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Enabling Electricity Access: A Comprehensive Energy Efficient Approach Mitigating Climate/Weather Variability-Part II

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Abstract: Population dispersion necessitates grid expansion to meet electricity demand. For many developing countries and remote communities, meeting electricity demand is a challenge due to a power generation shortage and load variability that is highly driven by weather uncertainty. Electric utilities' practical planning solutions are to disable electricity access from new residential regions, supply at least 10 percent of the non-electrified regions, or follow a rotating feeder curtailment such that the new regions are electrified for few hours daily. This paper proposes an alternative framework to plan electricity access more efficiently in developing countries. A probabilistic multi-stage optimization framework that first incorporates in-depth analysis of appliance operational models, second accounts for AC grid codes of operation and third anticipates consumers' actions is deployed. The framework is formulated to account for climate/weather uncertainty factors. Results show that energy efficiency can reach up to 97%, and the computation time can be improved by 99.6% with respect to the existing current state of the art approaches.

Acronyms

α	Free variable replacing the multiplication of two binary variables, one showing if a device is to be ON/OFF based on comfort level or consumer's preference, and one describing electricity availability for the device at the time of demand.
∂	Voltage angle
δ	Binary variable indicating whether or not hot water is demanded
Ψ	Binary variable indicating whether or not electricity is available to supply WH
À	Total number of appliances in house *n* including light bulbs
b	Active part of the admittance matrix of the network lines
c	Weather scenario number
$\underline{C}$	Last considered weather scenario number
Ç	Binary variable indicating whether or not electricity is available to supply WP
$\hat{f}$	Binary variable with a value of one when the m device schedule of house *n* at time *t* under SEC_c that is obtained from the first optimization problem can be met and that is zero otherwise
g	Reactive part of the admittance matrix of the network lines
i, j	Bus number
light	Two light bulbs' demand identified as essential loads to be supplied in each house
m and *s*	Appliance preference order in the $\underline{M}$ devices set (1, …., $\underline{M}$). If m is the first device to enter the optimization problem them m=s=1. Otherwise, m>s
max	An abbreviation of maximize
$\underline{n}$	Total number of houses in the new region to be electrified
ObF	The objective function of the second stage optimization problem
obj	The objective function of the first probabilistic mixed integer linear programming optimization problem
Pd	Real power demand in per unit (pu)
Pg	Active power supply for new region (pu)
PF	Tangent of inverse of cosine function of power factor at which WM/WP operates and is set to zero for other devices
Ploss	Active power losses (pu)
Plow	Minimum limit on available *Pg* (pu)
P_m	The power consumed by device *m*
$prob_{t,c}$	Probability of outdoor ambient air temperature at *t* under SEC_c
Pup	Maximum limit on *Pg* (pu)
Qd	Reactive power demand (pu)
Qg	Reactive power supply for the new region (pu)
Qloss	Reactive power losses (pu)
Qlow	Minimum limit on the available *Qg* (pu)
Qup	Maximum limit on *Qg* (pu)
R	Factor for converting power demand to the per unit system (pu)
RTS	Hourly variation factor of critical and essential loads at bus *i* according to the IEEE Reliability Test System following [5]
$\hat{S}$	Free variable replacing the multiplication of two binary variables, one representing whether WP is to be turned ON or OFF according to the preference and working hours and one describing electricity availability for WP at time of demand.
SH	Space heater
SEC_c	A scenario c of the ambient outdoor temperature as obtained from Monte-Carlo Simulation and data clustering
t	Time of the day
T_{in}	Indoor temperature (ºC)
v	Voltage magnitude
WH	Water heater
WM	Washing machine
W_{new}	Free variable replacing the multiplication of two binary variables, one representing whether SH is to be turned ON or OFF according to the comfort level and the other one describes the electricity availability for SH at the time of demand.
WP	Well pump
WS	Binary variable embedded in the WM load model and indicating when the WM is demanded
ω_{sh}	Binary variable indicating whether or not electricity is available to supply SH
X_{Pump}	Binary variable indicating whether or not WP is demanded
$Z_{washing}$	Electricity consumed by washing machine (kWh)
Zwh	Electricity consumed by water heater (kWh)

1. Introduction

Electric utilities in many developing countries cannot accommodate electricity demand growth due to a power generation shortage. In India, forty-five million residential units do not have access to electricity [1]. Electric utilities' solutions to overcome the deficient power generation capacity [2] and the limited funds to economically evaluate or invest in renewable energy projects [3, 4] are to continue the scenario of non-electrification, recognize areas as electricity enabled if 0.1 of such areas have access to electricity, or permit electricity access over grid regions under the condition of a rotating load shedding [5, 6]. Even though the latter solution is preferable compared to the scenario of non-electrification, the main issue is the long hours of no electricity access and that can reach almost 12 hours in some regions in the developing world [5, 7].

Some researchers had proposed solutions to enhance

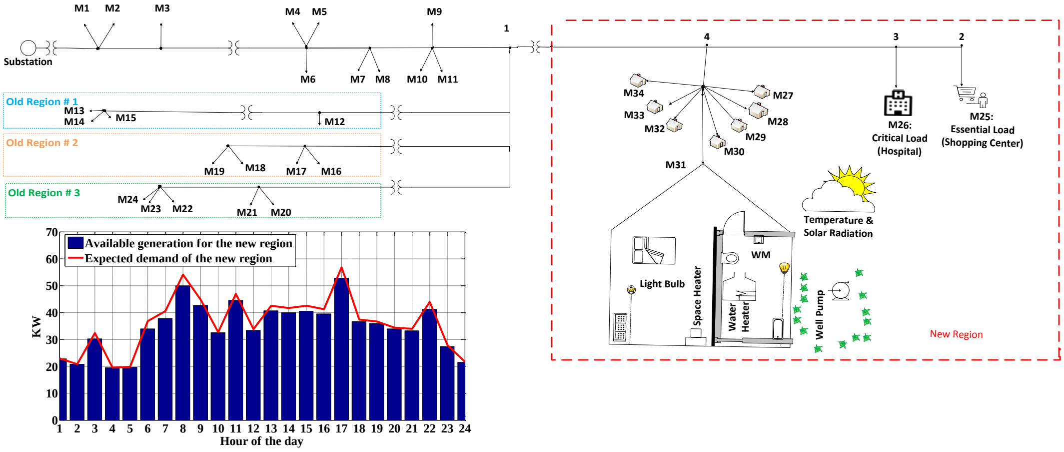

Fig. 1. System under study (M indicates a connected load)

electricity accessibility through off grid electrification [8] but this option is not feasible for the low income category [7, 9]. An alternative approach can be demand side management [10, 11]; however, researches considered such an option either under the availability of supply [12, 13] or time of use tariff [14]. Thus, such an option does not apply for developing countries where electricity unit pricing is the pricing strategy [9] rather than the time of use pricing. A more applicable approach is the work in [5] where enabling electricity access was proposed from a house curtailment option instead of a feeder curtailment as a more promising solution. Nevertheless, the work did not resemble the actual operation of in-home appliances and consumers' tendencies towards them during hours of electricity availability.

The objective of this paper is to present a comprehensive energy efficient optimization approach to electrify non-electrified regions in developing countries in comparison to the current state of the art. This paper is a continuation of Part I [7] and targets the demonstration of simulation results of the optimization framework. To achieve this goal, this paper will present a probabilistic multi-stage optimization framework to enable electricity access from an appliance aspect along with meeting the operational grid codes when the house demand contributes to the hourly profile of the network load. The proposed work considers two atmospheric factors driving planning electricity access: 1) climate, and 2) weather uncertainty. The approach is investigated under all possible scenarios of appliance ownership and preference in terms of receiving the electricity service. A comprehensive analysis and comparisons are conducted to demonstrate the effectiveness of the proposed work with respect to utilities' practice in the view of improving electricity access, energy efficiency and computation time. This paper is organized as follows: Section 2 will present the problem under study. Section 3 will present optimization framework developed to meet the objective of this work. Section 4 will demonstrate simulation results and provide a comparison with respect to the current state of the art. Conclusion is in Section 5.

2. Problem under study

An electric utility has addressed the power generation shortage problem of the current grid, shown in Fig. 1, by introducing a rotating zonal load curtailment to the old regions. Each old region in Fig. 1 is curtailed for 12hours in three-time slots for non-overlapping periods. Since a new residential region is to be accommodated into the grid (New Region in Fig.1), the current utility's approaches addressed in [5] are to: 1) leave such a region non-electrified (option 1) as electricity is not available for 100% electrification, 2) permit at least 10% of the region to access electricity if it is partially available (option 2) such that the region is announced as electricity enabled even though many consumers would still live in the dark, 3) apply a zonal load curtailment as per the strategy applied for the old zones in the grid and assume the region to be defined as electricity enabled (option 3) [6], or 4) invest in alternative sources of supply such as distributed generations (option 4) [4]. Although the last option is promising, it is subject to the uncertainty in the power generation if renewable energy is considered and the need for energy storage system besides the high capital cost of the investment [15], or alternatively, the high costs of fuel and its transportation in case of operating diesel generators [2, 16] making them to be unviable options for many poor customers in developing countries. The last option is beyond the scope of this work.

The new region to be electricity enabled, upon the availability of electricity at any percentage, is represented by the lateral feeder [17] with three buses, an essential load (shopping center) at bus 2, a critical load (hospital) at bus 3 and a normal load (houses) at bus 4 [5]. In this paper, bus 2 and bus 3 are given the priority of supply and are not to undergo power interruption if electricity is available for these buses. Such availability for 24 hours is assumed here following [5]. If not, then they can be supplied with power through uninterruptable power supply units and diesel generators owned by the electric utility. The hourly demand of such buses (bus 2 and bus 3) are assumed to vary according to the IEEE Reliability Test System following [5]. On the other hand, houses connected to bus 4 will undergo a predictive load curtailment but from an appliance perspective rather than a feeder's perspective as driven by climate and weather uncertainty. The predictive load curtailment is different from the reviewed literature in [7] as it is appliance based driven by electricity status, climate/weather uncertainty and consumers' behavior. To elaborate more, modified load models of appliances considering electricity status (availability/absence) as binary decision variables in their formulation are considered so that they can fit the load curtailment optimization problem under study. Also, the problem under study accounts for predicting

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(a)

(b)

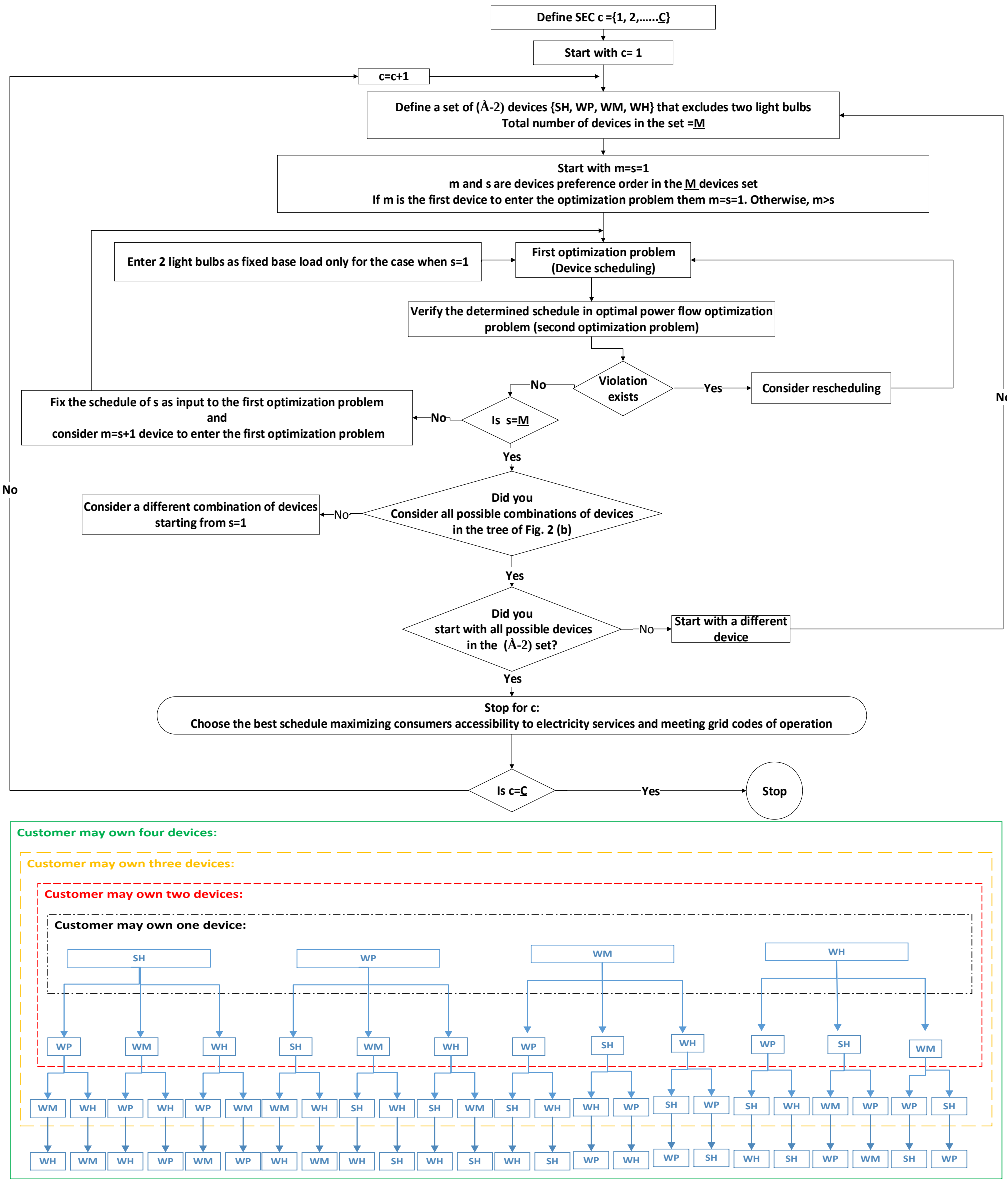

Fig. 2. *Framework*
(a) Scheduling flowchart (followed for all devices' possible combination), **(b)** Ownership/device preference scenarios

future tendencies of consumers towards their appliances as per their comfort level, working hours and preferences and current and future electricity statuses. In more details, a consumer's future decisions towards an appliance is subject to his/her current tendency towards the device and the current electricity status. The modified load models are continuous in terms that they provide hourly temperature measurements accounting for electricity status if appliances are weather dependent or provide anticipated customers' actions if appliances are weather independent. More elaboration on these concepts can be found in Part I [7].

The appliances selected to be under study are based on the survey results used in [9]. The expected available power generation to supply the new region is about 66kVA; while the expected demand of such a region is 72.05kVA [5]. In this work, the demand-generation gap ratio is based on a realistic scenario from India [18]. The power generation is not enough to integrate the new residential region into the grid. Under such a condition, the electric utility usually does not enable electricity access to the new region. In this work, the deficient power generation is well utilized to electrify the new region and improve system efficiency.

3. A probabilistic multi-stage optimization framework

A probabilistic multi-stage optimization framework to address the power generation shortage problem in developing countries from both appliance and grid perspectives is proposed. This type of framework is chosen

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for its features as summarized here: 1) The framework considers all appliance ownership and preference scenarios and appliance operation under climate/weather uncertainty, 2) The first stage of the optimization framework represents a linearized mixed integer nonlinear programming problem (MILP) formulated in this manner to enable obtaining a global optimal solution in an efficient time and avoid the extensive computation time, and 3) The second stage of the optimization framework focuses on a simple mixed integer nonlinear optimization problem (MINLP) that takes the results from the MILP and verifies the alignment of results as per the operational requirements of the grid to avoid any AC power flow and voltage level violations. Even though it is an MINLP problem, it involves one type of binary decision variables indicating whether the schedule from the previous stage can be met or not. If not, the problem is tracked in a cycle after accounting for new curtailment decisions, if necessary, and system losses from the second problem until the framework confirms a global optimal solution. The framework is developed as two stages to avoid software solver failure as a result of a limited computer memory or reaching the maximum cycle/iteration limit as recommended in [5]. The general framework, shown in Fig. 2 (a), is defined to be probabilistic when the MILP (first optimization problem) and the MINLP (second optimization problem) are both run for planning electricity access in the short or medium term. In this aspect, the framework is to be evaluated under weather uncertainty scenarios while accounting for the corresponding probability of each scenario. Readers are encouraged to refer to Part I of this work [7] for further elaboration on the modeling philosophy of the weather uncertainty.

3.1. Appliance Ownership Scenarios

Appliances under study are space heater (SH), water heater (WH), washing machine (WM), well pump (WP) and light bulbs. Light bulbs, basic needs, are given the priority of supply over other appliances.

The problem formulation considers all possible scenarios of appliance ownership and the preference of device accessibility. The preference is assumed to be the same for all houses in the new region. In this case, $({}^{\grave{A}-2}P_{\grave{A}-2} + {}^{\grave{A}-2}P_{\grave{A}-3} + {}^{\grave{A}-2}P_{\grave{A}-4} + {}^{\grave{A}-2}P_{\grave{A}-5} =$ 64 preference scenarios) are investigated given the maximum number of appliances each house can have is ($\grave{A}$ = 6 including 2lightbulbs/house), and P stands for a permutation. Fig. 2 (b) shows a tree diagram that provides further clarification on this concept. The tree diagram can be divided into levels. The first level (in black color) indicates that the customer may own one of four devices (SH, WP, WM and WH) or has a preference of this device over other devices in terms of receiving electricity if he/she owns more than one device as clarified by tracing the tree diagram from top to bottom. The first level's device (the only owned device or the preferred device over others if tracing the tree down to further levels) is to be scheduled first, as driven by the weather factor, working hours,…etc., as per the first stage optimization problem in Section 3.2. Such a schedule is to be verified with grid codes of operation in terms of not violating voltage levels of the network and the power flow in the lines since this demand would contribute to the hourly load profile of bus 4. This is to be further explained in the second stage optimization problem in Section 3.3. If violation exists, rescheduling is considered by revisiting the first stage optimization problem. The second level of the tree diagram (indicated by red color in Fig. 2 (b)) presents the ownership scenario of two appliances such that the second row represents a second choice of a device preference to access the electricity service. In this case, there are 12 possible scenarios describing all preferences that can be generated and to be simulated when tracing the tree from the first level to the second level. The optimal scheduling decisions are to be made based on the optimization framework in Fig. 2 (a). The third level of the tree diagram (orange color) accounts for three devices owned by each customer connected to bus 4 of the feeder. In this case, the preferences of accessing devices can be looked at by tracing Fig. 2 (b) from top to bottom. Thus, 24 preference scenarios are generated. In the fourth level (pink color), the customer owns four devices and the fourth choice of preferred devices to have access to electricity can include 24 scenarios based on what devices are considered as choices in earlier levels. In total, 64 preference scenarios are evaluated. Such scenarios are also based on what devices the customer owns. The investigated number of scenarios does not account for the preference of accessing light bulbs as such an access is assumed to be essential. Thus, such devices are given the priority of electricity supply. $\grave{A}$ and the type of devices in each house is set based on [9]. If weather uncertainty is to be accounted for, then the ownership scenarios are to be evaluated under *SECc* scenarios of weather temperature. This condition can increase the size of the problem.

In this work, all possible ownership scenarios are evaluated and the simulation section will provide an in-depth analysis of the results for a selected appliance ownership scenario. Also, the effect of weather uncertainty on scheduling appliances under the ownership and preference scenarios, and how that would affect electricity delivery when considering grid codes of operation are investigated in Section 4.

3.2. First Optimization Problem

Under power generation deficiency, not all consumers' owned devices can be supplied with electricity. The goal is to schedule consumers' devices such that they can have more access to electricity services rather than not being electrified in the worst case scenario or having their houses out of electricity supply for many hours as another solution. The latter case implies no devices would be supplied during hours of load curtailment. On the other hand, the objective here is to present an alternative approach where some consumers can have access to a certain type of devices at hour t while others have it at later hours. Similarly, those other consumers can have access to other type of devices during that time. This approach is targeted as a more flexible approach that can enhance electricity access. The scheduling problem accounts for load operational models where electricity availability/absence for each appliance is accounted for as a decision variable, and consumers' future actions towards their devices are anticipated as per their current and previous actions as driven by many factors as explained earlier in Part I of this work (Refer to Section 3.2 in [7]). Also, the scheduling problem accounts for the appliance ownership and preference scenarios as discussed in Section 3.1 as well as how the decision of supplying a device would impact the operation of other devices and

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consumers' tendencies towards such a device and other devices. The scheduling problem is evaluated under the probabilistic nature of weather and under the climate concept. Outputs of the first optimization problem are sent to the second optimization problem (Section 3.3) to validate the schedule as per AC grid's codes of operation, and any violations in the determined schedule would necessitate revisiting the first optimization problem for rescheduling as driven by the output of the second optimization problem.

In this section, the objective function and the structure of the first optimization problem are presented. The objective function of the first probabilistic MILP optimization problem (*obj*) is to maximize the energy demand that can be met for all houses of the new region under all-weather probable scenarios as given by the generic form in (1).

$$\max \quad obj_m = \sum_{n=1}^{n} \sum_{t=1}^{24} \sum_{c=1}^{c} prob_{t,c} * P_{m,n,t,c} * \alpha_{m,n,t,c} \quad (1)$$

Where α is a free variable that originally replaces the multiplication of two binary decision variables of a nonlinear programing problem, one representing whether the device is to be turned ON or OFF according to the comfort level or a consumer's preference, and the other one is representing the availability/absence of electricity for the device at the time of demand. The latter inherently implies if the available electricity is sufficient to supply the device as per its power consumption.

To clarify the generic form of the objective function, α represents W_{new} when dealing with SH and $\hat{S}$ when dealing with WP. In this case, these terms represent free variables relating the electricity availability status and the demand for the device. For example, the term ($X_{sh}{}^{*}\,\omega_{sh}$), where ω_{sh} indicates electricity availability/absence for SH and X_{sh} indicates whether the SH should be ON/OFF based on comfort level, is linearized by replacing it by W_{new} and adding constraints (3)-(7) in [7] to the SH load model. *m* is the order of the device in terms of entering the optimization problem or as driven by a consumer's preference towards it over other devices. It is important to emphasize that the whole multiplication term ($P_m * \alpha_m$) denotes the electricity consumed by each device (SH, WH, WM or WP). The term ($P_m * \alpha_m$) is referred to as *Zwh* and $Z_{washing}$ when dealing with WH and WM, respectively. In this case, the electricity status (available or absent) and the demand for the device are embedded in *Zwh* and $Z_{washing}$ formulations as explained in [7]. On the other hand, P_m refers to the power consumed by SH or WP if the corresponding device is demanded and supplied with electricity as per α_m. For full definitions of the terms (W_{new}, $\hat{S}$, *Zwh* and $Z_{washing}$) and their links with the objective function and constraints of the optimization problem, refer to [7]. $prob_{t,c}$ is the probability of the outdoor ambient air temperature at time *t* under SEC_c when targeting the uncertainty/randomness of the weather temperature (case study 2). On the other hand, such a parameter is given a value of one when the problem is addressed under the climate concept (case study 1).

The first stage optimization problem is subject to the power generation-electricity demand constraints (2-5) where (2) and (3) represent the active and reactive power balance equations for the first device entering the optimization problem, and (4) and (5) correspond to the power balance equations for other devices entering the optimization problem in a sequence. Also, the problem is subject to the available power generation limits in (6) and (7) and the proposed reformulations of the operational load models of houses' appliances in [7]. The proposed reformulation accounts for electricity availability/absence as binary decision variables (ω_{sh} in the case of SH, Ç in the case of WP, *É* in the case of WM, Ψ in the case of WH) as discussed in [7]. Other binary decision variables include δ, Λ and β embedded in the WH load model, *WS* embedded in the WM load model, X_{Pump} embedded in the WP load model, and X_{sh} embedded in the SH load model. The positive variables represent the active power and reactive power supply to the system under study. The free variables include *α* and *obj* in this optimization problem and the other free variables shown in the loads' operational models in [7] and embedded in this optimization problem. Such variables include T_{in}, *D*, *G*, T_w, dT_{loss} and $\bar{q}$. Descriptions of these notations can be found in [7]. Section 4.3 of this paper will provide further details on the size of the first optimization problem and the number of equations and decision variables considered.

$$Pg_{i=1,t,c} - Pd_{i=2} * RTS_{t,c} - Pd_{i=3} * RTS_{t,c} - R * \sum_{n=1}^{n} light_{n,t,c} - Ploss_{t,c} = \sum_{n=1}^{n} R * P_{m,n,t,c} * \alpha_{m,n,t,c} \quad \forall m = s = 1 \quad (2)$$

$$Qg_{i=1,t,c} - Qd_{i=2} * RTS_{t,c} - Qd_{i=3} * RTS_{t,c} - Qloss_{t,c} = \sum_{n=1}^{n} R * P_{m,n,t,c} * PF_{m,n} * \alpha_{m,n,t,c} \quad \forall m = s = 1 \quad (3)$$

$$Pg_{i=1,t,c} - Pd_{i=2} * RTS_{t,c} - Pd_{i=3} * RTS_{t,c} - R * \sum_{n=1}^{n} light_{n,t,c} - \sum_{s=1}^{m-1} \sum_{n=1}^{n} R * P_{m-s,n,t,c} * \alpha_{m-s,n,t,c} - Ploss_{t,c} = \sum_{n=1}^{n} R * P_{m,n,t,c} * \alpha_{m,n,t,c} \quad \forall m > s \quad (4)$$

$$Qg_{i=1,t,c} - Qd_{i=2} * RTS_{t,c} - Qd_{i=3} * RTS_{t,c} - Qloss_{t,c} - \sum_{s=1}^{m-1} \sum_{n=1}^{n} R * P_{m-s,n,t,c} * \alpha_{m-s,n,t,c} * PF_{m.-s,n} = \sum_{n=1}^{n} R * P_{m,n,t,c} * PF_{m,n} * \alpha_{m,n,t,c} \quad \forall m > s \quad (5)$$

$$Plow_{i=1,t,c} \le Pg_{i=1,t,c} \le Pup_{i=1,t,c} \quad (6)$$

$$Qlow_{i=1,t,c} \le Qg_{i=1,t,c} \le Qup_{i=1,t,c} \quad (7)$$

Where *Ploss* is an estimated bound on feeder's losses as found from an optimization problem whose objective is to minimize system losses subject to AC power flow constraints given that each house expected demand under SEC_c is provided, and the generation is assumed to be adequate to meet the demand. In such a case, such a value is set for the purpose of providing a rough estimate on what losses of the lines could be and to reserve part of the available electricity for it as a priority since line losses cannot be overcome. *light* is an essential load for each house, and it is assumed to be supplied in each house as it is assigned the priority of supply subject to electricity availability from the sunset hour to midnight. The multiplication term (P_{m-s} * α_{m-s}) is a representation of the demand of the scheduled device with an order of (*m-s*) and that has entered the first optimization problem earlier to device *m* and whose schedule is confirmed in the second optimization problem and set as a fixed input to the first optimization problem when considering the next iteration

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and the target is to schedule device *m* in the sequence of devices under investigation. For example, if SH is the first device scheduled and WM is the second device to be scheduled, α_{m-s} will denote the schedule of SH that is confirmed not to violate the second optimization problem and set as a fixed input to the first optimization problem when considering scheduling WM. α_m will be a free variable representing the schedule of WM that is to be found. The main reason behind considering such an approach in scheduling devices iteratively is to evaluate all scenarios of ownerships and preferences in terms of devices' electricity supply. Other reasons include avoiding long computation time and running out of computer memory.

3.3. Second Optimization Problem

The second MINLP optimization problem is introduced to guarantee that the schedule of devices' electricity supply, found from the first optimization problem, is the best schedule that meets the operational constraints of the AC power system. The objective function (*ObF*) is to maximize the possibility of meeting the obtained device schedule from the first optimization problem as shown in (8).

$$\max \ ObF_m = \sum_{n=1}^{n} \sum_{t=1}^{24} \sum_{c=1}^{C} prob_{t,c} \ \hat{f}_{m,n,t,c} \tag{8}$$

Where $\hat{f}$ is a binary decision variable with a value of one when the *m* device schedule of house *n* at time *t* under SEC_c that is obtained from the first optimization problem can be met and that is zero otherwise.

If the appliance of house *n* is scheduled to have access to electricity, then the power demand of this appliance will contribute to the total hourly load profile at bus 4 of the feeder. In this case, such a contribution is set as a parameter in the power flow constraints (41-44) in [7] and to be multiplied by $\hat{f}$. To obtain a feasible solution, the power flow constraints must be satisfied. If the determined schedule of the appliance would violate such constraints, then the corresponding $\hat{f}$ value would be set by the optimization problem to zero such that no violations in the constraints exist. If such a scenario is experienced, then rescheduling of the appliance would be needed. The earlier schedule when found was continuous in nature. By continuity, we imply that future decisions towards the appliance are driven by current and past decisions towards it. Therefore, if a schedule is not met at a certain instant of time as determined from the second optimization problem, then consumers' tendencies towards their devices would change and the earlier determined schedule from the first optimization problem would interfere with the concept of maximizing consumers' comfort and trying to meet his/her preference of electricity services. Therefore, rescheduling is needed, taking into consideration the time instants when the interruptions in the determined schedule occur and the new system losses (see below equations (9) and (10) [5]) found when considering such interruptions. The problem is tracked in a cycle until both optimization problems are consistent and no interruptions in the schedule, found from the first problem, is experienced as a result of the second problem.

$$Ploss_{t,c} = \sum_{i=1}^{4}\sum_{j=1}^{4}\frac{1}{2}*g_{i,j}*(v^2{}_{i,t,c}+v^2{}_{j,t,c}-2*v_{i,t,c}*v_{j,t,c}*\cos(\partial_{j,t,c}-\partial_{i,t,c})) \tag{9}$$

$$Qloss_{t,c} = -\sum_{i=1}^{4}\sum_{j=1}^{4}\frac{1}{2}*b_{i,j}*(v^2{}_{i,t,c}+v^2{}_{j,t,c}-2*v_{i,t,c}*v_{j,t,c}*\cos(\partial_{j,t,c}-\partial_{i,t,c})) \tag{10}$$

In summary, the objective function is subject to the power system operational constraints given by (39-50) in Part I [7]. Also, such a work demonstrates how the variable $\hat{f}$ is linked to the *m* device schedule (refer to constraints (41-44) in [7]). The second optimization problem includes a variety of decision variables. The positive variables represent the active and reactive power supply to the system under study and the voltage magnitude at the nodes of the feeder. The free variables represent the objective function and the angles of the voltages at the feeder's nodes. The binary decision variable corresponds to the value of $\hat{f}$ for the *m* device in house *n* under weather scenario SEC_c at time *t* of the day. Section 4.3 of this paper will provide further emphasis on the size of the second optimization problem and the number of equations and decision variables involved.

4. Simulation results and analysis

A probabilistic multi-stage optimization framework is proposed to enable electricity access to non-electrified regions or remote communities in developing countries. The framework can be decomposed into two formulated optimization problems linked in the form of a cycle, and modeled and solved using a General Algebraic Modeling System (GAMS) [19]. Two solvers of GAMS are used to simulate the framework, Cplex to simulate the MILP problem and Dicopt to simulate the MINLP problem. Cplex is based on a branch and cut algorithm and is used for finding a solution for a chain of linear programming problems as explained in [5]. On the other hand, Dicopt operates based on the outer approximation algorithm. The stopping criteria of the search is defined by reaching an integer solution. More elaboration on the operation of the solver can be found in [5].

The probabilistic scheduling framework targets first, maximizing consumers' benefit from accessing electricity supply by investigating all possible permutations and combinations of devices to reflect various scenarios of ownerships and preferences in the first stage of the optimization framework, and second maintaining the feasibility of the problem as per the AC grid codes in the second stage of the optimization framework. The link between the first optimization problem and the second optimization problem is established to include more devices into the scheduling problem in accordance to their priority of supply, rescheduling purposes when the determined schedule from the first problem is violating AC grid codes of operation, or updating the first problem with AC grid losses as found from the second optimization problem.

Given the first objective of the first stage optimization problem, examples of ownership scenarios include: (a), (a,b),(a,b,c), (a,b,c,d), (d,a,b,c)...etc. The letters represent devices, and the device order can change such that all possible scenarios are simulated. The best scenario that maximizes consumers' benefit and meets AC grid codes of operation is chosen. The simulation is investigated under two case studies: 1) under the average temperature as an indication of climate, and this consideration is suitable for a feasibility planning stage (long term) of an electrification project, and 2) under the probabilistic nature of weather to account for all possible scenarios of weather temperature uncertainty in the operational planning problem (short and medium terms).

4.1. Long Term Planning of Electricity Access under Climate Concept

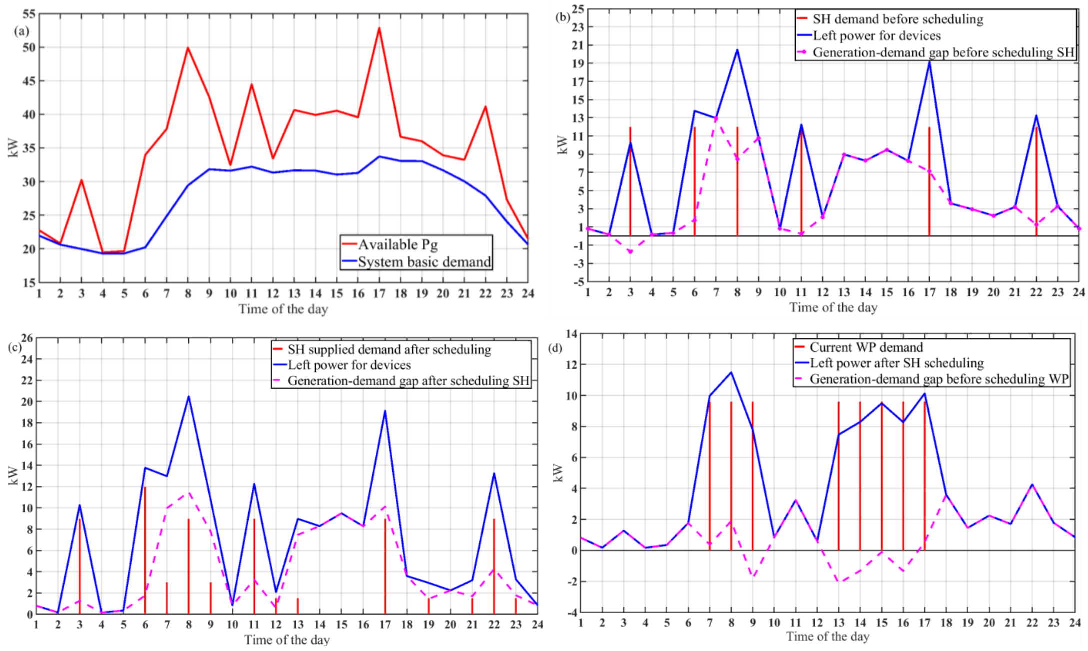

Fig. 3. *Electricity supply-demand status when scheduling SH and before scheduling WP*
(a) available power supply to the new region and its basic demand, **(b)** SH demand and electricity status before scheduling SH, **(c)** SH supplied demand and electricity status before and after scheduling SH, **(d)** WP demand and electricity status before scheduling WP

through a multi-stage optimization framework is investigated under the climate effect as a first case study. Such an effect is modelled and considered in this work for an early stage of a long-term planning of an electrification project (feasibility study stage). The available power generation to the new region of the grid, after applying the curtailment schedule to the other zones of the grid, is shown in Fig. 3 (a). Also, Fig. 3 (a) demonstrates the system's basic demand (light demand of this region, essential load, critical load of the new region and basic system losses) that is to be given the priority of supply in this work if the new region is to be electricity enabled. Subtracting the new region's basic demand from the available power generation to the new region, the generation-demand gap is given by the blue curve in Fig. 3 (b). This gap is not enough to include the new residential region into the grid. Therefore, electric utilities would consider either the region out of electricity service or would accommodate the region into the grid given that a percentage of it is electricity enabled. In this case, many consumers will still not be electricity enabled. In this work, this electricity gap is to be utilized to supply home devices such that all the region is electricity enabled.

Sixty four scenarios of a consumer's appliance ownership and preference in electricity access are investigated when scheduling appliances' electricity access. Table 1 presents a selected sample of results on the met energy demand of houses in the new region when appliances are scheduled through the approach described earlier in Fig. 2. The energy demand shown in Table 1 excludes the energy demand for lights as such energy demand is assumed to be met as a basic demand since lights are essential loads. The table shows the order in which appliances enter the optimization problem. The best ordered scenario representing all devices and the achievement of the maximum consumers' benefit is presented here (SH, WP, WM, WH) for further demonstration and analysis of results as follows: The expected space heater demand is given by the red bars in Fig. 3 (b). If the generation-demand gap is utilized to supply SHs' demand (red bars), then the current expected demand of SHs will not be met at certain hours as demonstrated by the pink curve in this figure. Therefore, scheduling SHs is necessary to account for consequent actions towards utilizing such a type of devices governed by the weather condition. Thus, SHs' demand is scheduled considering the available power. The scheduled demand is given in Fig. 3 (c). This figure also presents the generation-demand gap after scheduling SHs' demand. Such a gap is also presented in Fig 3 (d) as a blue curve along with the current expected demand of WPs in the new region. This current expected hourly demand cannot be met with the power remaining after scheduling SHs (see pink curve). Therefore, WPs are to be scheduled with respect to the generation-demand gap as shown in Fig. 4 (a). In Fig. 4 (b), the current WMs' demand is shown. The generation-demand gap after scheduling SHs and WPs is less than the demand of WMs. WMs are scheduled such that the maximum

Table 1 Sample of the sixty four ownership and preference in electricity service scenarios discussed in Fig. 2

Owned appliances	kWh
SH	70.5
SH-WM	72.9
SH-WP	140.1
SH-WM-WP	141.3
WH-WM-SH	100.4
WM	2.4
WM-WP	78
SH-WP-WM-WH	155.9

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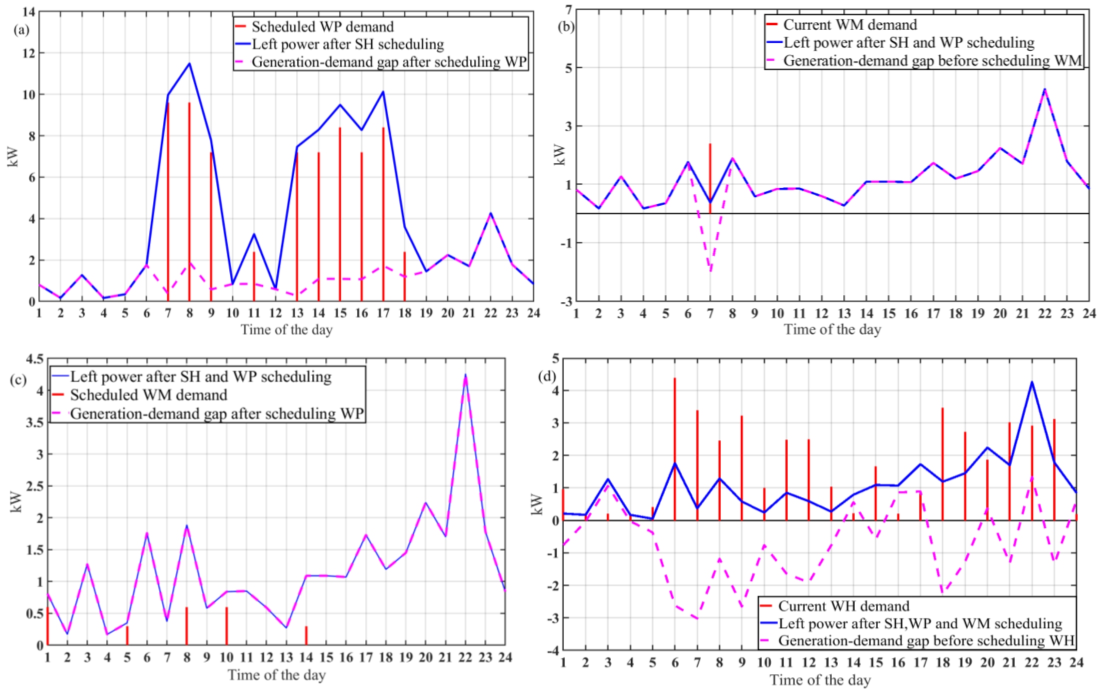


Fig. 4. *Electricity supply-demand status when scheduling WP, WM and before scheduling WH*
(a) WP demand and electricity status after scheduling WP, **(b)** WM demand and electricity status before scheduling WM, **(c)** WM supplied demand and electricity status before and after scheduling WM, **(d)** WH demand and electricity status before scheduling WH

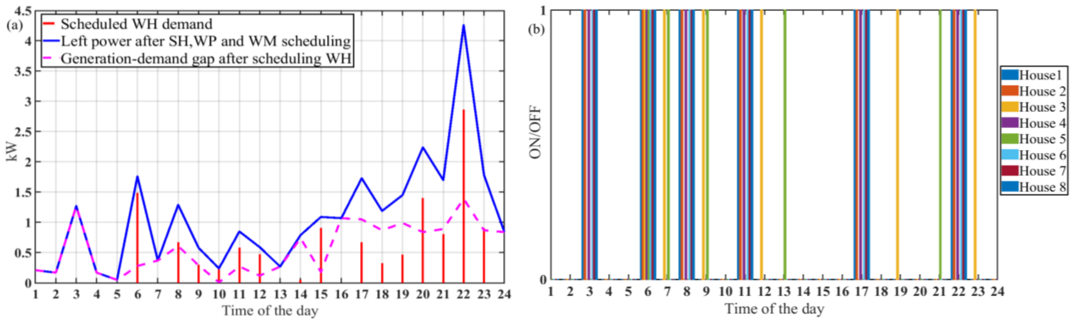


Fig. 5. *Electricity status and device ON-OFF operation*
(a) Electricity status when scheduling WH, **(b)** SH schedule at different houses where 0 means the device is to be OFF and 1 means the device is to be ON

demand of houses is met with respect to this gap as given by Fig. 4 (c). Fig. 4 (d) shows the WHs' demand before scheduling; while Fig. 5 (a) presents the scheduled WHs' demand. Fig. 5 (b) serves as an example of the time slots during which SHs of the eight houses are to be ON. In a future work, consumers' fairness of accessing the same type of devices will be studied. Also, scheduling devices without defining the ordered preference of device accessibility is to be studied considering a variety of objective functions.

The proposed solution does not only maximize consumers' access to electricity but also considers climate and consumers' consequent decisions of utilizing their devices based on their preferences, comfort levels and the availability of electricity. In other words, consumers' tendencies towards high electricity consumption devices such as SHs are governed by comfort levels that are functions of rooms' temperatures. A clarifying example is as follows: If electricity supply is disabled at hour *t* when a demand exists for SH and is available at hour *t+1* when the room temperature has risen due to an increase in the outdoor temperature, then electricity will not be supplied for SH at *t+1* as no demand exists for the device at that time. Conversely, if the outdoor temperature continues to decrease and the comfort level at *t+1* is not met, then the electricity is to supply SH at this hour if available. For further emphasis, overheating is not permitted in this work to avoid interfering with the upper bound on the warmth level set in the SH load model in [7]. Also, overheating is not considered as that can result in more energy consumption and thus leading other appliances to be out of supply. In other words, overheating

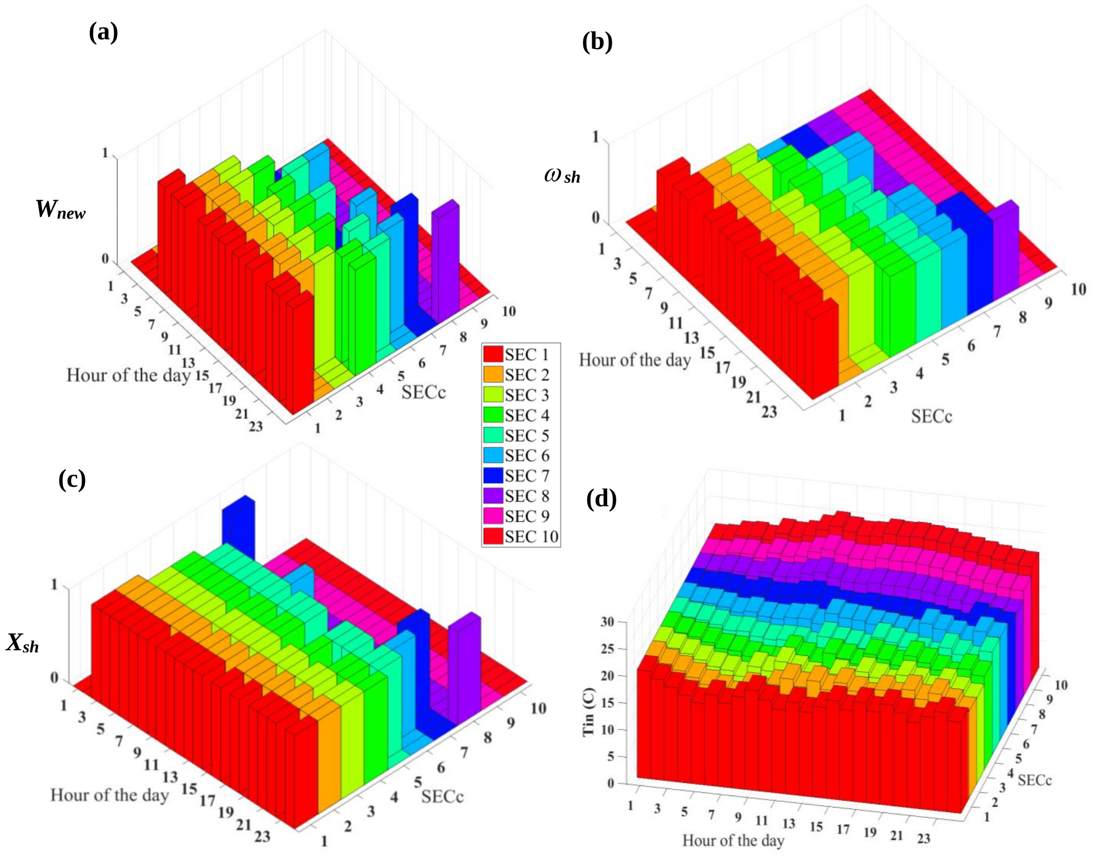


Fig. 6. *Space heater schedule for House # 1 under weather temperature uncertainty*
(a) W_{new}=1 indicates ON SH operation **(b)** $\omega_{sh}=1$ indicates electricity availability to supply SH of House 1 **(c)** X_{sh}=1 indicates SH demand due to comfort level, **(d)** Indoor temperature variation over the day

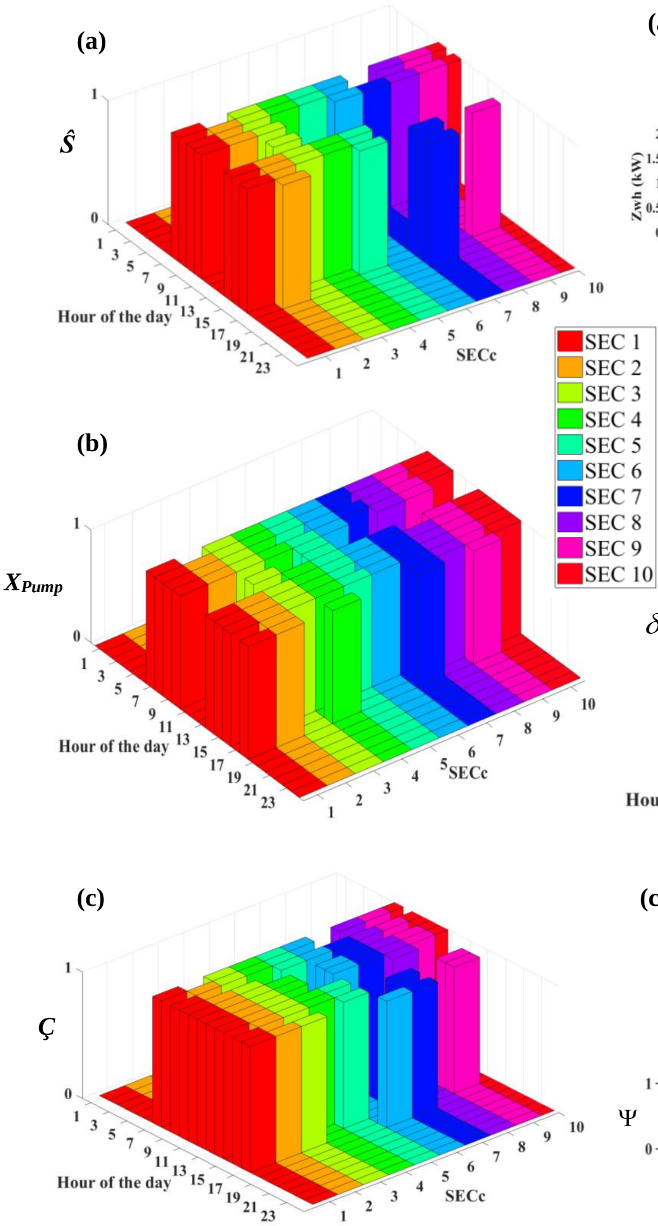
is not a topic of investigation in this work.

4.2. Enabling Electricity Access under Weather Uncertainty

The second case study focuses on investigating consequences of weather uncertainty/randomness on enabling a universal electricity access to a new region of the grid that currently does not have access to electricity. Such a problem is defined as an operational planning problem as it accounts for all possible scenarios of appliance operation when scheduled under the uncertainty of weather condition. Appliance scheduling governed by the probabilistic behavior of the weather condition (modelled through both probability paper plots [9] and a Monte-Carlo Simulation [5, 9]) is simulated.

Fig. 6 shows the SH schedule under weather uncertainty for one of the eight houses of the new region. Also, it presents the demand for SH as per the user's comfort, shows electricity availability time slots, and displays the indoor temperature. We will focus on House 1 as an example to analyze the link between the subfigures of Fig. 6. By looking at the outdoor temperature under various weather scenarios shown previously in Part I [7], and the status of electricity (ω_{sh}) in Fig. 6 and the demand for the SH as governed by the comfort level (X_{sh}), it can be seen that the SH is demanded under SEC 3 for House 1 at 12pm; however, electricity is not available at that time to supply the demand of the SH. Hence, the SH will not be supplied and that will be reflected on the indoor temperature. Although the outdoor temperature has increased the hour after (refer to Fig. 1 in [7]), it does not lead to an enough increase in the indoor temperature to reach the comfort level. Thus, a consumer's demand for a SH is anticipated at 1pm. At such an hour, electricity is available. Therefore, the SH will be supplied and the indoor temperature will increase over the hour and will reach 17.5ºC by 2pm.

On the other hand, there is no need for the SH to be ON in House 1 at 3pm under SEC 2. Even though electricity is available at this time slot, the device will not be supplied as the temperature inside the house is within the comfort level (≈19ºC). Thus, the available energy will be used for supplying other devices to enable a universal electricity access to the new region under consideration. For SEC 10, the SH of House 1 will not be supplied with electricity at any time. The reason behind that is in the weather condition



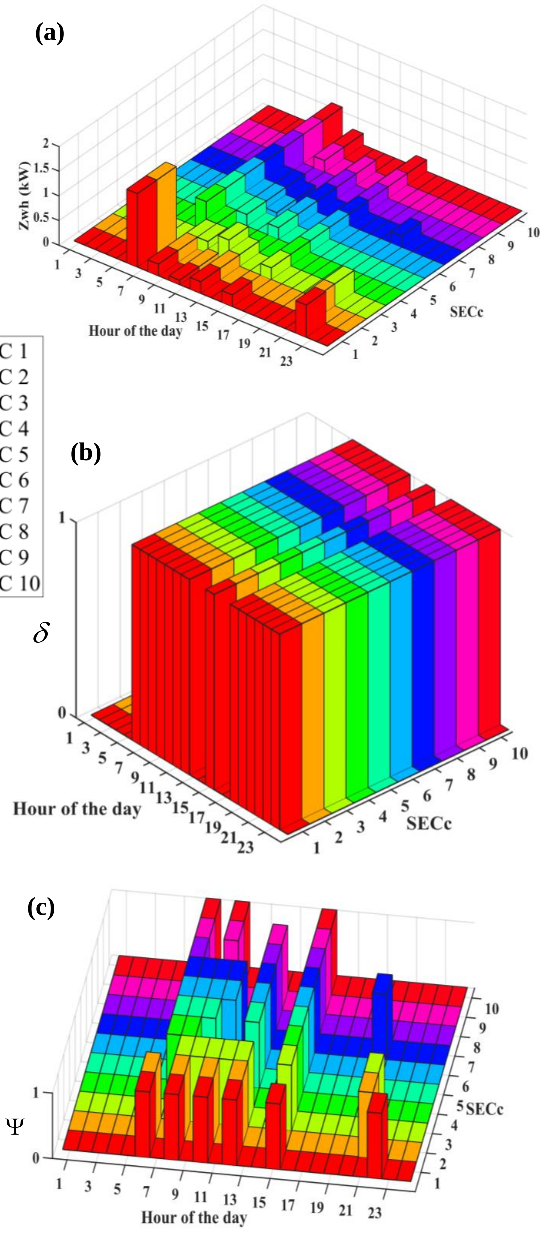


Fig. 7. *Well pump scheduling results for House # 8*
(a) Well pump schedule (Ŝ=1, ON), **(b)** Well pump demand due to agricultural activities (X_{Pump}=1), **(c)** Electricity availability status for well pumps (Ç=1, available)

Fig. 8. *WH scheduling results for House # 1*
(a) Zwh electricity consumption, **(b)** Hot water is needed (δ =1, ON), **(c)** Electricity availability status for WH (Ψ =1, available)

that does not necessitate the demand for SH. Even though the outdoor temperature is very high for a winter season and thus making the indoor temperature to be high as governed by the house thermodynamic model, it is important to emphasize that such a weather uncertain scenario (SEC 10) occurs with a very low probability ($0.0001 \leq prob_{t,c=10} \leq 0.05$) (refer to Fig. 1 in [7]). Since the problem is investigated as a short/medium term operational planning problem, considering all possible weather outcomes is necessary. Thus, such a low probability range is to be considered.

Although WP and WM models are very similar in terms of being independent on weather, their scheduling is influenced by the weather dependent devices and the consumer's preferences towards them. For a demonstration of results purpose, we will focus the analysis on the scheduling of WP of House 8. When WPs enter the

Table 2 A comparison between the current and the proposed approach

Symbol	Case study 1		Case study 2		Current approaches		
	Actual demand [5]	Supplied demand	Actual demand	Supplied demand	Supplied demand under option 1 [5]	Supplied demand under option 2 [5]	Supplied demand under option 3 [5]
kWh/day	199.6	161.5	187	137.7	0	25.52	90.1
#Lights	112	112	112	112	0	14	64
#SH	48	47	48.7	47.2	0	6	16
#WP	64	58	64	35.1	0	7	32
#WM	8	8	8	8	0	1	8
#WH	103	38	103	40.4	0	13	55
Efficiency	-	97%	-	89%	0%	15%	54%

optimization problem as the second type of devices, WP of House 8 is scheduled as shown in Fig.7 (a) and the schedule is denoted by ($\hat{S}$); while the demand for such a device is shown in Fig. 7 (b) as (X_{Pump}), and the availability of supply for the WP is shown in Fig. 7(c) as ($Ç$). Although electricity is available to supply the WP of House 8 under SEC 1 at 11am, and such a time slot is within the period where the WP can be demanded, it is not supplied. The reason behind that is due to first, an optimality search for the best schedule that will maximize consumers' benefit form electricity services while accounting for the weather factor and second, the availability of other time slots within the period over which the device can be scheduled. On the other hand, there is a demand for the WP of such a house at 2pm, and the electricity is available. Thus, the WP will be supplied with electricity as scheduling such a device at such a time can lead to global optimality in terms of maximizing the new region's benefit from electricity services besides ensuring that the determined schedule will not violate the AC grid codes of operation. Given the latter condition, the voltage operational limits at the buses will be maintained. Such a scenario also applies for House 3 and House 1 at such an hour. Under SEC 2, House 1, House 3 and House 8 would demand WPs at 10am; however, only WPs of House 1 and House 8 would be supplied as electricity will be sufficient to supply 6 out of 8 well pumps at such a time slot given that each house would own one well pump.

Fig. 8 presents the WH scheduling results. It displays the energy consumption of the WH (Zwh) of House 1, a function of the demanded hot water volume varying from one house to another, the indoor temperature, the effect of the outdoor temperature on the source where the water is obtained from (well), and specific decision variables considered within the appliance model described earlier in Part I of this work [7]. The demanded hot water use time slots (δ =1) subfigure indicates the time slots during which the hot water is to be utilized, where a value of one indicates that there is a demand for hot water at the corresponding time slot. For example, one gallon of hot water is demanded for House 1 at 8pm. Since there is a demand for hot water at this hour (δ =1), the electricity will supply the WH of House 1 at this hour (Ψ =1) only when it is available and that is under SEC 1-SEC 7.

4.3 Comparison of Results

Enabling electricity access in developing countries where power generation is in shortage is a challenge. The current state of the art will restrict 100% electrification such that the new region is left in the dark (option 1), will electrify at least 10% of the new region such that the area is recognized as an electrified region (option 2) or will follow a rotating load curtailment as with other grid regions (option 3) according to [5]. With the proposed multi-stage optimization framework in this paper, the met energy when dealing with the first case study incorporating the climate concept is 161.5kWh/day. This value represents the supplied devices' daily electricity demand. The generation-demand gap of the feeder when accounting for system losses is almost 0.21kWh. On the other hand, incorporating the probabilistic nature of the weather condition in the simulation can result in an expected met demand of 137.7kWh/day in comparison to an expected actual demand of 187kWh/day under such a nature of weather condition.

Table 2 presents a comparison between the current approaches (options) applied in developing countries and shows the advantage of the proposed solution accounting for both the climate concept at early stages of a long-term planning of an electrification project (feasibility study phase) and the probabilistic nature of weather condition for an operational planning term (short or medium). When considering the climate concept, the proposed approach can meet almost 81% of the expected demand, which is more than the current state of the art (option 1 = 0%, option 2≈13% and option 3≈ 45%). In such a case, the met light demand with the presented approach shows 43% improvement compared to option 3, 94% improvement compared to option 2 and 100% improvement compared to option 1. Also, the met SHs' demand shows 65% improvement compared to option 3, 83% improvement compared to option 2 and 98% improvement compared to option 1. For WPs, scheduling such devices under case study 1 can result in almost 41% improvement compared to option 3, almost 80% improvement compared to option 2 and almost 91% improvement compared to option 1.

On the other hand, it is evident from Table 2 that the electricity supplied under the probabilistic nature of the weather condition (case study 2) represents almost 74% of the actual demand of the region that the current approaches cannot accommodate due to an underfunded capacity of power generation and less efficient application scheme to handle the issue. In this paper, 100% of the light demand is met and that shows a significant improvement compared to options 1, 2, and 3. Moreover, almost 97% of the SHs' demand is met with the proposed approach in comparison to 33% with option 3, 12.5% with option 2 and 0% with option 1 where the latter is the most dominant applied approach for such a region. The proposed scheduling approach under the uncertainty of the weather condition in the probabilistic multi-stage scheduling problem meeting grid codes of operation can result in almost 55% of WPs' demand being met rather than meeting 50% of WPs' demand with option 3, 11% of WPs' demand with option 2 or 0% of such a demand with option 1. The case for WMs is the same in the proposed approach and in option 3 but these are considered improvements compared to option 1 where no WMs have access to electricity and option 2 where only one WM can have the electricity service.

Table 3 Multi-stage optimization problem characteristics

Case study	Case study 1				Case study 2			
Appliance	SH	WP	WM	WH	SH	WP	WM	WH
MILP EXT $x(10^{-3}s)$	15	16	16	16	1357	94	109	172
#equations Blocks	35	10	9	20	36	12	11	22
# Single equations	6193	1025	1017	3135	61921	12161	12081	33261
#variable blocks	7	6	6	12	7	6	6	10
#Single variables	817	625	625	1777	8161	6241	6241	13921
# non-zero elements	1651	2545	2545	6886	165529	27289	27289	66859
#Discrete variables	384	384	384	576	3,840	3840	3840	5760
MINLP EXT $x(10^{-3}s)$	16	15	15	31	187	250	375	250
#equations Blocks	9	9	9	9	11	11	11	11
# Single equations	769	769	769	769	9601	9601	9601	9601
#variable blocks	6	6	6	6	6	6	6	6
#Single variables	577	577	577	577	5761	5761	5761	5761
# non-zero elements	4989	5265	4957	5197	51,209	53313	53873	55101
#Discrete variables	192	192	192	192	1920	1920	1920	1920

Under both case studies, it can be seen from Table 2 that the number of devices met with the proposed approach is more compared to other approaches except for the case of WHs. This number is less than such a number in option 3 because scheduling WH is not only dependent on hot water demand, but also temperature. The latter governess electricity consumption and energy losses from the tank surfaces. It can be true that WH is met less often than with option 3, but the energy supplied to such a device is more as it is a function of the outdoor and indoor temperatures. In other words, other approaches (option 1, option 2, and option 3) do not consider meeting consumers' comfort.

The presented approaches can rise energy efficiency to 97% under case study 1 and 89% under case study 2 compared to 54% energy efficiency achieved with a rotating load shedding. GAMS execution time (EXT) and the optimization problems' code features are shown in Table 3. The codes were run on a laptop (2.6 GHz Intel Core 5). EXT is improved by 91.3%-99.6% compared to [20] using a nonlinear programming device scheduling for a net benefit maximization when power generation shortage is not an issue. The proposed work in this paper can be implemented in practice following the recommendations in [5] where 1) device schedules can be followed voluntary given the voluntary initiatives that took place in India as an example of a developing country where consumers either supervise electricity consumption or sacrifice their devices at specific hours of the day to enable electricity access for education [2, 5], 2) the feeder can be disabled through circuit breaker if schedules are not maintained, or 3) utilities are responsible for the smart control of in-home appliances.

5. Conclusion

This paper proposed a promising solution that can address the shortage problem of power in developing countries and remote communities. The presented solution focused on scheduling residential home devices in a probabilistic multi-stage optimization framework. The presented solution relies on appliance operational models incorporating electricity availability to appliances as decision variables, climate consideration (essential for a feasibility stage of a long-term planning of an electrification project), a consideration of the probabilistic nature of weather condition for any operational planning stage of an electrification project, and consumers' comfort and preferences. The proposed appliance scheduling approach accounts for both concepts of appliance ownership and preference in terms of receiving the electricity service. The proposed approach can maximize consumers' benefits from electricity services by having it all day, maximize their comfort, and improve energy efficiency by up to 97% compared to 54% energy efficiency through a rotating load shedding for 12 hours daily. Moreover, the optimization framework guarantees a significant computation time imporvement such that it is much faster compared to literature.

6. References

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