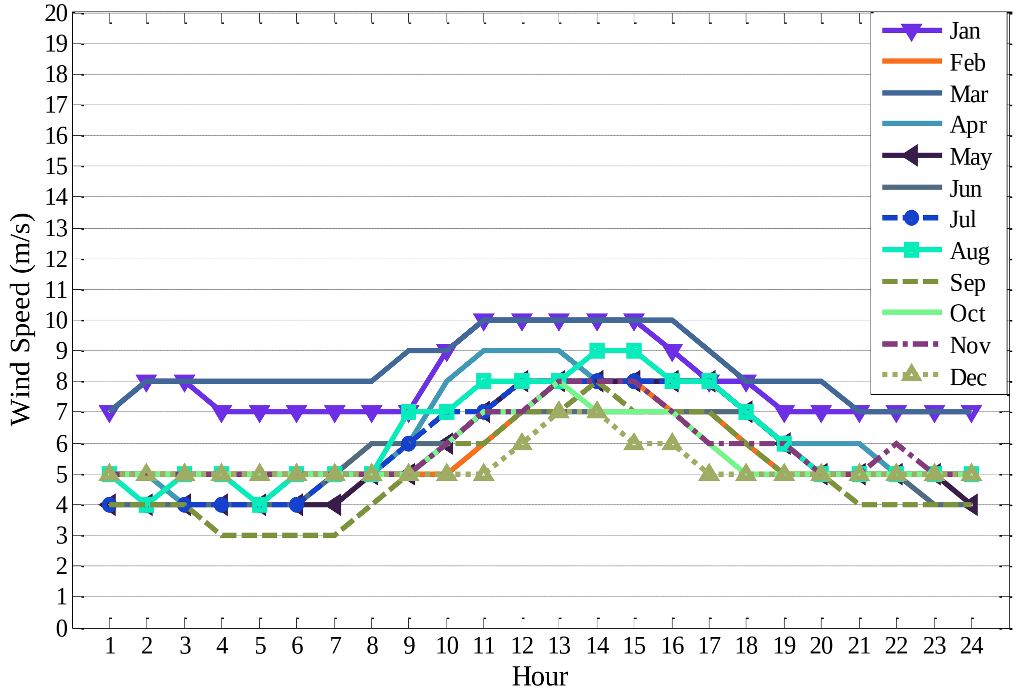


Figure 4-2 Average Hourly Wind Speed

Technical and economical characteristics of the system components are given in Table 1-1.

The battery bank is sized based on three days of autonomy and the overall $DPSP$ of the system is considered to be less than $DPSP_{desired} = 1\%$

Table 4-1 Optimum solution based on common design method

Optimum Solution				
WT Rotor Disk Area (m2)	**PV Panel Area (m2)**	**Number of Batteries**	**DPSP (%)**	**Cost ($)**
40.715	0	187	0.4658	124285

4.4 Results and Discussion

Through an optimisation method the optimum size of wind turbine and PV panel is obtained. Table 4-1 presents the optimum sizes of wind turbine rotor disk area, PV panel area, number of batteries and the overall $DPSP$ of the system. As expected the optimum size for PV is calculated as zero due to the fact that wind is dominant in the site under study. Although the optimum solution has $DPSP$ of 0.47% as a system with high reliability, a more detailed look to the times of power supply deficiency occurrences and their possible blackout duration shows that this configuration may not be the most satisfactory solution to the user because majority of power shortages are most likely to happen very close to each other during the evening in the winter season.

Figure 4-3 shows a comparison with produced power of HRES and the demand of a typical day in winter with the possibility of power shortage. The figure shows that the blackout may actually continue for long hours in this day. From Figure 4-4 it is seen that in some months when the wind speed is not high enough to produce enough power to cover the load demand and charge the battery bank long blackouts may happen even though the battery bank is sized to cover the maximum load level for three days.

The case study introduced a problem on the common design methods in optimal sizing of HRES based on a predefined reliability. As a preliminary solution to the stated problem, adding a constant on the maximum duration of the blackouts is proposed here. The state of charge (SOC) of the battery can be used as an indicator for the blackout occurrence. The times when the battery bank is at its maximum depth of discharge the blackouts are more likely to happen and can be counted as blackout occurrences. The proposed solution is used to redesign the HRES for desired site in the case study and new optimum sizes of the HRES components are presented in Table 4-2.

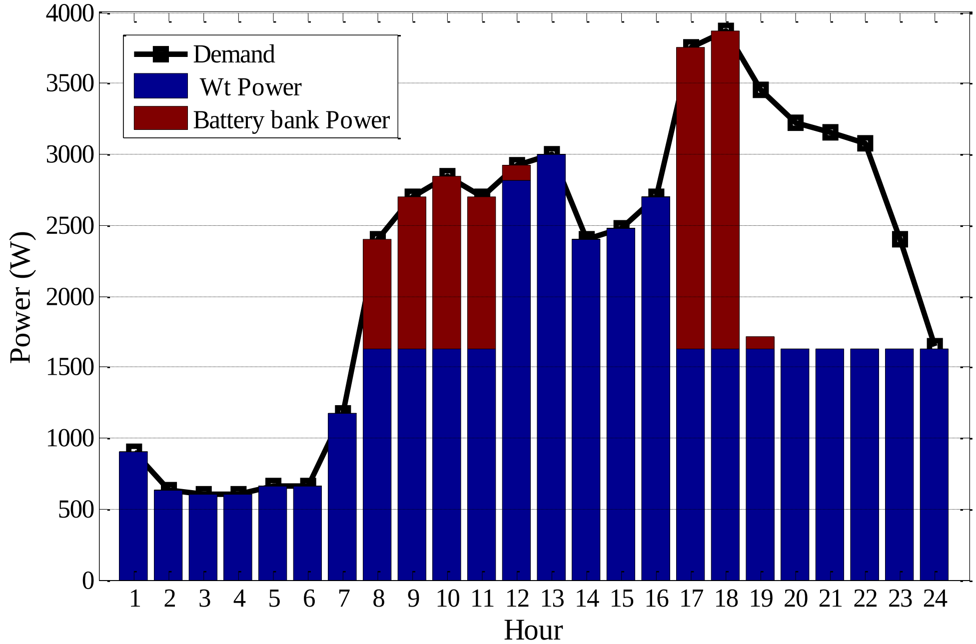


Figure 4-3 Typical Day with Power Shortage

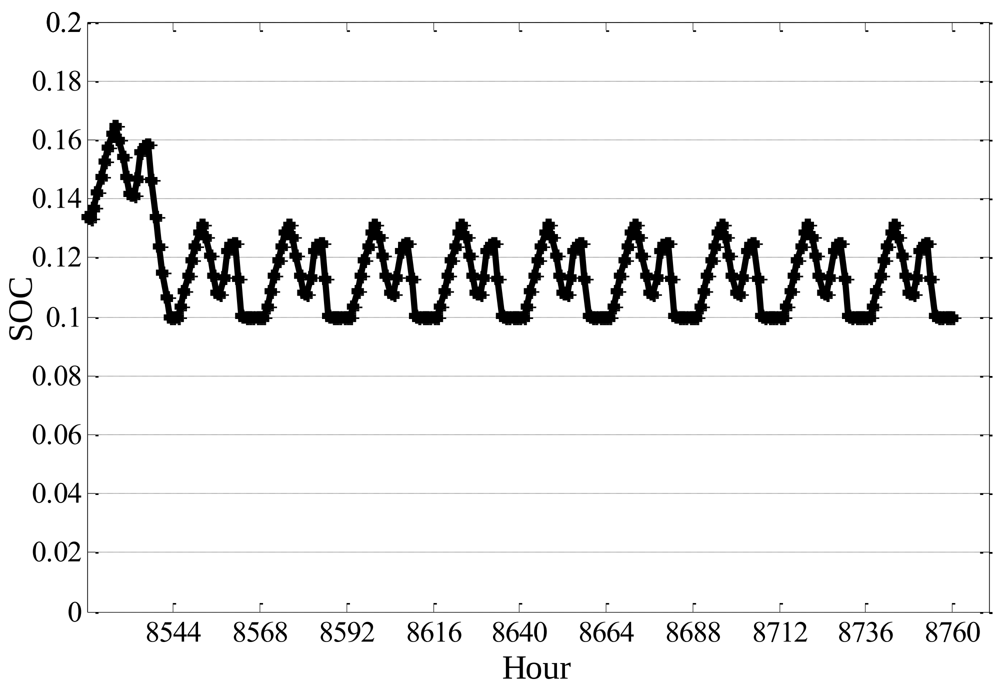


Figure 4-4 State of Charge of the Battery Bank

Table 4-2 Optimum solution after adding constraint on maximum blackout hours

Optimum Solution				
WT Rotor Disk Area (m2)	**PV Panel Area (m2)**	**Number of Batteries**	**DPSP (%)**	**Cost ($)**
55.418	0	187	0	144045

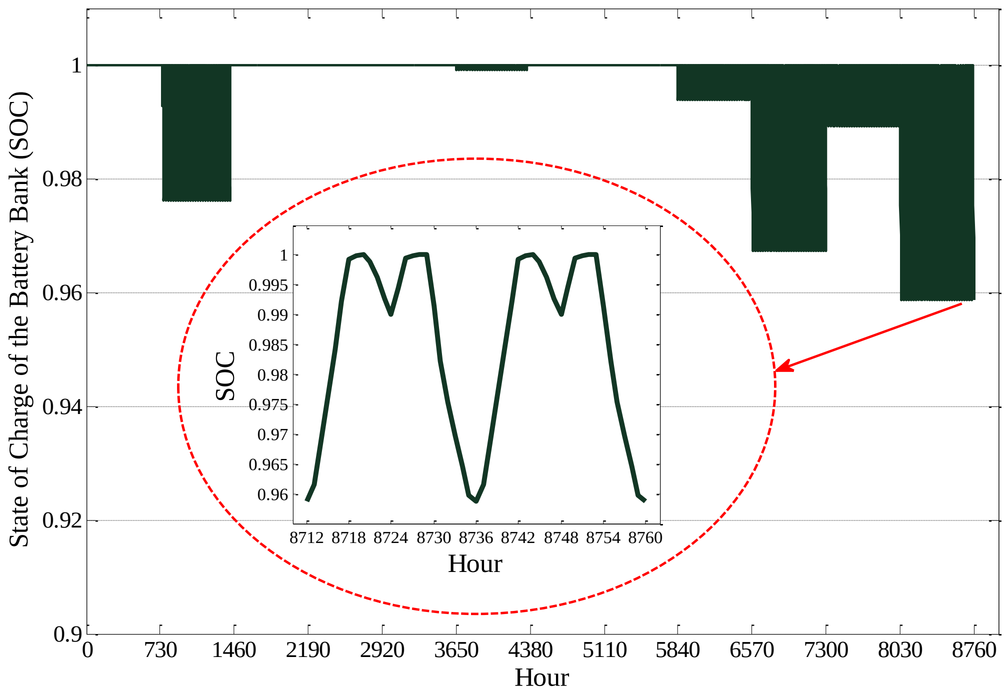


Figure 4-5 State of Charge of the Battery Bank after considering maximum blackout hours in design

Figure 4-5 shows the state of charge of the battery through the whole year in new design. Since this value never reaches in the neighbourhood of the maximum depth of discharge of the battery, the blackouts are very unlikely to happen in the designed system.

4.5 Summary

Traditional reliability measurement criterions in design of HRES only consider the overall performance of the HRES in design period (for example in a year) and ignore the time and duration of blackouts occurrences in short times. That is why even though the designed system has an overall high reliability measure; it may not be satisfactory as majority of power shortages may happen during a short period.

This study shows that in addition to traditional reliability measurements during the design a more precise design criterion should be considered in order to prevent design failures.

5 Stochastic design approach in optimal sizing of HRES

5.1 Introduction

Considering uncertainties when designing the system, could improve the HRES performance. For that, a realistic method is required to simulate the wind speed and solar irradiance variations. Different approaches are used to model the renewable sources behaviour. One of common approaches is fitting the uncertainties to known distributions such as Weibull or Beta distributions [77]. However researches show that, for some locations like UK using predefined distributions may not simulate the weather data properly[105]. Erken [106] used different distributions to find the best fitted distribution for each hourly meteorological data. Another method in considering uncertainties is adding a random disturbance to average values of wind speed and solar irradiance [107]. Lujano-Rojas [76] and Ji [108] used time series analysis to model wind speed and solar irradiance variations accordingly. Time series could be a viable solution to model the uncertainties with unknown distributions.

Different methods to integrate the uncertainties in renewable resources in the design of HRES have been reported. Giannakoudis et al [107] considered adding a known disturbance to the design inputs to maintain optimum mix of renewable resources. Nandi and Himri [55, 109] fitted wind speed variation with Weibull distribution. Lujano-Rojas el al [76] used time series theory to simulate the uncertainties in wind speed in the design of small wind/battery systems. Usually, the Monte Carlo simulation approach is used in solving probabilistic problems. Given a significantly large sample size, this method can provide highly accurate results. However, the main drawback is the computational burden associated with the large number of repeated calculations [110]. In addition to the common 'under uncertainties' design methods, the chance constrained programming approach is also a popular method in solving the problems dealing with random parameters. This method was first introduced by Charnes and Cooper [78] in 1959. Its main feature is that the resulting decision ensures the probability of complying with constraints [83]. The chance constrained

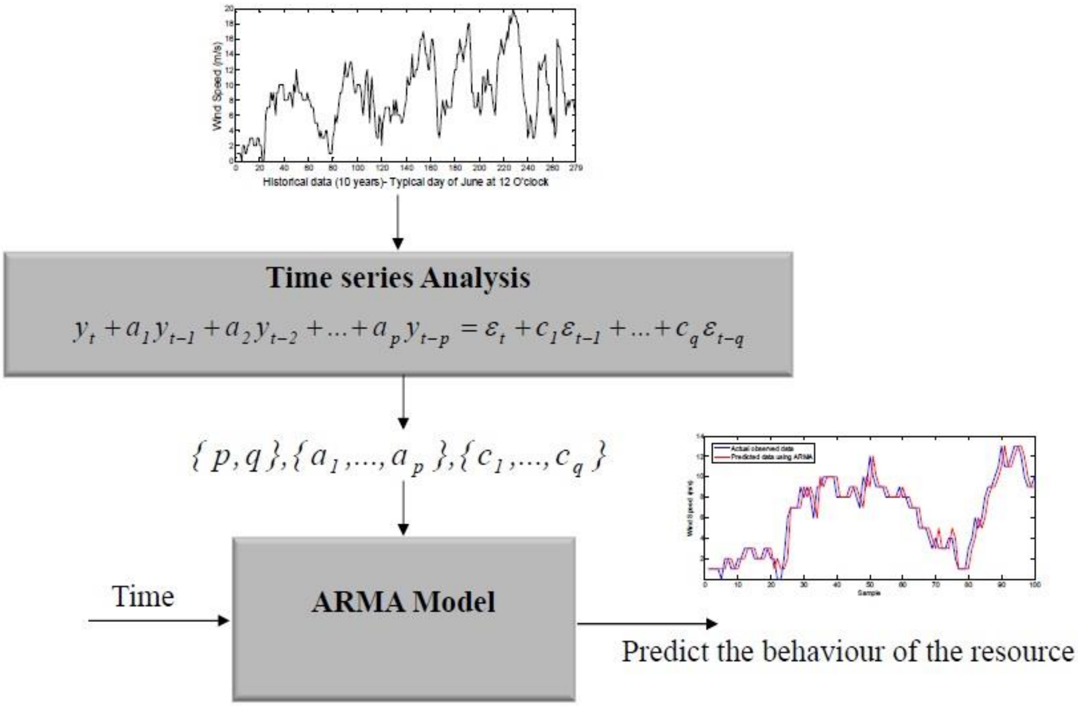


Figure 5-1 Block diagram of applying time analysis on historical weather data

method has been widely applied in different disciplines for optimisation under uncertainty[111], but a very few studies are reported using this method in the design of HRES. Arun et al [112] used the chance constrained programming approach in the design of photovoltaic battery system to deal with the uncertainties in the solar radiation. Seeraj et al [113] used this method to find the battery bank size when renewable energy resource availability, ratings and load demand were assumed to be known.

This chapter proposes a method in simulation of wind speed and solar radiation variations with time series analysis and Monte-Carlo simulation to design a stand-alone HRES. Here the historical hourly values of wind speed and solar irradiance are fitted to proper auto-regressive moving average (ARMA) models to simulate the uncertainties in wind speed and solar irradiance values. Using Monte-Carlo simulation method, design candidates are evaluated based on reliability and the system total cost. The latter is introduced as the optimum solution.

5.2 The wind speed and solar irradiance simulation model

In this chapter the uncertainties in wind speed and solar irradiance is simulated using time series method. An ARMA model is fitted to historical meteorological data of each hour of a typical day of each month of the year. Block diagram of applying time analysis on historical weather data is presented in Figure 5-1. The output is used to simulate the variability in wind speed and solar irradiance data of each particular hour which will be used in Monte-Carlo simulation of design candidates.

5.2.1 Problem formulation and design methodology

The objective is to find the optimum configuration of a standalone HRES with minimum total cost while satisfying the load demand at the desired reliability level. The reliability is measures by calculation the deficiency of power supply probability (DPSP).

The optimisation problem can be formulated as:

$$\min TC = C_{IC} + C_{rep} + C_{O\&M} \tag{5.1}$$

while

$$DPSP \leq DPSP_{desired} \tag{5.2}$$

$DPSP$ is the overall probability of deficiency in annual total power generated by the hybrid system (Equation 4.3) and any configuration of hybrid system which satisfies above constraint is considered as feasible solution.

The design variables are the rotor swept area of wind turbine and area of PV panel.

The wind turbine rotor area is varied in the range from 0 to 300 m^2, PV panels' area is from 0 to 175 m^2. The battery bank is sized using Equation 3.6.

The performance of whole system is then simulated as:

$$P_{Total\_HRES} = \begin{cases} P_{WT} + P_{PV}, & (a) \\ P_{WT} + P_{PV} + P_{Bat} & (b) \end{cases} \tag{5.3}$$

(a) if total power generated by wind turbine and PV is sufficient to cover the load demand otherwise,

(b) the battery supplies the difference P_{Bat} as long as the state of charge the battery is:

$$SOC \geq SOC_{\min} \tag{5.4}$$

Considering the uncertainties in renewable resources (modelled using times series analysis), the reliability of each HRES design candidate is analysed using Monte-Carlo simulation and the optimum solution with minimum total cost is selected among design candidates that satisfy the reliability constraint using exhaustive search.

5.2.2 Case study

The proposed method is used to design a stand-alone HRES for a household in Kent, UK. The input data for the design are typical summer and winter load profiles which are presented in Figure 1-2 in addition to historical hourly data of wind speed and solar irradiance data for 12 months of the year. The ARMA parameters for wind speed and solar irradiance of each individual hour is estimated based on historical meteorological data for one typical day of each month. The output of ARMA simulation is used as hourly wind speed and solar irradiance in Monte-Carlo simulation. Examples of simulated wind speed and solar irradiance variations for a typical day in January are presented in Figure 5-2 & Figure 5-3.

The results of technical and economical characteristics of the system components are given in Table 1-1.

The battery bank is sized based on three days of autonomy and the overall $DPSP$ of the system is considered to be less than $DPSP_{desired} = 15\%$.

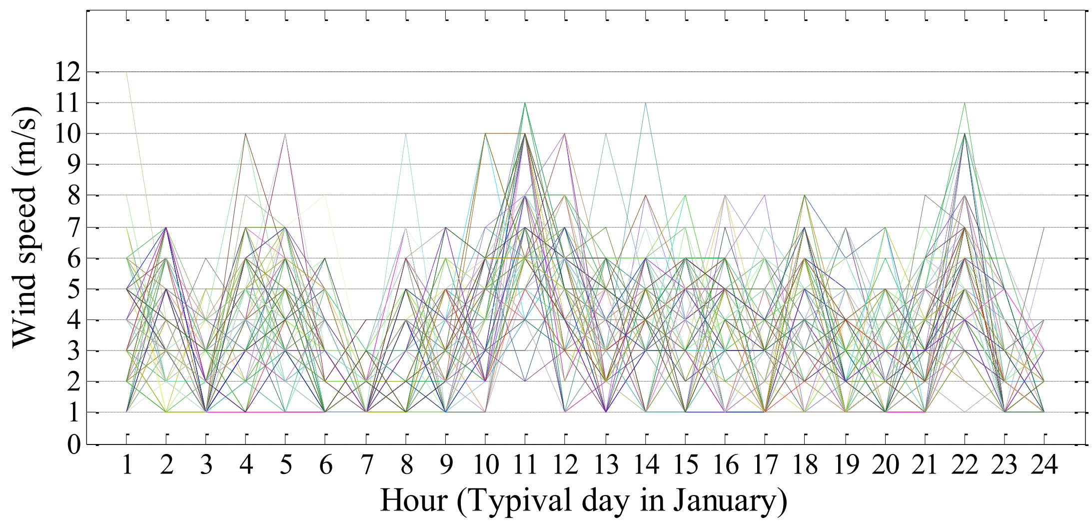


Figure 5-2 An example of simulated wind speed

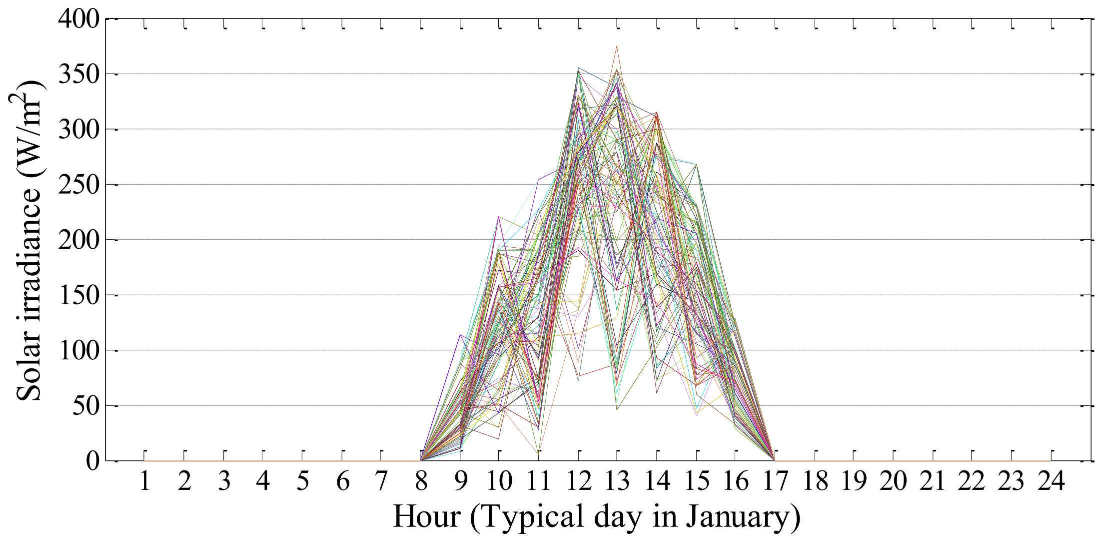


Figure 5-3 An example of simulated solar irradiance

5.2.3 Results and Discussion

In order to investigate the performance of modelling uncertainties with method explained in Section (5.2.1) in optimal design of HRES, an exhaustive search is performed to solve the optimisation problem Equation (5.1) the mean value of DPSPs obtained by performing 10,000 Monte-Carlo simulations on each design candidate is considered as its overall DPSP and the optimum solution which satisfies the Figure 5-4 compares the upper and lower limits of DPSP values in different configurations of HRES. The optimum configuration is marked in Figure 5-4 and Table 5-1.

Figure 5-5 & Figure 5-6 show the values and the distribution of DPSP values for the optimum solution obtained using Monte-Carlo simulation.

The probability of blackout occurrence can be calculated using Monte-Carlo simulation result. The hours, when the battery bank is at its minimum state of charge or the overall available power of HRES is less than load demand, are counted as blackout hours. The probability of blackout occurrence is then calculated with:

$$\Pr obability_{Blachout,Hour} = \frac{n_{Blackouts}}{N_{Simulations}} \tag{5.5}$$

Figure 5-7 represents the probability of blackout occurrence in each day of the year for the optimum solution which is calculated with Equation 5.5. The figure clearly shows that the blackouts have strong probability to happen in the last three months of the year when renewable resources availability is not high enough to cover the load demand and charge the battery bank.

Table 5-1 Optimum Configuration

Optimum Solution			
WT Rotor Disk Area (m^2)	**PV Panel Area (m^2)**	**Number of Batteries**	**DPSP (%)**
92	150	187	15

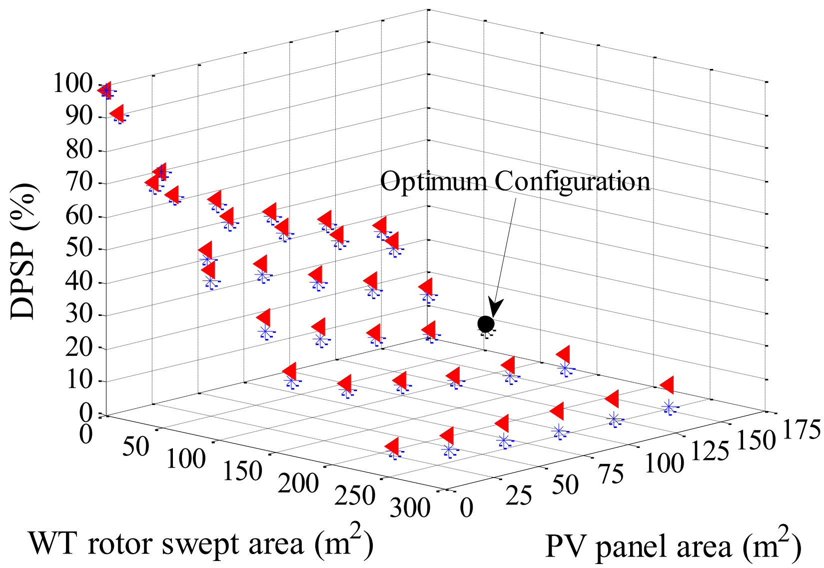


Figure 5-4 Upper & lower DPSP for design candidates

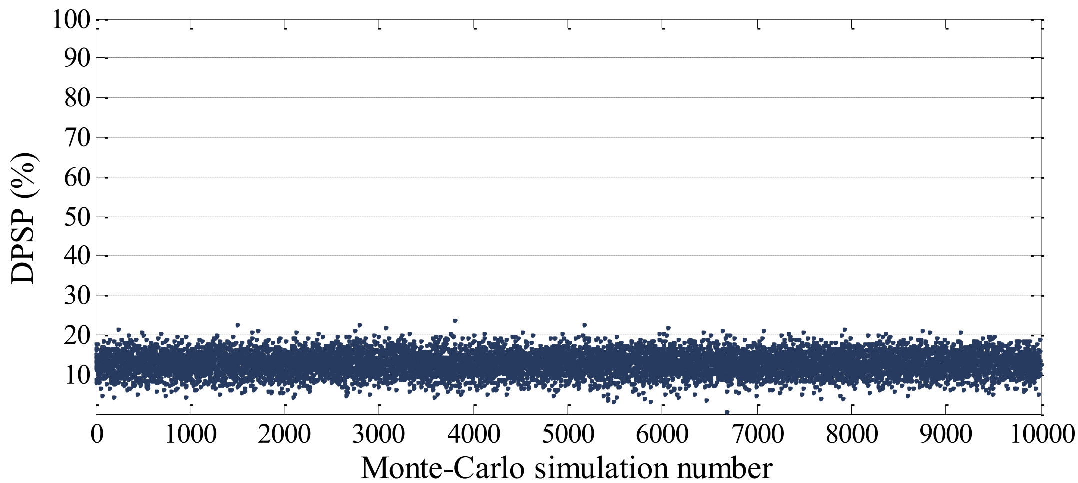


Figure 5-5 DPSP values of optimum solution

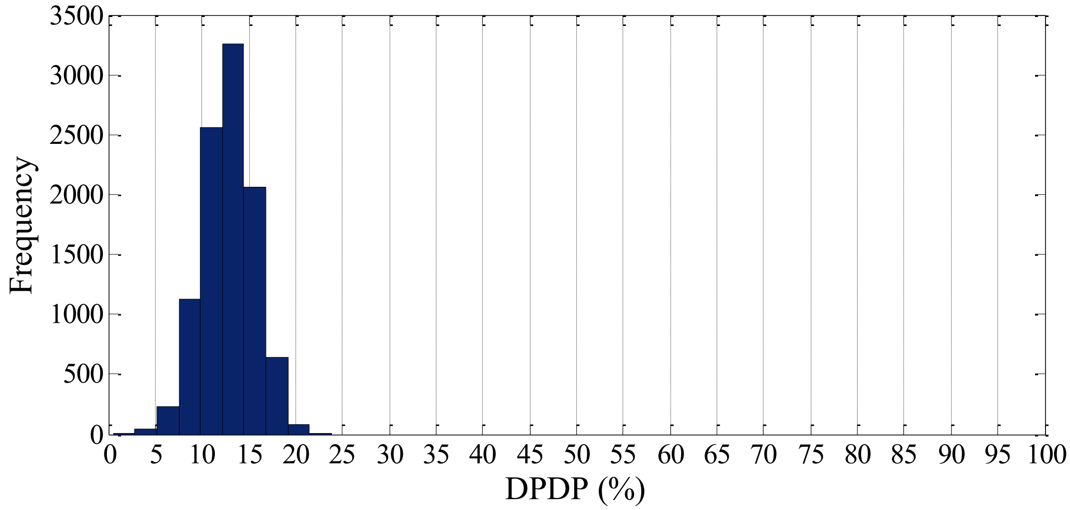


Figure 5-6 Distribution of DPSP values for optimum solution

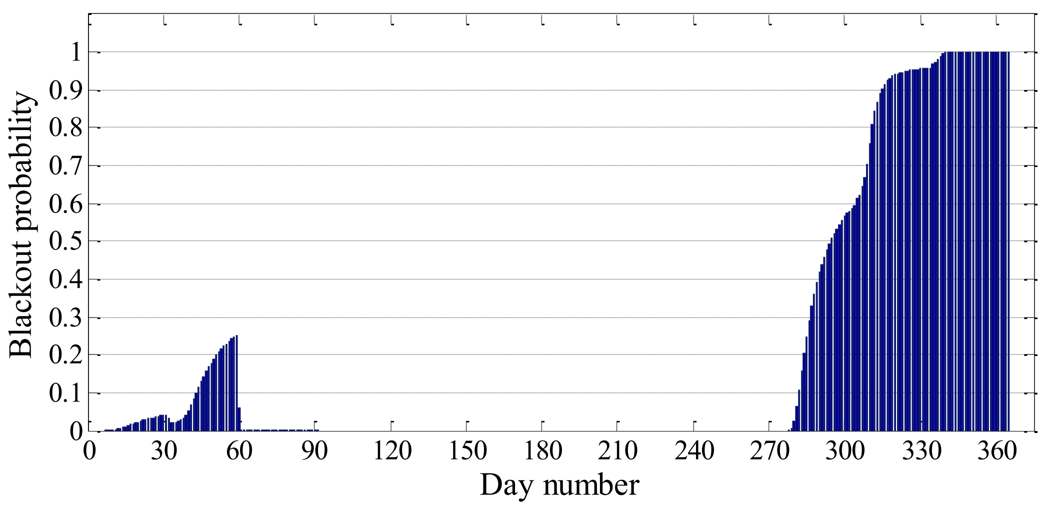


Figure 5-7 Probability of blackout occurrence for each day of year

5.2.4 On the Sensitivity Analysis

As the wind turbine and PV panel models presented in Equations 2.1 & 2.11 are dependent on wind speed and solar irradiance data of desired site and the unpredictable nature of renewable resources have been considered in stochastic design approach , performing sensitivity analysis would not result in additional useful information here.

5.2.5 Summary

The Hybrid Renewable Energy System (HRES) can be a reliable solution to bring electricity to isolated areas where there is no access to the grid by considering uncertainties in resources at the design stage. Appropriate modelling of wind speed and solar irradiance variations, at the design stage, would give a more realistic picture of the designed system performance. This study shows that ARMA models can be used as a proper method in simulating the wind speed and solar irradiance data in design of HRES.

6 Chance Constrained Programming Using Non-Gaussian Joint Distribution Function in Design of Standalone Hybrid Renewable Energy Systems

6.1 Introduction

Performance of a Hybrid Renewable Energy Systems (HRES) is highly affected by changes in renewable resources and therefore interruptions of electricity supply may happen in such systems. In this chapter, a method to determine the optimal size of HRES components is proposed, considering uncertainties in renewable resources. The method is based on chance-constrained programming (CCP) to handle the uncertainties in power produced by renewable resources. The design variables are wind turbine rotor swept area, PV panel area and number of batteries. The common approach in solving problems with CCP is based on assuming the uncertainties to follow Gaussian distribution. The analysis presented in this chapter shows that this assumption may result in a conservative solution rather than an optimum. The analysis is based on comparing the results of the common approach with those obtained by using the proposed method. The performance of the proposed method in design of HRES is validated by using the Monte Carlo simulation approach. To obtain accurate results in Monte Carlo simulation, the wind speed and solar irradiance variations are modelled with known distributions as well as using time series analysis; and the best fit models are selected as the random generators in Monte Carlo simulation.

Increasing energy demand and depletion of fossil fuel resources have made renewable energy resources more attractive [114] and advances in technologies had led to reduced cost, making renewable energy systems competitive with fossil fuels especially in remote places where grid connection is not available [115].The power generated from renewable resources is completely dependent on renewable resources and therefore, largely unpredictable. There are many research works reported on the assessment of global energy potentials resources [116] and on investigating the vulnerability of renewable systems and improvement of their performance. Kalogirou [117] investigated the effect of environmental pollutants and dust that are transferred with the air on performance of PV panels. Greening [118] performed an evaluation on the life cycle environmental sustainability of micro-wind turbines in the UK , as compared with grid electricity and solar PV panels. As the isolated operation (standalone operation) of these power units may not be effective in terms of cost and reliability [119] unless properly optimised for those qualities. In recent years there has been an increased interest in the use and optimisation of hybrid renewable energy systems (HRES) as a viable solution to provide a reliable power supply, particularly in rural areas with standalone systems [120]. Generally, a HRES combines two or more energy sources to generate reliable power to satisfy the load demand at all times and under various weather conditions. Conventionally, the balance between demand and the system output in standalone systems is obtained by using an auxiliary power source such as a diesel generator and/or storage such as battery bank. To ensure an effective use of available renewable energy resources (wind, sun,...), optimal design and sizing of HRES are essential. The aim is to optimise the mix of renewable energy systems available to meet the load power demand, minimise the combined intermittency in power generation, maximize their contribution to the peak load (thus minimising power generation from the auxiliary power source)and do this at a minimum cost [121]. That is, using optimal design to achieve cost effective and reliable HRES. Generally two approaches are followed in design of HRES; deterministic or stochastic.

In the deterministic approach, all design inputs and variables are considered as known variables without any randomness involved during system design and analysis. Common deterministic approaches use mean values as the systems' inputs and most of the work reported on the deterministic design approach of HRES implement the hourly average of solar radiation, wind speed and power demand as the design inputs [37, 98, 99]. To ensure the system reliability, the system is designed based on worst case scenarios (for example the system is designed based on the month with least available renewable resources) [100] or a margin of safety is usually considered.

Stochastic approaches attempt to solve the optimisation problem involving uncertainties. They deal with uncertainties by using resource functions and chance constraints to transform the stochastic optimisation to an equivalent deterministic optimisation problem [122]. Chance constrained programming approach is a popular method in solving the problems dealing with random parameters. The chance constrained method has been widely applied in different disciplines for optimisation under uncertainty[111], but a very few studies are reported using this method in the design of HRES. Arun et al [112] used the chance constrained programming approach in the design of photovoltaic battery system to deal with the uncertainties in the solar radiation. Seeraj et al [113] used this method to find the battery bank size when renewable energy resource availability, ratings and load demand were assumed to be known. For simplicity the power produced by photovoltaic array and wind turbines are assumed to follow a bivariate normal distribution with known mean and standard deviation.

In this chapter, the chance constrained programming approach is used to design a standalone hybrid wind turbine/PV and battery bank system. The design variables are the rotor swept area of wind turbine, area of photovoltaic panel and the size of battery bank. However, assuming normal distribution as the joint distribution of produced power by wind turbine and PV panel may not result in a realistic output of the system. Therefore, in this study the joint distribution of the wind turbine and PV panel output power is considered to follow an unknown distribution and individual cumulative distribution function (CDF) of the produced power by wind turbine and PV panel. The CDF, corresponding to each hour of typical days of 12 months of the year, is calculated based on the hourly historical data of wind speed and solar irradiance. The design candidates are constrained in satisfying the load demand, which is achieved when the overall probability of the load demand to be satisfied is more than a certain value. The design candidates satisfying the reliability constraints are evaluated by their total cost. The design candidate with minimum total cost is defined as the optimum configuration. The reliability of the design output is validated through Monte Carlo simulation. As the performance of Monte Carlo simulation is directly dependent on the accuracy of its random data generator, two common methods in modelling wind speed and solar irradiance variations are used to deal with this. These methods are the time series analysis and fitting historical data to the known distributions. They are performed on historical meteorological data of the desired site and the statistical characteristic of their output is compared to the observed data in order to ensure accurate modelling of wind speed and solar irradiance variation in the Monte Carlo simulation. The performance of the proposed design method is demonstrated in the design of an HRES for a household in Kent, UK, as explained in section 6.3.

The concept block diagram of the designed system used in this study is shown in Figure 1-1. The power generated from the wind turbine and PV panels follows the supply priority of first load; second the battery bank and last the dump load. When the total output of wind turbine and PV panels is more than load demand and the battery is not fully charged the excess energy is used to charge the battery. When the wind turbine and PV panel output is not enough to cover the load demand, the battery will supply the difference.

The development of this chapter is presented as follows:

The components modelling and cost modelling are presented in chapter 2.

Problem formulation and design methodology are presented in section 6.2 and a case study is described in section 6.3.

Validation with Monte Carlo simulation is described in section 6.4 and finally conclusions are presented in section 6.5.

6.2 Problem formulation and design methodology

The methodology of finding the optimum size of a standalone wind turbine/PV/Battery bank following a stochastic approach is discussed in this section. The objective is to find the optimum configuration of a standalone HRES with minimum total cost while satisfying the load demand at the desired reliability level. The objective function can be formulated as:

$$\min_{A_{WT}, A_{PV}, N_{Bat}} TC = C_{IC} + C_{O\&M} + C_{replacement} \tag{6.1}$$

The energy balance of the system can be simulated with:

$$P_{HRES} = \begin{cases} P_{WT} + P_{PV}, & (a) \\ P_{WT} + P_{PV} + P_{Bat} & (b) \end{cases} \tag{6.2}$$

(a) if total power generated by wind turbine and PV is sufficient to cover the load demand, otherwise

(b) when $P_{WT} + P_{PV}$ is not sufficient to meet the demand and the battery supplied the difference.

As mentioned before, ignoring the uncertainties in wind speed and solar irradiance leads to unreliable supply system. The design of HRES under uncertainties can be generally described as a nonlinear stochastic optimisation problem. Using the chance constrained programming the optimisation problem of optimal sizing of HRES can be defined as:

$$\min_{A_{WT}, A_{PV}, N_{Bat}} \{C_{IC} + C_{O\&M} + C_{replacement}\} \tag{6.3}$$

s.t.

$$\Pr(\sum P_i \geq Demand_i) \geq \alpha, i = 1,2,...,8760 \tag{6.4}$$

$$SOC \geq SOC_{\min} \tag{6.5}$$

where

$$P_i = P_{WT_i} + P_{PV\,i} + P_{Bat_i}, i = 1,2,...,8760 \tag{6.6}$$

Here the values of power generated by the wind turbine and PV system are dependent random variables following known distributions and the power of battery bank is dependent random variable. The historical hourly data of wind speed and solar irradiance are used to estimate the joint cumulative distribution function (CDF) of the power produced by the wind turbine and PV system at each time step (each hour) of calculation. The load demand is assumed to be deterministic and known at each time step and α is the reliability of compliance of the constraint or confidence level given as:

$$\alpha = 1 - DPSP/100 \tag{6.7}$$

where $DPSP$ of each design candidate which is calculated as Equation 4.3.

The probabilistic constraint in Equation 6.4 can to be changed to a deterministic constraint as follows:

$$\Pr(P_{WT_t} + P_{PV_t} \geq Demand_t - (SOC_{t+1} - SOC_t)\frac{V_{Bat}C_{Bat}}{\Delta t}) \geq \alpha \tag{6.8}$$

$$\Pr(P_{WT_t} + P_{PV_t} \leq Demand_t - (SOC_{t+1} - SOC_t)\frac{V_{Bat}C_{Bat}}{\Delta t}) \leq 1 - \alpha \tag{6.9}$$

The number of batteries for a given wind turbine rotor area and PV panel area can be obtained by solving Equation 6.9 which requires the calculation of joint CDF of WT and PV panel output powers at each hour.

To solve Equarion 6.9, two approaches are followed: the common method used in previous studies and a new method proposed in this chapter.

6.2.1 Common method used in previous studies-Using normal distribution

To solve Equation 6.9, P_{WT_t} and P_{PV_t} at each hour are assumed to follow normal Gaussian distribution with mean values of $\mu_{P_{WT_t}}$, $\mu_{P_{PV_t}}$ and standard deviations $\delta_{P_{WT_t}}$, $\delta_{P_{PV_t}}$ [113].

The sum of P_{WT_t} and P_{PV_t} is assumed to have a new random variable P_t with mean value of μ_{P_t} and the variance $\delta^2_{P_t}$ such that:

$$\mu_{P_t} = \mu_{P_{PV_t}} + \mu_{P_{WT_t}} \tag{6.10}$$

$$\delta^2_{P_t} = \delta^2_{P_{PV_t}} + \delta^2_{P_{WT_t}} + 2\delta_{P_{PV_t}}\delta_{P_{WT_t}}\rho_{P_{PV_t},P_{WT_t}} \tag{6.11}$$

where $\rho_{P_{PV_t},P_{WT_t}}$ is coefficient of correlation between P_{WT_t} and P_{PV_t} at each hour. The deterministic equivalent of Equation 6.9 is expressed as:

$$Demand_t - (SOC_{t+1} - SOC_t)\frac{V_{Bat}c_{Bat}}{\Delta t} = \mu_{P_t} - \delta_{P_t}Z_\alpha \tag{6.12}$$

where Z_α is the inverse of the cumulative normal probability distribution corresponding to the required reliability of compliance of the constraint or confidence level , α .Equation 6.12 is used to obtain the minimum battery size for each configuration of WT and PV panel and the configuration with minimum cost is selected as the best design.

6.2.2 The proposed method

In the proposed method, it is assumed that P_{WT} and P_{PV} are independent random variables following known distributions (Weibull and Beta distributions, accordingly) and the joint cumulative distribution function of these is calculated as:

$$F_{P_{WT},P_{PV}} = F_{P_{WT}}.F_{P_{PV}} \tag{6.13}$$

Equation 6.9 can be re-written as:

$$Demand_t - (SOC_{t+1} - SOC_t)\frac{V_{Bat}c_{Bat}}{\Delta t} \leq F^{-1}_{P_{WT},P_{PV}}(1-\alpha) \tag{6.14}$$

Equation 6.14 is a deterministic constraint which can be satisfied by calculating the inverse of the joint cumulative distribution function of wind turbine and PV panel power, corresponding to the required reliability of compliance of the constraint α . The values of WT and PV panel output powers are used to obtain the minimum battery size for each configuration of WT and PV panel and the configuration with minimum cost is selected as the best design. The performance of the proposed method is validated using Monte Carlo simulation.

The flowchart of the design and validation process is presented in Figure 6-1.

6.3 Case study

The chance constrained programming is used to design a standalone HRES for a household in Kent, UK. The input data for the design are historical hourly data (2000-2008) of wind speed and solar irradiance for 12 months of the year together with typical summer and winter load profiles shown in Figure 1-2. The two methods explained in section 6.2 are used to find the optimum solution for the desired location and the results obtained with two methods are compared for five different confidence levels from 0.1 to 0.5.

Details of technical and economical characteristics of the system components are given in Table 1-1.

The system under study consists of a wind turbine, a PV panel and a battery bank. The wind turbine rotor area is varied in the range from 0 to 154 m^2, PV panels' area is from 0 to 260 m^2 and minimum number of batteries required to meet the probabilistic constraint is determined for each case. Upper limits of each renewable power generation unit is calculated assuming that it is the only source of power. The number of batteries is assumed to vary from 0 to 478. The maximum permitted number of batteries in the study is calculated, using Equation 3.6, considering required storage for one day of autonomy for a day with highest daily load demand; here typical winter load demand is used.

Figure 6-2 shows a sample contour plot for different α values obtained by calculating the joint CDF of P_{WT} and P_{PV} for a typical day in August at 12.00 noon using the method proposed in this chapter.

The optimum configurations and their total costs, obtained with the two methods explained in section 6.2 for five different confidence levels from 0.1 to 0.5 are presented in Table 6-1. As shown in this table, the results of the two methods are close in lower reliability; lower α ; but as the reliability increases the difference between total costs of optimum solutions of the two methods becomes more significant. Figure 6-3 compares the total cost of the optimum solutions of the two methods for five values of α .Figure 6-4 shows a three dimensional space formed by the wind turbine rotor swept area, PV panel area and minimum battery capacity required to meet the load, using the two design methods for α value of 0.8. As can be seen from the figure, using the method proposed in this chapter results in a bigger design space as compared with using the normal Gaussian distribution, which leads to a larger number of feasible optimum solutions. Figure 6-5 and Figure 6-6 show a 3D view of feasible design options based on different number of batteries for each of the two design methods explained in sections 4.1 and 4.2, for α value of 0.8. As the objective function in the defined optimisation problem of Equation 6.3 is the present value of total cost, the optimum solution of each method is selected based on having minimum total cost and is marked in Figure 6-5 and Figure 6-6.

Table 6-1 The comparison between results obtained using two design methods

α	DPSP (%)	Optimum Solutions Obtained Using Proposed Method				Optimum Solutions Obtained Using Normal Distrobution			
		WT Rotor Area (m^2)	PV Panel Area (m^2)	Number of Batteries	Total Cost ($)	WT Rotor Area (m^2)	PV Panel Area (m^2)	Number of Batteries	Total Cost ($)
0.5	50	113	0	61	174,413	116	0	61	178,091
0.6	40	128	0	61	195,103	134	0	61	202,919
0.7	30	149	0	61	222,688	154	17	61	245,237
0.8	20	154	69	61	292,193	154	139	61	354,801
0.9	10	154	234	61	440,887	154	260	421	598,285

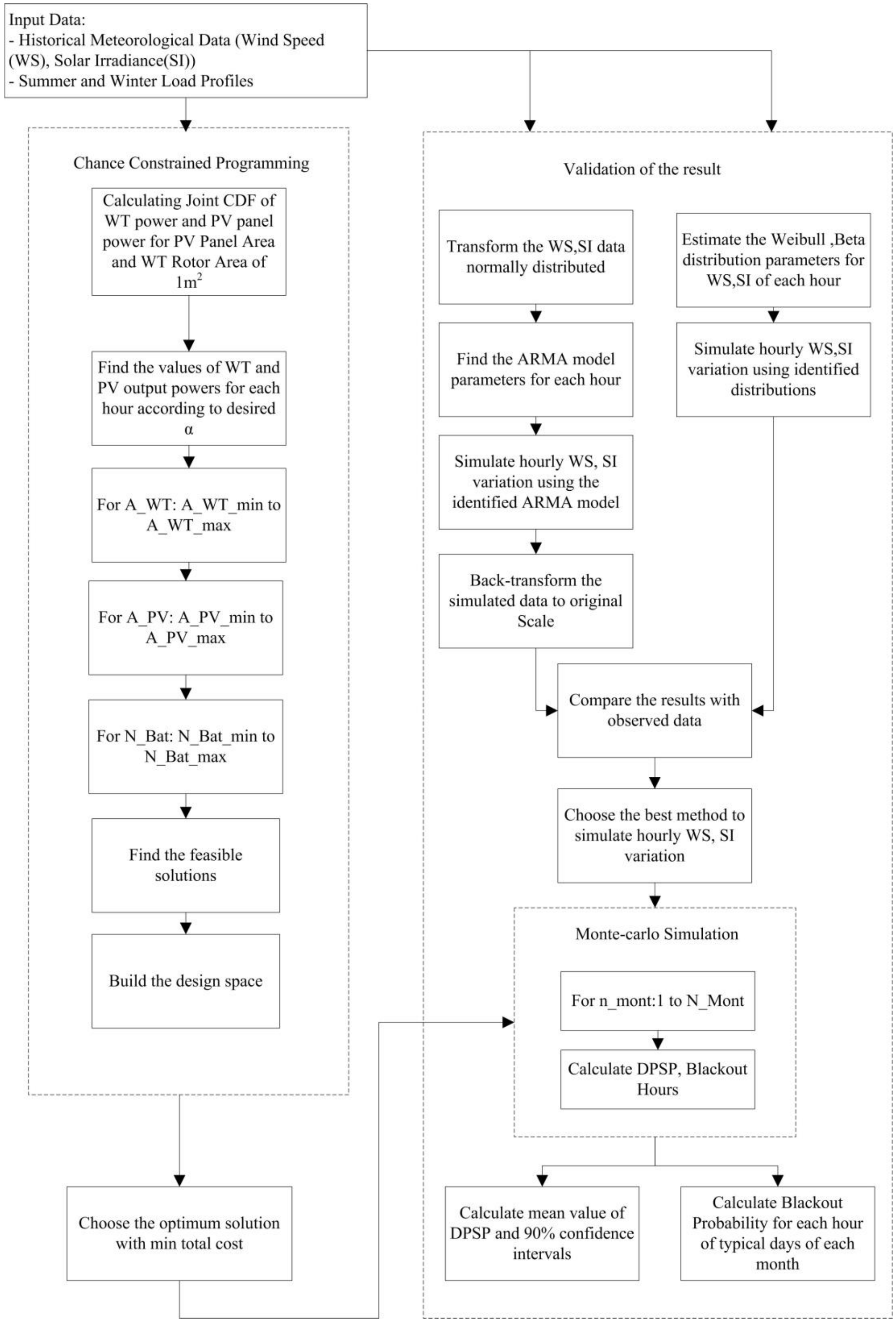


Figure 6-1 Block diagram of proposed design method and validation process

6.4 Validation with Monte Carlo simulation

Monte Carlo simulation is used to validate the reliability of the optimum solution obtained with the proposed method as well as comparing the performance of the optimum solutions marked in Figure 6-5 and Figure 6-6 as the optimum solution of two discussed methods. The performance of the Monte Carlo simulation is dependent on the accurate modelling of the uncertainties in the wind speed and solar irradiance. Different approaches are used to model the renewable sources behaviour. One of the common approaches is by fitting the uncertainties to known distributions such as Weibull or Beta distributions [77]. However, research show that for some locations (e.g. in the UK), using predefined distributions may not simulate the weather data properly[105]. Erken [106] used different distributions to find the best fitted distribution for each hourly meteorological data. Another method in considering uncertainties is adding a random disturbance to average values of wind speed and solar irradiance [107]. Lujano-Rojas [76] and Ji [108] used time series analysis to model wind speed and solar irradiance variations, accordingly. To obtain the most accurate model in wind speed and solar irradiance variations of the desired location, two different methods are used for fitting the historical data to known distributions and time series analysis using autoregressive moving average models (ARMA) explained in chapter5. The results obtained by using ARMA simulation are compared with the results obtained from fitting the historical data of wind speed to Weibull distribution and solar irradiance to Beta distribution and then calculating the mean squared error (MSE) of each method as:

$$MSE = \frac{1}{h}\sum_{i=1}^{h}(\hat{Y}_i - Y_i)^2 \tag{6.15}$$

where $\hat{Y}_i$ is the mean value of vector of simulated values and Y_i is the mean value of vector of observed values for hour no i. Calculated values of MSE for desired site show that wind speed variation is best fitted to Weibull distribution than ARMA model. The MSE of the simulation with Weibull distribution is 0.0007 which is significantly lower than that for ARMA simulation which is 0.27. However for solar radiation simulation, the ARMA model performs better than Beta distribution with MSE of 6.94 as compared to 36.24. It can be seen that the values of MSE are considerably bigger for solar radiation than for wind speed. It should be noted that the values of solar radiation calculated are mostly in the range of 100 to 600 and wind speed changes in the range between 2 to 5.5. Figure 6-7 & Figure 6-10 present the result of comparison between the mean values of simulated data and observed values. The Monte Carlo simulation is repeated as long as the statistical characteristics of the modelled variation in wind speed and solar radiation are close enough to the actual observed data. The reliability of optimum solution obtained using the proposed method; marked in Figure 6-5 is then estimated as the mean of the results obtained over the number of the simulation; 5000 times. Figure 6-11 compares the DPSP values obtained at each run of simulation, its mean value and 90% confidence intervals of the results. The overall $DPSP$ of the optimum configuration which is calculated as the mean value of $DPSP$ values obtained from Monte Carlo simulation. If we consider α as $1 - DPSP/100$ and calculate α based on the results from Monte Carlo simulation; the results show that the optimum solution obtained by using the method proposed in this chapter complies with the design constraint which requires an overall load satisfaction with a probability of α; here = 0.8.

Monte-Carlo simulation is also used to compare the performance of optimum solutions obtained using each of explained methods in terms of blackout occurrence probability as well as the average excess power that is produced by the wind turbine and PV panel in case of choosing either of these optimum solutions and the results are presented in Figure 6-12 and Figure 6-13. The probability of blackout occurrence for each hour for a typical day of each month is shown in Figure 6-12. This figure shows that the probability of blackout occurrence in each hour of the optimum solution obtained by proposed method is less that 18%. The Figure 6-12 also shows that the probability of blackout for both optimum solutions is higher in the last three months of the year. Also the value of this probability does not differ significantly between two optimum solutions for each particular month. However the amount of average daily excess power shown in Figure 6-13 proves that the proposed method results in less conservative design option as compared to the output of common method as there is less excess power produced by wind turbine and PV panel in the output design of this method.

6.5 Summary

This chapter suggests the use of the chance constrained programming in the design of HRES. To solve the chance constrained problem two methods are compared:

- The common approach which solves the problem based on the assumption of the uncertain variables following the normal Gaussian distribution
- A new method is proposed in this chapter to solve the chance constrained problem without initial assumption on the type of joint distribution of two uncertain variables; wind speed and solar irradiance.

Analysis of comparing the results obtained in this study shows that by using the first method some feasible configurations are ignored and the output configuration of the design may not be the best configuration.

A case study, design of a standalone hybrid wind /PV /battery bank system is presented for a farm in Kent, UK. The outcome of the design is validated based on deficiency of power supply probability through performing Monte Carlo simulation. Historical meteorological data of the desired location is used to find the best method in modelling wind speed and solar irradiance variations. This is done by comparing the statistical characteristics of fitting the variations to known distributions as well as using time series analysis; ARMA models. It is shown that, for the desired location, the Weibull distribution is the best fitted model for wind speed variation and that ARMA model performs better in modelling solar radiation variations. However it should be noted that conclusions might be different for other locations, as the best fit model should be chosen after performing similar analysis based on the desired locations historical weather data. The outputs of each of these models are compared with observed data and best model is chosen to simulate renewable resources variation in Monte Carlo simulation.

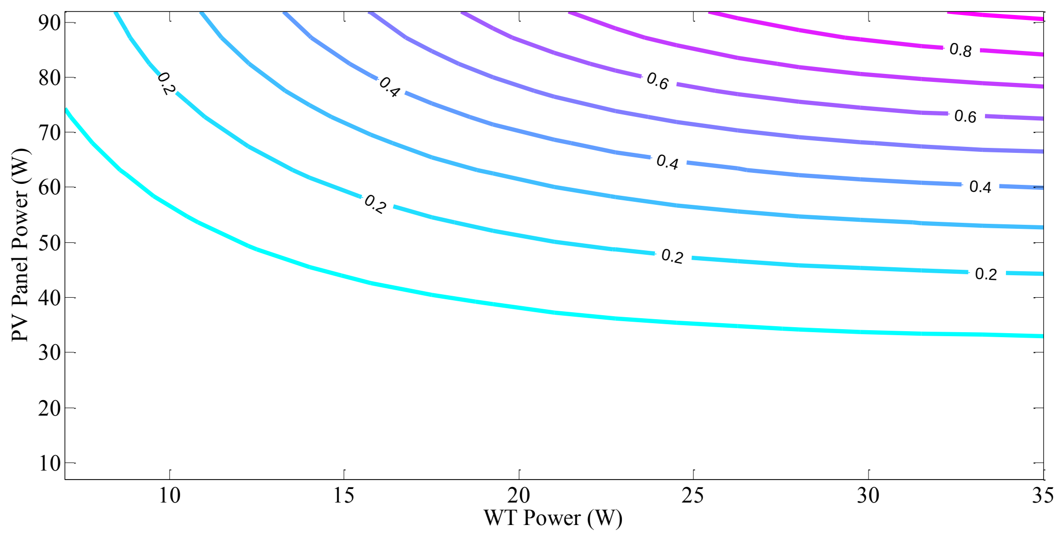


Figure 6-2 Contour plot of joint probability of WT and PV panel output powers for Aug at 12:00

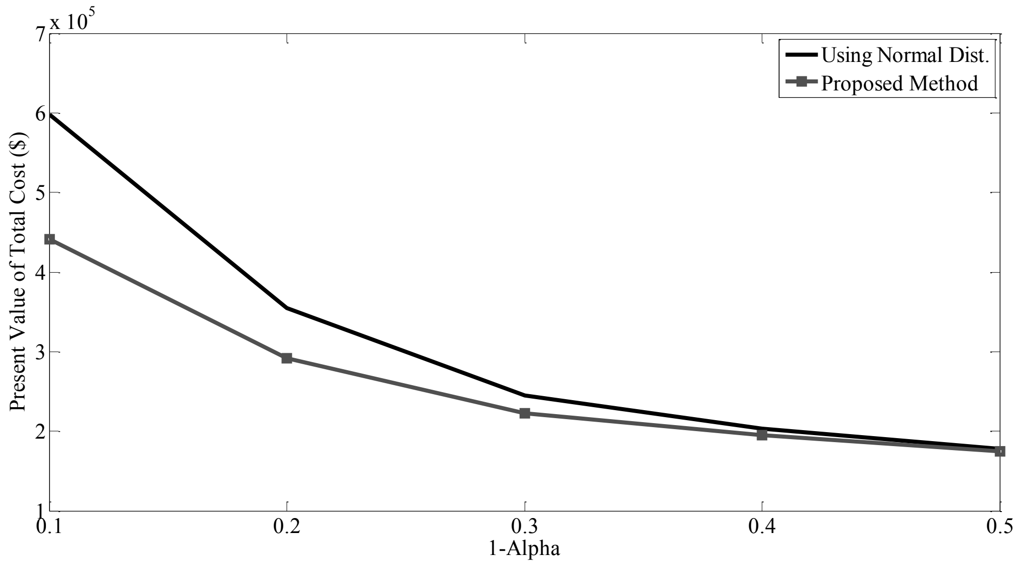


Figure 6-3 The total cost of optimum solutions of two methods for different confidence levels

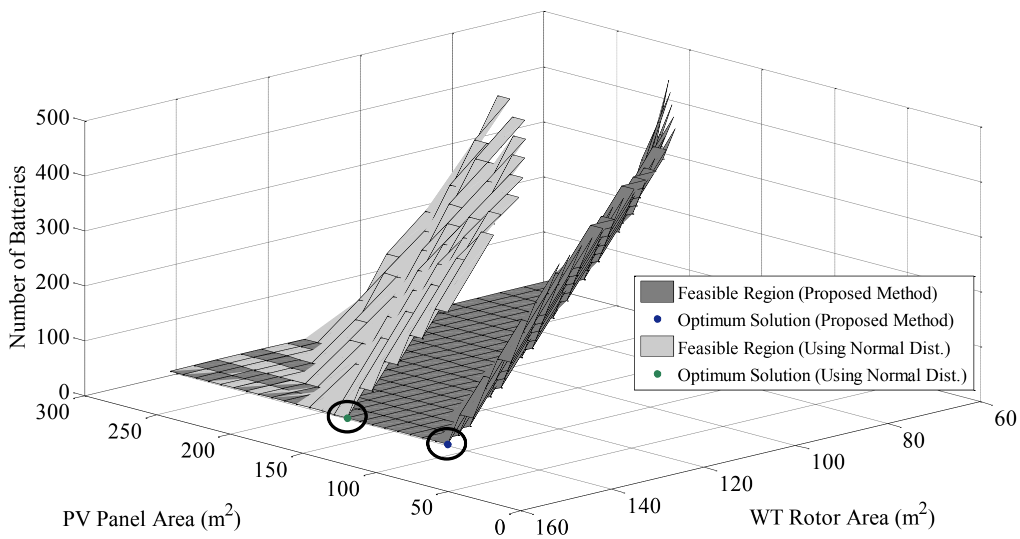


Figure 6-4 The design spaces of two methods for α=0.8

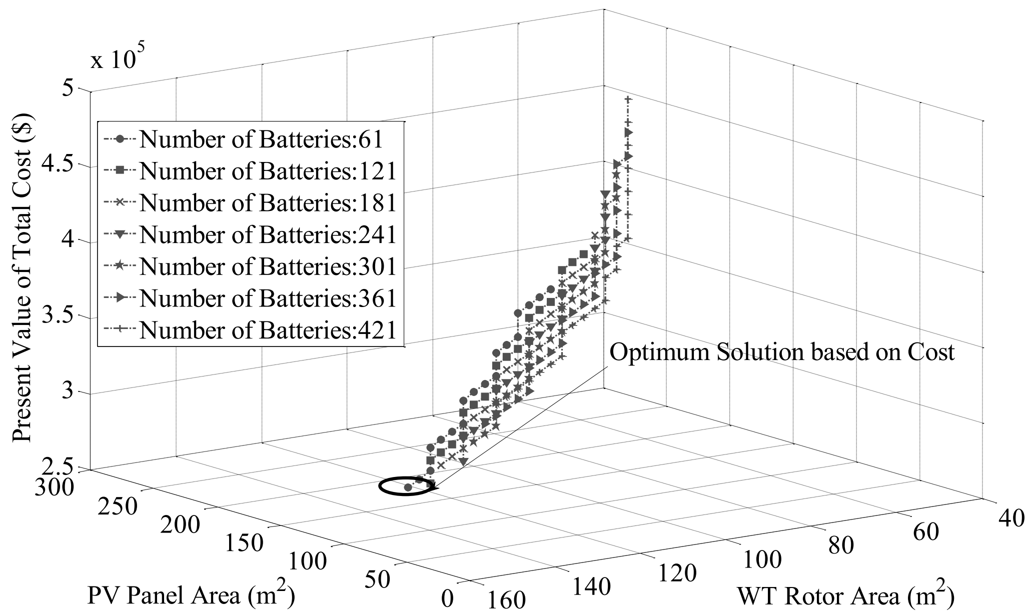


Figure 6-5 Feasible design solutions & selected optimum solution of optimisation problem Eq. 6.14- Using proposed method for α=0.8

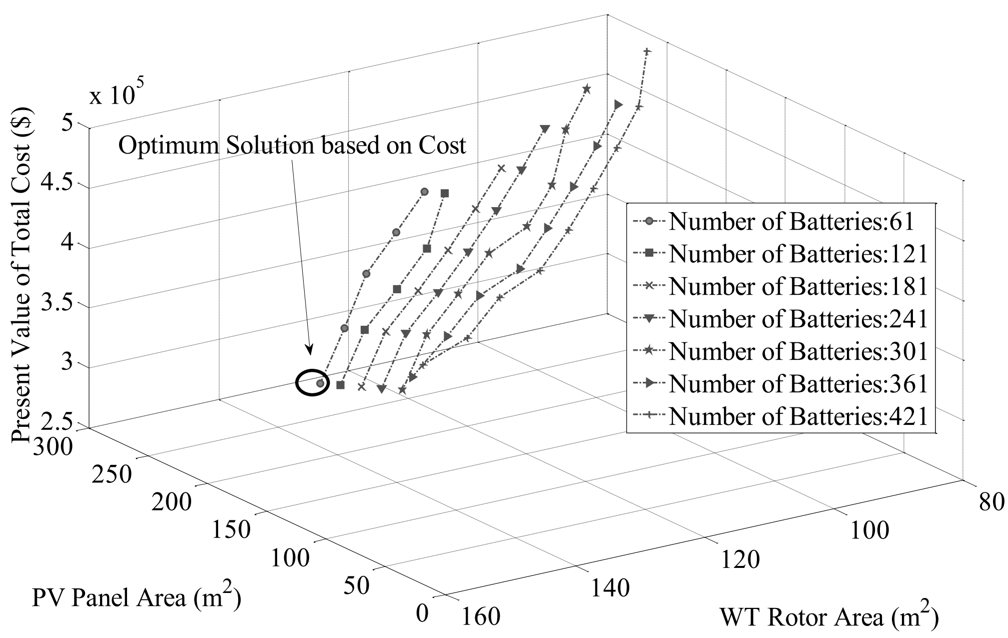


Figure 6-6 Feasible design solutions & selected optimum solution of optimisation problem Eq. 6.14- Using normal dist. for α=0.8

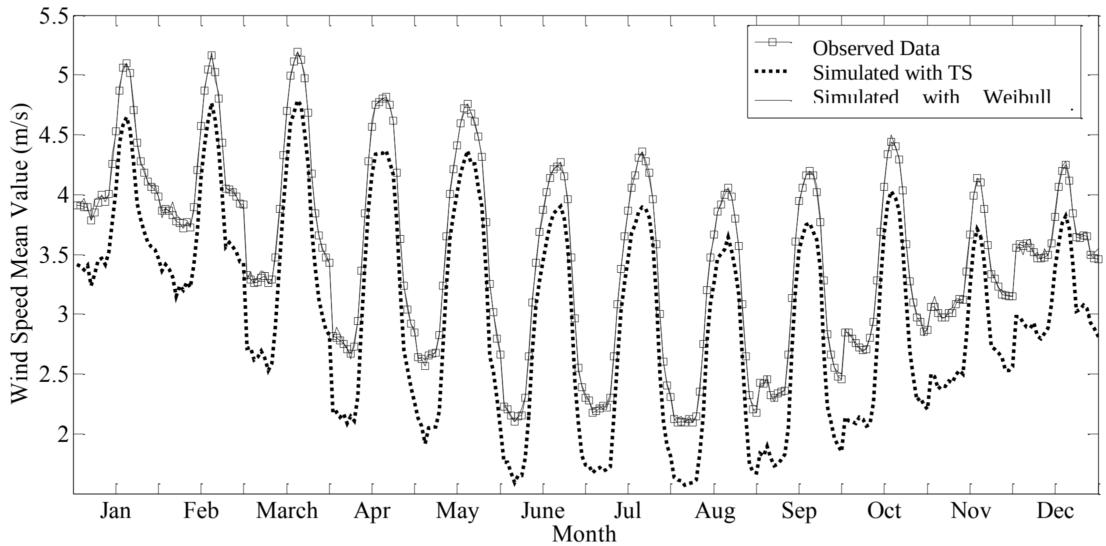


Figure 6-7 Mean values of simulated and observed data of wind speed

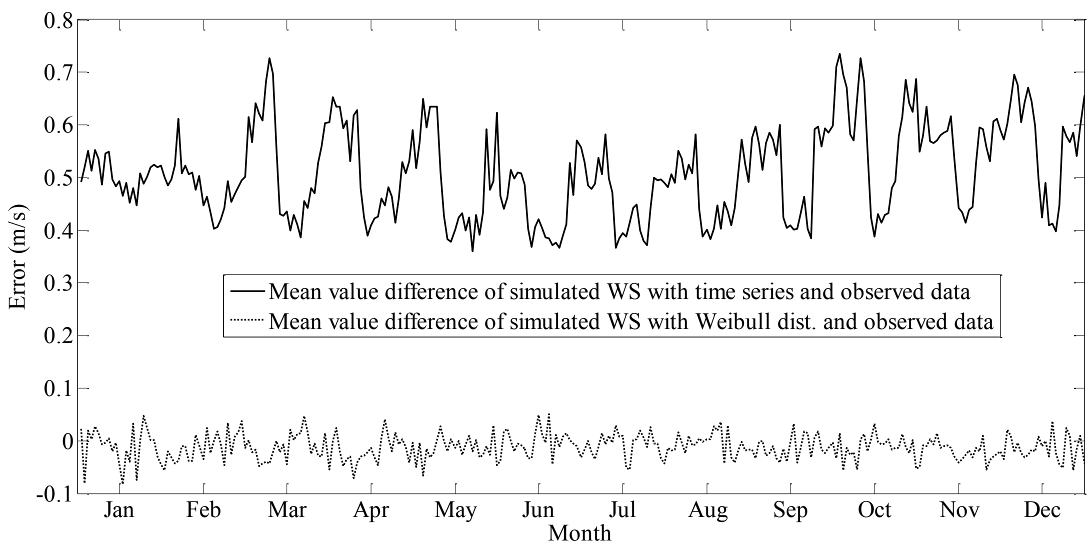


Figure 6-8 Error values of simulated and observed data of wind speed

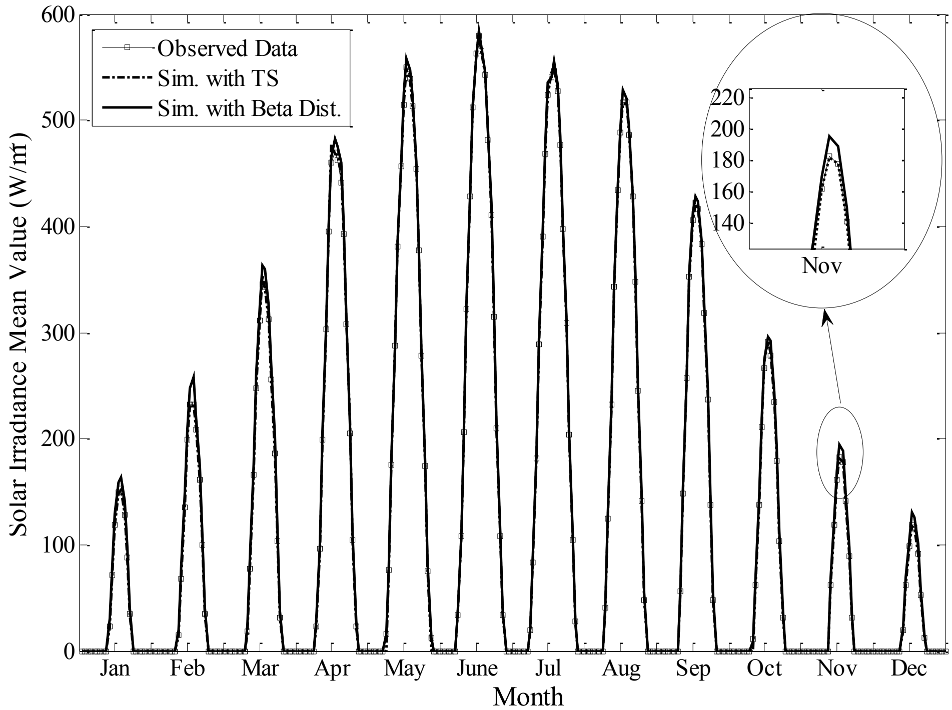


Figure 6-9 Mean values of simulated and observed data of solar irradiance

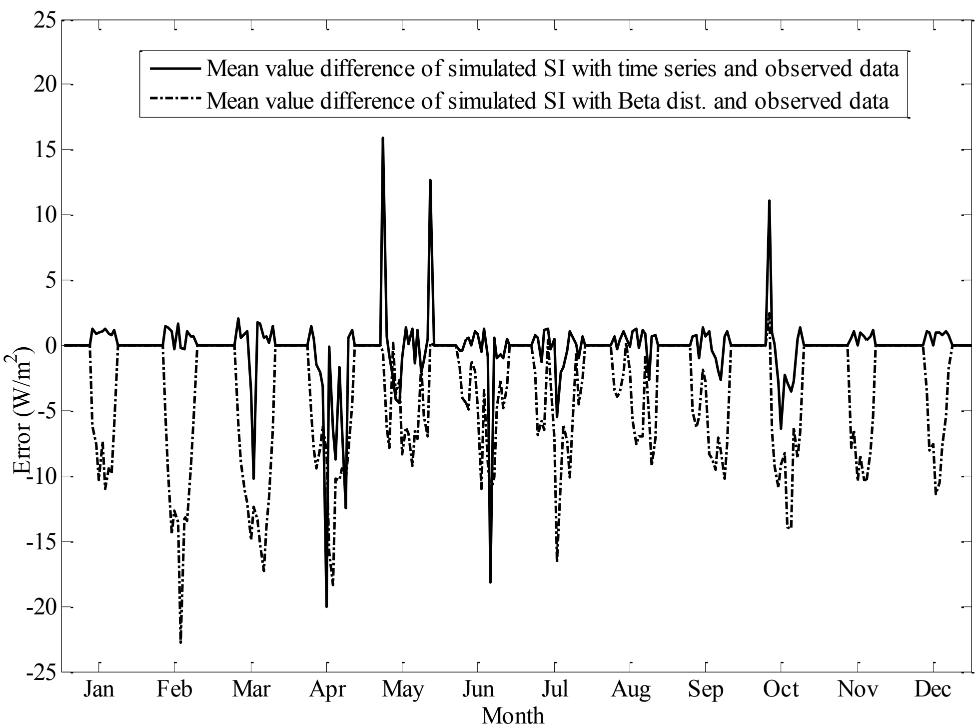


Figure 6-10 Error values of simulated and observed data of solar irradiance

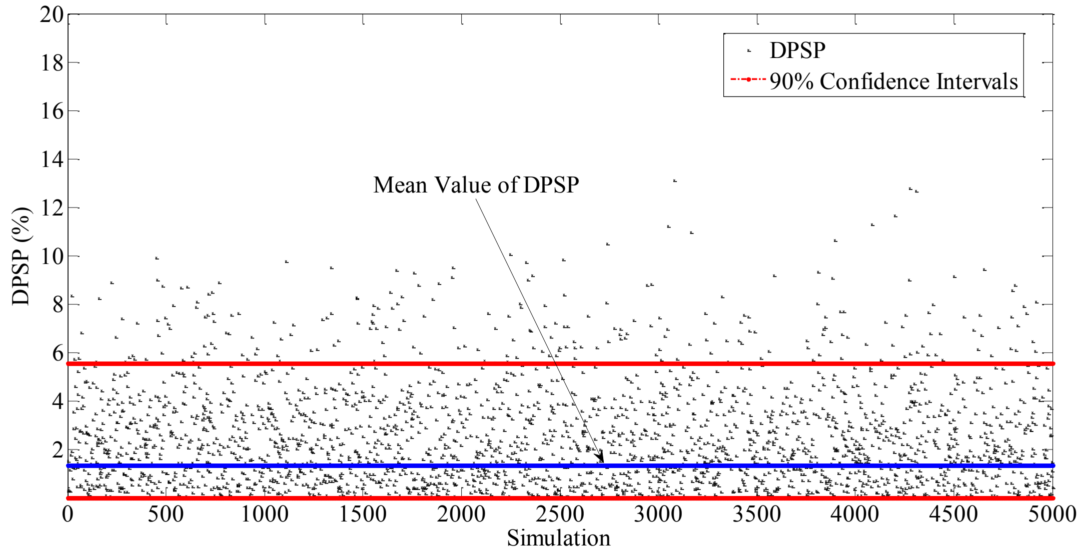


Figure 6-11 Deficiency of power supply probability of optimum solution obtained with Monte Carlo simulation

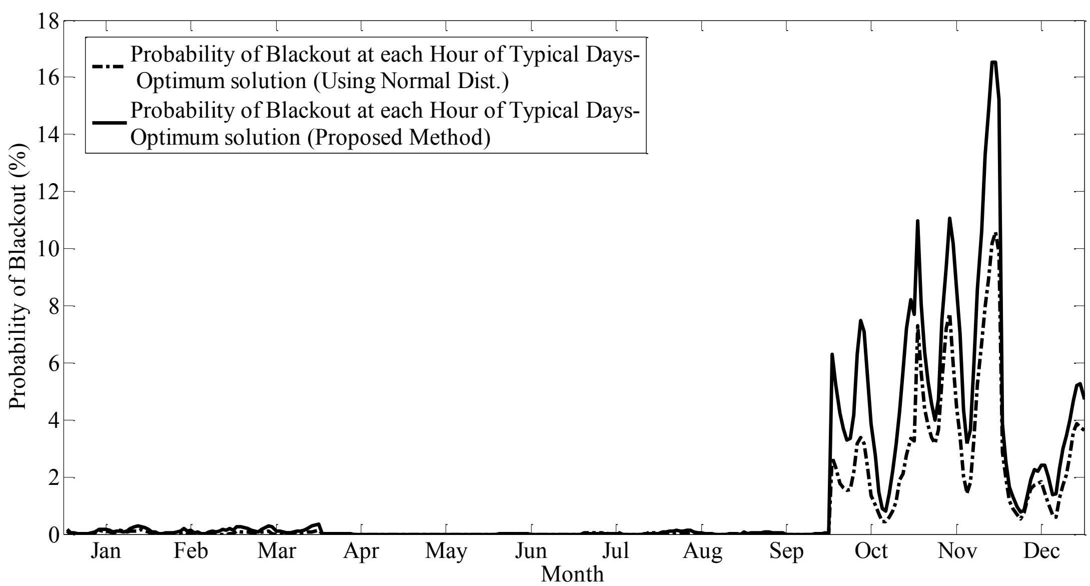


Figure 6-12 Comparison between probability of blackout occurrences of two optimum solutions for α=0.8

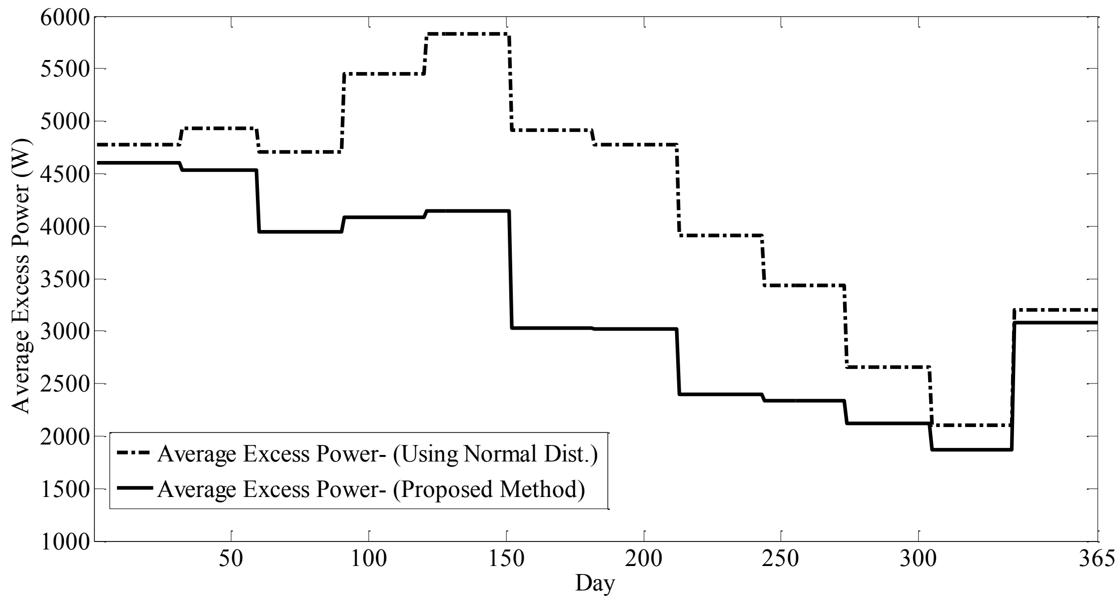


Figure 6-13 Comparison between average daily power excess of two optimum solutions for α=0.8

7 Multi-Objective Design under Uncertainties of Hybrid Renewable Energy System Using NSGA-II and Chance Constrained Programming

7.1 Introduction

The optimum design of Hybrid Renewable Energy Systems (HRES) depends on different economic, environmental and performance related criteria which are often conflicting objectives. The Non-dominated Sorting Genetic Algorithm (NSGA-II) provides a decision support mechanism in solving multi-objective problems and providing a set of non-dominated solutions where finding an absolute optimum solution is not possible. The present study uses NSGA-II algorithm in the design of a standalone HRES comprising wind turbine, PV panel and battery bank with the (economic) objective of minimum system total cost and (performance) objective of maximum reliability. To address the uncertainties in renewable resources (wind speed and solar irradiance), an innovative method is proposed which is based on Chance Constrained Programming (CCP). A case study is used to validate the proposed method, where the results obtained are compared with the conventional method of incorporating uncertainties using Monte Carlo simulation.

Decision making problems can be categorized in two classes based on the number of objective functions that are involved in the problem; single objective and multi-objective. In a single objective problem, the aim is to identify the best solution corresponding to minimising or maximising a single objective function. However, in real life, the decision making process usually involves more than one objective function. Multi-objective problems do not have a single optimal solution but they have a set of compromised solutions between different objective functions known as Pareto set.

In optimal sizing of HRESs, there is normally more than one objective function to be considered. Two important objective functions in the design of a HRES are cost and reliability. Since these objectives are contradicting, a single optimal solution cannot be found (with minimum cost and maximum reliability) and a multi-objective optimisation is needed to find a trade-off; Pareto set solutions. Several studies have been reported in multi-objective optimisation of HRES considering different objection functions and using various optimisation techniques.

Genetic Algorithms (GA) proved to be popular in solving optimisation problems. Ould [41] proposed a Pareto-based multi-objective GA for sizing a hybrid solar–wind-battery system with the aim of minimising the annualized cost and minimising the probability of loss of power supply. Montoya et al. [53] presented a hybrid Pareto- based multi-objective meta-heuristic approach to minimise voltage deviations and power losses in power networks, which can be extended to hybrid systems. Yang et al. [42] proposed a GA based optimal sizing technique using typical meteorological yearly data. The proposed optimisation model determines the system optimum configuration which is able to provide the desired Loss of Power Supply Probability (LPSP) with minimum Annualized Cost.

The Non-dominated Sorting Genetic Algorithm (NSGA-II) was proposed [46] to perform multi-objective evolutionary algorithms (MOEA) in which an elite-preserving operator gives the best individuals the opportunity to be directly transferred to the next generation. By doing so, a ‘good’ solution which is found in early generations is never removed from the population unless a better solution is discovered. Katsigiannis [20] used the NSGA-II to design a small autonomous hybrid power system that contained both renewable and conventional power sources with the objectives of minimising the energy cost of the system and total greenhouse gas emission during the system life time. However, the effects of uncertainties in renewable energy generation were not considered in this study.

Different methods to include the uncertainties in renewable resources in the design of HRES have been reported. Giannakoudis et al [107] considered adding a known disturbance to the design inputs to maintain optimum mix of renewable resources. Nandi et al.[55] assumed that wind speed variation follows the Weibull distribution. Lujano-Rojas el al [76] used time series theory to simulate the uncertainties in wind speed in the design of small wind/battery systems. Usually, the Monte Carlo simulation approach is used in solving probabilistic problems. Given a significantly large sample size, this method can provide highly accurate results. However, the main drawback is the computational burden associated with the large number of repeated calculations [110]. The Chance Constrained Programming (CCP) approach, first introduced by Charnes and Cooper [78] in 1959, is now popular method in solving problems that include random parameters. Its main feature is that it ensures the probability of the resulting decision to comply with the specified constraints [83]. The CCP method has been widely applied in different disciplines for optimisation under uncertainty[111], but very few studies are reported on using this method for the design of HRES. Arun et al. [112] used the CCP approach in the design of a PV-battery system to deal with the uncertainties in the solar radiation. Seeraj et al. [113] used this method to find the battery bank size when renewable energy resource availability, ratings and load demand were assumed to be known.

This chapter presents the results of a multi-optimisation NSGA-II based approach for the design of a standalone HRES, shown in Figure 1-1, considering uncertainties in the resources available. The approach employs the chance constrained programming to deal with the effects of uncertainties in renewable resources instead of common approach of using Monte Carlo simulation. It is shown in Chapter 6 that chance constrained programming can result in optimum solution for a predefined reliability in a single-objective optimisation problem in design of HRES, however in a multi-objective optimisation problem where there is no predefined reliability, conventionally Monte Carlo simulation is employed. This study proposes a novel method in employing chance constrained programming in multi-objective problems as a substitute of Monte Carlo simulation. The study proposes a method in which chance constrained programing is used as a tool in estimating the expected value of the objective function which is affected by the uncertainties, in other words instead of finding the optimum solution for a predefined value of reliability, chance constrained programing is used to estimate the expected value of the reliability of the design candidates in a multi-objective optimisation problem. To evaluate the performance of the proposed method, the results obtained are compared with those obtained by employing the Monte Carlo simulation.

The outline of this chapter is as follows:

The components modelling and cost modelling are presented in chapter 2.

Problem formulation and design methodology are presented in section 7.2.

A case study is described in section 7.5. Results and discussion are described in section 7.6 and finally conclusions are presented in section 7.7.

7.2 Problem formulation and design methodology

The proposed technique adopts the non-dominated sorting genetic algorithm (NSGA-II) [46] in combination with the chance constrained programming (CCP) [78] to effectively solve the multi-objective optimisation problem of design of a HRES under uncertainties. The aim is to find the Pareto set solutions based on the desired objective functions using NSGA-II. The NSGA-II provides a very efficient procedure in keeping the elitism optimisation process as well as preserving the diversity which assures a good convergence towards the Pareto-optimal front without losing the solution diversity [47].

The following steps are implemented in the NSGA-II algorithm.

1: Initial population is generated based on defined decision variables and number of populations.

2: Evaluation of each chromosome in terms of defined objective functions. The adopted methods in evaluation the objective functions affected by uncertainties are explained in sub-section (7.3) and (7.4).

3: Set the generation count

4: Prepare the mating pool

5: Perform crossover and mutation operators

6: Perform non-dominated sorting

7: Calculate the crowding distance

8: Perform the selection based on rank. If individuals with the same rank are encountered, crowding distance is compared. A lower rank and higher crowding distance is the selection criteria.

9: Increment the generation count and repeat steps 4 to 8 until the counter reaches the maximum number of generation

The decision variables are the wind turbine rotor swept area (A_{WT}), the PV panel area (A_{PV}) and the number of batteries (N_{Bat}).

The optimisation problem can be defined as:

$$\min_{A_{WT}, A_{PV}, N_{Bat}} \{TC, DPSP\} \quad (7.1)$$

s.t.

$$SOC \geq SOC_{\min} \quad (7.2)$$

where

$$TC = C_{IC} + C_{O\&M} + C_{replacement} \quad (7.3)$$

As Equation 7.1 shows, two objective functions have been considered associated with both minimisation of the system total cost (TC) and the deficiency of power supply probability ($DPSP$); where DPS is the amount of power shortage at each hour and h is the total hours under study.

The energy balance of the system can be modelled as:

$$P_{HRES} = \begin{cases} P_{WT} + P_{PV}, & (a) \\ P_{WT} + P_{PV} + P_{Bat} & (b) \end{cases} \quad (7.4)$$

(a) if total power generated by the wind turbine and PV is sufficient to cover the load demand, otherwise

(b) $P_{WT} + P_{PV}$ is not sufficient to meet the demand and the battery has to supply the difference.

In order to compare the performance of the proposed method, the NSGA-II algorithm objectives affected by uncertainties are evaluated with CCP (explained in section 7.3) as well as a conventional method based on Monte Carlo simulation (explained in section 7.4).

7.3 Optimal Estimation of the Objective Functions Affected by Uncertainties Using CCP

Each design candidate in the main optimisation process needs to be evaluated in terms of the desired objective functions; here these are the total cost (TC) and deficiency of power supply probability $(DPSP)$. As uncertainties with renewable resources have direct effects on the second objective function (DPSP); finding an exact value for $DPSP$ is not realistically possible. Therefore, this objective function needs to be estimated using stochastic methods, in this study using chance constrained programming.

As $DPSP_{estimated}$ is completely dependent on the correct estimation of uncertain variables, here the aim would be to estimate the hourly values of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$. The estimation problem of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$ can be written as a chance constrained problem. The aim of this problem would be to estimate the hourly values of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$ in such way that their sum would have a value with a desired confidence level α. The estimation problem can be described as a chance constrained problem, as:

$$\Pr(P_{WT_t} + P_{PV_t} \geq P_{WT_{t,estimated}} + P_{PV_{t,estimated}}) \geq \alpha \tag{7.5}$$

Following the method proposed in Chapter 6, the hourly values of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$ are extracted and then used to calculate the $DPSP_{estimated}$. As shown in the case study , this method requires considerably shorter process time as compared with the conventional Monte Carlo simulation.

7.4 Monte Carlo Simulation

Monte Carlo simulation is conventionally used to estimate the expected value of the parameters with uncertainties. The performance of the Monte Carlo simulation is dependent on the accurate modelling of uncertainties in the wind speed and solar irradiance. Different approaches are used to model the renewable sources. One of the common approaches is by fitting the uncertainties to known distributions such as Weibull or Beta distributions [77]. However, research show that for some locations (e.g. in the UK), using predefined distributions may not simulate the weather data properly[105]. Erken [106] used different distributions to find the best fitted distribution for each hourly meteorological data. Another method in considering uncertainties is adding a random disturbance to the average values of wind speed and solar irradiance [107]. Lujano-Rojas [76] and Ji [108] used a time series analysis to model wind speed and solar irradiance variations. To obtain accurate modelling of wind speed and solar irradiance variations, two methods are used to correlate historical data to known distributions and time series analysis using autoregressive moving average models (ARMA). Based on the location of the desired site, the performance of different modelling methods should be investigated and the most suitable model selected as the random data generator to model the uncertainties in Monte Carlo simulation. Using these random data generators, the Monte Carlo simulation is repeated enough for each configuration until the expected values of the objective function; here $E[DPSP]$, is calculated with the confidence level of %90 and variation value of less than %3. The confidence level in Monte Carlo simulation is estimated using

Table 7-1 Monte Carlo simulation parameters

Confidence Level (%)	99.75	99	98	96	95.5	95	90	80	68
Confidence Coefficient (Zc)	3	2.58	2.33	2.05	2	1.96	1.645	1.28	1

$$(L,U) = \mu \pm Z_c \frac{\delta}{\sqrt{N}} \tag{7.6}$$

Where the L and U are the lower and upper values of the estimation, μ and δ are the mean value and standard deviation of the simulation results, Z_c is the confidence coefficient and N the number of the repeatation of the Monte Carlo simulation. The relevant values of Z_c to different confidence levels are presented in Table 7-1.

7.5 Case study

The proposed method is used to design a standalone HRES for a household in Kent, UK. The input data for the design are historical hourly data (2000-2008) of wind speed and solar irradiance for 12 months of the year together with typical summer and winter load profiles shown in Figure 1-2. The load profile is a typical load profile in the UK which is adopted from [84].

Details of technical and economical characteristics of the system components are given in Table 1-1.

The system under study consists of a wind turbine, a PV panel and a battery bank. The wind turbine rotor area is varied in the range from 0 to 154 m^2 (in 10 steps), PV panels area is from 0 to 260 m^2 and minimum number of batteries required to meet the probabilistic constraint is determined for each case. The number of batteries is assumed to vary from 0 to 478. The maximum permitted number of batteries in this study is calculated, using Equation 3.6, considering required storage for one day of autonomy with highest daily load demand; here typical winter load demand is used.

The NSGA-II algorithm is performed for 250 iterations with a population number of 100, the mating pool size is considered as 0.5 of the population, crossover probability pc = 0.9 and mutation probability of $1/n$; where n is the number of variables; here 3.

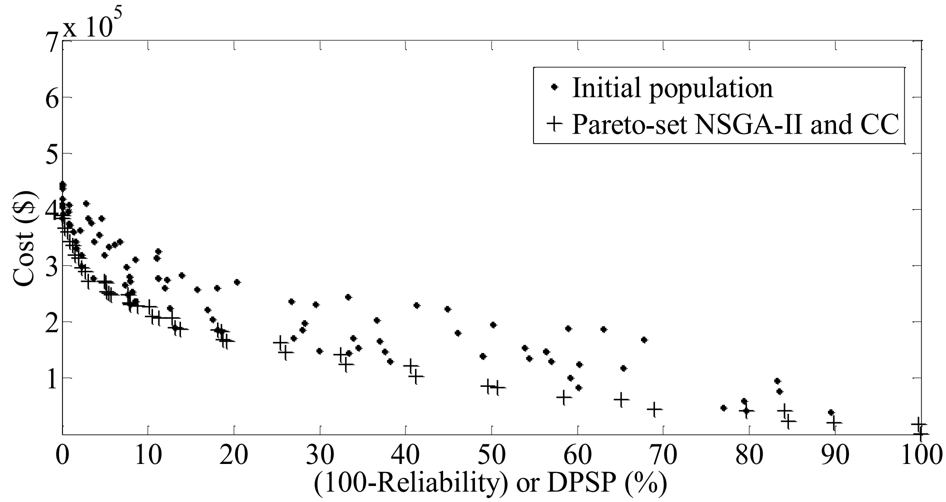
To select the best model for wind speed and solar irradiance in Monte Carlo simulation, the results of ARMA simulation are compared with those obtained from fitting the historical data of wind speed to Weibull distribution and solar irradiance to Beta distribution. Based on the results presented in Chapter 6 Weibull distribution showed better performance in modelling wind speed variation and ARMA simulation is used to model solar irradiance in the desired site.

7.6 Results and discussion

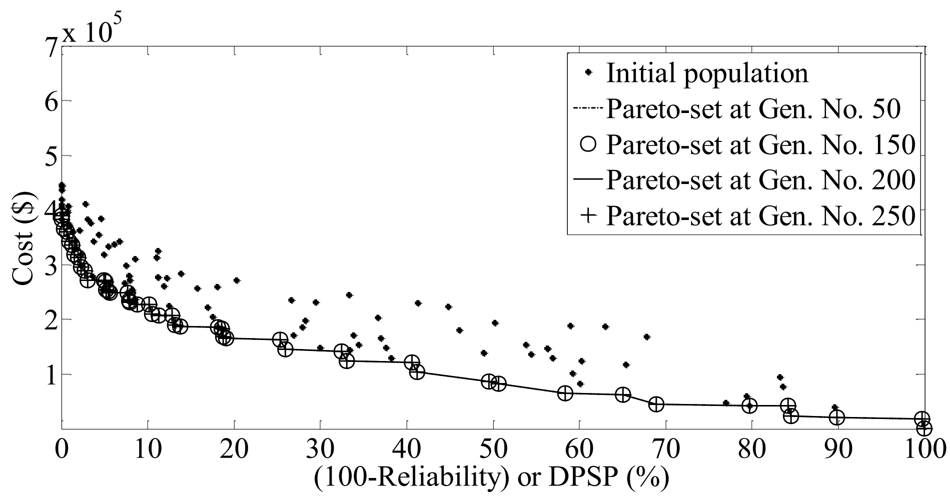
The system under study was designed based on the methodologies explained in section 7.2 and results are presented in this section.

Figure 7-1-a and Figure 7-2-a present a comparison between the initial populations and the final Pareto sets of performing NSGA-II in combination with CCP and Monte Carlo simulation. It can be observed that the NSGA-II with CCP produces more conservative results as compared to the other method, as it results in solutions with higher total cost. However, it obtains better results in high reliabilities close to 100%; with lower total cost of the system.Figure 7-1-b and Figure 7-2-b show how the output of each technique converges to its final Pareto set. As can be seen, in both cases (using the CCP and Monte Carlo simulation), the outputs of the NSGA-II converges to the final Pareto set at generation 150.

The final Pareto sets of performing optimisation process using proposed NSGA-II algorithm on the site under study; in combination with CCP as well as Monte Carlo simulation are compared in Figure 7-3. The Pareto sets obtained in both cases of employing NSGA-II are well defined and solutions are spread over the reliability axis. It should be noted that a solution with zero total cost is not feasible. Although using CCP instead of Monte Carlo simulation results in more conservative set of solutions (as shown in Figure 7-3); the execution time is significantly lower. The calculation time for evaluating the objective function of each chromosome is 11.44 seconds using CCP which is significantly lower than performing the Monte Carlo simulation, which takes 56.81 seconds for each design candidate.

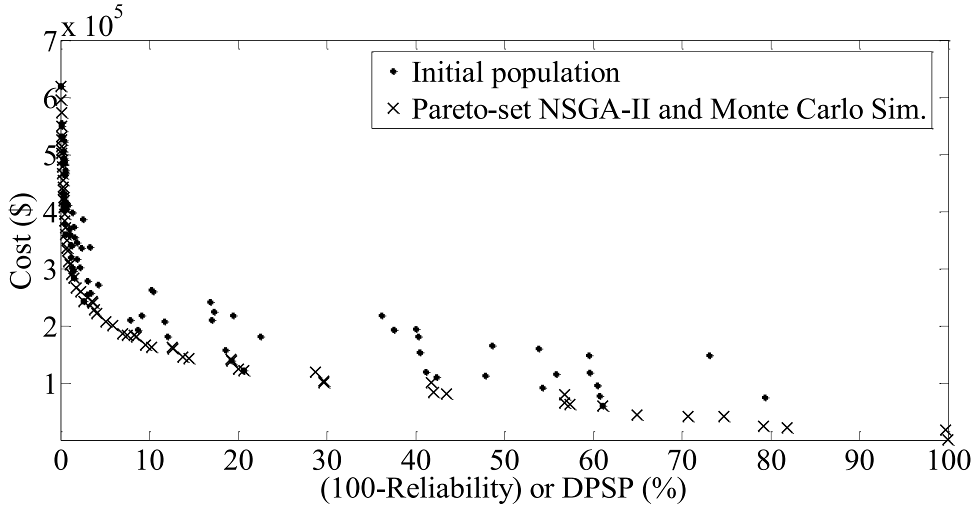


(a)

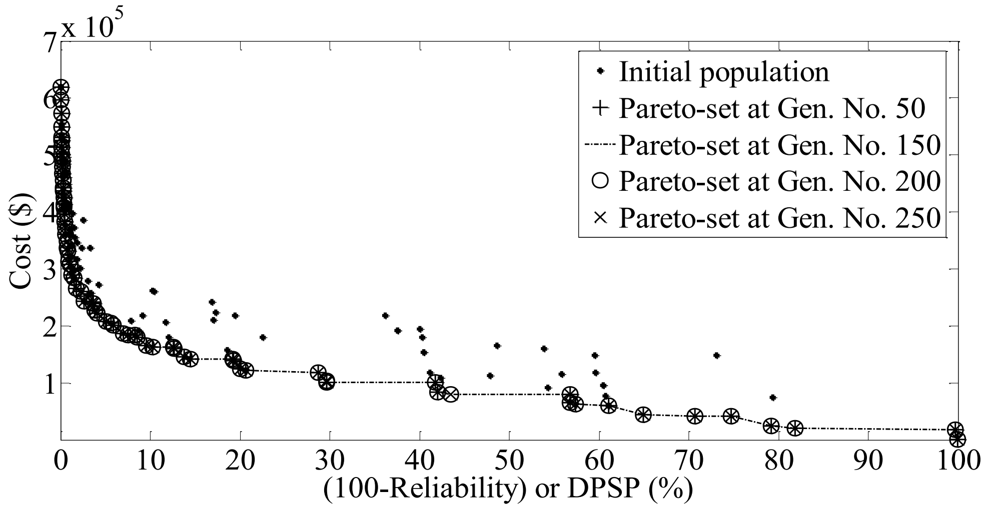


(b)

Figure 7-1.NSGA-II with chance constrained programming



(a)



(b)

Figure 7-2 NSGA-II with Monte Carlo simulation

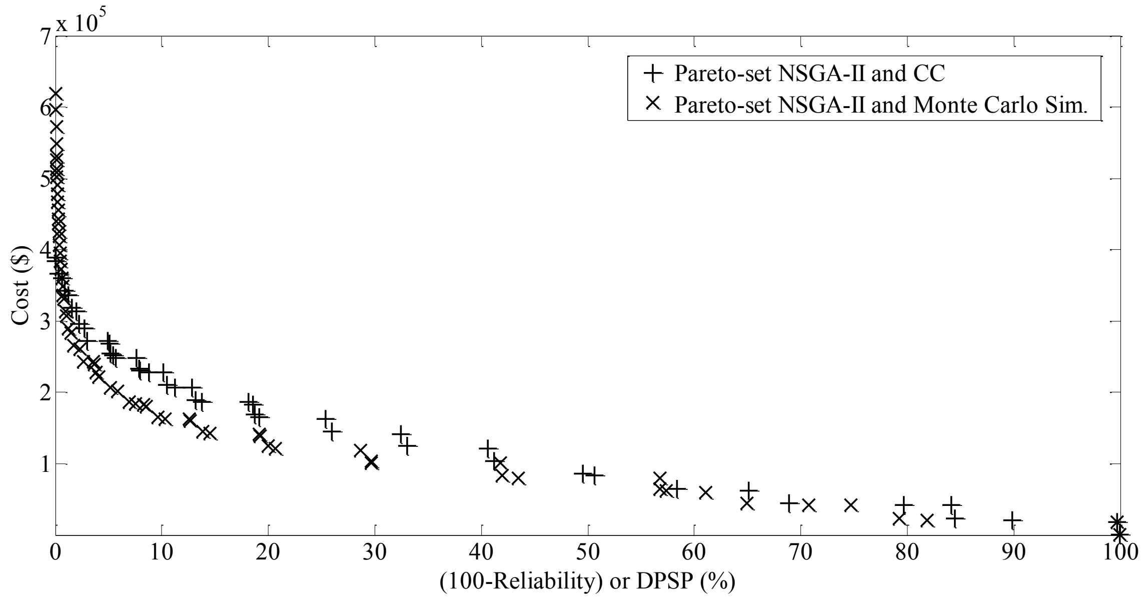


Figure 7-3 Comparison of Pareto sets obtained with different optimisation methods

The Figure 7-3 also shows that maximum deviation between two Pareto sets happens when the DPSP is from 15% to 35%.

To help the decision maker to choose the solution which fits the requirements, the output solution of two design methods for reliability of 80% or DPSP of 20% is studied in detail. Design parameters of CCP and the optimum solutions of two design methods are presented in Table 7-2. To evaluate the performance of each of the selected solutions; Monte-Carlo Monte Carlo simulation is performed for the simulation number of 2500 runs. A selection of results is presented in Figure 7-4 and Figure 7-5. Figure 7-4-a and Figure 7-5-a present probability distribution of hourly blackout occurrence in a year. By comparing these two graphs one can see that there are more hours in the year with very little chance of having power shortages in solution -1 than in solution-2. It is also observed that the maximum hourly blackout occurrence probability is less in solution-1 than solution-2; 0.6 for solution-1 and around 0.8 for solution-2.

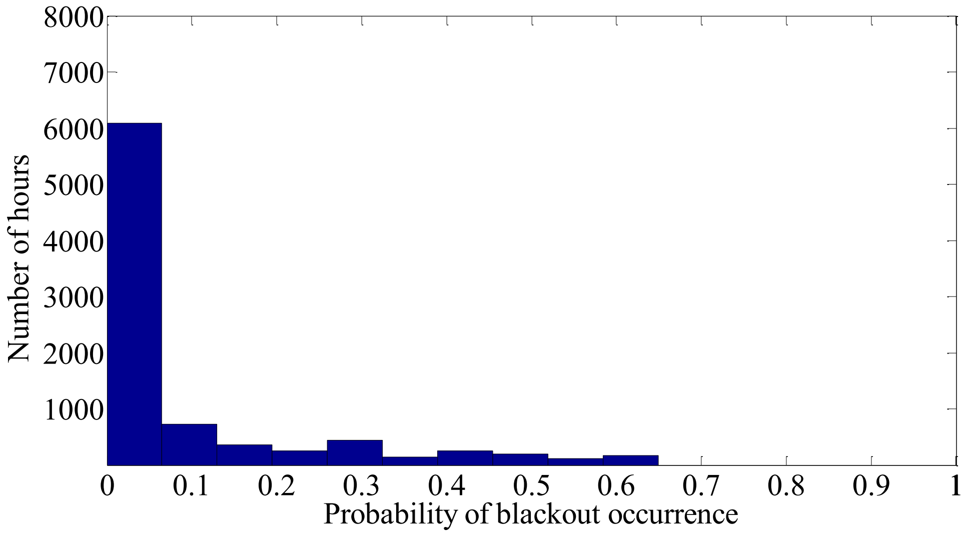
Table 7-2 Optimum solutions of two design methods for reliability=0.8

α	NSGA-II and chance constrained programming (Solution-1)			NSGA-II and MonteCarlo simulation (Solution-2)		
	WT Rotor Area (m2)	PV Panel Area (m2)	Number of Batteries	WT Rotor Area (m2)	PV Panel Area (m2)	Number of Batteries
0.9	92	26	49	77	0	96

Figure 7-4-b and Figure 7-5-b present the average daily probability of blackout occurrence throughout the year. Comparing these to figures shows that in solution-1 the last three months of the year have the highest probability of blackout occurrence which is due higher load demand in winter (see Figure 1-2) as well as less renewable resources available in these months. However, in solution-2 the second half of the year has higher probability of power loss.

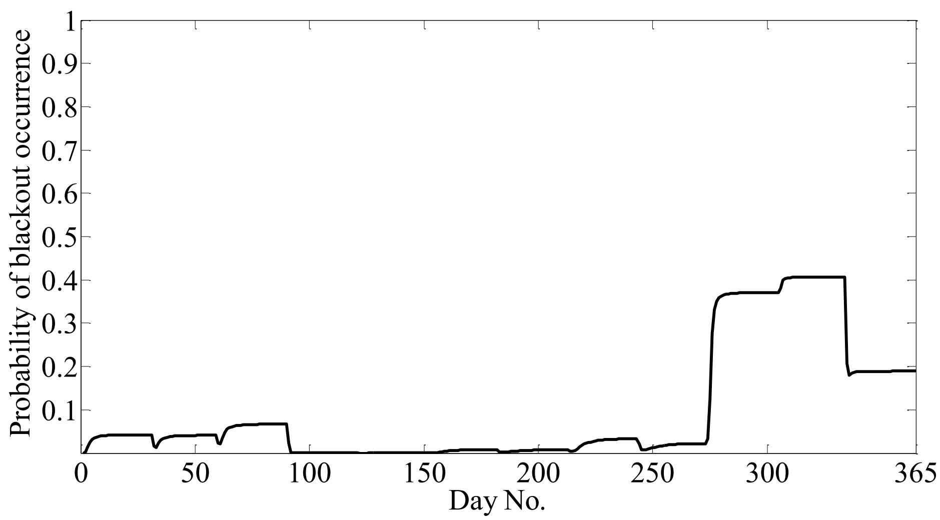
The day that has the largest probability of blackout occurrence in Figure 7-4-b and Figure 7-5-b is selected and details of having blackout at each hour of that day is presented in Figure 7-4-c and Figure 7-5-c.

Figure 7-4-d and Figure 7-5-d show the results of performing Monte Carlo simulation for 2500 times on the hour with most probability of blackout and presents the frequency and load satisfaction percentage for that hour.



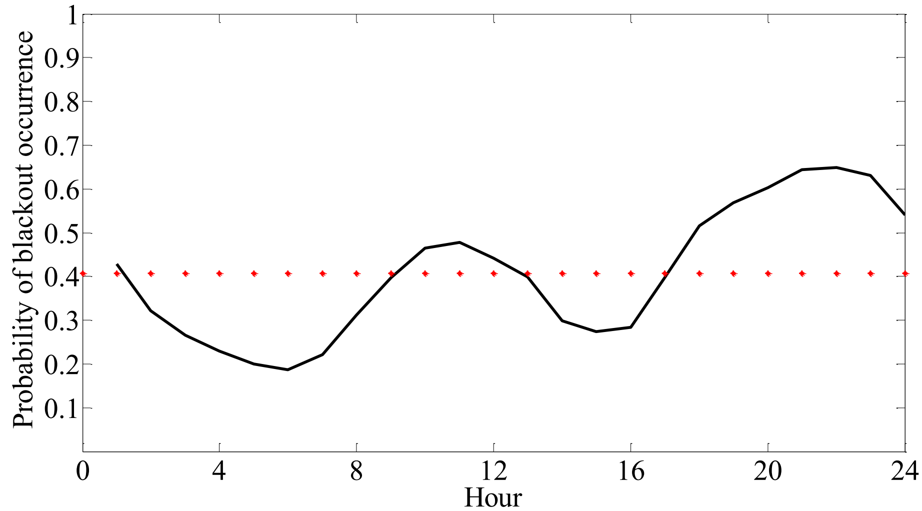
8000
7000
6000
5000
4000
3000
2000
1000
Number of hours
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Probability of blackout occurrence

(a)

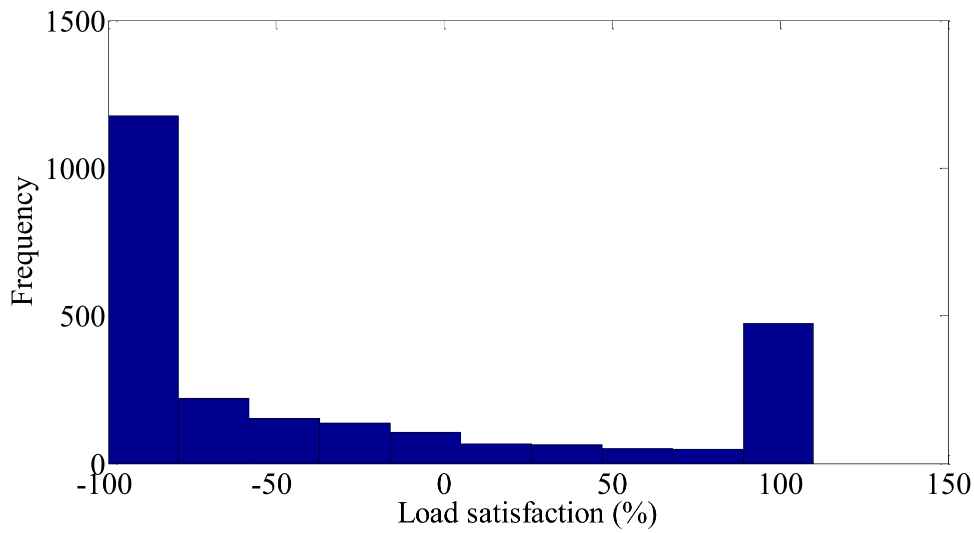


1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Probability of blackout occurrence
0
50
100
150
200
250
300
365
Day No.

(b)

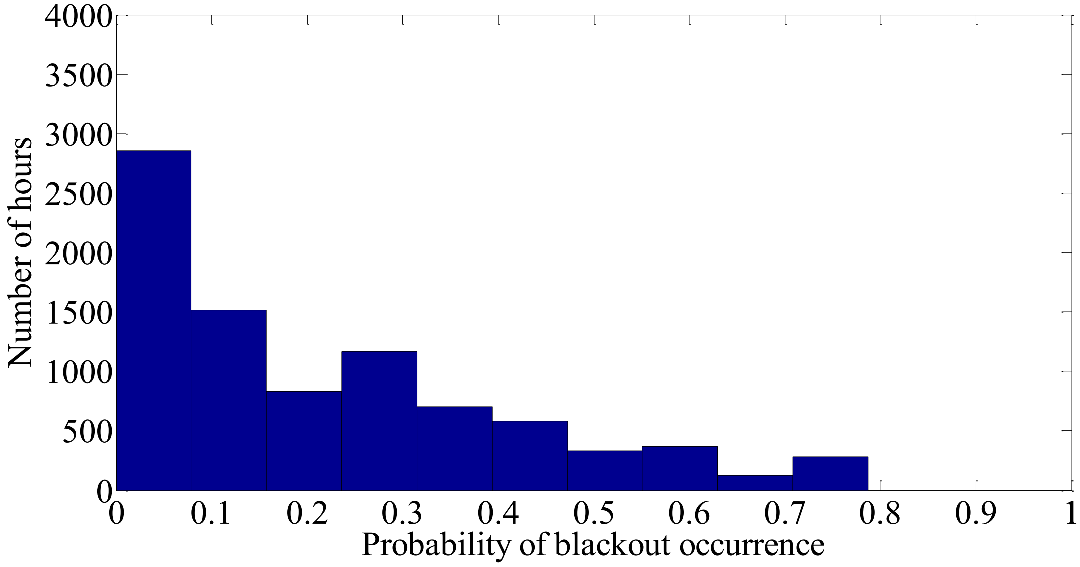


(c)

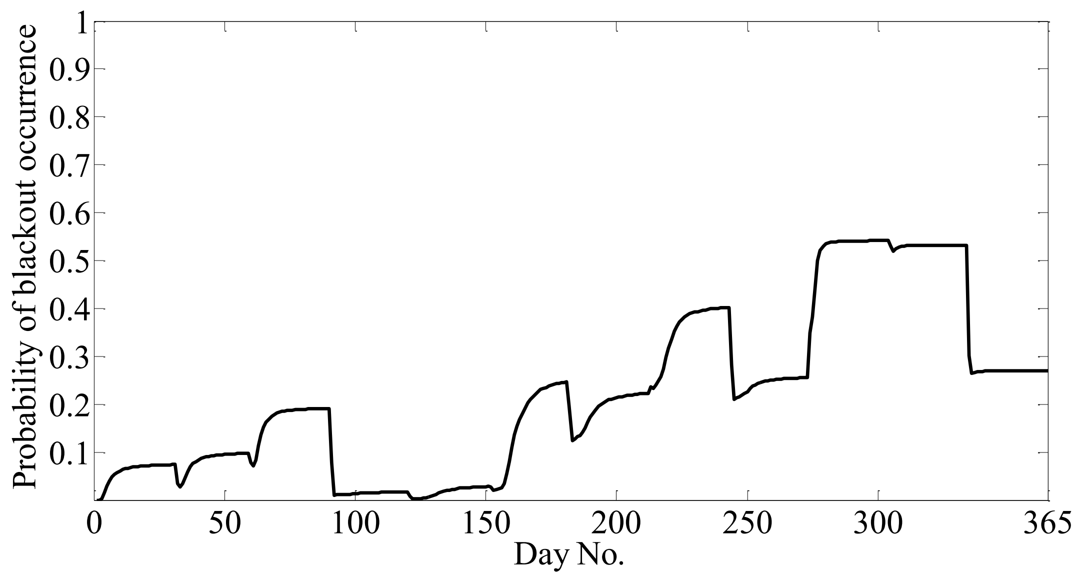


(d)

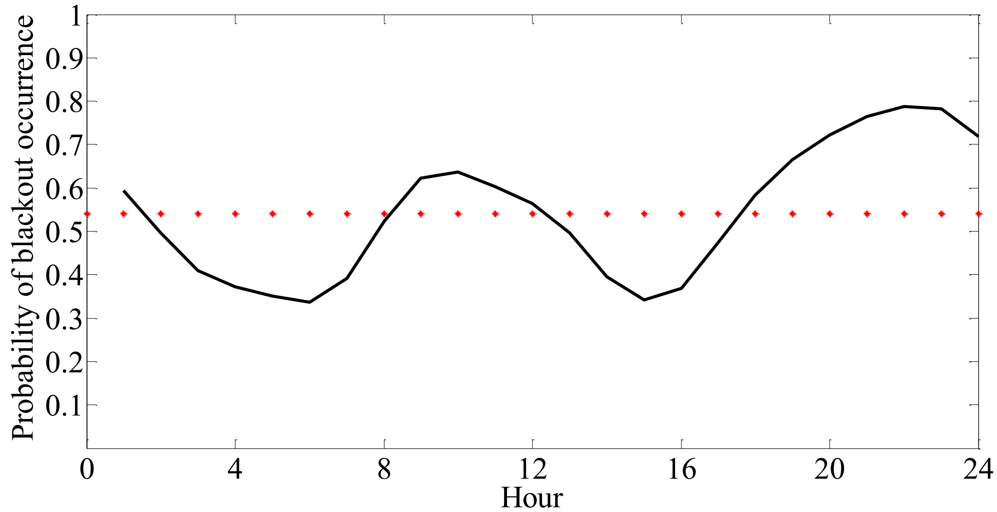
Figure 7-4 Monte-Carlo simulation results on optimum solution of NSGA-II with chance constrained programming for reliability=0.8


Number of hours
4000
3500
3000
2500
2000
1500
1000
500
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Probability of blackout occurrence

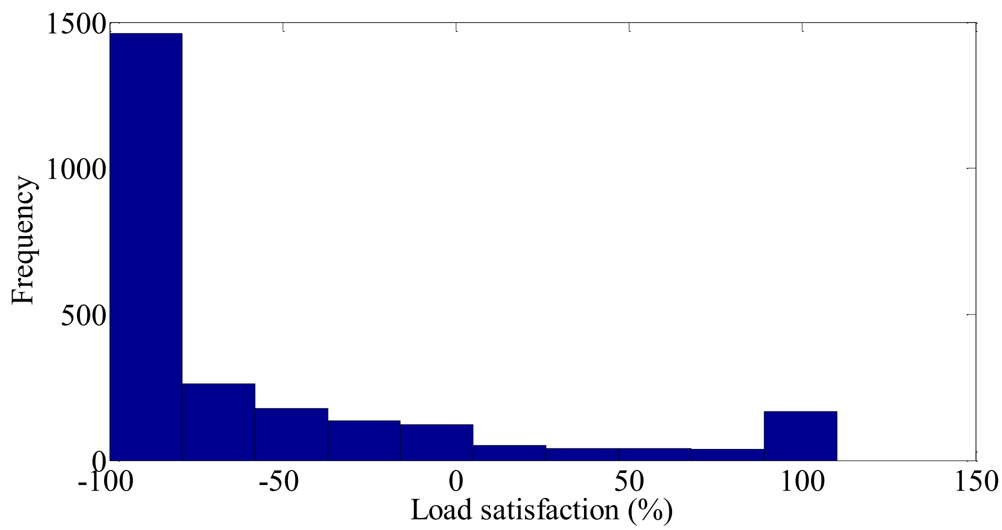
(a)


Probability of blackout occurrence
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
50
100
150
200
250
300
365
Day No.

(b)



(c)



(d)

Figure 7-5 Monte-Carlo simulation results on optimum solution of NSGA-II with Monte Carlo simulation for reliability=0.8

7.7 Summary

This chapter proposes a multi-objective optimisation algorithm for optimum economic and reliability oriented design of hybrid renewable energy system. The algorithm takes into account the uncertainties in renewable resources. The decision variables are the wind turbine rotor swept area, the PV panel area and the number of batteries. Two conflicting objectives which are total cost and system reliability are considered. A novel method in using chance constrained programming is proposed in this study to estimate the expected value of the objective function; the reliability of design candidate; affected by uncertain values of wind speed and solar irradiance at each jour under study. This reduces the evaluation time of the design candidate and consequently the run time of the NSGA-II program.

The results obtained by using the proposed methods are compared with those obtained using a conventional Monte Carlo simulation. The comparison shows that the proposed method yields conservative results in lower reliability values and better results in high reliability values.

8 Summary and Conclusion

This dissertation work comprised a study on optimum design of hybrid renewable energy systems including wind turbine, PV panels and battery bank. This dissertation work involved investigating different design methods; deterministic and stochastic optimization techniques; components modeling and formulating the uncertainties.

This chapter summarizes main contributions of the work as well as point directions for further research in this area.

8.1 Original contribution

The thesis contributes to the following domains:

- Design of grid-connected HRES considering a back-up storage
- Investigation on the reliability of deterministic design approach
- Modelling the variation of power coefficient of the wind turbine.
- Modelling the uncertainties of renewable resources
- Optimal design of HRES under uncertainties.
- Multi objective optimal design of HRES under uncertainties

The obtained results are discussed in more detail throughout the following subsections.

8.1.1 Design of grid-connected HRES considering a back-up storage

Conventional grid-connected HRES rely on grid to obtain the required amount of electricity they require to satisfy the load demand in case of deficit in produced power. However new concepts in buying electricity from grid at different prices at different hours requires development of new design methods in grid-connected HRES This study proposed an investigation on the possibility of adding a small storage system to cover the electricity shortage during peak hours. Through a sample case study it is shown that depending on the grid electricity price it might be economically more profitable to consider adding a small storage to HRES to maintain the shortage at the peak hours.

8.1.2 Investigation on the reliability of deterministic design approach

It is shown that by considering the overall values of traditional reliability criterions during the design some valuable and essential reliability information might be ignored and the outcome of the design may not be able to perform satisfactory. It is shown that in order to prevent the design failures, additional detail performance evaluations are required to be considered on top of the usual reliability measurements during the design of the system.

8.1.3 Modelling the variation of power coefficient of the wind turbine

Since in this work the focus is on optimal sizing of HRES based on the penetration of the renewable resources and specific type of components are not necessarily chosen, to obtain a mathematical model independent of the type of the wind turbine the power curve of the different wind turbines are used to calculate the corresponding Cp value to different wind speeds and through an least square optimisation a best fitted mathematical model is found to model the wind turbine power coefficient variations at different wind speed values. This model is particularly created for use in case studies reported in this thesis and the input data for the modelling is extracted from wind turbines in response to the demand of the load used in the case study.

8.1.4 Modelling the uncertainties of renewable resources

The Hybrid Renewable Energy System (HRES) can be a reliable solution to bring electricity to isolated areas where there is no access to the grid by considering uncertainties in resources at the design stage. Appropriate modelling of wind speed and solar irradiance variations, at the design stage, would give a more realistic picture of the designed system performance and would result in more reliable HRES. The precision in modelling uncertainties would reduce the economic effect of over design of the system which might have been caused because of over estimation of the uncertainties. Monte Carlo simulation is proven to perform well in design under uncertainties however its performance is completely dependent n its random data generator. To obtain the most accurate model in wind speed and solar irradiance variations of the desired location, two different methods are used for fitting the historical data to known distributions and time series analysis using autoregressive moving average models (ARMA) The results obtained by using ARMA simulation are compared with the results obtained from fitting the historical data of wind speed to Weibull distribution and solar irradiance to Beta distribution. Comparing the statistical characteristics of the generated data by mentioned methods it is shown that the random data generator to model the uncertainties in Monte Carlo simulation should be selected based on the location of the desired site.

8.1.5 Optimal design of HRES under uncertainties using CCP

Chance-constrained problems are performing well in solving optimisation problems involving uncertainties. However they are conventionally solved based on an initial assumption that is the uncertainties to follow Gaussian distribution. Though the performed analysis in this work it is shown that this assumption may result in a conservative solution rather than an optimum. This thesis proposes a analytical method in solving chance constrained programming with unknown joint distribution of the random variables. It also shows that by using the common approach the design space would be smaller than the design space obtained by the proposed method and therefore the outcome of the common method is more conservative. Though by using proposed method can obtain a less conservative yet equally reliable HRES.

8.1.6 Multi objective optimal design of HRES under uncertainties

Many of the reported researched on optimal design of HRES in the literature are either single objective or they are ignoring the resource uncertainties. In this work two contradicting objectives; cost and reliability are selected and NSGA-II is used as the base for performing the multi objective optimisation. The work also proposes a novel method in employing chance constrained programming in multi-objective problems as a substitute of Monte Carlo simulation in estimating the expected value of the objective function which is affected by the uncertainties, in other words instead of finding the optimum solution for a predefined value of reliability, chance constrained programing is used to estimate the expected value of the reliability of the design candidates in a multi-objective optimisation problem.

8.2 Critical appraisal and future works

The techniques and results, presented throughout this thesis, can be possibly improved as the objectives of the following future research directions.

The economic and demand parameters are considered as deterministic values. Considering the uncertainties in the economic aspect such as inflation and interest rates can be done in future works. The unpredictable nature of the demand especially for small sites can also be taken into account in future improvements.

Adding other renewable sources such as ground source can be considered in further researches.

List of Publications

- A. Kamjoo, A. Maheri, G. A. Putrus, and A. M. Dizqah, ”Optimal Sizing of Grid-Connected Hybrid Wind-PV Systems with Battery Bank Storage,” in World Renewable Energy Forum (WREF), 2012
- Kamjoo, A., A. Maheri, and G. Putrus, ” Reliability Criteria in Optimal Sizing of Stand-alone Hybrid Wind-PV-Battery bank System,” Environment Friendly Energies and Applications (EFEA) Symposium, 2012
- Kamjoo, A., A. Maheri, and G. Putrus, ”Wind Speed and Solar Irradiance Variation Simulation Using ARMA Models in Design of Hybrid Wind-PV Battery System,” Journal of Clean Energy Technologies, 2013.1: p. 14-17
- Kamjoo, A., A. Maheri, and G.A. Putrus, ”Chance constrained programming using non-Gaussian joint distribution function in design of standalone hybrid renewable energy systems,” Energy, 2014. 66(0): p. 677-688
- Kamjoo, A. Maheri, A. M. Dizqah, and G. A. Putrus, ”Multi-Objective Design Under Uncertainties of Standalone Hybrid Renewable Energy System Using NSGAII and Chance Constrained Programming,” Electrical Power and Energy Systems,01/ 2016; 74; 187-194
- A.M. Dizqah, A. Maheri, K. Busawon, and A. Kamjoo, ”Modeling and Simulation of Standalone Solar Power Systems,” International Journal of Computational Methods and Experimental Measurements 01/2014; 2(1):107-125 / WIT Press Journals
- A.M. Dizqah, A. Maheri, K. Busawon, A. Kamjoo, ”A Multivariable Optimal Energy Management Strategy for the Standalone DC Microgrids,” IEEE Transactions on Power Systems, ,PP(99):1-10, DOI:10.1109/TPWRS.2014.2360434 (Open-Access)

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