ON THE PLANNING AND OPERATION OF COMPLETELY GREEN MICROGRIDS

by

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This dissertation is dedicated to my family,

who always believes in me.
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by

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ON THE PLANNING AND OPERATION OF COMPLETELY GREEN MICROGRIDS

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Due to concerns over the rise in global greenhouse emissions from electricity production, an increase in the utilization of renewable energy sources (RES) is becoming imperative in the energy industry. Green microgrids are isolated, small-scale power systems that combine distributed RES and loads into autonomous systems. A completely green microgrid relies exclusively on RES as its energy source. It is expected that green systems, such as green microgrids, will boost the RES usage. Though the planning and operation of microgrids (MGs) have been researched extensively, few current studies exploit MG loads’ characteristics. Accordingly, this research seeks to utilize load characteristics in completely green MGs to: (1) minimize the MG planning and operations costs, (2) characterize the MG performance, and (3) devise time-efficient resource scheduling schemes for MGs.

I first considered planning a completely green MG located in a residential community with smart homes. These would contain programmable appliances such as laundry machines and dishwashers, whose operation can be interrupted or shifted in time. The planning problem seeks to determine the optimal number of RES (such as solar panels and wind turbines), as well as the energy storage size that meets the appliances’ load demand in a cost-effective way, while satisfying MG reliability
constraints. I use stochastic methods, including Chance Constrained Programming and Monte Carlo Simulation, to account for the randomness in renewable energy production. The study’s numerical analyses show that appliance scheduling can typically reduce MG planning costs by over 40%.

Isolated green MGs can also include thermal generators, such as diesel engines and fuel cells, as back-up energy sources to offset unforeseen shortages of renewable energy production. Thus, it becomes crucial to optimally schedule the power generation of these thermal generators to minimize MG operation costs. I exploit the flexibility to schedule programmable appliances in an isolated residential MG to design a time-efficient algorithm that determines a cost-efficient schedule for the thermal generators. The proposed algorithm returns schedules that are very close to those of the optimal or near optimal solutions based on search optimization methods, and with significantly lower time complexity.

Finally, I investigate the optimal planning of a completely green charging system for electric vehicles (EVs), which is a completely green MG that supplies energy for EV charging. The study determines the optimal number of solar panels and energy storage capacity that minimizes MG investment costs, while satisfying EV charging performance requirements. I use a three dimensional Markov chain model to account for the intermittency in renewable energy production. Simulation is used to validate the model’s performance results.
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CHAPTER 1
INTRODUCTION

1.1 Motivation

In the conventional electricity system, also known as the grid, electric power is generated from a few, mostly fossil-fueled central power plants and is then transmitted to the distribution system, which in turn delivers the generated power to customers. However, concerns over the growing energy demand, the high cost of new transmission and distribution lines, and the rise of global greenhouse gas emissions have stimulated new research efforts that seek alternatives to the currently strained centralized grid [1]. In particular, the US Environmental Protection Agency (EPA) indicates that the burning of oil, coal, and natural gas for electricity and heat production is the largest contributor to the global carbon footprint [2]. This problem has fueled the urgency to increase the utilization of renewable energy sources. A logical solution to these challenges has been the deployment of distributed energy resources (DER) to promote the development of a new power system paradigm called Microgrid (MG). Expected to be one of the cornerstones of the future enhanced grid [3], a MG groups locally distributed energy resources and electric loads into an entity that can operate autonomously from the main power grid [4]. Seeking to address the issue of growing greenhouse emissions, this dissertation investigates the optimal planning and operation of completely green MGs (CGMGs), which are zero-emission isolated MGs whose power is generated entirely by distributed renewable energy sources (RES).

Figure 1.1 illustrates an exemplary CGMG, whose power is produced exclusively by solar panels and wind turbines. Renewable energy generation, especially solar and wind power, tends
to be intermittent and weather-dependent, so energy storage systems (ESS) (batteries in Figure 1.1) are indispensable components of the CGMG as they stabilize the RES’ fluctuant energy supply [5]. CGMGs are useful for remote areas, where the extension of an existing power grid is impractical, such as is often the case in developing countries. CGMGs are also appropriate sources of substitute power for local communities in case of grid attacks (cyber-attack or physical sabotage) or other power outages either due to grid collapse or load shedding.

![Figure 1.1. Completely Green Microgrid](image)

Though many technical studies have investigated the optimal planning and control of MGs [4-8], few exploit the characteristics of MG loads, especially in the context of CGMGs. These characteristics include timing demands, which define when and for how long the loads require energy and power demands, which indicate how much power is needed per load. One of the considerations of this dissertation is load characteristics in smart homes, which are homes containing programmable appliances, such as dishwashers and laundry machines, that are centrally controlled by a home energy management system (HEMS) [9]. In this case, load attributes refer to
the number of kWh of energy required per domestic appliance as well as the preferred period of appliance operation; the appliances’ preferred operation period is set by the residents via the HEMS. Accordingly, the appliances can be scheduled within the resident-defined chosen periods so as to operate when CGMG’s solar power or wind power is abundant, thus reducing the MG’s need to store/discharge energy from the energy storage system. However, to the best of my knowledge, smart homes’ load characteristics have not been considered in conjunction with CGMG planning. Hence, this dissertation concentrates on the analysis and utilization of load demand attributes in the design and control of CGMGs in order to (1) further minimize MG planning and operation costs, (2) characterize/evaluate MG reliability, and (3) determine time-efficient algorithms for MG resource scheduling.

1.2 Completely Green Microgrid Concept

A CGMG is small-scale power system consisting of RES, energy storages, and controllable loads integrated in a local area such as a small residential community, university, or commercial area. The RES can be comprised of solar panels, wind turbines, geothermal sources, and hydraulic turbines. Additionally, CGMGs can contain thermal generators, such as diesel engines, microturbines, and fuel cells as backup energy sources to cover unforeseen shortages of renewable energy production. For instance, the deficiency in renewable energy might be due to insufficient solar radiation to drive solar panels or lack of wind to operate wind turbines. The CGMG behaves as a controllable system that operates autonomously, isolated from the main power grid [10].

The CGMG concept is of significant interest in MG research because of the benefits it provides, which are outlined as follows.
• Most importantly, CGMGs reduce greenhouse emissions and energy costs by increasing the penetration of RES in the energy sector [10],[11].
• CGMGs defer the need for costly grid expansion by supplying electricity to secluded areas [12].
• CGMGs reduce the energy losses in electricity and heat transmission/distribution by placing RES close to the loads [7].
• As previously mentioned, CGMGs improve power quality and reliability by functioning as backup power sources for regional communities in case of grid outages [13].
• As a new paradigm in the energy sector, CGMGs are expected to foster economic development through the creation of new jobs, products, services, and markets [4].

1.3 Completely Green Microgrid Components

The convergence of communication and information technology with the grid’s power system engineering is considered a crucial step to transform the current grid into a smart and distributed power system [14]. As part of the smart grid, CGMGs will also be enhanced with an intelligence layer that allows a two-way flow of electricity and information to ensure efficient delivery and management of electricity [4].

As shown in Figure 1.2, the main components of a CGMG include:
• Distributed RES and thermal generators, which are usually placed at customers’ sites [15] with capacities varying from a few kWs to 1-2 MWs [16].
• Energy storage devices, which are used to balance the CGMG following abrupt system changes such as disturbances, considerable load fluctuations, and intermittent energy supply. Among
currently available energy storage technologies, batteries, fly-wheels, and super-capacitors are considered the most appropriate for MGs [17].

- MG Central Control (MGCC), which is the center of control and data collection for the MG power system. MGCC is in charge of scheduling the flow of electricity from the RES and thermal generators to the customers [18].

- Communication and control network, a medium via which data and control messages are exchanged between the MGCC, the load controllers (LCs), and the source controllers (SCs). These messages include monitoring information about the supply-load balance, set points for the LCs and SCs, and efficient operation scheduling for the DER [17] [19].

- LCs and SCs, which are in charge of the management and protection of individual loads and DER respectively and are coordinated by MGCC [20].

- Electrical network, which distributes the electricity among the MG components and is controlled by the MGCC.

- Customers, who may also produce energy by deploying their own generators and are the source of the MG’s load demand; customers also affect the CGMG’s load control and efficient operation [4].
1.4 Research Challenges in Completely Green Microgrids

1.4.1 Microgrid Planning

Considering that the MG concept is still new and just beginning to gain wide adoption in the energy industry, MG planning, also known as capacity sizing, will become a crucial issue that need to be addressed in the next few years. MG planning is usually performed years in advance of the actual MG deployment and consists of finding the optimal combination, size, and design of DERs to meet both the future energy and heat demands as well as some specified system reliability constraints [21]. For the CGMG, the technical challenge in its planning arises from the randomness in renewable energy generation, since the actual renewable energy produced may deviate from forecasted values. In addition, the operation of CGMGs’ RES may be affected by the seasonal variations in weather conditions, especially in the case of solar panels or wind turbines, and should be investigated carefully. In this regard, stochastic models and optimization methods have been
shown to be more appropriate for CGMG planning since they are able to account for the randomness in renewable energy production [22].

Hence, this dissertation will examine CGMG planning by employing stochastic modeling and optimization methods including Chance Constrained Programming, Monte Carlo Simulation optimization, and the Markov Chain queuing model to study CGMG planning. Chance constrained programming and Monte Carlo Simulation are used to investigate the optimal planning for a completely green village, which denotes a CGMG installed in a residential neighborhood. The Markov chain queueing model is used for the optimal capacity sizing of a completely green charging system for electric vehicles (EVs), which is a CGMG whose load is a collection of charging stations for EVs. The stochastic methods allow me to account for the intermittency in renewable generation, but also the randomness caused by load demand. As aforementioned, the novelty in this dissertation is the exploitation of load characteristics in CGMG planning. For the completely green village, I utilize the attributes of programmable appliances’ load demand in smart homes to further reduce the planning cost and ensure MG reliability, while for the completely green charging system, I take advantage of the EV charging demand characteristics to ensure that the planned RES capacity meets a set average delay for EV charging.

1.4.2 Microgrid Unit Commitment

Another key area in MG research is MG Unit Commitment, also known as optimal power scheduling, which seeks to determine the optimal operation schedule of thermal generators (which generator should be on/off) to minimize the MG’s operation costs; it is usually executed from one day to one week ahead of time [23]. For the CGMG, the thermal generators will be operational for
days with renewable energy shortage. Considering that most thermal generators, especially fossil-fueled generators, are associated with standby costs, the optimal schedule for the thermal generators seeks to minimize the number of on-line thermal generators. However, these generators are also associated with non-negligible startup cost and delay, so that the optimal schedule also needs to minimize the switching on/off of generators. Consequently, it becomes a challenging task to find a time-efficient algorithm to determine the optimal schedule that accounts for all these competing generators’ constraints and also ensures that the load demand is met.

In this dissertation, the optimal operation problem for a CGMG is considered, when the thermal generators are relied on to supply energy for smart homes during a renewable energy-deficient day. The generators’ stand-by and start-up costs are also considered to allow for a more realistic model for the thermal generators. Taking advantage of the timing and energy demand of the smart homes’ programmable appliances, I devise a time-efficient heuristic algorithm PRO-S to determine the optimal schedule for the thermal generators that also meets the smart home’s load demand. PRO-S finds the cost-efficient power schedule for the generators in a few seconds, while incurring negligible cost penalties compared to a search-based genetic algorithm; the latter returns optimal or near-optimal schedules, but with long execution times (from one hour to one day).

1.5 Dissertation Contributions

This dissertation contributes the following:

**On the Optimal Planning of CGMGs:**

- Combining load scheduling with CGMG planning to further minimize the MG investment costs. Performed numerical analyses show that load scheduling can further reduce MG planning cost by 40% or more.
• Describing stochastic methods for modeling and analyzing the planning problem for CGMGs, including the Chance Constrained Programming method, the Monte Carlo Simulation method and the Markov chain queueing model, to account for the randomness due to load demand and renewable energy generation.

• Using load demand attributes to characterize the reliability of CGMGs.

**On the Optimal Operation of Thermal Generators in CGMGs:**

• Modeling the stand-by and start-up costs of the thermal generators in order to achieve a more realistic model of the generators.

• Exploiting load scheduling to further minimize MG operation costs.

• Devising a time-efficient heuristic algorithm that determines an economical power generation schedule for the generators in a few seconds, while incurring minimal cost penalties compared to optimal solutions returned by time-costly search-based algorithms.

**1.6 Roadmap**

The rest of this dissertation is organized as follows. Chapter 2 deals with the planning problem for a completely green village, while Chapter 3 describes the unit commitment of thermal generators for a completely green village during a day with a shortage in renewable energy. The planning problem in the context of a completely green charging system is presented in Chapter 4. Finally, Chapter 5 describes future works.
CHAPTER 2

OPTIMAL PLANNING FOR A COMPLETELY GREEN VILLAGE WITH PROGRAMMABLE APPLIANCES

As previously mentioned, combining Microgrids (MGs) with renewable energy sources (RES), such as solar panels and wind turbines, allows the reduction of energy costs and carbon emissions [10],[11]. However, the unpredictability of the RES electricity generation is a great challenge to their integration into MGs. This is particularly relevant in the context of a completely green village (CGV), which is an isolated residential MG, whose energy is produced exclusively by RES. A promising solution to stabilize RES’ power generation is the adoption of energy storage systems (ESS) and controllable loads [24], as well as electric vehicles (EVs) [25]. EVs are a special type of controllable loads, which, similar to the ESS, can absorb the extra energy generated by RES, and can later discharge this energy when needed [26]. Schedulable loads allow me to match the load profile to the RES’s power generation curve.

A CGV is composed of smart homes, whose load demands are comprised of spontaneous loads, such as lights, TVs, and microwave ovens, as well as in-advance programmable appliances, such as laundry machines, dishwashers, and EVs. The programmable appliances have power and timing demands, which, when violated, incur customer discomfort and dissatisfaction. In this chapter, I address the optimal planning problem of a CGV, where I seek to determine the minimum number of RES and the size of ESS needed to satisfy the smart homes’ load demands in a cost-

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efficient manner, while meeting MG reliability requirements.

2.1 Literature Review

Although deterministic MG planning and operation have been studied extensively in the literature in the past (e.g., [27],[28],[29]), stochastic models are more suited to capture the uncertainty associated with renewable energy and with certain types of (programmable and nonprogrammable) loads. Hence, I utilize the Chance Constrained Programming (CCP) stochastic method to account for the randomness in the planning problem constraints. To solve the planning problem, I use the Monte Carlo Simulation (MCS) method to generate a large number of scenarios that represent the renewable energy and load demand realizations. However, unlike previous works where MCS is combined with scenario reduction processes to reduce the computational complexity [30],[31],[32], the proposed MCS solution approach allows me to increase the solution accuracy [33].

In [5], Bahramirad et al. utilizes the MCS method to determine the optimal size of an ESS in a MG, while considering power shortage due to outage of thermal units and the RES intermittency. Similarly, reference [34] seeks to determine the optimal size of ESS in order to schedule the commitment of fuel cell power plants, where a two-stage scenario-based stochastic model is used to deal with the uncertainty from load demand and RES output power. However, both [5] and [34] only focus on ESS sizing, while this study considers the planning of RES (i.e., the number of RES elements) in addition to ESS sizing.

In [31], the authors present a stochastic model for the capacity expansion of a remote MG in terms of wind farms, thermal generators, and ESS; the MCS method coupled with scenario reduction is used to account for renewable energy uncertainty. Likewise, reference [35] seeks to
simultaneously minimize the total present net cost and carbon emissions for a MG with diesel generators, solar panels, wind turbines, and lead-acid batteries. CCP is also used to ensure that the capacity shortage is below a certain confidence level. However, unlike this study, none of the above studies exploits the appliance schedulability feature to further reduce the MG’s investment costs.

The study in [36] combines the MCS method with Particle Swarm Optimization to determine the optimal capacity of distributed-generation system and battery for a smart home with time-shiftable loads. While [36] assumes a rule-based electricity management system for the smart household, this study makes no such assumption. Rather, this study seeks to determine the scheduling of appliances that minimizes the CGV planning cost. Additionally, this study focuses on the optimal planning of a completely green MG, which is in contrast to studies [5] [34], [35], and [36] that consider a MG that relies on fossil-fueled generators or that has a connection to the main grid.

In summary, this chapter’s contributions include:

- Formulation of a CCP problem to determine the optimal number of RES elements (e.g., solar panels and wind turbine) and the size of the ESS that minimize the investment costs of a CGV.
- Design of a MCS-based algorithm to solve the formulated CCP problem.
- Determination of the optimal scheduling for programmable appliances that minimizes the investment costs.
- Investigation of the impact of appliance schedulability and ESS on MG investment costs.
2.2 System Model

I model a CGV that contains smart appliances, EVs, RES, and ESS. I use a discrete time model, where each time slot represents an hour of operation and the optimization is performed over a period of \( T = 24 \) hours. I consider the load demand and RES generation characteristics over one year. The CGV investment cost comprises the purchasing costs and the installation costs of wind turbines and solar panels, as well as the ESS’ investment cost.

2.2.1 Monte Carlo Scenario Generation

The MCS method can be used to account for uncertainty in the planning problem. The main source of randomness in the planning problem is the power production of RES and the load demand. Since the RES performance and load profile depend on weather conditions, I consider four representative days, each corresponding to one of the four seasons of the year [31].

The MCS method seeks to estimate the problem’s random variables by evaluating a large number of representative scenarios. Each such scenario is generated as an outcome of the random variables and represents a sample system state. Indeed, [33] indicates that the MCS approach is very suitable when analyzing large systems, such as power systems.

2.2.2 Chance-Constrained Programming

The CCP method is typically used to solve problems with constraint stochastic variables. Since the constraints might be violated in some extreme conditions, CCP allows the solutions to violate the constraints to some degree, as long as the probability to meet these constraints is above an established confidence level. A typical CCP problem can be expressed as follows:

\[
\min f(x), \quad s.t \quad \Pr\{g_i(x, \xi) \leq 0, i = 1,2,...\} \geq \lambda
\]  

(2.1)
where $f(x)$ is an objective function, $x$ is an n-dimensional decision variable, $\xi$ is an m-dimensional random vector, $g_i: \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}$, and $\lambda$ represents the required confidence level that takes values in the interval $(0,1)$. The probability $\Pr\{g_i(x,\xi) \leq 0, i = 1,2,\ldots\} \geq \lambda$ represents the joint probability constraint over all the $g_i(x,\xi) \leq 0$ constraint functions.

### 2.2.3 RES Model

**Wind Turbines**

$W$ identical wind turbines are modeled. Each wind turbine $w$ has a power generation capacity of $P_{cw}$ [kW] and is associated with an investment cost per generated kW of power of $\Gamma_w$ [$/kW]$. The wind turbine’s output power at time $t$ is mostly related to the wind speed, $v$ [m/s]. To simulate the randomness of wind speed, Weibull probability density function (pdf) is used [31]:

$$
    f_w(v) = \left( \frac{I}{Q} \right) \left( \frac{v}{Q} \right)^{I-1} \exp \left[ - \left( \frac{v}{Q} \right)^I \right]
$$

where $I$, $Q$, and $v$ are the shape factor, scale factor, and wind speed, respectively.

Since the wind distribution parameters change with the seasons of the year, four different values are used for the shape factor and scale factor, as per empirical studies [37]. The electric output of the wind turbine $w$, as a function of $v$, is expressed as:

$$
    p_w = \begin{cases} 
    0, & v < V_{in} \text{ or } v \geq V_{out} \\
    \frac{P_{rate}}{V_{rate}} \left( \frac{v - V_{in}}{V_{rate} - V_{in}} \right), & V_{in} \leq v < V_{rate} \\
    \frac{P_{rate}}{V_{rate}}, & V_{rate} \leq v < V_{out} 
\end{cases}
$$

where $V_{in}$ and $V_{out}$ refer, respectively, to the turbine’s cut-in speed (minimum wind speed) and cut-out speed (maximum wind speed) both in [m/s], established for safety reasons. $P_{rate}$ and $V_{rate}$ denote the turbine’s rated power and its corresponding wind speed, respectively. When the wind
speed is greater or equal to $V_{out}$, the turbine rotor is stopped, so as to prevent damage. Hence, as indicated by (2.3), the turbine’s output power is zero once $v$ is greater or equal to $V_{out}$.

**Solar Panels**

$K$ identical solar panels are modeled. Each solar panel unit $k$ has a power generating capacity of $Pc_k$ [kW] and is also associated with an investment cost per generated kW of power of $\Gamma_k$ [$$/kW$$], which includes purchasing and installation costs. The solar panels’ output power depends on the sun irradiation $ir$ [kW/m$^2$], which is modelled by a Beta distribution function. The probability density function of the Beta distribution is [38]:

$$f_k(ir) = \frac{1}{B(\alpha, \beta)} \left( \frac{ir}{IR_{max}} \right)^{\alpha-1} \left( 1 - \frac{ir}{IR_{max}} \right)^{\beta-1}$$

(2.4)

where $B(\alpha, \beta)$ is the Beta function, $\alpha$ and $\beta$ are the shape parameters of the Beta distribution, and $ir$ and $IR_{max}$ are the actual sunlight and the maximum irradiation, respectively.

The parameters $\alpha$ and $\beta$ are calculated from the solar radiation mean ($\mu$) and standard ($\sigma$) deviation values, as follows [39]:

$$\beta = (1 - \mu) \left[ \frac{\mu(1 + \mu)}{\sigma^2} - 1 \right]$$

$$\alpha = \frac{\mu \cdot \beta}{1 - \mu}$$

(2.5)

Using $ir$, the solar panel’s output power is found by:

$$p_k = \eta_k \cdot A_k \cdot ir$$

(2.6)

where $\eta_k$ and $A_k$ represent the solar panel’s efficiency [%] and solar panel’s total area [m$^2$], respectively.
2.2.4 Smart Home and Appliance Models

Non-Schedulable Load

The smart homes’ static load curve is due to non-programmable appliances, such as lights or TVs. The hourly static load $\eta_t$ is modeled using a load range, where the hourly load value is randomly chosen between a minimum and a maximum values using a uniform distribution function. Reference [40] provides an observed load range for hourly static load demand per house, as shown in Figure 2.1.

![Static Load Range per House per Day](image)

Figure 2.1. Static Load Range per House per Day [40]

Programmable Appliances

$H$ smart homes are modeled, where each smart home contains $J$ programmable appliances, such as a dishwasher, a laundry machine, and a spin dryer. A programmable appliance’s operation can be interrupted and rescheduled (i.e., shifted in time) in contrast to non-programmable appliances, whose operation cannot be altered once started. (As an example of a programmable appliance operation, consider a washing machine that can be scheduled to operate anytime between 9:00am...
and 5:00pm, when the owner is at work, and needs 2 hours to finish its cycle.) Each appliance $j$ in home $h$ is characterized by the tuple \( \{p_{h,j}, r_{h,j}, a_{h,j}, d_{h,j}\} \), where $p_{h,j}$ is the appliance $j$’s power consumption in kW, $r_{h,j}$ is its operation duration (in hours), $a_{h,j}$ is its earliest possible start time, and $d_{h,j}$ is the appliance’s latest possible finish time; (i.e., $d_{h,j}$ provides a deadline by which appliance $j$ in home $h$ has to complete its operation).

The start time $a_{h,j}$ and the deadline $d_{h,j}$ are modelled as random variables and are generated as follows: $a_{h,j}$ is a random integer drawn from the discrete uniform distribution in the interval $[1, T - r_{h,j} + 1]$, and $d_{h,j}$ is a discrete uniform random integer drawn from the interval $[a_{h,j} + r_{h,j} - 1, \min(a_{h,j} + SP \cdot r_{h,j}, T)]$. $SP$ is an integer parameter and represents the schedulability of the programmable appliances; that is the flexibility in appliance scheduling increases as $SP$ increases.

I use the variable $u_{h,j,t}$ to show the operation status of appliance $j$; $u_{h,j,t}$ is 1 if appliance $j$ in home $h$ is operating during slot $t$ and 0 otherwise. In order for a programmable appliance to complete its operation, the following must hold:

$$\sum_{t=a_{h,j}}^{d_{h,j}} u_{h,j,t} = r_{h,j} \quad (2.7)$$

**Electric Vehicle**

EVs are a special type of programmable appliances that, based on their operation, can charge/discharge electricity. Each of the $M$ EVs belongs to a home $h$ and is characterized by the tuple \( (PL_{m,a_m}, PL_{m,tg}, a_m, d_m, p_m^{\text{max}}, z_m) \). The $a_m$ and $d_m$ values indicate the EV’s arrival time at the MG and its scheduled departure time, respectively. $z_m$ identifies the smart home that the $m^{th}$
EV belongs to, where \( z_m \in [1, ..., H] \). \( PL_{m,a_m} \) refers to the \( m^{th} \) EV arrival energy level, while \( PL_{m,tg} \) denotes the \( m^{th} \) EV’s departure target energy level. \( p_m^{max} \) denotes the maximum amount of energy transferrable to/from the \( m^{th} \) EV during time slot \( t \). Here, I note that \( PL_{m,a_m}, PL_{m,tg}, a_m, \) and \( d_m \) are all random variables in the planning problem generated as follows: \( PL_{m,a_m} \) is a uniform random number in the interval \([PL_{m,a_m}^{min}, PL_{m,a_m}^{max}]\), where \( PL_{m,a_m}^{min} \) and \( PL_{m,a_m}^{max} \) are the minimum battery discharge level and the maximum battery charge level. \( PL_{m,tg} \) is a random number generated from a uniform distribution in the interval \([PL_{m,tg}, PL_{m,a_m}^{max}]\). The \( m^{th} \) EV’s arrival time \( a_m \) is a random integer in interval \([1, T - c_h m]\) following a discrete uniform distribution, where \( c_h m \) is the required charging time needed to achieve the target power level; \( c_h m \) is obtained by \((PL_{m,tg} - PL_{m,a_m})/p_m^{max}\). \( d_m \) is a random integer selected from a discrete uniform distribution drawn from interval \([a_m + c_h m - 1, \min(a_m + SP \cdot c_h m, T)]\).

The \( m^{th} \) EV’s energy level in slot \( t \), \( PL_{m,t} \), is calculated as:

\[
PL_{m,t} = PL_{m,a_m} - \sum_{i=1}^{t} p_{m,i} \cdot \psi_{m,i} \cdot y_{m,i}
\]

(2.8)

where \( \psi_{m,i} \) is a binary variable that is 1 if the EV is at home (in the interval \([a_m, d_m]\)), and zero otherwise. \( y_{m,i} \) is 1 if the \( m^{th} \) EV is charging, -1 if the EV is discharging, and zero if the EV is idle. \( p_{m,i} \) is the energy transferred to/from the EV during the \( i^{th} \) hour. For safety and longevity, each EV should not charge beyond its capacity \( PL_{m}^{max} \), discharge below its minimum discharge level \( PL_{m}^{min} \), or transfer more than \( p_m^{max} \) kWh during an hour:

\[
PL_{m}^{min} \leq PL_{m,t} \leq PL_{m}^{max}
0 \leq p_{m,t} \leq p_m^{max}
\]

(2.9)
The scheduling of EV’s charging has to ensure that each EV has the target energy level before it departs again for driving:

\[ PL_{m,d_m} \geq PL_{m,tg} \]  (2.10)

### 2.2.5 Energy Storage System

The ESS investment cost per kWh of stored energy is the energy rating cost, \( \Gamma_e \) [$/kWh] [41]. Parameter \( \gamma \) is used to compare the ESS investment cost and the renewable energy investment cost; (i.e., \( \gamma = \Gamma_e / (\Gamma_w, \Gamma_k) \), where \( \langle \Gamma_w, \Gamma_k \rangle \) is a simple arithmetic average of \( \Gamma_w \) and \( \Gamma_k \)). I want to analyze how the investment costs, the RES capacity, and the ESS capacity change as \( \gamma \) varies. ESS’s charging power \( p_{t,ch} \) and discharging power \( p_{t,dch} \) in slot \( t \) are subject to the following minimum and maximum constraints:

\[ 0 \leq p_{t,ch}, p_{t,dch} \leq P_{ESS} \]  (2.11)

where \( P_{ESS} \) is the maximum ESS charging/discharging power.

The ESS’ state (the amount of energy stored) \( C_t \) in slot \( t \) is found by (2.12) and, to ensure repeatability from a day to the next, is assumed to be the same at the beginning and at the end of a day, as indicated by (2.13). \( C_t \) is also restricted by ESS capacity limits as shown by (2.14). The parameter \( eff \) is the charging and discharging efficiency of the ESS (in %), while \( DoD_{min} \) and \( DoD_{max} \) are the minimum and the maximum allowed depth of discharge; \( C_{ESS} \) is the ESS’s maximum energy capacity. The ESS’ state of charge is maintained within an allowed range, as specified by the depth of discharge values.

\[ C_t = C_{t-1} + eff \cdot p_{t,ch} - 1/eff \cdot p_{t,dch} \]  (2.12)
\[ C_1 = C_T \]  

\[ (1 - DoD_{\text{max}})C_{\text{ESS}} \leq C_t \leq (1 - DoD_{\text{min}})C_{\text{ESS}} \]

2.2.6 Power Balance

The generated wind and solar powers are random variables that depend on the wind speed and the irradiation stochastic variables, respectively. In addition, the load demand is also stochastic and depends on the appliances’ earliest start times and deadlines as well the EVs’ arrival and departure times. Hence, the power balance constraints are expressed by probabilistic equations. This allows the following constraints to be met with a certain confidence level:

\[
\Pr\{g_t(x_t, \xi_t) \leq 0, \forall t\} \geq \lambda,
\]

\[ g_t(x_t, \xi_t) := \eta_t + \sum_{h=1}^{H} \sum_{j=1}^{J_h} u_{h,j,t} p_{h,j} - \sum_{m=1}^{M} p_{m,t} \psi_{m,t} y_{m,t} \]

\[ + p_{t}^{ch} - p_{t}^{dch} - W \cdot p_{w,t} - K \cdot p_{k,t} \]

\[ u_{h,j,t}, \psi_{m,t} \in \{0,1\}, \quad \forall t, \forall h, \forall j, \forall s \]

\[ p_{m,t} \geq 0, \delta_{m,t} \in \{-1,0,1\}, \quad \forall t, \forall m, \forall j \]

where, as defined above, \( \lambda \) is the constraints’ confidence level and \( \eta_t \) is the hourly static load. Vector \( x_t \) is made up of variables \( \{W, K, C_{\text{ESS}}\} \), as well as variables \( u_{h,j,t} \) and \( y_{m,t} \). The random vector \( \xi_t \) results from the random variables \( \psi_{m,t} \) (uncertainty due to EVs arrival and departure times), \( p_{w,t} \) (intermittency due to wind speed), and \( p_{k,t} \) (intermittency due to solar irradiation). Constraints in (2.15) states that the probability of the power generated by the renewable sources and the available ESS energy meeting the load demand in every timeslot \( t \) has to be greater or equal to the predefined value of \( \lambda \). All variables are restricted to their respective ranges by (2.16).
2.2.7 Problem Statement

My goal is to minimize the MG investment cost, while ensuring that the smart homes’ load demands are guaranteed to be satisfied with probability \( \lambda \).

\[
\begin{align*}
\min & \quad (W \cdot P_{cw} \cdot \Gamma_w + K \cdot P_{ck} \cdot \Gamma_k + C_{ESS} \cdot \Gamma_e) \\
\text{s.t} & \quad (2.1) - (2.16) \text{ hold.}
\end{align*}
\] (2.17)

2.3 Solution Methodology

The formulated problem has a linear objective function and linear constraints with some variables restricted to be integers. Hence, the problem in (2.17) could be solved as mixed integer linear programming problems (MILP). The difficulty lies with the joint probability constraint in (2.15). The closed form of (2.15) is intractable, since the joint spatio-temporal probability distribution of the wind and the solar powers is not known and is generally non-convex [42].

To solve the problem in (2.17), I use the MCS method to generate scenarios that capture the uncertainties in the wind speed, the solar irradiation, and the load demand. Below is the description of the MCS-based designed algorithm:

1. Generate \( NS \) scenarios, where each scenario \( s \) is characterized by a wind speed sample \( v_s \), a solar irradiation sample \( i_{rs} \), and a load profile sample \( l_s \). Assuming that all the scenarios are independent, I set the probability of each scenario to be \( 1/NS \).

2. Solve the sizing problem for all the \( NS \) scenarios; for each scenario \( s \), I save the values for the computed optimal number of wind turbines and solar panels \( O_{ws} \) and \( O_{ks} \), respectively), the optimal ESS capacity \( O_{es} \), and the optimal cost \( O_{cs} \). I also keep track of \( NW_{\text{min}} \) and \( NW_{\text{max}} \), the minimum number and the maximum number of wind turbines observed among the returned
solutions; similarly, I also record $Nk_{\text{min}}$ and $Nk_{\text{max}}$ – the minimum and the maximum number of solar panels observed, and $Se_{\text{min}}$ and $Se_{\text{max}}$ – the minimum and the maximum ESS capacity, as returned by the solutions of the scenarios ($Se_{\text{min}}$ is rounded down to the closest integer, and $Se_{\text{max}}$ is rounded up to the closest integer).

3. Given the confidence level $\lambda$, I determine the minimal cost solution that ensures that $\lambda \cdot 100\%$ of the scenarios are satisfied as follows:

\[
\begin{align*}
\text{For } i &= Nw_{\text{min}} \text{ up to } Nw_{\text{max}} \\
\text{For } j &= Nk_{\text{min}} \text{ up to } Nk_{\text{max}} \\
\text{Prob} &= 0; \ k = Se_{\text{min}}; \ \text{optCost} = 0; \ \text{optNw} = 0; \ \text{optNk} = 0; \ \text{optSe} = 0; \\
\text{While } (k \leq Se_{\text{max}}) & \quad \text{s} = 1; \\
\text{While } (s \leq NS) & \quad \text{If } (\text{Ow}_{\text{s}} \leq i \text{ and } \text{Ok}_{\text{s}} \leq j \text{ and } \text{Oe}_{\text{s}} \leq k) \\
& \quad \quad \text{Prob} = \text{Prob} + \Pr(s); \\
& \quad \text{End} \\
& \quad \text{s} = s + 1; \\
& \text{End} \\
\text{If } (\text{Prob} \geq \lambda) & \quad \text{tempCost} = \text{sizing cost using (2.17) given:} \\
& \quad \quad \text{i wind turbines, j solar panels and ESS of size k.} \\
& \quad \text{If } (\text{optCost} > \text{tempCost} \text{ or } \text{OptCost} == 0) \\
& \quad \quad \text{OptNw} = i; \ \text{OptNk} = j; \ \text{OptSe} = k; \ \text{OptCost} = \text{tempCost}; \\
& \quad \text{End} \\
& \text{End} \\
& \ k = k + 1; \\
\text{End} \\
\text{End} \\
\text{End} \\
\text{Return } \text{OptNw, OptNk, OptSe, and OptCost}
\end{align*}
\]

The “While $(k \leq Se_{\text{max}})$” seeks to determine the portion of the scenarios whose load can be satisfied by a MG composed by $\Theta$ wind turbines, $\Phi$ solar panels, and a ESS of size $\Omega$; that is, scenarios than require $\Theta$ or less wind turbines, $\Phi$ or fewer solar panels, and an ESS of size $\Omega$ or smaller.
2.4 Simulation Parameters

2.4.1 RES Parameters

The RES parameters are shown in Table 2.1; I consider all wind turbines to be identical and all solar panels to be identical. As I mentioned in section 2.2.3, the wind speed distribution is modeled by considering four different values for the scale factor and shape factor as described in Table 2.2. For the solar panel simulations, I use the 2010 solar irradiation mean and standard deviation values of the Boise Air Terminal site in Idaho obtained from the National Solar Radiation Data Base [43].

<table>
<thead>
<tr>
<th>Wind Turbine</th>
<th>Solar Panel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cut-in speed (m/s) = 3.5</td>
<td>Area (m²) = 100</td>
</tr>
<tr>
<td>Cut-out speed (m/s) = 25</td>
<td>Efficiency (%) = 20</td>
</tr>
<tr>
<td>Rated speed (m/s) = 14</td>
<td>Max Power Capacity (kW) = 20</td>
</tr>
<tr>
<td>Rated Power (kW) = 20</td>
<td>Investment Cost ($/kW) = 200</td>
</tr>
<tr>
<td>Investment Cost ($/kW) = 200</td>
<td></td>
</tr>
</tbody>
</table>

2.4.2 EV and ESS Parameters

The EVs and ESS’s parameters are as shown in Table 2.3. I assume that each home has two EVs. Since I considered a total of 5 smart homes, 10 EVs are modeled in total. In these simulations, the schedulability parameter $SP$ is set to 5, except for section 2.5.3, where the $SP$ is varied.

2.4.3 Static Load

Since, as shown in Figure 2.1, the gap between the hourly minimum and the maximum static load is negligible (no greater than 1 kW), I assume for simplicity that each home’s static load curve is equal to the average of the max and the min values.
2.4.4 Appliance Parameters

Table 2.4 describes the appliance parameters. All the appliances can start operating anytime during the day based on the resident’s choice. With $SP = 5$, the deadline for each appliance is chosen as $\min(T, a_{h,j} + 5 \cdot r_{h,j})$, where $a_{h,j}$ and $r_{h,j}$ are the start time and the duration of the appliance $j$’s operation in home $h$. The resident’s appliance use varies with the seasons of the year; in particular, I assume that the space heater is only operated during the winter, while the air conditioner is used during the other three seasons. Additionally, I assume that the air conditioner usage doubles during the summer. Table 2.5 shows the total number of operations per appliance type per season of the 5 smart homes. As an example, Figure 2.2 illustrates one sample of the load profile for non-static load, resulting from the appliance power demand during the summer season. When compared to static load in Figure 2.1, I note that the appliances’ load demand is significantly more irregular compared to the static load demand.

<table>
<thead>
<tr>
<th>Season</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I$</td>
<td>1.4</td>
<td>1.2</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td>$Q$</td>
<td>9</td>
<td>8</td>
<td>7.5</td>
<td>8.5</td>
</tr>
</tbody>
</table>

Figure 2.2. Wind Speed Distribution Factors [31]

Figure 2.2. Non-Static Load for Winter Season
Table 2.3. EVs and ESS Parameters

<table>
<thead>
<tr>
<th>EV Parameters (kWh)</th>
<th>ESS Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min Capacity = 3</td>
<td>Charging/discharging efficiency = 0.9</td>
</tr>
<tr>
<td>Max Capacity = 15</td>
<td>DoD\textsubscript{max} = 1; DoD\textsubscript{Min} = 0</td>
</tr>
<tr>
<td>Charging Rate = 3</td>
<td>Energy rating Cost ($/kWh) = 200</td>
</tr>
</tbody>
</table>

Table 2.4. Appliance Parameters [44]

<table>
<thead>
<tr>
<th>Appliance Type</th>
<th>( p_j ) (kW)</th>
<th>( r_j ) (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dish-Washer</td>
<td>2.8</td>
<td>2</td>
</tr>
<tr>
<td>Spin Dryer</td>
<td>2.5</td>
<td>3</td>
</tr>
<tr>
<td>Air Conditioner</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Laundry Machine</td>
<td>2.5</td>
<td>3</td>
</tr>
<tr>
<td>Water Heater</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Space Heater</td>
<td>3.4</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 2.5. Total Number of Daily Operations per Appliance Type per Season

<table>
<thead>
<tr>
<th>Season</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dish-Washer</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Spin Dryer</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Air Conditioner</td>
<td>-</td>
<td>10</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>Laundry Machine</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Water Heater</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Space Heater</td>
<td>20</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

2.4.5 Scenario Generation

The scenarios were generated following the MCS method. For each season, 25,000 scenarios were generated, where each scenario is characterized by a wind speed sample, a solar irradiance sample, and a load demand sample. A total of 100,000 scenarios were simulated; that is \( NS = 100,000 \). As aforementioned, previous studies that use the MCS method usually start with a large number of scenarios, and then use some scenario reduction process to decrease the number of scenarios
(usually to less than 10 scenarios). This in turn reduces the solution accuracy. However, by using a large number of samples in my solution method, I improve the solution accuracy.

2.4.6 Comparison Schemes

I compared two planning schemes. The first scheme is the optimal planning scheme (Opt-P) that utilizes appliances’ programmability, as well as the EVs and ESS’ charging/discharging capacity, so as to minimize the total investment cost. I compare the Opt-P scheme to a planning scheme that does not perform any load scheduling (NoSch-P); NoSch-P places appliances and EVs into operation as soon as they are ready, without shifting in time or interrupting their operation.

2.5 Simulation Results

2.5.1 Varying Confidence Level

Figure 2.3 shows the cost reduction of the Opt-P scheme over the NoSch-P scheme, as the confidence level $\lambda$ varies. For instance, $\lambda = 0.9$ means that the returned solution has to satisfy the load demand for at least 90% of the scenarios. In these simulations, $\gamma = 1$, which means that the ESS investment cost per kWh is equal to the RES’ investment cost per kW. Figure 2.3 shows that as long as $\lambda$ is less or equal to 0.9, Opt-P reduces the investment costs by 20% or more in comparison to NoSch-P scheme.

As shown in Figure 2.4 and Figure 2.5, when $\lambda \leq 0.9$ NoSch-P generally requires more resources than Opt-P; in particular, NoSch-P’s always needs more ESS capacity (24 kWh or more) in comparison to Opt-P, which explains the Opt-P’s cost reduction of 20% or more in Figure 2.3. Thus, as long as I allow the power balance constraint in (2.15) to be violated in 10% or more of scenarios, I save at least 20% in cost reduction with appliance scheduling. When $\lambda > 0.9$, the
difference in the RES and ESS capacity needed by Opt-P and NoSch-P diminishes (Figure 2.5 and Figure 2.6), which explains the decrease in Opt-P’s performance in Figure 2.3.

Figure 2.3. Cost Reduction Comparison

Figure 2.4. Comparison of Number of RES
2.5.2 Varying $\gamma$

In this section, I compare the Opt-P and the NoSch-P schemes, while varying $\gamma$ and maintaining a confidence level of 90% ($\lambda = 0.9$). As demonstrated in Figure 2.6, Opt-P outperforms NoSch-P by 42% or more when $\gamma \geq 10$ (ESS investment cost per kWh is 10 times greater or more in comparison to the investment cost per kW of the RES). For $\gamma = 1$, Opt-P needs a total number of 7 RES and 113 kWh of storage, while NoSch-P needs 9 RES and 137 kWh of storage (Figure 2.7 and Figure 2.8). Through the use of load scheduling, Opt-P is able to reduce the required number of RES and the storage capacity, thus decreasing the investment cost by 20%.

Figure 2.7 shows that Opt-P’s ESS investment cost is always less than NoSch-P’s and decreases as ESS becomes more costly than RES. For $\gamma \geq 10$, Opt-P uses load scheduling to decrease its ESS’ capacity to 55 kWh or less. However, NoSch-P always needs at least 90 kWh or more for energy storage when $\gamma \geq 10$, since it does not utilize load scheduling. In addition, Figure 2.8 illustrates that for $\gamma \geq 10$, NoSch-P generally needs more RES compared to Opt-P. This explains Opt-P’s significant cost reduction over NoSch-P in Figure 2.6 (more than 42%) when $\gamma \geq$
10. Figure 2.8 also shows that as the cost of energy storage increases, the investment in RES increases for both Opt-P and NoSch-P to take advantage of the relatively cheaper energy generation costs (compared to energy storage).

![Figure 2.6. Opt-P Cost Reduction Comparison as γ Varies](chart1)

![Figure 2.7. Energy Storage Comparison](chart2)

When $10^{-5} < \gamma \leq 0.01$, NoSch-P is able to utilize the cheap storage, so as to reduce the number of RES needed, thus only incurring negligible cost penalties in comparison to Opt-P (7% or less as illustrated in Figure 2.6). For $\gamma = 10^{-5}$ and $\gamma = 10^3$, NoSch-P had to satisfy 95% of scenarios to satisfy $\lambda = 0.9$, while Opt-P only met 90% of all cases (for the other $\gamma$ points in Figure
2.6, NoSch-P and Opt-P’s returned confidence levels that were in range 90%-92%). This confidence level of 95% explains the sharp increase in NoSch-P’s number of RES when \( \gamma = 10^{-5} \) and \( \gamma = 10^3 \) compared to other nearby NoSch-P points. For instance, from \( \gamma = 10^3 \) to \( \gamma = 10^5 \), NoSch-P’s number of RES does not change, while from \( \gamma = 10^1 \) to \( \gamma = 10^3 \), NoSch-P’s number of RES increases by 690 RES (Figure 2.8). This explains the non-monotonic character of Opt-P performance over NoSch-P at these points in Figure 2.6, since NoSch-P’s investment cost greatly increases.

![Figure 2.8. Comparison of Number of RES](image)

On the other hand, for \( \lambda = 0.7 \), Opt-P and NoSch-P returned confidence level values that were in the interval 70%–72%. This explains why, as illustrated in Figure 2.9, Opt-P’s performance over NoSch-P increase monotonically when compared to the curve for \( \lambda = 0.9 \). Hence, I observe that if both schemes are evaluated at exactly the same confidence level or within 0.02 of the required confidence level, then Opt-P’s performance over NoSch-P increases monotonically with the rise in \( \gamma \) values. Hence, the curve for \( \lambda = 0.9 \) in Figure 2.6 and Figure 2.9
would be monotonically increasing if I simulated a larger number of scenarios that would allow to evaluate both Opt-P and NoSch-P at exactly $\lambda = 0.9$ or within 0.02 of this value.

![Figure 2.9. Opt-P Cost Reduction for $\lambda = 0.7$ versus $\lambda = 0.9$](image)

**2.5.3 Varying SP**

In this section, I compare Opt-P to NoSch-P while varying the schedulability parameter $SP$ and while maintaining the confidence level at 90% ($\lambda = 0.9$). Figure 2.10 shows that Opt-P’s cost reduction for $SP = 1.5$ is significantly lower compared to when $SP = 5$ ($SP = 1.5$ means that the deadline for each programmable appliance $j$ is within $1.5 \cdot r_{h,j}$, where $r_{h,j}$ is the appliance’s duration of operation). In fact, Opt-P’s cost reduction was always less or equal to 18% relative to the NoSch-P scheme for $SP = 1.5$. However, for $SP = 2$ Opt-P registers a cost reduction of 28% or more when $\gamma \geq 10$. Hence, I observe that Opt-P leads to higher cost reduction when the residents allow for more flexibility in their appliance scheduling. In particular, when energy storage is more expensive than renewable energy, I observe considerable cost savings whenever appliances’ deadlines are at least within double of their operation duration ($d_{h,j} = \min(a_{h,j} + 2 \cdot r_{h,j}, T)$).
2.5.4 Varying Load

Figure 2.11 illustrates Opt-P’s cost reduction over NoSch-P as the load demand increases with the number of homes. For these simulations, $\gamma \geq 10$ (the energy storage investment cost per kWh is 10 times greater than RES’ investment cost per kW). The confidence level was set to 90% ($\lambda = 0.9$). I observe that Opt-P cost reduction remains greater than 41% even as the load demand increases (from a 5 home MG to a 50 home MG) and $\gamma$ varies. Hence, I note that even in medium size MGs, Opt-P is able to schedule all the CGV’s programmable appliances to decrease the investment cost.
2.6 Chapter Conclusion

In summary, this chapter demonstrates that the planning cost of a completely green MG with smart homes can be significantly reduced by accounting for the programmability of smart appliances. In particular, when the ESS investment cost per kWh is 10 times greater or more in comparison to the RES’ investment per kW, a cost reduction of 41% or more is observed for small to medium size MGs (MGs that have 5 to 50 homes). When the ESS is cheaper than the RES’ investment cost, NoSch-P utilizes the low-cost ESS to decrease the number of RES needed, thus only incurring 7% or less in cost increases. Numerical results also demonstrated that the greatest cost savings were observed when the confidence level was less or equal to 0.9; that is when I allowed the load demand to be violated in 10% or more of the systems realization scenarios. Varying the appliances’ schedulability parameter $SP$, I also noted that cost savings decreased as the appliances’ scheduling flexibility decreased. However, as long as $SP \geq 2$, there was a significant cost reduction due to the appliances’ programmability.
CHAPTER 3

OPTIMAL OPERATION FOR A MICROGRID WITH PROGRAMMABLE APPLIANCES

As previously stated, renewable energy production is intermittent and generally weather-dependent. Accordingly, completely green Microgrids (CGMGs), which mainly rely on renewable energy, need to also include thermal generators to compensate for days when shortages of renewable energy occur. The problem of optimal power generation scheduling of these thermal generators, also known as the Unit Commitment (UC) problem, is one of the most challenging problems in power systems optimization [13]. In a MG, the MG Central Controller (MGCC) has to coordinate the distributed thermal generators (DTG) in order to provide enough power to satisfy the load demand, while striving to optimize some objective. This optimization process usually involves determining hundreds of discrete and continuous variables subject to numerous linear, quadratic, and sometimes non-linear constraints depending on the DTG characteristics and load demands. The DTG can include different technologies, including diesel engines, micro turbines, and fuel cells, with capacity ranging from a few kW to 1-2 MWs [10], [16].

In this chapter, I address the UC problem in the context of a CGMG that supplies electricity for smart homes. The smart homes contain programmable appliances, which can be scheduled for operation [9]. I consider appliance operations as schedulable tasks with power and timing demands. The smart appliances exchange information with the MGCC about user-scheduled tasks,
for example, over power lines. Figure 3.1 depicts an exemplary schematic description of the system under consideration.

![Figure 3.1. System under Consideration](image)

I assume that tasks are scheduled on a day-ahead basis, so that the MGCC can schedule the DTG operation for the upcoming day. I do not consider the power demands from spontaneous small loads, such as a TV set, computer, or microwave oven, but rather assume that the MG has a reserved generator capacity to produce enough continuous power to meet those needs.

### 3.1 Literature Review

The UC problem in MGs has gained interest in the past few years. Study [13] as well as [45-49] investigate MG optimal power generation for forecasted fixed (mostly hourly) electric loads. By contrast, [50-54] investigate the UC problem for MG with schedulable load/tasks, a concern which is similar to this study. However, unlike [50], [51], and [52], this study is based on a practical model of generators, which includes startup costs and generators’ states in addition to methods for scheduling energy-consuming tasks. Furthermore, I allow the optimization procedure to interrupt
and resume the tasks’ execution, in contrast to non-interruptible tasks in [50] and [52]. This study also focuses on scheduling the operation of thermal generators, as opposed to the study presented by Angelis et al. in [53] that considers the main grid energy and renewable energy. [54] considers the startup costs of dispatchable sources in the problem formulations but does not use these costs in the numerical simulations performed.

A genetic algorithm (GA), GA-INT, is used to solve the non-linear optimization problem formulated in this chapter. GAs are search techniques based on the principal of natural selection and “survival of the fittest” drawn from natural evolution [55]. GAs have been proven to be efficient in solving problems similar to the UC problem and have been successfully applied to UC problems in power systems in recent decades [49], [56-61]. My contribution also includes a heuristic based algorithm, PRO-S, which seeks to flatten the load profile in order to reduce the extra costs due to DTG’s on/off switching. PRO-S greatly decreases the time needed to solve the problem, while incurring only negligible cost penalties.

Thus, this chapter’s contributions include:

- Formulating the UC problem for MG utilizing a more realistic generator model that comprises generator’s startup costs and operation states.
- Determining the DTG’s optimal power scheduling by exploiting task scheduling.
- Evaluating the effect of task schedulability and generators’ startup costs on MG operation costs.
- Designing PRO-S, a heuristic algorithm that greatly reduces the UC problem’s time complexity, while earning minimal cost increases.
3.2 System Model

A discrete time model is used, where the total scheduling time is $T$ timeslots corresponding to 24 hours. Knowing that it takes a few minutes to start up a thermal generator, the model uses a shorter sampling rate (5 min).

3.2.1 Thermal Generator Model

The CGMG contains $N$ identical thermal generators, characterized by production cost coefficients $MC$ and $FC$, where $MC$ is the maintenance cost per timeslot [$/timeslot] and $FC$ is the fuel cost per timeslot per kilowatt [$/kW]. The generators have the same power generating capacity $PG$ [kW]. Each generator $n$ also has a time-dependent startup cost $SC_n(t)$ [$/timeslot]. In practice, a generator’s capacity varies between a minimum and a maximum power generating limit [62]. However, in this study, I assume constant output power for simplicity. I also assume that the shutdown cost for each generator is equal to zero. The total cost to generate $PG$ kW is calculated as [41]:

$$C_{PG} = MC + FC \cdot PG$$  \hspace{1cm} (3.1)

The generators also have a minimum up time $UT$ [timeslots] and a minimum down time $DT$ [timeslots]. The violation of such constraints can shorten the generator’s lifetime [45]. The startup cost $SC_n(t)$ depends on how long a generator has been off by timeslot $t$ [13]:

$$SC_n(t) = \begin{cases} 
    hc: DT \leq td(t) \leq DT + CS \\
    cc: td(t) > DT + CS 
\end{cases}$$  \hspace{1cm} (3.2)

where $td(t)$ is the continuous off time of generator $n$ by time $t$, and $CS$ is the start time [timeslots] of cold state for a generator; a thermal generator is considered to be cold if it has been off for more than $CS$ timeslots. $hc$ and $cc$ are the hot startup cost and cold startup cost, respectively. In other
words, (3.2) states that the start-up cost at time $t$, $SC_n(t)$, equals to $hc$ if a generator is still hot ($td(t) \in [DT, DT + CS]$). Otherwise $SC_n(t) = cc$. $cc$ is always greater than $hc$, since it is more costly (in terms of fuel consumed) to restart a cold generator than to restart a hot generator.

Each thermal generator also has a startup time $ST$ (in timeslots), which is the required time [timeslots] to switch the generator from the off state to the active state. I also consider the generators initial states using $G_n$, and $L_n$. $G_n$ is the number of timeslots generator $n$ has to be initially online due to $UT$, while $L_n$ is the number of timeslots generator $n$ has to be off at the outset due to $DT$.

### 3.2.2 The Task Model

I consider $J$ tasks planned by residents for their appliances for the next day. Each task $j$ is characterized by the tuple $\{p_j, r_j, s_i, f_i\}$, where $p_j$ is task $j$’s power demand [kW], $r_j$ is its duration [timeslots], $s_i$ is its earliest possible start time, and $f_j$ is its latest possible finish time.

### 3.2.3 The Task Allocation Model

I design a $J \times T \times N$ matrix $A$ to keep track of the task allocations to the different generators during the considered time. In this matrix, an entry $a_{n,j,t}$ indicates the amount of power produced by generator $n$ for the task $j$ during the timeslot $t$. As shown in (3.3), a generator cannot produce negative power. Equation (3.4) states that the power generation limit for each generator has to be maintained.

$$a_{n,j,t} \geq 0$$  \hspace{1cm} (3.3)
\[
\sum_{j=1}^{J} a_{n,j,t} \leq PG
\]

A horizontal plane matrix in \( \mathbf{A} \) is a \( T \times N \) dimensional matrix \( \mathbf{A}_j \) that shows the power generation for task \( j \) on the different generators over the \( T \) timeslots. Given a matrix \( \mathbf{A}_j \), I define a unary matrix operation \( lz: \mathbf{A}_j \rightarrow \mathbb{Z}^+ \), which returns the number of all-zeroes leading columns in \( \mathbf{A}_j \). Task \( j \) starts execution at \( x_j = lz(\mathbf{A}_j) + 1 \). Power scheduling has to insure that \( x_j \) is greater or equal to \( s_j \), the earliest start time of task \( j \):

\[
x_j \geq s_j
\]

I design another function \( tz: \mathbf{A}_j \rightarrow \mathbb{Z}^+ \), which returns the number of all-zeroes trailing columns in \( \mathbf{A}_j \). I can then find task \( j \)'s finish time as: \( y_j = T - tz(\mathbf{A}_j) \). \( y_j \) has to be less or equal to \( f_j \) in order to meet the task’s deadline:

\[
y_j \leq f_j
\]

I also use a unary function \( nz: \mathbf{A}_j \rightarrow \mathbb{Z}^+ \) to determine the number of non-zero columns (columns with at least one non-zero entry) in \( \mathbf{A}_j \), so as to find the number of timeslot where power was generated for task \( j \). The number of non-zero columns for a task \( j \) has to be equal to its duration value:

\[
nz(\mathbf{A}_j) = r_j
\]

and the power generated for a task \( j \) during slot \( t \) is either zero or \( p_j \), where \( p_j \) is task \( j \)'s power demand (in kW) as stated in (3.8).
\[
\sum_{n=1}^{N} a_{n,j,t} = p_j \cdot \Gamma, \Gamma \in \{0,1\}
\] (3.8)

### 3.2.4 Thermal Generator States

I construct another \(N \times T\) dimensional matrix \(B\), where each entry \(b_{n,t}\) indicates the state of a thermal generator \(b_{n,t}\) during timeslot \(t\). I let 0, 1, and 2 refer to the online state, the off state, and the startup state, respectively; that is, \(b_{n,t} \in \{0,1,2\}\). Matrix \(B\) is obtained from matrix \(A\), since the generators have to be online whenever they are producing power for tasks. Accordingly, as the online state is indicated by 0, the following constraint must hold:

\[
\left( \sum_{n=1}^{N} a_{n,j,t} \right) \cdot b_{n,t} = 0
\] (3.9)

Equation (3.9) ensures that generator \(n\) is online whenever matrix \(A\) indicates that generator \(n\) is generating power \((\sum_{j=1}^{J} a_{n,j,t} > 0)\).

I define the following unary matrix operations to determine a generator’s state during a particular timeslot \(t\):

- **os**: \(b_{n,t} \rightarrow \mathbb{Z}^+\), which returns 1 if \(b_{n,t}\) is equal to 0, and returns 0 otherwise.
- **ds**: \(b_{n,t} \rightarrow \mathbb{Z}^+\), which returns 1 if \(b_{n,t}\) has value 1, and returns 0 otherwise.
- **ss**: \(b_{n,t} \rightarrow \mathbb{Z}^+\), which returns 1 if \(b_{n,t}\) has value 2, and returns 0 otherwise.

I use the above operators to ensure that the generators’ initial states are maintained as specified by \(G_n\), and \(L_n\) as shown in (3.10) and (3.11).
I also define permissible state transitions for the thermal generators from one timeslot to the next, as shown in the Table 3.1:

<table>
<thead>
<tr>
<th>State at $t$</th>
<th>0</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>State at $t + 1$</td>
<td>0, 1</td>
<td>1, 2</td>
<td>2, 0</td>
</tr>
</tbody>
</table>

I use the following constraint to ensure proper state transition for the generators:

$$b_{n,t+1} \in \{b_{n,t}, (b_{n,t} + 1) \bmod 3\}, \forall n = 1, ..., N, \forall t = 2, ..., T$$ (3.12)

where $mod$ represents the modulo operator and ensures that generators can switch from the startup state (indicated by 2) to the active state (designated by 0).

Constraint (3.13) indicates that a generator that switches from the startup state to the online state has to stay on for at least $UT$ timeslots, while constraint (3.14) specifies that a generator $n$ that switches from the off state to the startup state has to spend $ST$ timeslots in the startup state. Constraint (3.15) states that after $ST$ startup timeslots, the generator in the startup state has to be online. Constraint (3.16) indicates that a generator in the active state that is shut down will remain off until at least $DT$ timeslots have elapsed.

$$\sum_{t=1}^{t+G_n-1} os(b_{n,t}) \geq G_n$$ (3.10)
\[ \sum_{i=t+1}^{t+ST} ss(b_{n,i}) = ST, \quad b_{n,t} = 1 \text{ and } b_{n,t+1} = 2 \] (3.14)

\[ b_{n,t+ST+1} = 0, \quad b_{n,t} = 1 \text{ and } b_{n,t+1} = 2 \] (3.15)

\[ \sum_{i=t+1}^{t+DT} ds(b_{n,i}) = DT, \quad b_{n,t} = 0 \text{ and } b_{n,t+1} = 1 \] (3.16)

### 3.2.5 Problem Statement

The UC problem seeks to determine the thermal generators’ states during the \( T \) timeslots, so as to minimize the total operating costs, while meeting the tasks’ power and timing requirements. The MG operation cost is calculated from the generators’ power production costs and the startup costs. Accordingly, the UC problem is stated as follows:

\[
\min \sum_{t=1}^{T} \sum_{n=1}^{N} [C_{PG} \cdot os(b_{n,t}) + ss(b_{n,t}) \cdot SC_n(t)]
\]  

Such that (3.3) to (3.16) holds

where \( C_{PG} \) is found as shown in (3.1).

### 3.3 Solution Methods

#### 3.3.1 Genetic Algorithm

The UC problem as formulated in (3.17) is a non-linear mixed integer programming problem. I design a genetic algorithm, GA-INT, to solve it. I implement GA-INT in Matlab on a 3.20 GHz Intel Core computer with 4GB of RAM. The parameters in the GA-INT are described in Table 3.2.
Table 3.2. GA Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Size</td>
<td>1000</td>
</tr>
<tr>
<td>Probability of Crossover</td>
<td>60%</td>
</tr>
<tr>
<td>Probability of Mutation</td>
<td>40%</td>
</tr>
<tr>
<td>Stopping Criteria</td>
<td>No Improvement in fitness value for 50 generations</td>
</tr>
</tbody>
</table>

3.3.2 Heuristic Algorithm

The heuristic algorithm, PRO-S, is also implemented in Matlab. As shown in Figure 3.2, PRO-S first creates a $J \times T$ matrix, $D$, and populates it in the following way: each row, $D_j$, corresponding to task $j$’s power consumption, is populated with value $p_j$ in entries $D[j, a_j]$ through $D[j, y_j]$ ($s_j$ and $y_j$ are task $j$’s earliest start time and deadline). The remaining entries in $D_j$ contain zeros. Each row $D_j$ contains $y_j - s_j + 1 - r_j$ extra $p_j$ values. I derive a load profile array $Q$ of length $T$, such that:

$$Q[t] = \sum_{j=1}^{J} D[j, t]$$  \hspace{1cm} (3.18)

In order to remove the extraneous $p_j$, PRO-S proceeds in a greedy manner. In each iteration, PRO-S identifies elements in $Q$ with the largest value $q_{max}$. It then tries to lower $q_{max}$ in $Q$ by zeroing out some extraneous $p_j$’s in $D$ that contribute to the $q_{max}$ entries, starting with those rows with the largest $p_j$ values. At the end of the iteration, PRO-S updates $Q$ from the current $D$ matrix. It also saves the current $q_{max}$ value, so that in the following iterations only those $Q$ entries with value less than $q_{max}$ are considered. PRO-S repeats this greedy choice until all the extra $p_j$’s are eliminated from $D$. 

Create and populate a $3 \times T$ matrix $D_i$, with $p_j$ values for each task $j$ in timeslots $D_{i[a]}$ through $D_{i[j]}$.

Create an array $Q$ of length $T$ from matrix $D$, such that $Q[t]$ is the difference between $D[t]$ and predicted renewable energy generation.

Sort tasks according to their $p_j$ values so that task with index $i=1$ is task with highest $p_j$ value in load profile.

Still tasks with extra $p_j$ in matrix $D$?

Stop

Find timeslots with next maximum value, $q_{max}$, in load array $Q$.

Set $i$ to 1.

Does task $i$ contribute to any of the slots with $q_{max}$ value in $Q$?

Does task $i$ still have extra $p_j$ in matrix $D$?

Increment $i$.

Zero out task $i$'s entries corresponding to slots with $q_{max}$ in $Q$ as long as task $i$ duration is not violated.

Are all $q_{max}$ value eliminated from $Q$?

Update array $Q$ from current matrix $D$.

Figure 3.2. Heuristic Algorithm, PRO-S
The goal of PRO-S is to finish with a load curve that is as smooth as possible in order to minimize the change in power production from one slot to the next. I use the final load array \( Q \) to determine \( u_t \), the required number of active generators in each slot \( t \) by:

\[
    u_t = \text{ceil} \left( \frac{Q[t]}{PG} \right) \tag{3.19}
\]

Using the \( u_t \) values, I derive the generator state matrix \( B \), so that each timeslot \( t \) has \( u_t \) active generators. For each \( t \), the active generators are chosen starting with those generators with positive \( G_n \) values, since these generators are already on by the beginning of the scheduling period. The remainder of the generator states is determined so as to minimize the additional costs; (i.e., a generator is turned off whenever it is not needed, unless incurring the startup cost is more expensive, in which case it is kept on). From matrix \( B \), I determine the total operating cost using (3.17).

### 3.4 Case Study

The simulated MG holds small identical thermal generators and their characteristics are shown in Table 3.3. Each home is assumed to contain at most seven programmable appliances, where each appliance submits daily a number of tasks. The tasks’ arrivals were generated following a Poisson distribution, with the constraint that \( f_j - s_j \leq 4 \cdot r_j \). Other tasks’ characteristics are shown in Table 3.4, where \( M_k \) is the daily arrival rate per task type and \( H_k \) refers to the average number of tasks per task type, per home. I compare PRO-S to GA-INT, and show that PRO-S’s performance is nearly as good as GA-INT’s.

The performance of GA-INT and PRO-S are both compared to the Early Starting Time (EST) scheme [50]. In the EST scheme, domestic appliances are turned on at their given earliest starting
time, similar to common living habits where users turn on appliances as soon as they want to use them.

Table 3.3. Thermal Generators’ Parameters

<table>
<thead>
<tr>
<th>Generator Characteristics</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_G$ (kW)</td>
</tr>
<tr>
<td></td>
<td>$M_C$ ($/\text{timeslot}$)</td>
</tr>
<tr>
<td></td>
<td>$F_C$ ($/\text{kW}$)</td>
</tr>
<tr>
<td></td>
<td>$h_C$ ($/\text{timeslot}$)</td>
</tr>
<tr>
<td></td>
<td>$c_C$ ($/\text{timeslot}$)</td>
</tr>
<tr>
<td></td>
<td>$T_S$ (timeslots)</td>
</tr>
<tr>
<td></td>
<td>$U_T$ (timeslots)</td>
</tr>
<tr>
<td></td>
<td>$D_T$ (timeslots)</td>
</tr>
<tr>
<td></td>
<td>$S_T$ (timeslots)</td>
</tr>
</tbody>
</table>

Table 3.4. Electricity Consuming Tasks [63]

<table>
<thead>
<tr>
<th>Task Type</th>
<th>$p_j$ (kW)</th>
<th>$r_j$ (timeslots)</th>
<th>$M_k$ (tasks/day)</th>
<th>$H_k$ (tasks/home)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space Heater</td>
<td>3.4</td>
<td>18</td>
<td>60</td>
<td>6</td>
</tr>
<tr>
<td>Electric Car</td>
<td>3.5</td>
<td>30</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>Spin Dryer</td>
<td>3</td>
<td>12</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>Air Conditioner</td>
<td>3</td>
<td>12</td>
<td>80</td>
<td>8</td>
</tr>
<tr>
<td>Laundry Machine</td>
<td>1.5</td>
<td>6</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>Swimming Pool Heating</td>
<td>4.5</td>
<td>24</td>
<td>10</td>
<td>2</td>
</tr>
<tr>
<td>Dish Washer</td>
<td>1</td>
<td>8</td>
<td>20</td>
<td>2</td>
</tr>
</tbody>
</table>

3.4.1 Test Case Results

I first present results from one simulation trial, where appliances submit a total of 250 tasks, with a mean load of 42.37 kW. As depicted in Figure 3.3, without load scheduling, this simulation instance requires at least 39 generators in order to meet the peak load. On the other hand, GA-INT requires only 24 generators, while PRO-S needs no more than 26. Table 3.5 shows the initial conditions for the 39 generators in this trial run. Figure 3.4 demonstrates that PRO-S’ load
scheduling closely follows GA-INT’s. Hence, in this case, GA-INT’s cost reduction over PRO-S was less than 1% (Table 3.6).

Table 3.5. Generators’ Initial Conditions

<table>
<thead>
<tr>
<th>Number of Generators</th>
<th>( G_n )</th>
<th>( L_n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>5</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>13</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>-</td>
<td>2</td>
</tr>
</tbody>
</table>

Total Generation Capacity (kW) 82.68

Table 3.6. Cost Reduction Results

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Operation Cost ($)</th>
<th>Cost Reduction over EST (%)</th>
<th>GA-INT Cost Reduction over PRO-S (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA-INT</td>
<td>167.7632</td>
<td>31.52</td>
<td>0.95</td>
</tr>
<tr>
<td>Heuristic</td>
<td>169.376</td>
<td>30.86</td>
<td></td>
</tr>
<tr>
<td>EST</td>
<td>244.976</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3.3. Comparison of Number of Active Generators vs. time
3.4.2 Varying Mean Load

I compare PRO-S to GA-INT and EST in scenarios where the mean load varies. In each test scenario, the tasks’ $p_j$ values are multiplied by a constant that changes from 0.1 to 2. This in turn changes the mean load by the same factor. The generators’ capacity is kept the same. For each scenario, I run 10 instances that have the same mean load, but differ in their tasks’ starting times and deadlines as well as the generators’ initial conditions. I then determine the average cost reductions observed over those instances.

Figure 3.5 shows that PRO-S operation costs follow closely GA-INT’s as the mean load increases. Figure 3.6 demonstrates that GA-INT’s registers no more than 7% cost savings over PRO-S and falls below 5% as the load increases. This emphasizes that PRO-S performance is nearly as good as GA-INT’s whenever the load demand is not small. An important advantage of PRO-S is that PRO-S greatly reduces the problem’s time complexity, solving it in a few seconds only. In contrast,
GA-INT needs a computing time of about 4800 sec for the same case, which increases with the mean load (Figure 3.7).

Figure 3.5. Operation Costs Comparison

Figure 3.6. Cost Reduction over EST
3.4.3 Varying the Number of Tasks

I also evaluate how PRO-S performs vis-à-vis GA-INT and EST as the tasks’ daily arrival rate increases from 50 up to 500 tasks. A 50 task system corresponds to a two-home model, while 500 tasks simulate a 20 home system. For each model, I run 10 trials with the same number of tasks, and average out the results. As before, the 10 trials deviate in their tasks’ starting times and deadlines as well as the generators’ initial conditions.

From Figure 3.8, I notice that PRO-S’ operation costs approximate GA-INT’s even as the number of submitted tasks grows. Figure 3.9 shows that GA-INT performance improvement over PRO-S diminishes from about 9% to less than 5% as the tasks’ arrival rate rises. Figure 3.9 also illustrates that GA-INT’s and PRO-S’ cost reductions over EST decreases as the number of submitted tasks rises. This is due to the system’s load demand becoming more constant as the task arrival rate grows. This reduces the opportunity for load scheduling to curtail costs.
I also observe that GA-INT’s and PRO-S’ curves in Figure 3.9 are not smooth. This is explained by generators having a constant output power, so that even if the load demand requires only 0.1 kW from a generator, the generator still outputs 2.12 kW. Figure 3.10 shows PRO-S’ cost reduction curve when the tasks’ $p_j$ values are multiplied by 21.2, while the generators capacity remains the same. This curve is more regular compared to PRO-S’ curve when the $p_j$ values are unchanged. Thus, as the $p_j$’s grow, the generators’ output power becomes smaller and more continuous in relation to the tasks’ load demand. This smoothens out the cost reduction curve. GA-INT’s cost reduction profile also evens out as $p_j$’s rise, since PRO-S performance nears GA-INT’s.
In this case again, PRO-S only needs a few seconds on average to solve the problem, while GA-INT requires at least an hour to solve a 50 task problem and more than 10 hours when the number of daily tasks is greater than 200 as shown in Figure 3.11. Hence, since I know that GA-INT finds the best or nearly the best solution, I conclude that PRO-S returns solutions that are also close to the optimal solution, especially when the mean load and task arrival rate are high.
Chapter Conclusion

This chapter formulates the problem of optimal power generation in a microgrid with thermal generators as a non-linear mixed integer problem, and implements two algorithms, GA-INT and PRO-S, to solve it. GA-INT is a genetic algorithm that exploits task interruption and task shifting, and produces optimal or near-optimal solutions. Since GA-INT is time-consuming, I also designed a heuristic-based algorithm, PRO-S, to reduce the complexity of the problem. Simulation results demonstrate that, in medium to high load situations, PRO-S indeed reduces greatly the time complexity of the problem by solving it in a few seconds, while incurring less than 5% in extra cost in comparison to GA-INT. The latter requires at least an hour in low load situations, and can take more than 10 hours when the daily task arrival rate is greater than 200. However, even in low load scenarios, GA-INT cost reduction was no more than 9% over PRO-S.
CHAPTER 4

OPTIMAL PLANNING FOR A COMPLETELY GREEN CHARGING SYSTEM FOR ELECTRIC VEHICLES

Recently, growing environmental concerns, reinforced by advances in the field of energy storage devices, have contributed to the rapid development of electric vehicle (EV) technologies. Large-scale EV deployment in the transportation sector has the potential to reduce greenhouse emissions, improve the reliability of energy delivery, increase renewable energy penetration, and save fuel costs for drivers [26]. Since EVs run exclusively on their batteries’ electric power, an increase in availability of public EV charging stations is crucial for the widespread usage of EVs [64]. Accordingly, many studies have dealt with optimal placing and sizing of grid-connected EV charging stations [65-69], where the charging energy is mainly drawn from the existing power grid. However, the use of the power grid, whose power is mainly generated by fossil-fueled power plants, reduces the EVs benefits and can even increase the emission levels [70].

This chapter studies the optimal sizing of a completely green charging system (CGCS) for EVs, where the source of charging energy is produced entirely by renewable energy sources (RES), specifically solar panels. I consider a charging system located in a secluded, completely green village, which is a small-scale power system isolated from the main power grid. It meets the load demands entirely by distributed RES and stabilizes the energy production with an energy storage system (ESS) [5]. Accordingly, I seek to determine the optimal number of solar panels and the

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ESS capacity that satisfy the EVs’ charging demand and performance metrics (e.g., average EV charging delay), while minimizing investment costs.

4.1 Literature Review

The use of RES for EV charging has been considered in a number of studies. For example, [71] and [72] investigated the potential of day-time solar-based charging stations located in workplace parking garages to cover EVs power demand. In particular, simulations results in [72] showed that 48 parking lots in Frauenfeld Switzerland could meet 15-40% of transportation energy demand if covered with solar carports. The authors of [73] considered a grid-connected photovoltaic-based station located in a workplace parking garage in order to maximize the use of solar power. Similarly, [74] analyzed the possibility of charging EV batteries at workplaces in the Netherlands using solar energy, with the aim of minimizing grid dependency and maximizing solar power use. However, the above studies [71-74] neglect the optimal sizing of RES to minimize the EV charging systems’ investment costs, but rather assumed RES capacity that fits the available parking lot space.

The authors in [75] investigated the potential of renewable electricity generation for taxi services in Daejeon, South Korea, considering solar energy, wind energy, batteries, and electric-grid connection. The cost of energy for the resulting renewable generation system was assessed, without considering the randomness in renewable energy production or the performance level of EV charging. In contrast, in this study, I utilize a queueing model to formulate the charging system sizing problem to account for the randomness in renewable energy generation. In particular, I utilize a multi-dimensional discrete-time Markov chain model, in which each system state is defined by the number of EVs, the solar radiation intensity (for solar panels’ energy generation),
and the ESS state of charge. Additionally, whereas [75] considered static daily EV load, my study uses a queueing model that accounts for the randomness in EV arrival. The queueing performance measures are used to evaluate the charging system’s operation. As an example, the system’s throughput determines the number of EVs charged per unit time, while the expected system delay corresponds to the average time an EV spends in the charging system.

This chapter contributes:

- The formulation of a Markov chain queueing model for a renewable energy-fueled charging system for EVs to account for randomness in renewable energy and EV demand.
- The utilization of queueing performance measures to access the charging system’s quality of service.
- The validation of the proposed queueing model by simulating the charging system’s operation.

4.2 System Model

I consider a discrete-time Markov chain model for the CGCS. As illustrated in Figure 4.1, the CGCS is a collection of EV charging stations utilizing the energy produced by solar panels and the energy discharged from the ESS. For simplicity, I assume that the system’s charging stations are identical and deliver power at the same charging rate of $Y$ (in kW). Additionally, I also assume the following energy consumption policy for the charging system: (1) by default, EVs are charged by the power derived from solar panels; (2) when the produced solar energy is greater than the energy necessary to operate the required number of charging stations to serve the EVs in CGCS, the excess energy is stored in the ESS; and (3) when the solar panels’ energy is insufficient, the charging system discharges from the ESS as much energy as is available to cover the extra load. Other energy utilization protocols could be used, for example, putting a limit on the amount of
energy discharged from ESS within a particular time duration. Determining the optimal energy consumption protocol is outside the scope of this study.

4.2.1 EV Model

An EV in the system is characterized by the number of kWh, $C_f$, needed to fully charge its battery. The EV charge demand is discretized into equal-size levels, where $\delta_1 = C_{f+1} - C_f$ is the energy difference (in kWh) from one level of EV demand to the next. Accordingly, $C_1 = \delta_1$, while $C_0 = 0$ kWh corresponds to no energy demand – (i.e., a fully charged EV battery). The duration of a timeslot $\tau = \delta_1 / Y$ is the time interval required to charge an EV battery by $\delta_1$ kWh. The actual value of $\delta_1$ depends on the desired accuracy of the system model. In the above discretized model, a particular demand is approximated to the closest $C_f$ level, thus introducing some error since in practice the EV energy demand is continuous. Of course, the smaller $\delta_1$ is, the smaller is the discretization error.
4.2.2 Solar Panel Model

In this study, I consider only solar panels as RES, with plans to incorporate wind turbines in future. I model $K$ identical solar panels. Each solar panel unit has maximum power generating capacity of $G_{cp}$ [kW] and is also associated with a per-kW investment cost of $\zeta$ [$$/kW$$], which includes equipment and installation costs. The solar output power depends on the solar radiation, which is modeled following the discrete-time Markov chain presented in [76]. In this model, the intensity of solar radiation is affected by cloud thickness and wind speed $\omega$ [m/s]; I label $\bar{\omega}$ as the average daily wind speed.

The solar radiation intensity, $G$ [kW/m$^2$], can be in any of $R + 1$ distinct states: $r = R$ refers to the maximum solar radiation case (full sunlight, clear sky), when the solar panel produces its maximum power; $r = 0$ corresponds to a state when the solar panel does not produce any power ($G_0 = 0$ [kW/m$^2$]) because the sun is completely covered by clouds. I assume that the cloud size resulting in solar state $r$ is exponentially distributed with mean $c_r$ [76].

I also assume that the transitions among solar radiation states can occur only between two adjacent states [76]. Additionally, the order of transitioning among solar states depends on the wind’s direction, so that a transition from state $G_r$ to $G_{r+1}$ is reversed if the wind’s direction changes. The transition rate from state $r$ to an adjacent state is $\beta_r = \bar{\omega}/c_r$ [77]. Accordingly, the transition rate matrix is as follows:

$$Q = \begin{bmatrix}
-\beta_0 & \beta_0 & 0 & \ldots & 0 \\
\beta_1 & -2\beta_1 & \beta_1 & \ldots & 0 \\
\vdots & \ddots & \ddots & \ldots & \vdots \\
0 & \ldots & 0 & \beta_{R-1} & -2\beta_{R-1} & \beta_{R-1} \\
0 & \ldots & 0 & \beta_R & -\beta_R
\end{bmatrix} \quad (4.1)$$
To obtain the discrete-time transition probability matrix, \( \Psi \), I utilize the *uniformization* method as presented in [78]:

\[
\Psi = I + 1/\sigma \cdot Q
\]  

(4.2)

where \( I \) is the identity matrix and \( \sigma \geq \max_i |q_{i,i}| \) (\( q_{i,i} \) is row \( i \)’s diagonal element of the matrix \( Q \)).

Hence, the solar radiation process can be expressed as:

\[
\Psi = \begin{bmatrix}
\psi_{0,0} & \psi_{0,1} & 0 & 0 & \ldots & 0 \\
\psi_{1,0} & \psi_{1,1} & \psi_{1,2} & 0 & \ldots & 0 \\
\vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & \ldots & 0 & \psi_{R-1,R-2} & \psi_{R-1,R-1} & \psi_{R-1,R} \\
0 & \ldots & 0 & \psi_{R,R-1} & \psi_{R,R}
\end{bmatrix}
\]  

(4.3)

where \( \Psi \) represents the state transition probability matrix among solar radiation states and \( \psi_{r,r'} \) is the probability of switching from solar state \( r \) to \( r' \).

Using the radiation intensity \( G_r \), the solar panel’s output power [kW] is found by:

\[
\rho_r = \eta \cdot A_k \cdot G_r
\]  

(4.4)

where \( \eta \) and \( A_k \) represent the solar panel’s efficiency [%] and total area [m\(^2\)], respectively. Also, \( \rho_r \leq Gcp \).

Since the solar radiation intensity, wind speed and cloud size vary with the four seasons of the year, I will consider the system’s operation for 4 different days, each representative of a day in one of the seasons of the year (summer, winter, fall and spring).

### 4.2.3 Energy Storage System Model

I utilize a general model for the ESS that is not restricted to any particular energy storage technology. In this way, the ESS is mainly characterized by its *state of charge* (SOC), which is a
value within the range of $[0,1]$ that indicates the percentage of charged ESS’ total energy capacity [79],[80]. The ESS also has an investment cost per kWh of energy storage, $\xi$ [$$/kWh$$] [41]. Parameter $\gamma$ is used to express the ratio of the ESS investment cost to the solar energy investment cost; (i.e., $\gamma = \xi/\zeta$). I utilize a discretized model for the ESS [81], where the ESS SOC is divided into $L + 1$ equally spaced levels: $\{B_0, B_1, ..., B_L\}$, where $0 \leq B_l \leq 1$. When ESS’ SOC = $B_L = 0$, the ESS is completely depleted, while SOC = $B_0 = 1$ corresponds to the fully charged state. I label the ESS maximum energy capacity [kWh] as $Cess$.

I assume that $\delta_2 = Cess(B_l - B_{l+1}) = Cess/L$ for $0 \leq l \leq L - 1$. For simplicity, the $B_i$ levels are defined in such a way that $\delta_2$ is equal to the smallest possible transferrable energy to/from the ESS per timeslot, where a timeslot equals to $\tau$ as previously defined. As an example, $\delta_2$ could be the energy (in kWh) stored in the ESS during one timeslot by a solar panel operating in the state $G_1$, since $G_1$ is the solar radiation state that corresponds to the smallest solar energy production. Under the above assumptions, the ESS charging/discharging is a deterministic process, and hence the transition probability from state $l$ to state $l'$ of ESS is going to depend on transition probabilities between solar radiation states and the probability of EV arrival/departure.

The approach of ESS modeling could be customized to fit the charging/discharging process of many energy storage technologies including: energy storage methods with linear and non-linear charging/discharging process, as well as ESS that require a delay period before charging/discharging.
4.2.4 Queueing Model

I consider a discrete time Markov chain with a discrete Poisson arrival process of EVs of intensity \( \lambda \) [arrivals/timeslot]. The utilized service time model is inspired by [82], which assumes different battery sizes and corresponding exponentially distributed EV service time. However, due to my model being discrete-time, I assume an analogous geometric service time distribution, driven by the randomness in the amount of energy needed by the EVs’ batteries. I denote as \( d \) the EV charging completion probability during a timeslot [83]. Therefore, \( d \) is the probability that an EV battery requires \( \delta_1 \) kWh at the beginning of a timeslot, meaning that, if there is enough power, the EV battery will be fully charged at the end of the timeslot. All state transitions occur at the timeslot boundary. That is, if an EV arrives in the middle of a slot, it will start charging only at the beginning of the next timeslot. All changes in number of EVs happen at the timeslot boundary. Similarly, all solar radiation state and ESS’ SOC transitions also occur at the timeslot boundary.

I assume that a server in the queueing model corresponds to a charging station with rate \( Y \), so that each charging station can serve at most one EV at any time. The charging system has a maximum of \( C_s \) installed charging stations. The challenge in analyzing the charging system’s queueing model is that the number of operational servers/charging stations during a timeslot is a random variable that depends on the available insolation intensity \( G_r \) and on the ESS SOC. I note that in this model, the ESS discharges energy whenever available solar radiation is not enough to meet the EV demand. Additionally, the number of active charging stations cannot be greater than the number of EVs \( v \) in the charging system. Hence, given the number of solar panels \( K \), the available solar power \( \theta_r = K \cdot \rho_r \), the number of EVs in the system \( v \), and ESS’s SOC \( B_t \), the number of operational charging stations during a timeslot is found as stated in (4.5).
where $N_r = \theta_r / Y$ is the maximum number of charging stations that can be operated by the available solar power, and $N_l = Cess \cdot B_l / (Y \cdot \tau)$ is the highest number of charging stations that can be powered by the available ESS energy. Hence, given $v$ EVs in the system, the probability that $g$ out of $v$ EVs are fully charged within a timeslot is:

$$\phi_{v,g} = \binom{N_{v,r,l}}{g} d^g (1 - d)^{N_{v,r,l} - g} \tag{4.6}$$

I note that in case of a reduction in the number of operational charging stations $N_{v,r,l}$ due to a decline in solar radiation intensity and a lack of stored energy to compensate for the decline in the solar radiation, there is possibility of service interruption of the charged EVs. However, since the change $N_{v,r,l}$ happens at the timeslot boundary, the EV service time remains geometrically distributed. The suspension in service is reflected by a decrease in the system’s charging completion probability in (4.6) due to a decline in $N_{v,r,l}$. I also consider a maximum queueing capacity of $V$ EVs that is set by the charging system operator (i.e., there is space for maximum of $V$ EVs in the system). Once there are $V$ EVs in the system, no more EVs can enter the system. My goal is to minimize the average number of blocked EVs, which corresponds to loss revenues to the charging system owner.

### 4.2.5 State Space and Transition Probabilities

Each system state is represented by a tuple $(v, r, l)$, where $v$ $(0 \leq v \leq V)$ is the number of EVs in the system, $r$ $(0 \leq r \leq R)$ is the solar radiation state, and $l$ $(0 \leq l \leq L)$ is the ESS SOC. I derive the transition probabilities from state $(v, r, l)$ to state $(v', r', l')$, where the system’s one-step
transition probability $P_{v',r',l'}^{v,r,l}$ refers to the probability of transitioning from state $(v, r, l)$ to state $(v', r', l')$ in a timeslot. Some of the state transitions can be easily defined:

\[
P_{v+m,r,0}^{v,0,0} = \psi_{0,r} \Pr(m), \quad v + m < V
\]
\[
P_{v',r,0}^{v,0,0} = \psi_{0,r} \Pr(m \geq V - v)
\]

(4.7)

where $\Pr(m)$ is probability of having $m$ EV arrivals following a Poisson distribution with mean $\lambda$, and $\Pr(m \geq V - v)$ is the probability of having $V - v$ or more EV arrivals given a Poisson arrival process with mean $\lambda$.

For state transitions where the number of EVs varies and/or the solar radiation state varies, the ESS’ SOC also changes depending on the need to charge/discharge energy from the ESS. For instance, an increase in number of EVs might require discharging the ESS to serve the arriving EVs, while an excess of the renewable energy due to a rise in solar intensity could be stored in the ESS. The transition probability from state $(v, r, l)$ to state $(v', r', l')$ is:

\[
P_{v',r',l'}^{v,r,l} = \psi_{r,r'} \sum_{|\min(0,h)| \leq m \leq v'} \Pr(m) \cdot \phi_{v,m+h}
\]

(4.8)

where $h = v - v'$, $v' \neq V$, and $\phi_{v,g}$ is determined as shown in (4.6). In addition, since the change in ESS’ SOC depend on the current solar state $r$ and number of EVs $v$, $l'$ has to corresponds to $l_1$ or $l_2$ as defined in (4.9) in order for $P_{v',r',l'}^{v,r,l} \neq 0$:

\[
l_1 = \max \left( l - \left[ (N_r - N_{v,r,l}) \cdot Y \cdot \frac{\tau}{\delta_2} \right], 0 \right), N_r \geq \min(v, C_s)
\]
\[
l_2 = \min \left( l + \left[ (N_{v,r,l} - N_r) \cdot Y \cdot \frac{\tau}{\delta_2} \right], L \right), N_r < \min(v, C_s)
\]

(4.9)

When $v' = V$, the transition probability from state $(v, r, l)$ to state $(V, r', l')$ is as shown in (4.10).
\[ P_{v,r,l}^{v,r,l} = \psi_{r,r'} \sum_{h:s \leq V} \Pr(m) \sum_{h:s \leq m} \phi_{v,l-h} + \psi_{r,r'} \Pr(m > V) \sum_{h:s \leq V} \phi_{v,l-h} \quad (4.10) \]

where \( h = V - v, l' \) is defined by (4.9) and \( \Pr(m > V) \) is probability of having more than \( V \) EV arrivals. Additionally, there are states where \( P_{v,r,l}^{v,r,l} = 0 \) such as when:

- \((r = 0) \land (l = 0) \land (v' < v)\), where \( \land \) is the ‘and’ operator (EVs cannot complete charging without energy).
- \((l' \neq l_1) \land (l' \neq l_2)\) (i.e., \( l' \) does not indicate the correct ESS state).
- \( h = v' - v > N_{v,r,l} \) and \( v' < v \) (there is not enough energy to completely charge \( h \) EVs).

I define the one-step transition matrix \( U \) with \( J \) columns and \( J \) rows, where \( J = V \cdot R \cdot l \). The steady state probability vector \( \mathbf{\Pi} = [\Pi_{0}, ..., \Pi_{V}] \), where \( \Pi_{v} = [\Pi_{v,0}, ..., \Pi_{v,R}] \), \( \Pi_{v,r} = [\pi_{v,r,0}, ..., \pi_{v,r,L}] \) and \( \pi_{v,r,l} \) is the steady state probability of being in the state \((v, r, l)\). The rows and columns in matrix \( U \), which are numbered from 1 to \( J \), have a one-to-one corresponds with the CGCS’s states ordered from (0,0,0) up to \((V,R,L)\) following the ordering in vector \( \mathbf{\Pi} \). To determine the steady state probabilities, I solve the following equations:

\[ \mathbf{\Pi} = \mathbf{\Pi} \times U \]
\[ \sum \mathbf{\Pi} = 1 \quad (4.11) \]

### 4.2.6 Performance Measures and Sizing Problem

I utilize queueing theory performance metrics to evaluate the performance of the EV charging system. The expected number of electric vehicles at the charging system is:

\[ E[V] = \sum_{0 \leq v \leq V} e \cdot v \cdot \Pi_{v} \quad (4.12) \]
where $e$ denotes an identity column vector of size $R \cdot L$. The average number of EVs that leaves the charging system per timeslot, or the average system throughput per slot, is:

$$
\bar{\alpha} = \sum_{0 \leq v \leq V} \sum_{0 \leq r \leq R} \sum_{0 \leq l \leq L} \pi_{v,r,l} \left( \sum_{0 \leq g \leq N_{v,r,l}} g \cdot \phi_{v,g} \right)
$$

(4.13)

where $\phi_{v,g}$ is found as shown in (4.6). By Little’s law, the average delay time [timeslots] per EV is:

$$
D = E[V]/\bar{\alpha}
$$

(4.14)

The average delay is an important performance measure for the overall performance of the charging system, as the sizing problem seeks to determine the optimal number of solar panels $K$ and size of ESS $Cess$, such that the target EV delay $D_{td}$ [timeslots] is not exceeded. As the wind speed and cloud size vary per season, the charging system’s delay is evaluated for each season $s$ ($1 \leq s \leq 4$) of the year to ensure that the target delay is met in all the four seasons, (i.e. $D_s$ is the average delay [timeslots] per EV in season $s$ found by evaluating (4.14) for season $s$). Hence, the optimal sizing problem can be stated as:

$$
\min Cost(K,Cess) = K \cdot \zeta \cdot Gcp + \xi \cdot Cess
$$

s.t $D_s \leq D_{td}, 1 \leq s \leq 4$

(4.15)

4.3 Search-Based Algorithm

The EV average delay as a function of the number of solar panels and the ESS capacity is a highly complex and non-linear problem [84], making (15) hard to solve as a nonlinear integer programming problem. For such complex problems, search techniques have been proven to be effective in finding optimal or near optimal solutions [55]. Accordingly, I devise a search-based
algorithm to efficiently explore the problem’s solution space. A solution \( n \) in the search space is characterized by two parameters \([K_n, Cess_n]\), where \( K_n \) is the number of solar panels and \( Cess_n \) is the ESS capacity. The search-based algorithm seeks to find a solution \([K_{opt}, Cess_{opt}]\) that leads to the minimum system planning cost, while meeting the set EV target delay \( D_{td} \). A complete description of the search algorithm is outlined in Algorithm I.

Algorithm I:

Set \( K_{max} = V \cdot 10 \) and \( Cess_{max} = K_{max} \cdot Y \cdot \tau \)

Use Binary Search to find largest \(CESS \) value, \( Cess_{lg} \) such that \([K_{max}, Cess_{lg}]\) leads to \( D_s > D_{td} \) for one of the seasons, where \( D_s \) is found by evaluating (4.14) for season \( s \).

Set \( K_{min} = 1, Cess_n = Cess_{lg} + \delta_2; K_{opt} = -1, and Cess_{opt} = -1 \)

While \( Cess_n \leq Cess_{max} \)

Use Binary Search to find to find minimum \( K_n \) such that \( D_s \leq D_{td} \) for \( 1 \leq s \leq 4 \), where \( D_s \) is found by evaluating (4.14) for season \( s \).

If \((K_{opt} == -1 \text{ and } Cess_{opt} == -1) \text{ or } (Cost(K_n, Cess_n) < Cost(K_{opt}, Cess_{opt}))\)

Update \( K_{opt} = K_n \) and \( Cess_{opt} = Cess_n \)

Update \( Cess_n = Cess_n + \delta_2 \)

End

Return \([K_{opt}, Cess_{opt}]\) and \( Cost(K_{opt}, Cess_{opt}) \)

In my experience with simulating the charging system, I have observed that in the worst case the charging system requires up to \( K = V \cdot 7 \) solar panels and \( K \cdot Y \cdot \tau \) kWh of energy storage capacity. Hence, as shown in Algorithm I, I set the upper bound of the sizing solution to \( K_{max} = V \cdot 10 \) and \( Cess_{max} = K_{max} \cdot Y \cdot \tau \), since even in the worst case the charging system cannot require more than \( K = V \cdot 10 \) solar panels and \( K \cdot Y \cdot \tau \) kWh of ESS capacity to meet the target delay \( D_{td} \). In order to effectively search the solution space, I prune the space as follows. The algorithm starts by finding the largest ESS capacity \( Cess_{lg} \), such that \([K_{max}, Cess_{lg}]\) leads \( D_s > D_{td} \) for some season \( s \), where \( D_s \) is found as in (4.14) by evaluating the Markov chain for season \( s \). I utilize Binary Search method as described in [85] in order to find such a \( Cess_{lg} \) in the most
efficient way. Finding $Cess_{tg}$ allows me to disregard all solutions where $Cess_n \leq Cess_{tg}$ regardless of the number of solar panels, since if $[K_{max}, Cess_{tg}]$ does not satisfy $D_{td}$ then no solution with $Cess_n < Cess_{tg}$ will be able to meet the $D_{td}$ requirement. For each ESS capacity $Cess_n$ in the interval $[Cess_{tg} + \delta_2, Cess_{max}]$, the search-based algorithm finds the minimum value of $K_n$ that satisfy $D_{td}$ using the Binary Search method; clearly, this will corresponds to the minimum cost solution given ESS capacity of $Cess_n$. In order to determine whether a solution meets $D_{td}$, the Markov chain analysis is used again to obtain the average EV delay $D_s$ for each season $s$. The ESS capacity is always incremented by $\delta_2$, since an increment that is less than $\delta_2$ will not change the ESS state. The optimal solution is the $[K_n, Cess_n]$ pair that corresponds to the minimum planning cost, while also satisfying $D_{td}$.

4.4 Case Study Parameters

To demonstrate the proposed methodology, I evaluate as an example a solar radiation model that has two state ($R = 1$), where $r = 0$ corresponds to state where the sun is completely covered by clouds, and $r = 1$ matches the maximum solar radiation intensity (of 1 kW/m$^2$). The considered solar panels’ parameters are shown in Table 4.1.

<table>
<thead>
<tr>
<th>Solar Panel Parameters</th>
<th>ESS Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area (m$^2$) = 50</td>
<td>Charging/discharging Efficiency (%) = 1</td>
</tr>
<tr>
<td>Efficiency (%) = 50</td>
<td>$\delta_2 = 10$ kWh</td>
</tr>
<tr>
<td>Max Power Capacity (kW) = 25</td>
<td>Energy rating cost ($$/kWh) = 200</td>
</tr>
<tr>
<td>Investment cost ($$/kW) = 200</td>
<td></td>
</tr>
</tbody>
</table>

In the presented example, $Y = 25$ kW is the charging power per charging station. Since the maximum power capacity per solar panel $Gcp$ also equals to 25 kW (Table 4.1), this means that a
solar panel can drive at most one charging station when it is operating at maximum capacity. I assume that $c_0 = 1000$ [m], since a typical cloud has an average diameter of approximately 1 km [86] and the cloud diameter corresponds to $c_0$. The size for the clear sky state $c_1$ depends on the cloud coverage, which is the fraction of sky covered by clouds when observed from a particular point [87]. That is, given that the fraction of sky covered by clouds is $x$ ($0 \leq x \leq 1$), $c_1 = c_0 \cdot x/(1 - x)$.

I set $\delta_1 = 10$ [kWh], which corresponds to EV charging demand levels of: $C_0 = 0$ [kWh], $C_1 = 10$ [kWh], $C_2 = 20$ [kWh], etc. In this way, the charging completion probability $d$ corresponds to the probability that an EV demand equals to 10 [kWh]. The timeslot duration is found as $\tau = (C_{f+1} - C_f)/Y$, which is equal to 0.4 hours or 24 minutes. The ESS parameters are shown in Table 4.1. The maximum ESS’ SOC level depends on the ESS maximum energy storage capacity $C_{ess}$; that is $L = C_{ess}/\delta_2$. I utilize the weather condition for an average year in Dallas, Texas, USA, based on historical records from 1974 to 2012 [88]. Table 4.2 shows the average cloud cover and average wind speed [m/timeslot] per season.

<table>
<thead>
<tr>
<th>Season</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud Cover (%)</td>
<td>70</td>
<td>70</td>
<td>38</td>
<td>45</td>
</tr>
<tr>
<td>Wind Speed (m/timeslot)</td>
<td>5792</td>
<td>7080</td>
<td>5148</td>
<td>5792</td>
</tr>
</tbody>
</table>

### 4.5 Simulation Results

To validate our Markov chain model, I simulated the CGCS for the winter season (with the weather parameters defined in section 4.4) in Matlab and compared the simulation results to the results of the Markov chain evaluation. The EV arrival process follows a Poisson distribution process with the rate of $\lambda$ [EVs/timeslot], where a timeslot corresponds to 24 minutes, as defined in section 4.4.
Accordingly, the energy demand per EV is discretized into equal-sized quanta, where an energy demand quantum equals 10 [kWh]. The energy demand [kWh] per EV is generated according to a geometric distribution with success parameter $d = 0.5$. That is, $d = 0.5$ is the charging completion probability, which is the probability of an incoming EV having an energy demand of 10 [kWh].

The solar radiation states and the solar panel parameters are as defined in section 4.4. Using the solar states transition matrix in (4.1), I determined the steady state probability $p_0$ and $p_1$, which corresponds to the probability of the solar intensity of $G_0 = 0$ [kW] and $G_1 = 1$ [kW] (maximum solar radiation intensity), respectively. In this way, the discrete time simulation includes $p_0$ fraction of timeslots with the sun completely covered ($r = 0$) and $p_1$ fraction of timeslots with maximum solar radiation intensity ($r = 1$). The ESS is simulated by tracking its SOC from one timeslot to the next and ensuring that its maximum capacity $C_{ess}$ is not exceeded. The charging system was simulated for a total of 100,000 timeslots to guarantee stable simulation results. I record the observed EV average delay, the average number of EVs (number of EVs in the system in a timeslot), and the system throughput (the number of departures per timeslot). In the comparison results, I mainly focus on the EV average delay, since this is the main performance measure used in the sizing problem.

In Figure 4.2, I compare the evaluation and simulation results for the EV average delay as a function of the EV arrival rate $\lambda$, given 20 solar panels, $C_{ess} = 400$ kWh, and $C_s = \lambda$ (the number of installed charging stations equals to the average number of EVs arriving per timeslot). The Markov chain evaluation results strictly follow the simulated results, registering a difference of no more than for 1%. I observed similar accuracy of results for the throughput and average number of EVs ($E[V]$). I also compare the evaluated and simulated EV average delay as a function of the
ESS maximum capacity, for $\lambda = 5$, $C_s = \lambda$, and $K = 20$ solar panels. In this case, the simulation results also approximated the evaluation results well, leading to a difference of no more than 13%; this difference decreased to less than 7% for $Cess \geq 200$ kWh. I obtained similar comparison results (of no more than 6% difference for the EV average delay, throughput and average number of EVs) when I varied the number of solar panels and the system queue capacity for both the simulated system and for the Markov chain model. The above validations demonstrate that the Markov chain model is a close approximation for the EV charging system. I conclude that I can use the performance measures obtained from evaluating the Markov chain model in the sizing optimization problem.

![Figure 4.2. Average EV Delay as Arrival Rate $\lambda$ varies](image)

### 4.6 Evaluation Results

#### 4.6.1 Search-based Algorithm Results

I first look at the minimum cost solutions returned by the search-based algorithm given $d = 0.5$, $\lambda = 5$, $C_s = \lambda$, $D_{td} = 2$, and $V = 5$. The obtained $Cess_n$ values are within the interval $[500, 1000]$; that is $Cess_{lg} = 490$ kWh is the largest ESS capacity, such that $[K_{max}, Cess_{lg}]$ leads to
\( D_s > D_{td} \) for some season \( s \), where \( D_s \) is found by evaluating (4.14) for season \( s \). As expected and depicted in Figure 4.3, the solar panels capacity decreases as \( Cess_n \) grows. However, the system’s investment cost does not increase/decrease monotonically as the ESS capacity or/and number of solar panels rise/decline. Consequently, the optimal solution is the minimum cost point of the system cost curve in Figure 4.3, which corresponds to the pair [23,590] (in Solar Panels and kWh respectively) for this evaluation case.

\[\text{Figure 4.3. Number of Solar Panel and System Costs as ESS Capacity varies}\]

**4.6.2 Varying Target Average Delay**

In this section, I analyze how the optimal solar panels’ capacity and ESS capacity vary as a function of the target average EV delay. I maintain \( d = 0.5, \lambda = 5, C_s = \lambda, \) and \( V = 5 \). As expected, Figure 4.4 shows that the optimal number of solar panels and the ESS maximum capacity decreases as the target EV delay increases. That is, as EVs are allowed to spend more time in the charging system, the charging system can utilize less energy resources to meet the target average delay per EV. This is mirrored in Figure 4.5, which shows that the CGCS investment cost decreases with the rise in target average delay.
Figure 4.4. Solar Panel and ESS Capacity as $D_{td}$ varies

Figure 4.5. System Investment Cost as $D_{td}$ varies

On the other hand, as the target average delay per EV decreases, the number of solar panels and the ESS capacity increase in order to allow for fast EV charging. Accordingly, as $D_{td}$ approaches 2, the ESS capacity and the number of solar panels capacity is greatly increased in order to raise the probability of having enough energy to charge arriving EVs.

4.6.3 Varying $\gamma$

In Figure 4.6, I vary the ratio between the investment cost per kWh of ESS and the investment cost per kW of solar energy from $10^{-5}$ up to $10^5$, while $D_{td} = 2.5$, $d = 0.5$, $\lambda = 5$, $C_s = \lambda$, and $V = 5$. 
Whenever $\gamma = 10^{-1}$, the ESS is significantly cheaper than the solar energy production, so that the ESS capacity is greatly augmented in order to minimize the investment in solar panels. In other words, a large ESS capacity stores more energy, allowing for greater variations in the power generated by the solar panels, which in turn reduces the required solar panels’ capacity.

![Figure 4.6. Solar Panel and ESS Capacity as $\gamma$ varies](image)

Sufficiently stored energy allows the charging system to service EVs even in the absence of solar radiation. Accordingly, I observe that the ESS capacity cannot be less than 120 kWh even as $\gamma$ rises, which explains why the ESS and solar panel capacity stabilizes once $\gamma \geq 10$. Similarly, as the solar panels are the only source of energy, their number cannot be smaller than 13 solar panels even as they become more expensive than the ESS. This explains why the solar panels’ optimal capacity also flattens for $\gamma \leq 0.1$.

### 4.6.4 Varying EV Departure Probability and Queuing Capacity

In this section, I vary the EV departure probability $d$, while maintaining the arrival rate $\lambda = 5$, $C_s = \lambda$, and $V = 5$. As $d$ decreases, a larger fraction of the arriving EVs requires more than 10
[kWh] to be fully charged. Accordingly, a decline in $d$ corresponds to an increase in charge demand per EV, which explains the rise in the number of solar panels and the ESS capacity in Figure 4.7 as the $d$ decreases. I also observe that the charging system cannot satisfy the target average delay $D_{td} = 2.5$ when $d < 0.4$. However, when $D_{td} = 5$, I am able to find solutions for $d \geq 0.2$. I conclude that as the load demand augments (as $d$ decreases), a rise in target delay $D_{td}$ permits the charging system to accommodate more EV load demand.

![Figure 4.7. Solar Panel and ESS Capacity as $d$ varies with $D_{td} = 2.5$](image)

As the load demand and solar panels’ capacity increase (with the decline in $d$), storing the energy produced becomes more profitable in order to allow for better utilization of the generated energy. This explains why, as illustrated in Figure 4.7, the optimal ESS capacity increases as $d$ approaches 0.4.

Similar to the above results, when the system’s queueing capacity $V$ grows, the charging system has to also increase the energy resource capacity (solar panels and ESS) in order to handle the growing energy demand due to the rise in number of EV that can enter the system.
4.6.5 Varying Arrival Rate $\lambda$

In this section, I vary the arrival rate $\lambda$, while maintaining the queueing capacity $V = 20$, $C_s = \lambda$, and $D_{td} = 5$. As the system’s queueing capacity is not changed, the average number of EVs in the system increases only slightly (but stays within the interval $[19.8, 20]$) even as $\lambda$ grows. Since the number of installed charging stations grows with $\lambda$ ($C_s = \lambda$), the system’s throughput also rises as $\lambda$ increases. This explains why the required number of solar panels and the ESS capacity decline even as the $\lambda$ increases as depicted in Figure 4.8. In particular, as the system throughput rises with $C_s$ (as $\lambda$ increases), the necessity to store energy diminishes, which explains the significant decline in the ESS capacity. However, I also observed that for $\lambda = C_s < 8$, the system could not meet the target delay as the throughput was not large enough. Consequently, I did not find solutions for $\lambda < 8$.

On the other hand, if I limit the number of installed charging stations to $C_s = V/2$ (in this case $C_s = 20/2 = 10$), the number of solar panels and the ESS capacity grow as the average number of arriving EVs increases with $\lambda$, as shown in Figure 4.9. However, once $\lambda \geq 10$, the average number of EVs in the system and the system’s throughput, which mainly depends on $V$ and $C_s$ (which is constant in this case) respectively, stabilizes. This explains why the number of solar panels and the ESS optimal capacity also flatten for $\lambda \geq 10$ in Figure 4.9. Hence, I note that whenever $\lambda \geq C_s$, the optimal number of solar panels and the ESS capacity are influenced mostly by the system’s queueing capacity $V$ and the number of installed charging stations $C_s$, even as $\lambda$ varies.
4.7 Chapter Conclusion

In this chapter, I study the optimal planning problem for a completely green EV charging system, such as one which is situated in isolated green village, whose energy is generated exclusively by solar panels. The goal was to design a methodology for determining the optimal number of solar panels and the optimal ESS capacity that minimize the charging system’s investment costs while satisfying a specified target average EV delay. Due to the randomness of the solar power generation, I utilized a three dimensional Markov chain model, where each state is characterized
by the solar radiation state, the number of EVs in the system and the ESS state of charge. I designed a search-based algorithm to efficiently explore the solution space of the formulated non-linear integer programming problem in order to find an optimal solution. I validated my model by simulations. From the sizing problem evaluation results, I observed that the optimal number of solar panels and the ESS capacity depend mostly on the system’s queueing capacity and number of installed charging stations, which, by determining the system’s throughput and the average number of EVs respectively, determine the overall EV average delay.
CHAPTER 5

FUTURE WORK

In this dissertation, I demonstrated that rather than considering microgrid (MG) loads as one aggregate load or as static loads, analyzing and utilizing the characteristics of different load types in MGs can allow to (1) further optimize MG planning and operation, (2) evaluate MG reliability/performance, and (3) design time-efficient resource scheduling schemes. In particular, Chapter 2 showed that exploiting the timing and power characteristics of programmable appliances in smart homes can reduce the planning cost for a completely green village by 40% or more. The appliance parameters were also used to assess the reliability of the planned MG. In Chapter 3, I presented a heuristic algorithm PRO-S that utilized the flexibility in scheduling domestic programmable appliances to find cost-effective schedules for the operation of the MG’s thermal generators in a few seconds. PRO-S incurred less than 9% in extra cost in comparison to a genetic algorithm, a time-consuming search-based algorithm that returned optimal or near-optimal generators’ schedules. Chapter 4 described a three-dimensional Markov Chain model that employed the electric vehicles (EVs) load demand attributes, including the EVs’ arrival process and charging delay service requirement, to optimize the planning of a completely green EV charging system. Additionally, the EV demand attributes were used to ensure that the charging system performance met the target average delay per EV charging. In the sections that follow, I outline future research directions.
5.1 Wind Turbines in Charging Systems

The studies presented in Chapter 2 and Chapter 4 advance the state of the art in green MG planning by considering load characteristics to further minimize MG planning costs and evaluate MG performance respectively. In Chapter 4, the planning problem for the completely green charging system only considered solar panels as energy sources. However, solar power tends to be scarce during the winter season due to very low solar radiation intensities. In contrast, wind turbines are generally operational in all seasons due to the availability of wind throughout the year. Thus, I plan to incorporate wind turbines in the planning of completely green charging system for more reliability.

5.2 Prosumer-Supplied Microgrids

An advantage of MGs is the two-way flow of electricity, which allows electricity consumers to buy and operate distributed energy sources. These electricity consumers who also produce energy are referred to as prosumers [89], and those MGs containing such prosumers are called prosumer-supplied MGs. Chapter 3 described a novel time-efficient centralized scheme PRO-S for the optimal operation of a MG with programmable appliances. In this case, the MG central controller coordinated the operation of all MG components, including thermal generators. However, PRO-S is not suitable for a prosumer-supplied MG, since consumer-owned resources are not controlled by the MG central controller. PRO-S is designed from the point of view of the MG operator without considering of prosumers’ economic objectives.

On the other hand, MG operators and prosumers generally have conflicting goals. While MG operators seek to maximize their profit by selling energy to consumers and minimizing the MG operation costs, prosumers aim to reduce their electric bills and sell as much energy as possible.
The optimal operation of a prosumer-supplied MG becomes even more complicated if one considers the unpredictability in MG load. Hence, in future studies, I intend to apply conflict and cooperation mathematical methods, such as game theory, to study the optimal operation of prosumer-supplied MGs in order to account for competing decision-makers. These mathematical methods will also enable the development of new energy market models that account and enable the participation of profit-driven consumers.

5.3 Load Characteristics in Economic Dispatch and Microgrid Control

Though not addressed in this dissertation, economic dispatch and MG control are also important research areas in MG operation research. Economic dispatch is performed from a few minutes to an hour ahead and focuses on determining the short-term output of on-line energy sources to minimize MG operation costs, while ensuring that load balance, power-flow, and voltage constraints are met [90]. MG control seeks to balance MG demand and power generation in small time periods, such few minutes or seconds [91]. In the future, I plan to also explore load characteristics and load scheduling to further optimize MG economic dispatch and control. As small power capacity systems, MGs have a higher load and renewable energy variability compared to the total load in a conventional grid and utility-scale renewable energy production. Accordingly, I will use stochastic optimization methods to account for the high load and energy unpredictability. I will also investigate distributed/decentralized schemes for MG operation in order to minimize communication overhead and eliminate single-point failure in centralized protocols.
REFERENCES


BIOGRAPHICAL SKETCH

Juliette Ugirumurera was born in Gitarama, Rwanda. After completing her secondary school studies at Byimana Science School in 2007, she was awarded the Rwandan Presidential Scholarship to attend Oklahoma Christian University, in Edmond, Oklahoma. She received her BS in Computer Engineering from Oklahoma Christian University in 2012, where she finished as the outstanding Computer Engineering student. She subsequently received a MS degree in Computer Science from The University of Texas at Dallas in 2015. She is currently a PhD candidate in Computer Science at The University of Texas at Dallas, where she is a member of the Wireless Networks Lab. Her research interests include optimization, modeling and scheduling of resources in power networks, algorithm design, and Internet of things.
CURRICULUM VITAE

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EDUCATION

The University of Texas at Dallas (UTD) - PhD, Computer Science, GPA: 4.0
Advisor: Dr. Zygmunt Haas May 2017
The University of Texas at Dallas (UTD) – MS, Computer Science, GPA: 4.0 May 2015
Oklahoma Christian University (OC) – BS, Computer Engineering, GPA: 3.9 April 2012

RESEARCH INTERESTS
Optimization, Algorithm Design, Resource Scheduling, Distributed Computing, and Internet of Things.

RESEARCH EXPERIENCE

THE UNIVERSITY OF TEXAS AT DALLAS Richardson, TX
Graduate Research Assistant September 2013– Present

- Designed and implemented an efficient algorithm for optimal power scheduling in Microgrids, utilizing appliances scheduling in smart homes.
- Designed a Monte Carlo Simulation Based algorithm for the stochastic optimal planning of a completely green Microgrid, exploiting appliance scheduling to further minimize Microgrid investment cost.
- Designed a three-dimensional Markov chain for the optimal planning of a completely green charging system for electric vehicles, considering the intermittency in renewable energy and vehicle load demand. (Paper under review for IEEE Transactions on Transportation Electrification)

PUBLICATIONS

J. Ugirumurera and Z.J. Haas, “Power Scheduling for Programmable Appliances in Microgrids”, 2015 IEEE CAMAD, Sept.7-9, 2015, University of Surrey, Guildford, UK.
INTERNSHIP EXPERIENCE

GE TRANSPORTATION

Business Intelligence Intern

Erie, PA

May 2011 – August 2011

- Created business reports in RoamBI to replicate Oracle report.
- Developed training document for OBIEE Mobile.
- Participated in developing a website for new hires at GE Transportation.

PIVOT ACCESS

IT Intern

Kigali, Rwanda

June 2010 – August 2010

- Developed programming skills in C++ by completing the intern entry programming test.
- Installed LINUX on server and tested the server for full functionality.

ACADEMIC PROJECTS

Fault-Tolerant Google File System:

- Designed a distributed file system with a metadata server, file servers and clients in Java.
- Files were divided up into chunks, and the system saved three replicas for each chuck.
- System provided consistent read and write to all the replicas for client nodes.

Network Systems Design, Router Design:

- Created a router with physical, network, and android application layer in Java.
- The router supported encapsulating/decapsulating of packets, and ARP.
- The router also built and maintained routing and forwarding tables.

Christmas Lights and Sound Show Unit:

- Engineered a device that switched lights in synchronization to music.
- Coded program in C++ for the Arduino Mega2560 to control the device.

Computer System for Controlling a Laser System:

- Assembled a computer system using microcontrollers.
- Wrote assembly language program for the system to control a Laser System.
- Computer system received input from an alphanumeric keypad.
- System sent control to the laser system to draw alphanumeric characters on a white screen.

RISC Processor Design:

- Designed, implemented, and tested a RISC processor in Verilog.
- The processor supported loading from memory, storing to memory.
- It also implemented addition, subtraction, division, and multiplication.

Game Programming:

Wrote programs in C# for Space Invaders and Hangman games.
TEACHING EXPERIENCE
THE UNIVERSITY OF TEXAS AT DALLAS Richardson, TX
Teaching Assistant
August 2012– May 2015
- Graded assignments and projects, and assisted in proctoring exams.
- Held mentoring hours to help students better understand courses material.

OTHER ACTIVITIES
NON PROFIT WORK
Confounder/Secretary, Rwandans4Water (R4W) Project
June 2010– April 2012
- Participated in drilling two water wells in the eastern province of Rwanda.
- Created R4W web and fundraising content.
- Managed and maintained files and records for R4W activities.

WWC (Women Who Compute)
Member
September 2015– Present
- Participated in the mentoring of high school girls interested in computer science.

PRIMARY SKILLS
- Programming Languages: Java, C++
- Application: Visual Studio, Matlab, ILOG CPLEX
- Languages: Fluent in English, French, and Kinyarwanda

ADDITIONAL SKILLS
- Programming languages: C#, Verilog, Basic Stamp, Assembly Language, SQL, XML
- Applications: Mathcad
- Hardware tools: Logic Analyzer, Multimeter, and Signal Generator

AWARDS/HONORS
- Rwandan Presidential Scholarship (2008-2012)
- Outstanding Computer Engineering Student (2008-2012)
- Who’s Who Honors Society (2011-2012)
- UT Dallas scholarship to attend GHC’14
- Student Travel Grant for 2015 CRA-W Grad Cohort Workshop