EXPLORING SIMULATION-BASED DECISION MAKING FRAMEWORKS FOR ENERGY MANAGEMENT IN ELECTRICAL NETWORKS OF THE FUTURE

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As the single largest source of greenhouse gas emissions to the atmosphere, electricity generation is at the front and center of debates on climate change. Efforts to address these impacts have resulted in a critical need for cleaner energy technologies. To this end, there has been a significant shift towards the development and integration of renewable resources; in the United States, 17% of total electricity generation in 2019 was from solar and wind, which is only going to increase with improving technologies. However, significant integration of these resources in the electrical grid is no trivial task due as they are intermittent, and difficult to forecast, making them effectively non-dispatchable. As a result, renewable resources add significant variability to the supply side of power grid operations, which has to be managed with reserves from traditional, fossil-based, generating units. The need to enhance environmental protection and sustainable development are also leading to an evolution on the demand side with increasing presence of new technologies and small scale distributed energy resources near load centers. These technologies, combined with responsive demand, is leading towards a transformation of the distribution systems to include more community-owned independent networks or microgrids.

These changes in supply and demand-side technologies is adding a significant amount of stress to the daily operation of the system. The real-time un-
certainty induced by intermittent resources such as wind or price-responsive demand has created new and complex challenges for the operational security of power systems. As optimization and simulation approaches are a key part of the operation and control, the evolution of existing frameworks is essential for survival in the advent of smartening power systems. These frameworks need to provide robust operational decisions while being adaptable to the diverse expectations of both operators and stakeholders. Motivated by this need, this dissertation seeks to explore different frameworks that can efficiently support decision making under uncertainty, which is practical under the changing dynamics of the power system. This question is explored in three contexts: 1) Robust decision making for energy management in large scale networks with high renewable penetration while providing much-needed adaptability to the system operator, 2) Exploring the value of daily energy management in a micro-grid with a multiobjective perspective, and 3) Implementing a decision analysis tool for microgrid energy management to enhance stakeholder participation in grid operation and planning.

To this end, this body of work explores hybrid optimization frameworks that prioritize adaptability, scalability, and robust decision making, while staying true to the physics of power system networks.

The overarching conclusion of this work points to using hybrid frameworks for a more holistic approach to analyze system operation, which can then be followed by eliciting stakeholder preferences before selecting management actions. The different frameworks explored in this work introduce novel and interesting lines of questioning in power system literature. They add a dimension of explainability to optimization framework that can promote stakeholder participation in grid operation and planning in a meaningful manner. The various
case studies demonstrate these frameworks’ ability to critically analyze system performance under unplanned conditions as well as deconstruct the decision-making process which can help long term system planning and operation. The work also opens interesting possibilities for future research in grid operation under extreme operating scenarios and exploring the potential value of long term strategic planning in place of day-to-day approach. These contributions are critical in providing enhanced support in ever-evolving power systems.
Amandeep Gupta was born in Haryana, India in 1988. He received his Bachelor’s in Civil Engineering from National Institute of Technology, Kurukshetra in 2010. In January of 2011, he moved to Ithaca, NY to pursue Masters of Engineering in Civil and Environmental Engineering at Cornell University with a focus on water resources systems modeling and received his degree in January 2012. In June 2012, he joined Anderson Lab under the supervision of Prof C. Lindsay Anderson, where he worked on quantitative methodologies in the power system domain. The focus of his thesis has been in the developing hybrid decision-making frameworks for robust operation and planning of the electric grid. His research interests lie in exploring frameworks aimed at analyze interactions between public infrastructure systems especially to promote consumer participation.
To my family
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CHAPTER 1
INTRODUCTION

The electric power system is a large dynamic system consisting of numerous generation sources, transmission lines, and distribution networks. The main purpose of these three domains of the system is to generate electricity which can then be securely distributed to the consumers. This is accomplished with the help of electricity markets which ensure efficient use of the power system to provide sufficient and reliable electricity at least cost to consumers. In North America, the standard market design is an integrated system in which the system operator centrally optimizes the scheduling and dispatch of resources. The system operator accomplishes the above-mentioned goals with a combination of day-ahead scheduling and real-time economic dispatch decisions.

The goal of day-ahead scheduling (day-ahead unit commitment) is to schedule enough generating units to satisfy projected electricity load, for the next day. It is formulated in an optimization framework that determines the schedule of generating units in the system at minimum operational cost. This problem is solved while considering both system and resource characteristics such as start-up/shut-down costs, minimum up/down times, reserve requirements, etc. The decisions made during the day ahead scheduling are supported in real-time by dispatch of online units. As the electricity requirements of the system are being realized, the system operator runs optimization models throughout the day, to decide on dispatch values for the scheduled generating units while satisfying transmission and generation constraints at the lowest cost. Therefore, the day-ahead unit commitment and real-time economic dispatch are the two most critical processes in power system operation to reliably balance supply and de-
mand of electricity.

Prior to the 21st century, the generation units were largely based on fossil fuels such as coal, oil, and gas, which are controllable and dispatchable. As a result, system operational decisions could be made reasonably well with deterministic optimization techniques and ad-hoc methods for real-time adjustments to protect against the low level of load variability present in the system. However, power system operation and electricity markets are going through a radical transformation. The last decade has seen the electric power system under increasing stress due to fundamental changes in supply and demand-side technologies. On the supply side, there is a significant shift to renewable generation such as wind and solar which are plentiful, environment-friendly, and widely available[14]. On the demand side, there is a growing number of distributed generation resources, changing the nature of distribution systems as well as creating a need for demand-responsive operation strategies [74, 57].

The transformation on the supply side is primarily driven by a move away from fossil fuels to address climate change and reduce local pollution. Markets are experiencing a rapid increase in wind and solar supply. In the US, 60 percent of new generation capacity in 2016 was from solar and wind [17]. This trend is expected to continue until fossil fuels, especially coal, are largely eliminated from the energy mix. These renewable resources are difficult to predict, intermittent making them effectively non-dispatchable, thereby adding considerable variability in the system supply. The current system has sufficient dispatchable resources to neutralize the variability from moderate amounts of wind and solar energy. However, with the increasing market share of renewable sources, the uncertainty in the system will eventually become a burden.
The demand side transformation can be attributed to the increasing presence of new technologies and distributed energy resources (DERs) near load centers. These resources include residential solar, fuel cells, microturbines, electric vehicles, storage, and demand response programs. With the increasing penetration of DERs, the structure of traditional distribution systems is evolving rapidly. A microgrid (MG) is a modern form of local distribution network, integrating DERs, loads and battery storage units that will be a fundamental component of future of power networks. These local grids can potentially support small communities like hospitals, schools, residential centers, etc. One potential benefit of such entities are improved reliability and security of the macro grid, as a MG can exchange energy or disconnect from the macro grid based on need. Another impact of the increasing DERs, especially renewables, is the need for programs requiring load to be responsive to the increased variability in the system. Thus, consumers are incentivized to reduce/shift electricity usage based on system requirements. These demand response programs provide much-needed flexibility in the system for efficient daily operation.

The modern electrical grid can, therefore, be redefined as a dynamic system consisting of variable generation, transmission, DERs based distribution, and consumer participation. Each new domain adds another dimension of complexity to the daily operation of power systems. For example,

- Increasing penetration of renewables makes analyzing and quantifying the uncertainty in the system a complex and expensive process. Thereby optimization formulations need to be adaptable, scalable and should not require a detailed understanding of the uncertain behavior. The resulting operation decisions should be robust to evolving variability in the system.
• While the traditional commitment and dispatch decisions ignore environmental emissions from the generation units, growing consumer awareness requires the system operation to account for both economic and emission aspects in decision making. Thus, the optimization problem becomes a mathematical problem in which conflicting objectives are optimized simultaneously. Not only does this add a new dimension to the objective space, but it also requires non-traditional optimization frameworks to be solved efficiently.

• As microgrids become a growing component of the power system, the complexity of the electrical grid at large will only increase. As these distribution systems will be community-based, increased consumer participation in operating strategies and resource planning will be necessary [74]. This highlights the need for modeling frameworks that allow efficient and robust daily operations of local grids, while facilitating the needs and expectations of community stakeholders.

Thus, as the grid is becoming ”smarter”, optimization frameworks for power system operation and planning need to evolve accordingly. The optimization frameworks used in electric power systems can be classified into two major groups: (1) Exact or Analytical methods and (2) Approximate methods. The exact methods utilize classical optimization techniques such as nonlinear programming, mixed-integer linear and mixed-integer nonlinear methods, while approximate methods include heuristics and metaheuristics. Even though analytical methods can address some of these challenges, these methodologies generally are less adaptable, and susceptible to issues of scalability and tractability. Conversely, metaheuristic methods face solution convergence and computational deficiencies in large scale problems.
Inspired by this need for optimization frameworks that address the challenges of modern power system operation. The goal of this dissertation is to explore optimization frameworks that prioritize adaptability, scalability, and robust decision making, while staying true to the physics of power system networks. It is hoped that this work will provide some ideas and insight to support the planning and operation for the future grid.

1.1 Organization of the Dissertation

The dissertation is organized as follows:

**Chapter 2:** This chapter focuses on exploring a framework for robust operation decisions with high renewable integration in large electrical networks. A hybrid methodology is introduced, unifying statistical feature ranking with an analytical power system framework. The study takes advantage of the significant data and computational power available to the system operators to propose a formulation that is mathematically simple, customizable, scalable, as well as parallelizable. The solution performance of the methodology is validated against existing analytical techniques on large networks while the flexibility is demonstrated by computing robust decisions based on multiple operational metrics.

**Chapter 3:** The focus of this chapter is on exploring the value of daily energy management in a microgrid with a multiobjective perspective. This is accomplished with a simulation-based optimization approach generating parametric control policies instead of hourly decisions. The control policies provide a microgrid controller with diverse alternative strategies for utilizing resources efficiently. The study asserts the value of a multiobjective approach as compared to a single objective in modern-day power systems. The advantages of parametric
control strategies are also explored briefly in analyzing system performance.

**Chapter 4:** The aim of this study is to expand on the previous work by implementing a comprehensive robust decision analysis framework for microgrid energy management. The framework performs a comprehensive performance analysis of the adaptive control strategies obtained via the optimization approach implemented in Chapter 3. This includes; 1) testing the flexibility and resiliency of the policies under unplanned external conditions that could threaten system operation, and 2) using the policies to understand and quantify the operational limitations of system performance. The analysis demonstrates that the framework can be used as an efficient tool for enhancing stakeholder participation in grid operation and planning.

**Chapter 5:** This chapter presents overarching conclusions of the studies described in this dissertation.
CHAPTER 2
STATISTICAL BUS RANKING FOR FLEXIBLE ROBUST UNIT COMMITMENT

As the level of uncertain renewable capacity increases on power systems worldwide, industrial and academic researchers alike are seeking a scalable, transparent, effective approach to unit commitment under uncertainty. This paper presents a statistical ranking methodology that allows adaptive robust stochastic unit commitment using a modular structure, with much-needed flexibility. Specifically, this work describes a bus ranking methodology that identifies the most critical buses based on a worst-case metric. An important innovation is the ability to identify alternative metrics on which to rank the uncertainty set – for example to minimize economic dispatch cost or ramping needs, to provide a customized robust unit commitment solution.

Compared to traditional robust unit commitment models, the proposed model combines statistical tools with analytical framework of power system networks. The resulting formulation is easily implementable and customizable to the needs of the system operator. The method and its applications are validated against other established approaches, showing equivalent solution to the state-of-the-art approach. Case studies were conducted on the IEEE-30, IEEE-118 and the pegase-1354 networks. In addition, the flexibility of bus ranking formulation is illustrated through implementation of alternative definitions of worst-case metrics. Results show that the bus ranking method performs as well as the best of these methods, with the provision of additional flexibility and potential for parallelization.
2.1 Introduction

The last decade has seen the electric power system under increasing stress due to fundamental changes in both supply and demand technologies. On the supply side, there is a significant shift to renewable generation such as wind and solar which are plentiful, environment-friendly, and widely distributed [36]. On the demand side, there is a growing number of distributed generation resources and thereby necessity for viable demand response strategies. The real-time uncertainty induced by intermittent resources such as wind or price-responsive demand has created new and complex challenges for operational security of power systems.

Critical decision processes like day-ahead unit commitment (UC) and real-time economic dispatch (ED) require more complex and thorough analysis to manage the uncertainty or risk insufficient ramping capabilities, load surge, and transmission congestion [18]. Various approaches, both physical and operational, have been proposed and tested in the literature to address the impacts of uncertainties in order to obtain reliable solutions [56]. As physical measures, strategies such as balancing area consolidation, increasing flexibility in the resource portfolio, demand-side management, and use of storage devices [76] have been implemented. In addition to the physical means, updating current systems planning and operation with scenario-based, probabilistic and interval based methods has been particularly recommended as a promising solution to help maintain and improve system reliability with increasing penetration of variable energy resources [77]. These formulations and solution methodologies have evolved over the years from early tools based on a priority list and dynamic programming to the current to methods based on mixed integer pro-
There is significant literature on various approaches to tackle uncertainty, including stochastic optimization [79], chance-constrained optimization [51] and robust optimization [8]. Stochastic optimization approaches require probability distribution and scenario information about the uncertain processes before implementing the optimization model. The chance-constrained formulation allows for a compromise between risk and cost of solution through manipulation of the probability level. Recently, the robust optimization approach [6] has received significant attention as it does not require detailed analysis of the distribution of the underlying uncertainty. The methodology utilizes upper and lower bounds of the uncertain process to construct a solution immunized against all realizations within the bounds, and optimal for the worst case scenario. Different variations of analytical robust UC have been proposed in [36], [8], [37] and [86]. These models demonstrate significantly better solution efficiency and uncertainty management capabilities as compared to the deterministic approach [81]. Current industry approaches, however, still involve solving a deterministic unit commitment model with either ad-hoc reserves, storage or flexible ramping as protection against variability [24].

The reasons for the lack of implementation of complex analytical models in the industry are multifold. Stochastic optimization and traditional chance-constrained approaches face tractability issues as large number of scenarios are required to attain high probabilistic guarantees of system reliability. Robust optimization does well in terms of tractability because of the deterministic uncertainty set [49] but the approach is susceptible to implementation [81] or complexity [72] bottlenecks in bigger networks. Traditional two-stage robust UC
models, lack tools to render them customizable and adaptable in accordance to the needs of the system operator.

With increasing scale, complexity, and variability, in modern power systems, there is an increasing need for UC models combining the statistical tools in machine learning applications with the significant data and computational power available to the system operators. Making effective use of these resources supports the need for hybrid methodologies that are simple, customizable, scalable, as well as parallelizable. All the while, providing decisions comparable to proven analytical methods in the literature.

In this paper, a UC methodology is proposed based on a feature ranking algorithm traditionally used in pattern recognition problems to provide a robust unit commitment decision. The decision obtained is secure against all possible uncertainty realizations. This hybrid model unifies statistical tools with analytical framework of power system networks and such a formulation has not been proposed in the literature to our knowledge. The potential benefits of such a model are:

- A simpler and easily implementable formulation to compute a robust unit commitment solution. A case study is performed on an IEEE 30-bus system to demonstrate that the solution is superior to current deterministic models used in industry and on par with the analytical approaches in the literature.

- A customizable framework, as compared to models in literature, providing flexibility to the system operator while not compromising on solution performance. The adaptability of the bus ranking model is demonstrated by computing robust decisions with different definitions of worst-case sce-
narios. The paper compares robust solution for worst-case economic dispatch cost against flexible ramping products [82],[2] and a hybrid definition. The hybrid definition combines the properties of two differing worst-case metrics with the goal to provide more freedom to the system operator and obtain a solution that satisfies contrasting objectives. An example will be a situation where the system operator needs to be robust against both economic dispatch cost and ramping capacity, a middle ground approach in such a scenario could be the desirable solution. Results of the case study, performed on these definitions, provide interesting insights into potential applications of such an approach and highlight the flexibility of the formulation. This is the first robust UC model addressing flexible ramping proposed in the literature.

- A modular structure which renders it highly scalable and parallelizable, thus not susceptible to implementation and computation bottlenecks in bigger networks. The structure ensures that the methodology is not limited by execution times of sequentially operated processes.

The paper is organized as follows: Section 2.2 provides an overview of the robust unit commitment models, followed by the detailed description of the bus ranking model in Section 2.3. The performance of the approach is illustrated in Section 2.4 followed by concluding remarks in Section 2.5.

2.2 Robust Unit Commitment

The robust unit commitment model has been studied in great detail in the power system literature [40],[8],[71],[86],[85]. Most robust unit commitment frame-
works are two-stage formulations where the first stage handles unit commitment and the second stage manages dispatch decision which is immunized against all uncertainty realizations and is optimal for the worst case of system operation. Generally, the robust models developed are constructed based on worst-case ED cost. However, different definitions such as worst-case load shedding, operation cost variance etc. are used depending on the operational and economic security of the power system [35]. The first step in robust unit commitment models is to define a deterministic uncertainty set via limited information on uncertain variables like the expected wind power and ranges of possible variations around that expectation [26]. Modern robust models provide the system operator ability to adjust the robustness of the solution by incorporating a parameter, defined as budget of uncertainty in [8]. The budget parameter takes values between zero and the number of buses (N) with uncertainty variables. Thus a value of zero corresponds to a deterministic case while a value of N will mean immunization against uncertainties on all buses. One of the earliest robust formulations was proposed in [8]:

\[
\min_{x, y(\cdot)} \left( c^T x + \max_{d \in D} b^T y(d) \right)
\]

s.t.

\[
Fx \leq f, \ x \text{ is binary}
\]

\[
Hy(d) \leq h(d), \ \forall d \in D
\]

\[
Ax + By(d) \leq g, \ \forall d \in D
\]

\[
I_{u} y(d) = d, \ \forall d \in D
\]
The variable $x$ which is binary represents vector of decisions regarding generator status, while $y$ represents dispatch decision of the generating units at each time interval and $D$ represents the uncertainty set. The objective of the formulation is to minimize commitment cost as well as the highest dispatch cost under uncertainty, thus identifying it as the worst case scenario. The first set of constraints involve commitment variables, followed by dispatch related constraints, min/max generation capacity constraints and uncertain nodal injection constraints [8]. The above formulation is decomposed into two stages, where the master problem is unit commitment problem and the subproblem aims to solve the dispatch problem under the worst-case economic dispatch with fixed unit commitment solution [81]. The min-max subproblem can be converted to a maximization problem, resulting in non-linear terms in the objective function. Convergence of the robust formulation can take a long time if the subproblem is solved using an exact method [72]. Instead, various heuristic techniques such as outer approximation and equivalent MIP have been utilized in literature to overcome this hurdle. For example authors in [86] convert the bilinear subproblem into a mixed integer problem following the observation that for any given unit commitment decision the worst-case value of the uncertain variable is a vertex of the polyhedron uncertainty set. Similar observations motivated the formulation of bus ranking model, as will be discussed later.

### 2.3 Bus Ranking Model

The proposed methodology utilizes a deterministic uncertainty set, a feature ranking algorithm [70] and a simple UC model to compute a commitment schedule immunized against all uncertainties in the polyhedron set. Hence,
the formulation behaves like existing robust unit commitment models. The bus ranking formulation begins with constructing a deterministic polyhedron uncertainty followed by computing a baseline commitment schedule using expected net-load. The next step involves utilizing the feature ranking algorithm commonly implemented in machine learning applications, for example in facial recognition and text classification. This algorithm, combined with the baseline commitment schedule allows the model to rank buses of the network on the basis of worst-case metric such as dispatch cost. The last step involves computing a commitment and dispatch decision, based on the bus ranks, that is robust against worst-case uncertainty. The overall algorithm has been summarized in the Algorithms 1 and 2. The following section provides a comprehensive outline of the bus ranking formulation. The methodology can be applied to various metrics but will be described using worst-case economic dispatch cost, as it is the most commonly used definition.

2.3.1 Uncertainty Set

This section defines the uncertainty set used to obtain bus ranking. The uncertainty is introduced as a percentage of deviation from expected net load profile estimated using historical data. For a set of nodes $N$ with renewable integration, $d^t$ being the final net load set at time $t$, the uncertainty set can be defined as:

$$d^t := \left\{ d^t_i \in [\tilde{d}^t_i - \tilde{\delta}^t_i, \tilde{d}^t_i + \tilde{\delta}^t_i], \quad \forall i \in N \right\}$$

(2.1)

where $\tilde{d}^t_i$ is the expected net load and $\tilde{\delta}^t_i$ is the possible deviation for bus $i$ at time $t$. For the proposed methodology $\tilde{d}^t_i$ will be represented as a percentage
Thus the uncertainty set encompasses situations from maximum renewable injection at a bus to the minimum, which in the case of wind integration is generally zero.

### 2.3.2 Baseline Schedule

The first step in the approach is to run a deterministic unit commitment model [25] using expected net load at all buses to obtain a baseline schedule. Please see appendix 2.6 for description of a unit commitment formulation. The solution provides an initial schedule which can be used as a baseline for rest of the methodology.

### 2.3.3 Dispatch Simulations

For the analysis $Q$ dispatch simulations [25] are run using the baseline commitment schedule for randomly sampled net load values from the uncertainty set, which defines a range of net load values for each bus $i$ at time $t$. A set of uniformly distributed random load values are then sampled from this range to be used for each simulation. These simulations provide net-load vectors, called input vectors, for each bus $i$ and a dispatch cost vector, the output vector, of size $Q$. The input and output vectors obtained from the dispatch simulations can then be fed into a feature ranking algorithm which compares the net-load input vectors of each bus against the output dispatch cost vector ranks each pair according to the similarity between them.
2.3.4 Ranking Buses

To rank the buses, feature selection algorithms [29] applied in the field of pattern classification and text classification have been used. Specifically, the filters class of these algorithms, which rely on sorting individual variables based on their correlation to an output variable were analyzed. The bus ranking methodology utilizes a variation of the feature selection technique called the probe feature method [70],[29] with a modification inspired from [60]. The algorithm approximates a linear relationship between the input and output vectors.

The dispatch runs provide \( N \) candidate buses with a dataset containing \( Q \) input-output vector pairs. In the context of the current problem one such definition could be

\[
\text{Input variable} = \text{Net Load at a bus } \forall t \in T \\
\text{Output variable} = \text{Economic dispatch cost } \forall t \in T
\]

These vector pairs are then compared to find net load vector that is most similar to the dispatch cost. The metric used for comparison is called cosine similarity [54], which is a correlation criterion. A correlation criterion was selected over information theory or decision tree based metrics on account of simple formulation and better performance on continuous data [30]. Cosine similarity is defined as:

\[
\cos(x^{i,t},y) = \frac{<x^{i,t},y>}{\|x^{i,t}\|_2 \|y\|_2}, \forall i \in N, \forall t \in T
\]  

(2.2)

where \( x^{i,t} \) is the net-load vector for bus \( i \) at time \( t \), and \( y \) is the dispatch cost. The metric always assumes values within the range of -1 and +1 where the -/+ determine the nature of correlation between the input-output pair.

The buses are ranked through an iterative process as described in Algorithms
1 and 2. The Modified Gram-Schmidt orthogonalization [10],[9] is used for projecting features onto null subspaces which terminates once all net-load vectors have been ranked. The final ranking vector consists of bus indices in accordance with ranking. One such example could be $V_{rank}^t = [bus3, bus8, \ldots], \forall t \in T$, where bus3 vector is most correlated to dispatch cost in time period $t$.

Algorithm 1 Statistical Bus Ranking Formulation

1: Compute baseline commitment for $d_i^t \in \bar{d}_i^t$
2: Run $Q$ dispatch simulations
3: Define $V_{rank}^t = \emptyset$
4: while $n(V_{rank}^t) < N$ do
5: \hspace{1em} Run Ranking Algorithm
6: \hspace{1em} end while
7: $V_{rank}^t$ contains bus indices in order of their similarity to the economic dispatch vector.
8: Run deterministic unit commitment for a robust solution

Algorithm 2 Ranking Algorithm

1: $N$ is the set of buses that have uncertainty and $N$ is the number of such buses.
2: for every bus $i \in N$ do
3: \hspace{1em} Calculate $cos(x^i y)$
4: \hspace{1em} end for
5: Select bus with $argmax_i|cos(x^i y)|$
6: $V_{rank}^t = V_{rank}^t + \{selected \ bus\}$
7: $N = N - \{selected \ bus\}$
8: Project $y$ and remaining $x^i$ onto the null space of selected bus

2.3.5 Selecting Buses

Now that that bus ranking has been computed, the ranking vector details the order in which buses should be immunized against uncertainty. The selection can be made using the following criterion:
\[ \mathcal{V}^S_t = \left\{ i \in V_{\text{rank}}^t | V_{\text{rank}}^{i,t} \leq \Delta^t \right\} \]  

where $\mathcal{V}^S_t$ are the buses selected to be secured against uncertainty, and $V_{\text{rank}}^{i,t}$ is the index of the elements of $V_{\text{rank}}^t$. Similar to traditional robust unit commitment models, the level of conservativeness can be decided using $\Delta^t \in [0, N], \forall t$, called the budget of uncertainty [8]. Thus the value of $\Delta^t$ decides how many buses to be immunized. As the value of $\Delta^t$ increases from 0 to $N$ so does the size of the uncertainty set and hence level of conservativeness of the resulting commitment solution. Thus at $\Delta^t = 0$ the model will be solved for a deterministic case and at $\Delta^t = N$ the model will immunize against uncertainty at all buses.

### 2.3.6 Robust Unit Commitment

A deterministic optimization model can now be implemented obtain a robust UC decision. Once a value for the $\Delta^t$ is known the criterion in (2.3) can be used to decide which buses to secure while (2.4) helps select worst case net-load value for the respective bus. $nl^t_i$ being the worst case net-load for bus $i \in \mathcal{V}^S_t$ at time $t$.

\[ nl^t_i = \begin{cases} 
\bar{d}^t_i + \tilde{d}^t_i, & \text{if } \cos(x^i, y) \geq 0 \ \forall i \in \mathcal{V}^S_t \\
\bar{d}^t_i - \tilde{d}^t_i, & \text{if } \cos(x^i, y) \leq 0 \ \forall i \in \mathcal{V}^S_t \\
\tilde{d}^t_i & \text{otherwise}
\end{cases} \]  

(2.4)  

The selected net-load values for the buses to secured and expected net-load values for the rest can be fed into a deterministic framework which then provides a UC solution. The obtained UC solution is robust owing to the observa-
tion made by [86] and authors of this paper as mentioned earlier.

Traditionally, two-stage robust models utilize a commitment decision and a user-defined value such as budget of uncertainty, to decide whether the uncertainty at a particular bus should take the max or min value. The second stage of these models is used to make a decision on which bus to secure iteratively over the uncertainty set. This proposed bus ranking model, on the other hand, first calculates an order in which the buses of the network should be immunized against uncertainty. Once the order is known for any budget of uncertainty value and $V_{\text{rank}}$ set, a deterministic UC with the help of (3) and (4) can provide a solution as robust as other approaches, which will be illustrated with the help of case studies.

2.3.7 Bootstrap Aggregation

Accurate ranking of the buses can be one of the potential challenges in the proposed methodology. A resampling methodology, called bootstrap aggregation, is utilized to improve prediction accuracy [16]. Bootstrap aggregation is a method for generating multiple versions of a predictor and using these to get an aggregated predictor [11]. Please see the appendix for a more detailed description of bootstrap aggregation. Figure 2.1 depicts a bootstrap aggregation incorporated flow diagram of the bus ranking methodology. Once the baseline commitment is obtained, the formulation is divided into $m$ independent bootstrap modules each containing the baseline schedule. Each of these modules run $Q/m$ dispatch simulations and compute $m$ independent ranking vectors which are then aggregated to compute final ranking vector. The final ranking vector
$V_{\text{rank}}^t$ is obtained by taking mean of the individual vectors provided by the modules to obtain a better prediction. Figure 2.1 demonstrates this process with the help of a flowchart. It is worth noting that each bootstrap module can be further divided for dispatch simulations based on available computing power.

**Figure 2.1: Statistical Bus Ranking Model**
2.4 Results

This section presents computational studies performed to evaluate the functionality of statistical bus ranking model. The goal of these case studies is to demonstrate that the commitment and dispatch decision computed by the proposed model are comparable to traditional robust UC models and hence have similar solution integrity while maintaining a formulation structure which is easily customizable, adaptable and conducive to parallelization.

2.4.1 Solution Integrity

The statistical bus ranking methodology is a heuristic approach to defining the extremes of the uncertainty set in robust optimization. To validate this approach, we compare performance of this approach to analogous, validated approaches in the literature. To validate solution integrity, the statistical bus ranking methodology [StatMod] is compared against a traditional analytical robust optimization model [AdpRob] proposed in [8] and a reserve adjustment approach [AdjRes]. As one of the earliest adaptable robust UC models and having been used in various comparative studies, the AdpRob model is a good benchmark to test for a robust unit commitment decision where the worst case is defined as maximum economic dispatch cost. The AdjRes model handles uncertainty by defining reserve requirements based on deterministic criteria, which is a good representation of models used by system operators. The three models are implemented and compared with two versions of the IEEE 30-bus system, and the IEEE 118-bus system (see Section 2.4.5). In each of these models, the budget of uncertainty $\Delta^t$ takes values in the entire range of 0 to $N$ where
$N = 20$. The statistical and analytical robust models manage uncertainty as defined in equation 2.1, and [8]. For the reserve adjustment approach, uncertainty is considered through a deterministic criterion as defined in (5).

$$q_t = q_t^0 + \frac{\Delta'}{N_d} \sum_{i=1}^{N_d} \tilde{d}_i$$  \hspace{1cm} (2.5)

where $q_t$ is the system reserve requirement at time $t$, composed of a basic reserve level $q_t^0$ and an adjustment proportional to the variation of load. Thus, the uncertainty is controlled by $\Delta'$ as for the other models.

The three models are solved for a range of $\Delta'$ on the standard IEEE 30-bus system, which has (essentially) no transmission limits. Subsequent tests are conducted on a modified system, which has transmission capacity limits and reduced overall generation capacity, in order to provide some solution challenges to better compare the three methods.

In order to validate the performance of the model, it is necessary to test the solution in an out-of-sample context. Commitment decisions provided by each model are tested by solving 1000 dispatch problems for randomly generated net-load scenarios. These samples follow a normal distribution with parameters such that about 15% of the scenarios fall outside $[\tilde{d}_i - \bar{d}_i, \bar{d}_i + \tilde{d}_i]$ while negative values are discarded. Thus the model performances can also be analyzed for an inaccurate definition of the uncertainty set, as might be the case in real-world application. An expensive slack variable (penalty) with cost $5000/MWh$ is introduced in energy balance and transmission constraints to account for any violation during real-time dispatch operation. The planning horizon is kept at 24 hrs.
2.4.2 Solution Integrity - Results

The commitment schedule for the three models was identical for the standard IEEE 30-bus system with no penalties. This is a result of abundant generation and transmission capacities in this fairly simplified version of a power system.

For the modified system the StatMod, AdpRob, and AdjRes are compared along three metrics - mean dispatch costs, standard deviation of dispatch costs and penalty costs. Mean and standard deviation of dispatch costs illustrate economic efficiency and reliability, while penalty costs measure solution robustness. Table 2.1 illustrates monotonically decreasing average dispatch for the StatMod and AdpRob formulations with increasing levels of uncertainty budget. Conversely, the AdjRes solution does not change significantly until high levels of reserves have been committed at $\Delta' = 12$. Units committed (Figure 2.2) and total cost (Table 2.1) support this observation as both are significantly higher for AdjRes model especially as the solution becomes more conservative. Since the solutions for AdpRob and StatMod are identical, the red plot-line covers the blue in Figure 2.2. Also note that all three models provide an identical solution at $\Delta' = 0$, as it represents a deterministic case.

With increasing value of $\Delta'$, more units are committed and penalties decrease for the StatMod and AdpRob models. The AdjRes methodology commits extra generation resources based on an ad-hoc rule. At $\Delta' = 20$ the average penalty costs for the StatMod and AdpRob models are negligible while the AdjRes approach never manages to completely eliminate penalty costs even with a larger number of generating units switched on, as can be seen in Table 2.2. The two robust models are able to overcome congestion while computing commitment solutions, as uncertainty at individual buses is included in the decision, some-
<table>
<thead>
<tr>
<th>Delta</th>
<th>Average Dispatch Cost (k$)</th>
<th>Total Cost (k$)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>AdpRob</td>
<td>StatMod</td>
</tr>
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<td>170.4018</td>
</tr>
<tr>
<td>20</td>
<td>170.4018</td>
<td>170.4018</td>
</tr>
</tbody>
</table>

Table 2.1: Average Dispatch Cost and Total Cost for the Three Methods

![Figure 2.2: Total Units Committed across Horizon](image)

The economic reliability of three models can also be compared using Table...
2.2. As expected, the standard deviations of dispatch costs are highest for the deterministic scenario. The StatMod and AdpRob solutions become significantly more reliable than the AdjRes model and remain nearly 2× better even at \( \Delta' = 20 \).

<table>
<thead>
<tr>
<th>Delta</th>
<th>StatDev of Dispatch Costs (k$)</th>
<th>Average Penalty Costs ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AdpRob</td>
<td>StatMod</td>
</tr>
<tr>
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<td>4.1593</td>
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<tr>
<td>10</td>
<td>2.0085</td>
<td>2.0085</td>
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<tr>
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<td>1.531</td>
</tr>
<tr>
<td>20</td>
<td>1.531</td>
<td>1.531</td>
</tr>
</tbody>
</table>

Table 2.2: Standard Deviation of Dispatch Costs and Penalty Costs for the Three Methods

This case study demonstrates solution performance of the statistical approach. The proposed methodology performs as well as the analytical model while considerably outperforming the AdjRes approach. With more complex networks than a 30-bus system, the solution performance of the StatMod approach may vary but it will but it will provide an equivalent solution to the AdpRob model, with a simpler and more flexible structure.

2.4.3 Flexibility

A key feature of the StatMod approach is the ability to incorporate alternative metrics on which to assess the impact of uncertainty in the unit commitment framework. In order to demonstrate this feature, this section explores two ex-
amples of possible alternatives to the traditional metric used in the AdpRob model, the dispatch cost. In this case study, the buses are ranked on ramping requirements along the time horizon. Such a day-ahead formulation emulates the flexible ramping approach being implemented by system operators to manage uncertainty. Flexible ramping or, flexiramp, aids in ensuring that sufficient capacity is on-line to manage the increased volatility of net loads expected under high levels of renewable integration [78]. Using the StatMod approach two different definitions are tested, 1) worst-case flexiramp and 2) hybrid definition which combines worst-case economic dispatch and flexiramp requirements. The following sections provide an overview of the two definitions.

**Flexiramp Robust**

In this definition, robust unit commitment is obtained by changing the primary metric from economic dispatch to ramping. To obtain a robust solution the buses are now ranked on hourly ramp requirements over the planning horizon, instead of economic dispatch cost. To represent the cost of flexiramp products, a slack variable is added at $5000/MWh. The simpler structure of the statistical model allows for alternative worst-case definition while the model structure remains the same.

**Hybrid Robust**

To further demonstrate the flexibility of the StatMod approach, a hybrid definition is considered as proof of concept. This formulation combines two different worst-case definitions in order to obtain a solution that satisfies contrasting ob-
jectives. An example will be a situation where the system operator needs to be robust against both economic dispatch cost and ramping capacity. The StatMod approach, as a result of the simple structure, can be easily applied in these scenarios by assigning weights to different worst-case metrics according to the operator’s requirements. For the current study, equal weights are assigned to economic dispatch cost and ramping requirements, and the final ranking is the sum of the two. This type of modification is implementable in the bus ranking methodology with minimal modifications, making it very practical for real-world application.

### 2.4.4 Flexibility-Results

The customizability and performance of the StatMod approach are demonstrated by comparing three different definitions of worst-case, specifically economic dispatch cost (Ed), flexiramp, and hybrid. As before, the models are run on a modified IEEE 30-bus test case while penalty costs are added to transmission, energy balance, and ramp constraints. The three models are compared on the same metrics as previous study, as well as on efficient use of generating units. The results show that, although the three definitions provide similar solutions, there are distinctions resulting from the different priorities of the three formulations. These differences would likely be more pronounced when implemented on more complex networks.

Table 2.3 shows that although Ed has lower dispatch costs relative to flexiramp and hybrid approach, in terms of total cost, it is the most expensive. Table 2.3 also demonstrates that across different values of conservativeness the hy-
brid approach outperforms flexiramp in dispatch costs and Ed in total costs, implying that the hybrid approach may provide the best compromise.

<table>
<thead>
<tr>
<th>Delta</th>
<th>Average Dispatch Cost (k$)</th>
<th>Total Cost (k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ed</td>
<td>Flexiramp</td>
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Table 2.3: Average Dispatch Cost and Total Cost for the Three Methods

Examination of Table 2.4 shows that all three approaches incur similar penalties with the exception of $\Delta t = 6$ and 16. In these time periods, flexiramp has higher penalty costs, which can be attributed to the different worst-case metric. The hybrid approach again appears as a better model, performs as well as the worst-case Ed definition. Table 2.4 also illustrates that the flexiramp definition provides the most system reliability, with the hybrid approach as a close second.

The most significant difference between the three metrics can be seen in Figure 2.3, which shows total units committed across the planning horizon. The flexiramp definition, while considering flexible ramping products, commits a smaller number of units than Ed. As a result, while the flexiramp approach incurs more penalty, the committed generating units are used more efficiently. This is illustrated in Figure 2.4, which plots the average usage of a generating unit across the planning horizon, against levels of robustness. The hybrid ap-
Table 2.4: Standard Deviation of Dispatch Costs and Penalty Costs for the Three Methods

<table>
<thead>
<tr>
<th>Delta</th>
<th>Standard Deviation of Dispatch Costs (k$)</th>
<th>Penalty Costs ($)</th>
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<tr>
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<td>Ed</td>
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<td>38.4171</td>
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</table>

proach, as earlier, has better utilization pattern compared to Ed but also commits more units than flexiramp to obtain a middle-ground solution.

Figure 2.3: Total Units Committed across the Horizon, for Increasing Budget of Uncertainty
The results of this case study provide insight into the performance of this approach under three metrics of robustness; the worst-case Ed and flexiramp outperform other approaches in one-dimensional objective, while the hybrid definition provides a balanced perspective combining the two definitions for a better overall performance.

The above results demonstrate the ability of the StatMod framework to customize and adapt and these tools can assist the system operator in attaining multiobjective solutions as the system complexity increases, something that is not currently available in traditional robust methodologies.
### Table 2.5: Comparison of Average Dispatch Cost and Total Units Committed for AdpRob and StatMod Methods

<table>
<thead>
<tr>
<th>Delta</th>
<th>Average Dispatch Cost (k$)</th>
<th>Total Units Committed (across 24 hrs)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>AdpRob</td>
<td>StatMod</td>
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### Table 2.6: Standard Deviation of Dispatch Costs and Penalty Costs for AdpRob and StatMod Methods

<table>
<thead>
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<th>Delta</th>
<th>Standard Deviation of Dispatch Costs (k$)</th>
<th>Average Penalty Costs (k$)</th>
</tr>
</thead>
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<td>12.6071</td>
<td>12.6071</td>
</tr>
<tr>
<td>30</td>
<td>12.6071</td>
<td>12.6071</td>
</tr>
<tr>
<td>36</td>
<td>12.6071</td>
<td>12.6071</td>
</tr>
<tr>
<td>42</td>
<td>12.6071</td>
<td>12.6071</td>
</tr>
<tr>
<td>48</td>
<td>12.6071</td>
<td>12.6071</td>
</tr>
</tbody>
</table>

### 2.4.5 118-Bus System Analysis

The following section details the results of studies conducted on the IEEE 118-bus test system to compare solution performance of the AdpRob and StatMod on a larger network. The study parameters are adjusted to increase the size of the uncertainty set on the larger network. The results in Tables 2.5 and 2.6 show that, although there are small differences among the two approaches, overall the solutions are similar. The StatMod provides performs slightly better in terms of
economic efficiency, reliability, and robustness for $\Delta' = 6$ by committing one additional generating unit. However, for higher values of $\Delta'$ the StatMod needs to commit two to three extra generators to models provide the same solution as AdpRob. These results demonstrate that the StatMod performs on par with AdpRob and our initial assertion made in the 30-bus network study.

### 2.4.6 Computational Efficiency

This section compares computational efficiency of the ranking model against AdpRob. The models used in the study are implemented in Pyomo [32] with CPLEX as the solver on a Macbook laptop with an Intel Core i7 3.0-GHz CPU and 16 GB memory. To compare run-times of the two models, it is useful to clarify the key difference between the information provided by a single run of StatMod and a single run of AdpRob model. A single iteration of the AdpRob model computes a UC status for a pre-defined size of the uncertainty set or level of conservativeness (single value of $\Delta'$). The StatMod provides a ranking strategy for the entire uncertainty set, thus providing UC status for all possible values of $\Delta'$. For example, in case of the 30-bus test system where 20 buses have uncertain loads, $\Delta'$ can take any value from 0 to 20. A complete run of AdpRob model will provide the commitment solution for one specific value of $\Delta'$. Conversely, one run of the StatMod will rank all the buses and provide information on all possible values of $\Delta'$. Thus, for a fair comparison of the computation times, the models need to be solved for UC status across all the values of $\Delta'$ in the uncertainty set.

Average runtimes of the models are compared with increasing network un-
certainty. Here, uncertainty reflects the percentage of buses considered with variable net-load in the respective network. One runtime reflects the average amount of time the model takes to compute UC status for all possible values of $\Delta'$. 

<table>
<thead>
<tr>
<th>Uncertainty (% * Total Buses) for the Two Networks</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE-30 Average Runtimes (minutes)</td>
</tr>
<tr>
<td>AdpRob</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>0.1</td>
</tr>
<tr>
<td>0.2</td>
</tr>
<tr>
<td>0.3</td>
</tr>
<tr>
<td>0.4</td>
</tr>
<tr>
<td>0.5</td>
</tr>
<tr>
<td>0.6</td>
</tr>
<tr>
<td>0.7</td>
</tr>
<tr>
<td>0.8</td>
</tr>
</tbody>
</table>

Table 2.7: Average Computation Time across Varying Size Network Uncertainty (% * Total Buses) for the Two Networks

As can be seen from the results, in Table 2.7, although StatMod is considerably slow than AdpRob, for smaller network with lower percentage of uncertain buses, as the network size or the uncertainty increases, StatMod becomes appreciably faster. For the 30-bus system the StatMod is approximately 17 times slower when 10 percent of the buses have variable net-load, and is up to 2 times slower with 80 percent of buses considered uncertain. For the 118-bus network, the statistical model starts out at 5 times slower when only 10 percent of buses are uncertain, and is up to 1.4 times faster when 80 percent of the buses have variable net-load. Table 7 also shows that for similar uncertainty percentage, the proposed model becomes relatively faster with increasing network size.

These results demonstrate that, although the StatMod has higher computation time for one iteration, the quantity of information provided by the model allows it to be on par, or faster than the traditional robust approach as the network size or uncertainty increases. The statistical approach will be particularly
beneficial if the system operator intends to compute a commitment strategy for different levels of uncertainty, through the use of various sizes of the uncertainty set. It is worth noting that the statistical model’s structure also allows for straightforward parallelization, which will further help the system operator in reducing computation time.

2.4.7 1354-Bus System Analysis

The proposed methodology is further tested on a modified version of the pegase 1354-bus system [41], [20] to demonstrate performance on a real-world sized network. The network contains 1,354 buses, 260 generators, and 1,991 branches and represents the size and complexity of part of the European transmission system. The AdpRob and StatMod formulations are implemented on a 6-hr time horizon with 300 uncertain loads, and the study results are shown in Tables 2.8 and 2.9. The two models provide similar solutions, and costs, with only minor differences in specific units committed at larger $\Delta t$ values. The penalty costs are never reduced to zero because of transmission congestion in the network configuration. These results further validate the solution performance of the StatMod as compared to state-of-the-art robust methodologies.

<table>
<thead>
<tr>
<th>Delta</th>
<th>Average Dispatch CostS (k$)</th>
<th>Total Units Committed (across 6 hrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AdpRob</td>
<td>StatMod</td>
</tr>
<tr>
<td>0</td>
<td>1210.1637</td>
<td>1210.1637</td>
</tr>
<tr>
<td>75</td>
<td>1178.1932</td>
<td>1178.1932</td>
</tr>
<tr>
<td>150</td>
<td>1178.1932</td>
<td>1178.1932</td>
</tr>
<tr>
<td>225</td>
<td>1178.4757</td>
<td>1178.4757</td>
</tr>
<tr>
<td>300</td>
<td>1183.8361</td>
<td>1183.8361</td>
</tr>
</tbody>
</table>

Table 2.8: Comparison of Average Dispatch Cost and Total Units Committed for AdpRob and StatMod Methods
<table>
<thead>
<tr>
<th>Delta</th>
<th>AdpRob</th>
<th>StatMod</th>
<th>AdpRob</th>
<th>StatMod</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>362.9831</td>
<td>362.9831</td>
<td>608.3991</td>
<td>608.3991</td>
</tr>
<tr>
<td>75</td>
<td>343.0100</td>
<td>343.0100</td>
<td>577.5854</td>
<td>577.5854</td>
</tr>
<tr>
<td>150</td>
<td>343.0100</td>
<td>343.0100</td>
<td>577.5854</td>
<td>577.5854</td>
</tr>
<tr>
<td>225</td>
<td>342.9935</td>
<td>342.9816</td>
<td>577.5854</td>
<td>577.5854</td>
</tr>
<tr>
<td>300</td>
<td>342.9831</td>
<td>342.9819</td>
<td>577.5854</td>
<td>577.5854</td>
</tr>
</tbody>
</table>

Table 2.9: Standard Deviation of Dispatch Costs and Penalty Costs for AdpRob and StatMod Methods

### 2.5 Conclusion and Discussion

This paper proposes a data-driven statistical approach to account for the complexities and correlations within the power system, identifying the buses most critical to system performance, based on a pre-defined optimization objective. The ranking obtained can be utilized to implement a robust generation schedule. The method is demonstrated via a case study and validated against the state-of-the-art method proposed in [8]. The validation results on three separate test systems show that the StatMod approach provides similar solution as the accepted AdpRob model across all three metrics, supporting the validity of the approach. In addition, this approach consistently outperforms the ad-hoc reserve adjustment (AdjRes) approach typically implemented in practice. From these tests, it can be concluded that the statistical bus ranking approach also provided a correct solution to problems of unit commitment under uncertainty.

The proposed method also provides added utility to system operators with an easily customizable framework. Computational studies were performed with varying definitions of worst-case metric, and demonstrate some advanced capabilities of the model. For example, results of a hybrid definition of risk shows value in combining multiple worst-case criteria for robust unit commitment.
and is an interesting avenue for future work. [78] states the flexiramp product clearly improves the expected performance of market but can fail if used with deterministic models. While other methods require a complete reformulation of their models, the StatMod is easily adapted to this metric. Although out of scope of this paper, a comprehensive application of the proposed methodology with flexible ramping products could provide a better solution without creating implementation challenges. In addition to flexibility to handle various objectives, the statistical pre-processing of this approach is parallelizable and computationally efficient. Finally, it is worth noting that the statistical ranking is stable to moderate variations in system condition, providing additional computational efficiencies. A comprehensive ranking stability study will be a worthwhile problem for future work.

There is a large resource of literature on the feature ranking algorithms that are being utilized in the proposed model. It has been shown that these algorithms scale well and model performance does not decrease significantly with bigger datasets [59], [70]. Figure 2.1 depicts the structure of the proposed model. After computing baseline commitment schedule, the formulation is broken into a non-sequential modular structure as evident in the figure. These independent and self-contained bootstrap modules allow this model to take advantage of the computational power available to the system operator.

The current framework approximates a linear relationship between the input and output vectors. Modifications to the framework will be needed to capture convex non-linear and piecewise relationships. To our knowledge in the current form it will not be able to provide a convergence guarantee for a non-convex cost function. Approximation of the relationship using piecewise linear regres-
sion or local basis functions, before the ranking algorithm is implemented, may also provide improved solutions under new feature sets. However, given the approximation, the numerical studies performed on IEEE 30-bus, 118-bus and pegase 1354-bus networks demonstrate the validity of the solutions provided by this formulation.

The framework described here develops ranking vectors utilizing a baseline commitment decision. Our experiments, with different commitment decisions, revealed that the model produces solutions that are stable to the initial baseline unit commitment. The rate of convergence, however, might vary. During these studies, best performance was achieved using UC status with expected net load at all buses.

The proposed framework opens up many directions for future work. Testing the method on larger and more complicated networks will be important, as the ranking may be affected by correlations between net load at buses. The ranking can be used to study relationships between different elements of the electrical network. From studying interactions between buses, to finding optimum bus locations for microgrids. Simulating varying storage strategies in parallel for performance comparison is another potential application.
2.6 Appendix

2.6.1 Bootstrap Aggregation

Bootstrap Aggregation or bagging is a popular technique for constructing an ensemble of diverse and accurate predictors. The purpose of these collections or ensembles is to make highly accurate predictions by considering the decisions of individual predictors in the ensemble. As the name suggests in Bootstrap aggregation multiple versions of the predictor are generated and then used to calculate an aggregate predictor.

In the proposed model bagging is implemented to achieve better prediction for the bus rank vector. With the learning dataset $S$ defined as $\{(y_n, x_n), n = 1,..., N\}$ where the $y$'s are the economic dispatch costs and $x$'s, the input which will be dispatch costs and the net load values at any given bus in our model. The feature ranking algorithm yields bus ranks, $r = \phi(S)$, serving as the predictor for $y$. $k$ samples from the dataset $S$ are then taken to attain better aggregate prediction as compared to individual ranking. The $k$ rankings thus obtained are aggregated by computing a score $R_j = 1/k \sum \phi(S^j_k)$ for each bus $j$ as an average function of its rank $r^j_k$ in the $k$-th bootstrap sample.

2.6.2 Unit Commitment Model

This section contains a basic formulation of unit commitment model. The objective of the model is to minimize the cost of running the system based on the number of generators running, on/off status and the production levels of
the on-generators. The variable \( x \) which is binary represents vector of decisions regarding generator status, while \( y \) represents dispatch decision of the generating units at each time interval. The first set of constraints dictates minimum up/down times, and startup/shutdown costs. Energy balance constraints, reserve requirements, transmission limits and ramping constraints are represented in the second set. The third set contains the generator status and production level coupling constraints.

\[
\min_{x,y(\cdot)} c^T x + b^T y
\]

s.t.

\[
Fx \leq f, \quad x \text{ is binary}
\]

\[
Hy \leq h,
\]

\[
Ax + By \leq g,
\]
With an increasing focus on integration of distributed energy resources, it is likely that microgrids will proliferate globally. These microgrid systems will be expected to achieve multiple stakeholder objectives, motivating the study of microgrid operations using a multiobjective framework. A multiobjective perspective has the potential balance the trade-offs implicit to efficient use of available resources. To address this challenge, this chapter proposes a simulation based parametric approach for multiobjective optimization for microgrid energy management. The methodology generates a Pareto-approximate set of control policies, to provide a microgrid controller with diverse alternative strategies for utilizing resources to balance competing objectives. The policies also help to illustrate the complex relationships between the objectives, and the consequences of compromises across performance. The methodology is implemented on a test microgrid and the potential benefits are demonstrated with a set of illustrative case studies.

3.1 Introduction

Microgrids (MGs) are receiving increased attention as an effective mechanism for distributed energy and renewable resource integration, with additional benefits attainable through increasing coordinated use of the available resources in the system. MGs are generally considered autonomous networks connected
as single entities to the distribution or transmission grid, which are capable of buying and selling energy based on need [46]. These networks usually consist of local generators, storage units, renewable and traditional generation, and dispatchable/controllable loads. These distributed energy resources (DERs) can be operated for local electricity provision in an "islanded" mode, or with energy exchange capability between the microgrid and distribution/transmission, when the connection with the grid is active [46, 65].

A key research challenge for microgrids requires solving for the best set of sequential decisions (amount of generation or energy exchange with the grid at any given hour) over a planning horizon, which optimize predefined objectives while satisfying system constraints. The majority of existing research in this area has concentrated on minimizing the cost of energy, while maintaining stable operations in either grid connected or islanded mode. This approach neglects certain additional benefits available to MG users [44, 65]. As MGs become more sophisticated and ubiquitous, the stakeholders may want to utilize available DERs for more than minimizing cost of operation. As explored in [44, 88] MG energy management can be effectively utilized for different classes of objectives including capital and operations cost, environmental emissions, energy storage costs, and miscellaneous needs based objectives. Given that decision makers will want to use the MG for different purposes, it supports the assertion that MG operation should be studied in a multiobjective optimization (MO) context [44, 88].

To this effect there has been a shift towards optimizing multiple objectives when solving the energy management problem for MGs [73, 84, 80]. One MO approach explored in the literature includes weighted sums (or scalarization)
based on assigning weights to each objective and converting the problem into a single objective formulation [73, 27]. The single-objective optimization is then repeated using different scalarization values [69] to obtain Pareto optimal solutions. This process assumes availability of a consensus understanding of the consequences of alternative preference of weighting schemes a priori, which is prone to ignoring complex relationships between the objectives [22, 65, 73].

Alternative approaches use iterative population-based solution tools such as evolutionary algorithms with the intent of approximating the full Pareto front, so that decisions can be made with improved knowledge of the implications of performance tradeoffs. This approach to multiobjective formulation is termed a posterior analysis, as it does not assume prior information about objectives or stakeholder preferences. Emerging solution methods include genetic algorithms [84, 66], a cross entropy approach as described in [80], and variations of particle swarm optimization [48, 53, 4]. Even though the numerical techniques differ, multi-objective evolutionary algorithms (MOEAs) all evolve approximations to the full Pareto-front, which is a set of non-dominated solutions where improvement in performance in any single objective degrades performance in one or more of the remaining objectives [63, 65]. However, best practices for using meta-heuristic search methods, require a careful consideration of how decisions are represented during search (i.e., compact and effective abstractions of decision variables) [5].

Evolutionary multiobjective direct policy search (EMODPS) is a policy approximation abstraction of control problems [7]. The approach exploits MOEAs to search a parameterized space of candidate control policies in a manner that maximizes the efficiency and effectiveness of the algorithm’s global search fea-
tures [22]. EMODPS has been adopted in water resources literature to solve large-scale reservoir control problems [23]. This set of problems require solving for a sequence of decisions over time similar to MG control problem in power systems [22, 62]. The direct policy search (DPS) approach, utilized in EMODPS, falls under the umbrella of approximate dynamic programming class of problems [67]. Unlike traditional dynamic programming, DPS, solves for a parameterized control policy that maps state of the system to decision space, thus compacting and reducing the number of decision variables. Single objective formulations for DPS have been shown to perform well for an energy system with storage [39]. The EMODPS approach implements a multiobjective DPS formulation which can then be solved using MOEAs.

In this chapter, a novel methodology is implemented, utilizing EMODPS, to solve a MG energy management problem to explore the potential benefits of the approach. The formulation is implemented on a small MG while considering three stakeholder objectives (revenue, emissions, demand response). A set of case studies have been performed to demonstrate the following potential benefits of the formulation:

- consideration of microgrid energy management problem in a multiobjective context to broaden the scope of performance concerns that can be considered
- an extensible control framework that can incorporate a wide array of information sources, and
- provision a set of competing policy solutions which can provide a set of alternative control policies that can provide stakeholders with diverse set of strategies to utilize resources in the microgrid.
The chapter is organized as follows: Section 3.2 provides an overview of the EMODPS approach, followed by a detailed description of the formulation for MG energy management in Section 3.3. The performance of the approach is illustrated in Section 3.4 followed by concluding remarks in Section 3.5.

3.2 Evolutionary Multiobjective Direct Policy Search

EMODPS is a simulation based optimization approach for exploring a parameterized space of candidate control policies, which has proven to be an efficient methodology for application in problems where regular stochastic dynamic programming approaches struggle. This methodology accomplishes this by; parameterizing the decision space which reduces curse of dimensionality [22], directly incorporates simulation models which allows for more flexible formulation [22], and allows the users to explore multiple objectives without a priori assumptions about preferences [43]. The EMODPS framework has two main components: (1) Direct Policy Search and; (2) Multiobjective Evolutionary Algorithms.

3.2.1 Direct Policy Search

Direct Policy Search (DPS) is a control strategy that directly searches in the solution space of the parameteric decision variables [64]. DPS is based on defining a parameterized function(policy) which maps the system state(s) to decisions, which is followed by exploration of the parameter space to find a policy that optimizes the objectives under consideration. In other words, the parameters
are optimized rather than the decisions themselves. The result of the optimization process, therefore, is not a set of hourly decisions as would be the case in traditional MG operation formulations but a control policy that can be used to guide those decisions. Using the example from [58], we can describe our system in a state $S_t$, from which we take an action $x_t$ and then observe new information which takes us to a new state $S_{t+1}$. DPS can then represent the rule (or policy) for making this decision using the function $F(S_t)$. We, generally, also have a system model $S^M$ that describes how the system evolves from $S_t$ to $S_{t+1}$. The dynamics of our problem can then be described as

$$x_t = F(S_t)$$

$$S_{t+1} = S^M(S_t, x_t)$$

The function $F(.)$ is the operating policy approximating the relationship between the state and the decisions by learning from the feedback of the system simulations. It can vary from being a linear function for simple systems with single objective problems to more flexible mappings in complex systems (like Artificial Neural Networks) where high number of parameters might be required to avoid restricting the search for the optimal policy to a subspace of decision space [22]. Radial basis functions (RBFs) have proven to be efficient universal approximators and are widely adopted in many applications [63]. For the purpose of this chapter, RBFs have been used as the approximating function with further detail in Section 3.3.5.
3.2.2 Multiobjective Evolutionary Algorithms

The EMODPS approach utilizes MOEAs to search the parameter space for the optimal values. MOEAs are iterative search algorithms that generate a Pareto-approximate set of solutions by mimicking the randomized mating, selection, and mutation operations that occur in nature [31]. A Pareto optimal set (or a non-dominated set) constitutes solutions for which improvement in any one objective would result in the degradation of one or more of the other objectives. The term Pareto-approximate set is the best known approximation of a Pareto optimal set when formal global convergence cannot be guaranteed. MOEAs provide a promising alternative to gradient-based optimization methods when solving multiobjective optimization problems, given their efficacy in dealing with multimodality, nonlinearity and stochasticity associated with such problems. There are different MOEAs available to be coupled with DPS approach, for the purpose of this study the Borg MOEA [31] has been utilized based on its ability to obtain high quality tradeoff solutions [63, 62]. The Borg MOEA’s success has been attributed to its use of $\epsilon$-dominance archiving, $\epsilon$-progress, and multiple self-adaptive search operators that combine to allow the algorithm to earn effective exploration strategies while solving challenging problems. [31, 63]. [45] introduced the $\epsilon$-dominance relation as a way to eliminate deterioration by approximating the Pareto front, and also provided theoretical proofs of convergence and diversity for algorithms using this relation.
3.3 EMODPS for Microgrid Energy Management

A key research challenge for microgrids requires solving for the best set of sequential decisions (amount of generation or energy exchange with the grid at any given hour) over a planning horizon to optimize predefined objectives while satisfying system constraints. The majority of research in this area has concentrated on minimizing the cost of energy, while maintaining stable operations in either grid connected or islanded mode. These works, however, neglect certain additional benefits available to MG users [44, 65]. As MGs become smarter and more ubiquitous the stakeholders would want to utilize available DERs for more than minimizing cost of operation. As explored in [44, 88] MG energy management can be effectively utilized for different groups of objectives including capital and operations cost, environmental emissions, energy storage costs, and miscellaneous need based objectives. Given that decision makers would want to utilize the MG for different purposes, it stands to reason that MG operation should be studied in a multiobjective optimization (MO) context [44, 88].

In this study, we generate multiple MG energy management control strategies for generation and grid exchange decisions while balancing multiple stakeholder objectives. The proposed EMODPS methodology simulates daily operation of a MG over \( N \) stochastic samples of load, wind and solar while simultaneously optimizing three stakeholder objectives. This approach generates a Pareto-approximate set of control policies for conventional generation and grid exchange providing a diverse set of possible approaches for MG operation. These control policies use the battery storage levels to determine generation and buy/sell decisions with the grid.
For this demonstration, a test MG has been explored consisting of a battery, a
diesel generator, critical and non-critical loads, and connection to the distribu-
tion grid based on the configuration details provided in Section 3.4.1. The MG
is assumed to be community-owned with stakeholders that include residents
and/or local businesses. In this case study, revenue, emissions and demand re-
ponse use are included as objectives. The selection of revenue and emission
objective represent two possible competing points of view for the stakeholders.
Demand response (DR) is included as an objective in order to avoid setting a
preference or value for DR a priori, but to explore the leverage available to the
system with DR. In addition, DR can serve as a proxy for system reliability, in
that the necessity of overuse of DR implies that they system may be under stress.

The following sections provide a comprehensive outline of the EMODPS ap-
proach starting with defining the objectives, followed by the constraints, the
RBF policies and a description of the solution strategy.

### 3.3.1 Revenue Objective

The revenue objective is calculated as the expected value over $N$ simulations of
daily revenue as represented below.

$$
O_1 = -\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \left( C_{gen}(p_{i,t}) + \alpha_t(e_{i,t}) + C_{wt}(wt_{i,t}) \\
+C_{pv}(pv_{i,t}) + C_{ES} \left| ES_{i,t} - ES_{i,t-1} \right| \right)
$$

(3.1)

where $p_{i,t}$ and $e_{i,t}$ are generation and grid exchange decisions, $wt_{i,t}$ and $pv_{i,t}$ are
the wind and solar generation, and $ES_{i,t}$ is the battery storage level for simu-
lation $i$ at time $t$. The exchange decision $e_{i,t}$ takes negative values when selling
to the grid and positive when buying. $C_{\text{gen}}$, $C_{\text{wt}}$ and $C_{\text{pv}}$ are the cost for diesel, wind and solar generation while $C_{ES}$ is the battery charging/discharging costs. $\alpha_t$ represents the real-time energy prices to buy or sell from or to the utility at time $t$.

### 3.3.2 Emissions Objective

Equation 3.2 defines the emissions objective which is the expectation of daily emissions over the $N$ simulations. The formulation assumes emissions from diesel generation and any energy bought from the grid as shown below.

$$O_2 = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \left( C_{ef}(\max(e_{i,t}, 0) + p_{i,t}) \right)$$  \hspace{1cm} (3.2)

where grid emissions are non-zero when $e_{i,t} > 0$ and $C_{ef}$ represents the carbon emissions factor.

### 3.3.3 Demand Response

The objective is defined as reliability in the system under consideration and is utilized to explore the limits of demand response in a MG system. The structure of the objective is set to quantify load flexibility at each hour. The objective, $O_3$, is the expected percentage of hours in a day when demand response is required as shown below.
\[ O_3 = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T} \sum_{t=1}^{T} \varphi_{i,t} \]

\[ \varphi_{i,t} = \begin{cases} 
1, & 1 - \frac{d_{DR}^{i,t}}{d_{i,t}} > d_{crit} \\
0, & \text{otherwise}
\end{cases} \] (3.3)

where \( d_{DR}^{i,t} \) is the hourly flexible load for simulation \( i \). This implies that any given hour in a day is considered reliable i.e. \( \varphi_{i,t} = 1 \) when \( d_{DR}^{i,t} \) is less than a predefined critical threshold percentage, \( d_{crit} \), of the hourly load \( d_{i,t} \). For the purpose of this study \( d_{crit} \) was set to be 0.95 which implies that at any given hour a maximum of 5 percent of \( d_{i,t} \) can be curtailed.

### 3.3.4 Optimization Formulation

The three objectives are optimized simultaneously subject to constraints defined in equations (3.4) - (3.10). The optimization problem is formulated as described below.

\[ \min_{\theta_p, \theta_e} \ (-O_1, O_2, -O_3) \]

\[ p = (p_{1,i}, p_{1,i}, ..., p_{T,i}) \]

\[ e = (e_{1,i}, e_{1,i}, ..., e_{T,i}) \]

s.t.

\[ ES_{i,t+1} = ES_{i,t} + w_{i,t} + pv_{i,t} + e_{i,t} \]

\[ + p_{i,t} - (d_{i,t} - d_{DR}^{i,t}), \forall i \in N, t \in T \] (3.4)
\[ p_{i,t} - p_{i,t-1} \leq p_{\text{rmp,up}}, \forall i \in N, t \in T \] (3.5)

\[ p_{i,t-1} - p_{i,t} \leq p_{\text{rmp,down}}, \forall i \in N, t \in T \] (3.6)

\[ P_{\text{min}} \leq p_{i,t} \leq P_{\text{max}}, \forall i \in N, t \in T \] (3.7)

\[ E_{\text{min}} \leq e_{i,t} \leq E_{\text{max}}, \forall i \in N, t \in T \] (3.8)

\[ |ES_{i,t+1} - ES_{i,t}| \leq ES_{\text{chg/dischg}}, \forall i \in N, t \in T \] (3.9)

\[ ES_{\text{min}} \leq ES_{i,t} \leq ES_{\text{max}}, \forall i \in N, t \in T \] (3.10)

where equation (4.5) is energy balance constraint for the system dependent on battery storage levels at any time \( t \), equations (4.6) and (4.7) are the ramping constraints for the diesel generator, equations (4.8) and (4.9) are the upper and lower limits for the generator and energy exchange with the grid, equation (4.10) represents the limits on charging/discharging of the battery and equation (4.11) is the bounds on battery storage level. The formulation is solved to optimize the three objectives by finding the best set of parameters \( \theta_p \) and \( \theta_e \) for the operating policies \( p \) and \( e \) as explained in Section 3.3.5.

### 3.3.5 Formulation of Operating Policies

In this study cubic RBFs are implemented as the control policies described in section 3.2. The battery storage level and hour of the day \( t \) are the input variables representing the system state, which are then mapped to hourly diesel generation and buy/sell decisions as shown in equations (3.11) and (3.12).

\[ p_{i,t} = \sum_{j=1}^{n} w_j \left( \frac{ES_{i,t} - c_j}{r_j} + x_i^2 + y_i^2 \right)^3, \forall t, i \] (3.11)
\[ e_{i,t} = \sum_{j=1}^{n} w_j \left( \frac{ES_{i,t} - c_j}{r_j} \right) + x_t^2 + y_t^2 \right)^3, \forall t, i \]  

where \( x_t = \sin(2\pi t/T - a_1) \) and \( y_t = \cos(2\pi t/T - a_2) \). The variables \( p_{i,t} \) and \( e_{i,t} \) are the policy-prescribed generation and buy/sell decisions at hour \( t \) for sample \( i \); \( ES_{i,t} \) is the battery storage level at a given hour; \( n \) is the number of RBFs; \( x_t \) and \( y_t \) are phase shifted \( \sin(.) \) and \( \cos(.) \) functions for cyclic representation of time; \( w_j, c_j \) and \( r_j \) are the weights, centers and radii, respectively of \( j \)th RBF associated with the generation or buy/sell decision; and \( a_1, a_2 \) are the phase shifts on \([0, 2\pi]\).

As defined earlier, the goal of EMODPS is to find a non-dominated set of parameter vectors \( \theta_p \) and \( \theta_e \) minimizing the system objectives. Each of the parameter vectors are composed of the weights, centers and radii defining the RBF policies. For example, \( \theta_p = [w_j, c_j, r_j] \) where \( j \) is the number of RBFs. In this study there is a set of parameter vectors each for the diesel generator and the utility buy/sell decisions. For each decision \( n = 2 \) RBFs, are used with parameter limits set as \( w_j \in [0, 1] \), \( c_j \in [-2, 2] \), \( r_j \in (0, 2] \). The parameter vectors are then optimized with the help of MOEAs. These limits were selected after experimenting with multiple ranges and number of RBFs. The preferred ranges may differ they are dictated by the needs and the resources available to the operator. For example, setting a higher range translates into a larger decision space which will require more computation time to effectively explore, while setting a more restrictive range might result in less desirable results.

### 3.3.6 Model Implementation

The EMODPS formulation begins by defining initial policies for the buy/sell and generation decisions, which are then used to simulate MG operation over...
simulations. The resulting objective performance acts as a feedback for performance of the parametric policy. The BORG framework, as the MOEA solver, then uses this information to iterate over the parameter space of \( \theta_p \) and \( \theta_e \). This process is repeated for multiple seeds and the final set of solutions is a compilation of non-dominated policies that represent best performance across the three objectives. The Borg MOEA was parameterized according to the user guidelines [31].

3.4 Performance Evaluation

The goal of the following case studies is to demonstrate the utility of the multiobjective approach, through the EMODPS methodology to simulate and optimize microgrid control. Not only does this formulation provide the stakeholders with multiple control policies to achieve their objectives, but also allows for a deeper insight into the relationship between these objectives and the limits of the system. These insights then enable better control and utilization of the system resources.

3.4.1 System Overview

To test the EMODPS approach, it is implemented on a test MG system consisting of a battery, a diesel generator, critical and non-critical loads, and connection to the distribution grid. The MG has a peak load of 220 kW with a battery size of 200 kW. The installed capacity for wind and solar is set to be 20\% and 10\% with respect to the peak load. The load, wind, solar, and real-time market
energy price distributions were obtained by projecting daily CAISO data on to the test system. For this study, load, wind, and solar are modeled as uncertain parameters with a maximum possible variation of $10\%$ at any given hour. All other parameters used for the study are provided in the Appendix.

The DPS policies were optimized by simulating over $N = 1000$ randomly sampled scenarios of load, as well as wind and solar generation. The EMODPS approach generated 3000 pareto-approximate control policies that could be implemented to control the daily operations of the MG in consideration. To validate, each of these policies were then used to simulate MG operation over 1000 out-of-sample scenarios of load, wind and solar. For comparative purposes three separate energy management strategies were analyzed and validated as listed below.

- **Perfect Information Strategy** - Assuming availability of perfect forecast information about load, wind and solar. This strategy was used to provide a best performing baseline of hourly MG control decisions for the 1000 out-of-sample scenarios.

- **Expected Forecast Strategy** - This strategy optimized for a risk neutral energy management strategy based on the expected forecast distribution available for load, wind and solar, when determining the hourly control decisions.

- **Conservative Strategy** - This strategy decided hourly control decisions by assuming the worst-case scenario based on the available forecast.

The above mentioned control strategies were optimized as both single objective and scalarized multiobjective frameworks and compared with the DPS
policies as explained in the following sections.

### 3.4.2 Need for Multiobjective Framework

This section demonstrates the need for considering multiple objectives by comparing performance of the EMODPS policies against the Perfect Information, Conservative and Expected Forecast strategies while optimizing the revenue objective only.

Figure 3.1 shows a projection of the revenue objective performance for the different formulations in consideration. Each point in the plot represents average objective performance over 1000 out-of-sample test scenarios. The figure shows performance of each of the 3000 DPS policies for the revenue objective in green while, those from the perfect information are colored pink, solutions from robust policy are colored blue, and those from expected policy, light-blue. As expected, the single-objective Perfect Information formulation dominates all others in Figure 3.1, followed by DPS, Expected Forecast and Conservative methods. The DPS policies provide a wide range of solutions for the objective although a majority of them are worse than the expected forecast strategy. Using the Perfect Information as a benchmark, this projection illustrates that while some of the DPS policies are doing better, in the single objective case the expected forecast strategy is the right approach, as it will allow the MG controller to follow a simple strategy with a small compromise in objective performance.

The same solutions have been projected over two objectives in Figure 3.2. The x-axis represents the need for demand response (curtainable load) as percentage of total daily load and y-axis shows revenue while the arrows point towards
Figure 3.1: 1d comparison of solution performance for DPS policies, and single objective solutions for Perfect Information, Expected Forecast and Conservative strategies

direction of preference for each objective. Figure 3.2 provides more information and context than the one dimensional comparison. The perfect information solution still dominates all other formulations without any demand response requirement whereas the expected forecast strategy requires a relatively higher demand response to achieve it’s revenue performance. Figure 3.2 provides a new perspective on the results from different formulations, as the stakeholders might no longer be satisfied with the performance of the expected forecast formulation, and the conservative formulation may become a viable strategy as it does not require any demand response. However, the biggest improvement is for the DPS policies as there are multiple policies providing viable potential alternatives with high revenue performance and low demand response requirements.

Figure 3.3 depicts the solutions across the three objective space considered in the study. The x-axis represents emissions in kilograms, y-axis covers the need for demand response and z-axis is for revenue. The ideal point for the three objectives is near the upper left corner as annotated on Figure 3.3. It becomes apparent when looking at the figure that optimizing for only one objective provides myopic representation of the solution space. For example, the perfect information solutions that appeared so dominant in one- and two-objective views
of the problem now lie on the extreme edge with very poor performance in the emissions objective. Similarly, the conservative solution results in extremely high emissions even though it doesn’t require demand response. The single solutions occupy a small space and will not provide an accurate picture of possible solutions available to the decision maker. The DPS policies, however, represent a pareto approximate surface across the three objectives providing a diverse set of viable strategies across the solution space.

Figures 3.1, 3.2 and 3.3 demonstrate that solving a MG energy management in a multi-objective context could provide a better understanding of attainable system performance for the decision maker and introduce a broader suite of control strategies that could cause operator’s preference among solutions to change.
3.4.3 Comparing Multiobjective Frameworks

Having demonstrated the utility of multiobjective approach, this section compares the EMODPS formulation against frequently used scalarization method. Scalarization is an approach wherein the problem is converted into a single ob-

Figure 3.3: 3d comparison of solution performance for DPS policies, and single objective solutions for Perfect Information, Expected Forecast and Conservative strategies
dramatically.
jective framework by using valuation functions and weighting parameters for each objective. These parameters are either 1) chosen subjectively to obtain one optimal solution [27] or; 2) different parameters sampled randomly to obtain a set of solutions [69]. Both approaches result in inefficient performance, as the former assumes correct and complete prior knowledge about the system as well consensus among stakeholders, while the latter is unable to capture complex non-linear relationships between objectives [19]. The benefits of using an approach like EMODPS over scalarization are demonstrated in Figure 3.4. The figure compares performance of 3000 DPS policies against multiple scalarized objectives (with different weights) of the other three formulations. Ten different weighting parameters were chosen for each of the three formulations. Figure 3.4, however, shows only the six solutions per strategy as the other solutions were dominated by those presented in the figure. The scalarized solutions of the three formulations on Figure 3.4, are spread across the solution space and hardly any strategy seems worth exploring. This supports the earlier argument that sampling the weight parameters to obtain a Pareto-approximate surface with non-dominated solutions will not be a trivial task. In addition, it is apparent from Figure 3.4 that DPS approach is preferable among the formulations used, outperforming even perfect forecast approach in some cases.

3.4.4 Aggregate Analysis of DPS Policies

For a more detailed analysis of solution performance, the policies optimized by the DPS approach are shown in Figure 3.5 on a parallel axis plot. This figure is a representation of trade-offs across the three stakeholder objectives for all the DPS policies. For ease of comparison, each axis has been oriented such that the
Figure 3.4: 3d comparison of solution performance for DPS policies, and scalarized multiobjective solutions for Perfect Information, Expected Forecast and Conservative strategies.

The top of the axis represents best performance for the objective. Each line segment is a policy that is shaded according to performance on the revenue objective across 1000 out-of-sample simulations shown by the colorbar. Examining Figure 3.5 shows the value of the DPS approach as the policies cover a wide range of possibilities for all three metrics. Such a diverse set of solutions will provide stakeholders with useful insight into the complex trade-offs between the objectives. Figure 3.5 shows a strong trade-off between the revenue and emissions objectives which can be attributed their definitions. Equations (3.1) and (3.2) show that increased diesel generation is required for higher revenue, leading to
higher emissions and vice versa.

The trade-offs across the three objectives (especially for demand response) are more complex. For example, high revenue (or low emissions) policies can reside on both low and high end of demand response spectrum based on the emissions (or revenue) strategies. Similarly, other policies portray behavior which would be difficult to predict and replicate \textit{a priori} using a scalarized or single objective optimization. This figure provides stakeholders an overview of possibilities into the behavior of different performance objectives.

Figure 3.5 provides a comprehensive view of all solutions available to the stakeholders. However, in real-world decision support applications, stakehold-
ers would have certain performance criteria for each objective, allowing them to narrow down to policies attuned to those requirements. For illustrative purposes, Figure 3.6 is based on three possible sets of criteria a stakeholder might require.

- High Revenue policies (Policy Type 1)– Policies where average revenue performance in the 70th percentile (higher than 70% of the policies).

- Low Emission policies (Policy Type 2)– Policies with average emissions are in the 30th percentile (lower than 70% of policies).

- Balanced policies (Policy Type 3)– Policies with average revenue in the 40th percentile, average emissions in 70th percentile and average demand response requirement in the 30th percentile.

Figure 3.6 shows the average performance of specific policy types across 1000 out-of-sample scenarios. Type 1 policies generate high revenues by sacrificing on emissions and demand response objectives. These policies show a wide range of demand response values which is not translated to either emission reduction or revenue generation. Such information can be useful for stakeholders in understanding the limits of the system. Looking at policies of type 2 a wider range of leverage is available in both revenue and emissions objectives for a smaller variations in demand response requirements. While for policies of type 3 the available leverage for revenue and emissions objectives is much higher. Figure 3.6 points out a key pattern regarding stakeholder objectives in the test system, as the sensitivity of revenue and emissions objectives is decreasing with increasing value of demand response. A more detailed analysis of the interactions between the objectives will allow provide the stakeholders with un-
Figure 3.6: Parallel axis plot of the trade-off set for select policy types where Policy Type 1 are high revenue policies, Policy Type 2 are low emissions policies and Policy Type 3 are balanced policies.

3.4.5 Hourly Analysis of DPS Policies

This section examines the DPS policies across the 24 hour planning horizon. To accomplish this, a policy is selected from each policy type defined in the previous section, and hourly decision analyzed as shown in Figures 3.7, 3.8, and Table 3.1. As previously discussed, the EMODPS methodology used battery storage level as the system variable dictating the energy exchange (buy/sell) and generation decisions for these policies. Figures 3.7 and 3.8 illustrate the average understanding of the system allowing them to leverage the most value out of the MG resources.
storage level distribution across 24 hours for the three policies selected, with the colorbars representing the electricity buy/sell and generation decisions at those hours, respectively, with actual decision values provided in Table 3.1. The uppermost plot in both figures are the net load distribution for the horizon depicting the diurnal load requirements, and hence the electricity cost, for the MG system. The lower subfigures demonstrate the different decisions taken by the three policy types to accommodate the pattern.

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Table 3.1: Microgrid Control Decisions

Policy type 1 prioritizes high diesel generation and selling to the utility; the battery is charged earlier in the day, and focus on sales results in reduced availability for load peak later in the day, leading to high load curtailment relative to the other policies as can be seen in Table 3.1. Conversely, policy type 2 utilizes regulation of the conventional generation to reduce emissions, as shown in Figure 3.8 and Table 3.1. The resulting battery level is more variable than the other policy types. The deviation in the storage behavior occurs at peak load hours as both generation and stored electricity is required to meet the ex-
Figure 3.7: Sample control policies for electricity buy/sell decisions based on storage levels where (+) values represent buying and (-) values represent selling.

tra load requirements. Another interesting behavior from this policy type is the need for demand response in the middle of the day when generation is kept low.
Figure 3.8: Sample control policies for electricity generations decisions based on storage levels.

to reduce emissions. Policy type 3, as expected, is the most balanced approach compared to the other two policies, maintaining a balance between revenue, emissions and demand response utilization. As a result the high amounts of
diesel generation is used to maintain a balance between battery storage levels and selling. While the generation isn’t as constrained as the low emissions policy, it is reduced whenever possible to reduce emissions. This policy also requires very low levels of demand response, just after peak hours when the stored electricity in the system is less available. These policies are just three samples of the 3000 policies generated by the EMODPS approach, and each provides a different energy management strategy for the MG which in turn provide the decision-makers as many options. These results may also inform operators regarding the presence of excess conventional generation in the system given that all three policy types are selling to the grid frequently.

### 3.5 Conclusion

This study explores a parametric simulation based optimization approach to identify diverse control strategies for a stochastic microgrid system to address multiple objective decision-making problem. The utility of the approach is explored via case studies with promising results. Not only did the the EMODPS approach demonstrate the benefits of a multiobjective framework, it also showed potential value for stakeholders by providing diverse set of control strategies. Even though the framework is computationally expensive the policies generated could be used for long term decision making before retraining is required.

The control policies also provide information regarding the limits of the system as well the complex relationships between stakeholder objectives. A deeper analysis with help of the policies could provide useful insights to decision mak-
ers which among other things might drastically change their preferences. As EMODPS is a simulation-based method, it can include multiple state variables, multiple objectives as well as network constraints. The parameterized policies improve performance for MOEAs by reducing the curse of dimensionality. The current study should be explored in more detail to study the complex relationships between revenue/emissions and demand response. Initial experiments, in this direction, have shown that these interactions need to be studied in an empirical setup to be effectively utilized. The proposed framework provides such a framework and will be of great benefit in this line of questioning.

This methodology also opens up many interesting directions for future work. It could be used to perform life cycle analysis for microgrid configurations based on different stakeholder objectives. The simulation approach could be utilized to test systems under islanding conditions to better prepare control strategies. The objective of this work was to explore the applications of this approach on a test microgrid, however, future implementations could leverage physics based models for detailed grid representation in a hybrid formulation.

3.6 Appendix: Parameters

Cost parameters: $C_{\text{gen}} = 0.25$ ct/kWh, $C_{\text{wt}} = 1.0$ ct/kWh, $C_{\text{pv}} = 2.0$ ct/kWh, $C_{\text{ES}} = 0.30$ ct/kWh. Emissions factor: $C_{\text{ES}} = 0.437$ kg/kWh. Reliability criteria: $d_{\text{crit}} = 95\%$. System limits: $p_t \in [80, 200]$ kW, $ES_t \in [40, 160]$ kW. Buy/Sell limits: $e_t \in [-50, 50]$ kW. Ramp limits: $p_t \in [-50, 50]$ kW.
Microgrids (MGs) have been identified as key system components under increasing integration of renewable and distributed energy resources. Microgrid systems are envisioned to provide improved energy reliability and efficiency, while satisfying increasingly diverse consumer requirements. As these systems proliferate, so will the need for improved operations and decision frameworks that include multiple objectives and stakeholder preferences for resource planning and operations. To address this challenge, a simulation based framework for multi-objective optimization of daily microgrid energy management is proposed. The framework implements a parametrized methodology, generating a Pareto-approximate set of control policies, to provide a microgrid controller with diverse alternative strategies for utilizing resources. These policies help illustrate the complex performance tradeoffs between the objectives, and identify performance limitations of the system. The framework is implemented on a test microgrid and the potential benefits are demonstrated with a set of illustrative case studies. In addition, the framework explores the robustness of the control policies against unplanned external conditions that could threaten system operations.

4.1 Introduction

Under the current regime of ambitious renewable energy targets, growing populations, and the increasing frequency of extreme weather events, there is a clear
need for modernizing the current electric infrastructure to meet the requirements of 21st century users. In many contexts, the power system community is looking to microgrids as a key component of the future grid. Microgrids constitute a group of interconnected loads and distributed energy resources that act as a single controllable entity with respect to the grid [74]. These localized grids can work in conjunction with the macro-grid or disconnect on demand to work in an islanded mode. Under either configuration, additional research is required to understand the potential benefits and challenges of microgrids within the larger energy system context.

It is widely accepted that efficient deployment of microgrids can have technical, economical, societal, and environmental benefits. But one of the key challenges in microgrids operations lies in the ability of the operator to find the best set of sequential operating decisions, such as generation or energy exchange with the grid, to optimize predefined objectives under system constraints. The traditional strategy is to optimize for a single objective, such as minimizing the cost of energy, while maintaining stable operations for the microgrid, as explored in [50, 33, 15, 3, 68, 75]. However, this cost-centric approach not only neglects other benefits available to microgrid users [44, 65], it also fails to promote community stakeholder participation by assuming the needs and preferences of microgrid users a priori. As microgrids become more ubiquitous and sophisticated, stakeholders will increasingly connect distributed energy resources (DERs), and may target different operational objectives, including capital and/or operational cost, environmental impact, energy storage costs, and reliability [44, 88]. To address this need, it is essential to explore microgrid operations in a multi-objective optimization framework. The traditional multi-objective approaches explored in the literature use scalarization of multiple ob-
jectives, which converts the problem to a single objective by normalizing objectives to consistent units and assigning weights to each objective [83, 73, 27, 69]. This process assumes availability of a consensus understanding of the consequences of different weighting schemes *a priori*, which is prone to ignoring complex relationships between the objectives [28, 22, 65, 73]. In addition, scalarization approaches fail to provide useful information to aid stakeholder decision making.

A key approach to address this drawback is a posterior analysis, typically building on a simulation-based optimization method. Research has shown that iterative population-based evolutionary algorithms perform well in this context [88]. When used in multi-objective framework, these tools do not assume prior information regarding objective tradeoffs or stakeholder preferences, but instead search across the solution space and generate sets of non-dominated solutions, where improvement in performance in any single objective degrades performance in one or more of the remaining objectives [63, 65]. These algorithms and their varying formulations have been explored in [38, 84, 66, 55, 80, 48, 53, 4, 47, 34]. However, for these meta-heuristic methods, as the number of decision variables grow, so does the solution space, resulting in convergence and computational deficiencies. A promising approach to circumvent these issues is the use of parametric policies that map system states to the decision space, significantly reducing the number of decision variables.

Evolutionary multiobjective direct policy search (EMODPS) is a methodology that combines a policy approximation approach, called direct policy search, with the global search ability of evolutionary algorithms in a manner that maximizes the efficiency and effectiveness of the algorithm’s global
search features [22]. The direct policy search (DPS) approach falls under the umbrella of approximate dynamic programming class of problems [67] which have shown promise in energy system operations problems with storage [39, ?]. The EMODPS methodology can be extended to explore multiple objectives and identify a set of approximately pareto-optimal control policies for daily microgrid operation. Therefore, the results from the optimization are not a sequence of hourly decisions but a set of policies that are used to make these decisions. The application of this methodology to a microgrid was first described in a case study by the authors in [28], demonstrating the benefits of using a multiobjective framework, as well as briefly exploring parametric operation policies in the context of microgrid operations.

The aim of the current study is to extend EMODPS application to energy systems by implementing a comprehensive robust decision analysis framework for microgrid operations. The framework begins with the EMODPS formulation for identifying adaptive control strategies for the microgrid system, followed by a thorough re-evaluation to test resiliency of these policies under unplanned external scenarios that could threaten system operations. Initially developed by [42], and further advanced by [63], the framework focuses on aiding decision makers and stakeholders in analyzing performance of complex systems and discovering robust decisions that perform well across a broad range of system conditions. This is possible because the framework provides a posteriori decision support, meaning it first presents explicit representations of key system trade-offs and robustness challenges, then elicits stakeholder preferences in selecting management actions.

This chapter implements the robust decision making framework, which has
been used effectively in large-scale reservoir control problems, to the context of daily microgrid operation. The framework is tested on a small microgrid while considering three key stakeholder objectives; revenue, emissions, and reliability. The various case studies are used to demonstrate significant benefits in this innovative application of EMODPS in energy management decision making.

To summarize, the contribution of this chapter is the implementation of direct policy search as a robust multiobjective decision framework for microgrid energy management problems. Specifically, this chapter highlights:

- a set of competing control strategies that can act as efficient tools to analyze complex operational tradeoffs,
- the flexibility of this approach to allow operators to simulate long term performance of the system; deconstruct and analyze hourly decisions based on system conditions, and quantify potential mechanisms to adjust performance,
- robustness analysis to test resiliency of these control strategies under unforeseen system conditions, and identify the sensitivity to variation in system parameters, and
- an efficient and effective tool to communicate with stakeholders to enable integrate consumer participation into grid resource planning and operations.

The robust decision making framework is best described through EMODPS formulation, implementation, and detailed evaluation of policy performance under varying system conditions. Therefore, the chapter is organized as follows: Section 4.2 describes the formulation and implementation pipeline for
microgrid energy management, and comprehensive performance and robustness analysis are illustrated in Section 4.3. Concluding remarks are provided in Section 4.4.

4.2 EMODPS for Microgrid Energy Management

EMODPS is a simulation-optimization approach in which microgrid operating policies can be parameterized within a given family of functions (e.g., piecewise linear functions, radial basis functions, etc.), simulated over a series of stochastic inputs (wind, solar and load forecasts), and then optimized to improve performance over multiple system objectives computed in the simulation. EMODPS utilizes nonlinear universal approximators to parameterize candidate operating policies and multiobjective evolutionary algorithms (MOEAs) to optimize their performance over the problem’s conflicting objectives. Earlier work in [28] implemented this methodology in MG operation context to: 1) demonstrate the necessity of multi-objective formulation over traditional formulations for modern MGs; 2) briefly explore the potential of parameterized control policies for MG operation.

The current study aims to comprehensively explore the usability of these control strategies in MG operation. This section briefly discusses the EMODPS methodology, describing the optimization formulation and the system objectives in Section 4.2.1, the parametric policies definitions in Section 4.2.2, and the implementation pipeline in Section 4.2.3.

For the purpose of this study, a test MG has been explored consisting of a battery, a conventional diesel generator, critical and interruptible loads, and
connection to the distribution grid based on the configuration details provided in Section 4.3.1. The MG is assumed to be community-owned with stakeholders that include residents and/or local businesses. In this case study, revenue, emissions, and reliability are included as objectives. The selection of revenue and emission objectives represent two possible competing points of view for the stakeholders. Reliability is included in order to explore and quantify the potential benefits of responsive load in the system. By not setting a preference for reliability \textit{a priori}, the analysis of system performance can generate meaningful discussions about stakeholder preferences. The formulation simulates daily operation of the MG over \( N \) stochastic samples of load, wind and solar forecasts in order to optimize the three stakeholder objectives. This approach generates a Pareto-approximate set of control policies for conventional generation and grid exchange providing a diverse set of possible approaches for MG operation. The resultant control policies use the battery storage levels to determine generation and buy/sell decisions with the grid.

There are different MOEAs available to be coupled with DPS approach, for the purpose of this study the Borg MOEA [31] has been utilized based on its ability to obtain high quality tradeoff solutions [63, 62]. The Borg MOEA’s success has been attributed to its use of \( \epsilon \)-dominance archiving, \( \epsilon \)-progress, and multiple self-adaptive search operators that combine to allow the algorithm to earn effective exploration strategies while solving challenging problems [31, 63].
4.2.1 Optimization Formulation

Microgrid energy management operations require solving for the best set of sequential decisions (generation or energy exchange with the grid at any given hour) over a planning horizon, to optimize predefined objectives while satisfying system constraints [50, 33, 15, 3, 68, 75]. This section describes the multiobjective optimization framework that is then coupled with the EMODPS methodology to generate candidate operational control strategies. The three objectives considered in this study were defined while keeping in mind a microgrid operation primarily concerned with expected performance. This formulation quantifies the $O_{\text{revenue}}$, $O_{\text{emissions}}$, and $O_{\text{reliability}}$ as the expected revenue, emissions and number of reliable hours, respectively, calculating their averages across one thousand (N) uncertain scenarios of 24 hour (T) forecasts for load, wind, solar and grid price for buying/selling of electricity. Thus $d^{th}$ objective was calculated according to the equation

$$O_d = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} (g_d(t,i))$$

where $g_d(t,i)$ is the value of the $d^{th}$ objective at hour $t$ of the $i$-th scenario. The three objectives can be described as follows:

- The revenue objective ($O_{\text{revenue}}$) is the expected daily revenue over the $N$ uncertain scenarios. The objective accounts for cost of local generation, charging/discharging costs of the battery and the real-time cost of electricity. Selling surplus electricity to the grid is a source of revenue for the MG.

- Similarly, the emissions objective ($O_{\text{emissions}}$) is defined as the expected
emissions over the \( N \) training scenarios. The two sources of emissions considered are local conventional generation and electricity imported from the grid. Thus MG operation aimed at lower emissions will need to manage the two sources accordingly.

- The MG in this study is assumed to have interruptible load (IL) contracts with users allowing for flexible load in the system. Therefore, adding a reliability objective \((O_{\text{reliability}})\) can help the MG operator and stakeholders explore and quantify the ideal limits of this flexibility, as well the value of such non-critical loads in the system. The reliability objective captures the expected number of reliable hours in day over the \( N \) uncertain scenarios. Thus, the objective minimizes daily IL requirements by maximizing the number of reliable hours in a day, where an hour is considered reliable if the amount of IL required is less than 5% of the total hourly load. An additional constraint is added to the formulation to set minimum reliability standards, requiring all candidate policies to have an expected reliability \((O_{\text{reliability}})\) of more than 90% (21 reliable hours in the day).

Incorporating the three objectives described above, the general form of the multiobjective optimization problem can be summarized as:

\[
\theta^* = \arg \min_{\theta} (-O_{\text{revenue}}(\theta), O_{\text{emissions}}(\theta), -O_{\text{reliability}}(\theta))
\]

s.t.

\[
U(\theta) \leq B
\]

\[
ES_{t+1} = ES_t + U(\theta) + L
\]

\[
O_{\text{reliability}}(\theta) \geq 0.90
\]
where $\theta$ is a vector of parametric decision variables describing the operating policies as explained in section 4.2.2, $U(\cdot)$ are the MG operation decisions for controllable local generation and buying/selling with the grid. The first set of constraints represents the generation capacity, charge/discharge and ramping limits; followed by the energy storage ($ES$) balancing constraint. The third constraint ensures minimum reliability limits for all policies, as explained in the objective definition.

### 4.2.2 Formulation of Operating Policies

![EMODPS pipeline](image)

**Feedback:** Parameters of Control strategies

**Input:**
- Ensemble of Wind
- Solar Load Prediction
- Grid Price Signal and other system parameters

**Simulation Model:**
MG daily operation across N scenarios

**Optimization Algorithm:**
MOEA--Borg

**Output:**
- Expected Objective Performance: Revenue Emission, Reliability

Figure 4.1: EMODPS pipeline: The simulation model uses the parameter ($\theta$) values and exogenous information to simulate the MG operation over 1000 system scenarios. The expected objective performance is then used by the Borg MOEA to generate next set of parameter ($\theta$) values, thus completing one function evaluation of the formulation.

Instead of optimizing for hourly generation and energy exchange decision variables, the EMODPS methodology generates parametric operation policies that help make these decisions. These operating policies are flexible, nonlinear functions that do not require an assumed mathematical form but can universally approximate a variety of functional shapes [61]. For the purpose of this study, cubic radial basis functions (RBFs) are used to parametrize the policies for local generation and energy exchange decisions.
RBFs have been proven to be efficient universal approximators and are widely adopted in many applications [63].

Equation (4.1) represents RBF-based operation policies, where \( U_{gen/buy/sell}^t \) are the hourly generation and buy/sell decisions for the MG as a function of time varying inputs

\[
U_{gen/buy/sell}^t = \sum_{j=1}^{n} w_j \left( \left| \frac{(x_t) - c_j}{r_j} \right| \right)^3
\]  

(4.1)

where \((x_t)\) represents input (battery storage level and hour of the day) at time \(t\); \(n\) is the number of RBFs; \(w_j\), \(c_j\) and \(r_j\) are the weights, centers and radii, respectively of \(j^{th}\) RBF associated with the generation or buy/sell decision. The centers, radii and weights of the RBF policies compose the decision variables, \(\theta\), as described in the optimization formulation. The goal of EMODPS is to optimize these parametric decision variables and find a non-dominated set minimizing the system objectives. For example, \(\theta_p = [w_j, c_j, r_j]\) where \(j\) is the number of RBFs could represent set of parameter vectors used to define the RBF for making generation decisions. In this study there is a set of parameter vectors each for the diesel generator and the utility buy/sell decisions. For each decision \(n = 2\) RBFs, are used with parameter limits set as \(w_j \in [0, 1]\), \(c_j \in [-2, 2]\), \(r_j \in (0, 2]\). The parameter vectors are then optimized with the help of MOEAs. These limits were selected after experimenting with multiple ranges and number of RBFs. The preferred ranges may differ, as they are dictated by the needs and the resources available to the operator. For example, setting a higher range translates into a larger decision space which will require more computation time to effectively explore, while setting a more restrictive range might result in less comprehensive results. More detailed mathematical descriptions of each of the objectives, the optimization formulation, and the RBFs are provided in Appendix.
4.2.3 Model Implementation Pipeline

The EMODPS framework is a simulation-based optimization framework that has the core elements of any simulation-based approach as shown in Figure 4.1. In the loop, the simulation module models the battery state transition subject to power balance constraints. The input of the simulation module consists of two sources: exogenous information and feedback from the optimization strategy. For this study, the exogenous information consists of: wind, solar and load predictions; the grid price signal and other system parameters as described in the Appendix.

The formulation begins by defining initial policies for the buy/sell and generation decisions, based on randomly chosen parameter ($\theta$) values. These policies are then used to simulate MG operation over 1000 different system scenarios based on the exogenous information. The outputs of the simulation module are the expected objective performances. These objective values act as feedback when they are passed to the Borg MOEA; which then updates the parameter ($\theta$) values. These updated parameters are then sent back to the simulation module for the next function evaluation. This process is repeated for a pre-decided number of function evaluations. The Borg MOEA was parameterized according to the user guidelines[31].

4.3 Results

Given the candidate control strategies generated using the EMODPS formulation, the next steps in the decision analysis framework are to analyze performance and implement robustness of the candidate policies.

This section details various experiments to test the policies, and is organized as follows: Section 4.3.1 describes the system conditions and parameters for the test microgrid. Section 4.3.2 evaluates the solution performance (diversity and convergence) of
the EMODPS methodology, followed by an out-of-sample performance verification for the control policies in section 4.3.3. Section 4.3.4 focuses on the operational tradeoffs in the system and limitations of objective performances. Section 4.3.5 analyzes the aggregate and hourly performances of select policies across the different objective spaces. A comprehensive robustness analysis is performed in section 4.3.6 to explore policy performance under highly uncertain scenarios.

4.3.1 System Overview

The decision framework is implemented on a test MG system consisting of a battery, a diesel generator, critical and interruptible loads, and connection to the macro grid. The MG has a peak load of 220 kW with a battery size of 200 kW. Installed capacity for wind and solar is set to be 20% and 10% of peak load, respectively. The load, wind, solar, and real-time market energy price distributions were obtained by projecting daily CAISO data on to the test system [1]. For this study, load, wind, and solar are modeled as uncertain parameters with a baseline variation of 10% at any given hour. All other parameters used for the study are provided in the Appendix.

The DPS policies were optimized by simulating over \( N = 1000 \) randomly sampled scenarios of load requirements, as well as wind and solar generation. The EMODPS approach generated 3000 pareto-approximate control policies that could be implemented to control the daily operations of the MG in consideration (Figure 4.3).

4.3.2 Evaluation of Solution Performance

A key concern with multiobjective formulations and algorithms is the ability to measure goodness of solutions, relative a hypothetically perfect solution. Such a comparison is not straightforward because MO algorithms do not generate a single scalar ‘best-fitness’
value which can be subjected to univariate statistical tests. Instead, the optimized solution is a non-dominated collection of vectors (given any two vectors in such a set that are not equal on all objectives, one cannot be better or equal to the other on all objectives - i.e. no vector in the set dominates another[22]) which is also called an approximate-pareto front. These non-dominated sets of solutions need to be judged on two criteria; 1) Convergence - the proximity of the approximation set to the true Pareto Front; and 2) Diversity - the distribution of the approximate set over the objective space. In MO literature, one measure that has been accepted to verify the goodness of a pareto-approximate set, by capturing both convergence and diversity, is the hypervolume metric. The hypervolume metric is a measure of the multi-dimensional “volume” of space dominated by a set of Pareto approximate solutions [89] and can be used as a measure to an algorithms effectiveness in attaining high quality approximations of a problem’s Pareto frontier. This is especially useful in cases like the current MG study with no prior assumptions of factors such as preference for certain objectives, or particular regions of tradeoff surface. The metric can be used to quantify the relative quality of the approximate pareto sets generated using the EMODPS methodology.

For the purposes of this study, Borg MOEA was used to solve the multi-objective optimization. Borg MOEA is a stochastic optimization algorithm where the search depends on the initial values of the parameter population which are different for each random seed. To ascertain goodness of solutions generated using Borg MOEA:

- The energy management operation problem was solved for 60 different random seed runs. Performing a random seed analysis allows one to control for variability and evaluate the consistency in search performance.
- Each seed was run for 150,000 function evaluations (shown in Figure 1) in order to provide sufficient time for the Borg MOEA to attain high quality approximations of the tradeoffs for the three objectives.
- A best solution set or reference set was computed by aggregating the terminal set
of solutions found by each seed run and re-sorting them into one set. Thus, hypothetically, this reference set represents the closest approximation of the optimal pareto set.

- For each seed run, hypervolume was calculated at every 1000 function evaluations. These values were then normalized by the hypervolume achieved by the reference set.

Figure 4.2: Relative Hypervolume vs. the number of function evaluations for 60 different seed runs. Majority of the seeds performed within 90% of the reference set.

Figure 4.2 visualizes the performance of each seed run. Each line depicts the relative(normalized) hypervolume vs. the number of functions evaluations (NFEs) for a different seed run of the Borg MOEA. With majority of the seeds performing within 90% of the reference set, it is evident that Borg MOEA performs well in this context of this study.
Figure 4.3: Objective performances for the reference set across the three objectives. The x-axis represents emissions in kilograms, y-axis illustrates the need for interruptible load, and z-axis is for revenue. The upper left corner represents ideal performance for each objective.

The reference set result can be seen in Figure 4.3 depicting performance across the three objectives. The x-axis represents emissions in kilograms, y-axis illustrates the need for interruptible load, and z-axis is for revenue. The ideal point for the three objectives is near the upper left corner. The solution strategies have been discussed in detail in sections below.
4.3.3 Out of sample Performance Verification

Before considering the control policies in detail, it is necessary to verify stability of performance outside of the training set. This is analyzed by simulating daily MG operation under the candidate policies over 1000 out-of-sample scenarios for load, wind, and solar generation, where out of sample scenarios are generated under similar uncertainty characteristics.

A first criterion is validation against the interruptible load constraint. As previously described, this constraint ensures that expected interruptible load performance for each policy provides at least 21 reliable hours in a day. In other words for any viable policy, an average day should serve all loads at least 90% of hours. All of the candidate control policies satisfied this criteria in the out-of-sample test.

The second step was to validate the performance of these policies in the objective spaces using the out-of-sample results, to ensure that the policies didn’t overfit to the training data. The results of the reevaluation are shown in Figure 4.4. Within each plot, points representing the control policies are positioned along the primary axis at their expected objective values achieved in optimization, and along the secondary axis at

Figure 4.4: Policy performance validation via out-of-sample testing. Markers represent average policy performance on scenarios from the training set (primary axis) and out-of-sample scenario sets (secondary axis) for each of the three objectives. Solutions with stable performance out-of-sample lie near the identity line.
their objective values in validation. Each plot is oriented such that the lower left corner represents the most favorable direction, and solutions that achieve similar performance in optimization and validation will fall near the identity line. Examination of Figure 4.4 shows that the policies generalize well on the validation set. If the markers are above (below) this line, the policies improved (degraded) in out of sample tests. While the policies remain stable under out-of-sample conditions, it is no yet known whether policies remain robust if the uncertainties used during the training are poorly characterized. This will be further explored in Section 4.3.6.

4.3.4 Objective Performance and Tradeoffs

Having established the stability of the control policies outside of training data, it is important to analyze the performance of the policies across multi-objective space. Figure 4.5 is a parallel axis plot that highlights policies and their performances across the candidate set of policies.

Both the diversity of solutions, as well as trade-offs across the three stakeholder objectives are shown in Figure 4.5, which is oriented such that the top of the axis represents best performance for the objective. Each line is a policy shaded according to performance on the revenue objective across the test scenarios. Examination of Figure 4.5 shows a strong trade-off between the revenue and emissions objectives. However, introduction of the interruptible load objective complicates this relationship. For example, high revenue (or low emissions) policies can reside on both low and high end of interruptible load spectrum based on the emissions (or revenue) strategies. In general, policies portray behavior which would be difficult to predict and replicate a priori, using a scalarized or single objective optimization. This representation is a useful tool for stakeholders and operators to explore the dynamics of the system, as well as the limits and trade-offs of objective performance.
Figure 4.5: Performance diversity and trade-offs across the objective space is shown with parallel vertical axes each representing one objective.

As can be seen from Figure 4.5 performance in one objective space impacts the other dimensions. These relationships can be studied in greater detail using Figures 4.6 and 4.8.

The pareto front in Figure 4.6 depicts the combined expected daily performance of each control policy in revenue and emissions objectives, with the arrows indicating the direction of preference. Each policy is shaded to represent the influence use of interruptible load. The ideal performance for a policy would be at the top left corner of the figure representing maximum revenue and minimum emissions. However, existence of significant tradeoff between the revenue and emissions means that no policies can achieve the ideal performance. The policies near the upper right favor the revenue ob-
Figure 4.6: Two-dimensional representation of performance tradeoffs between objectives: revenue (ordinate), emissions (abscissa), with colorbar representing influence of interruptible load. Ideal performance with maximum revenue and minimum emissions would appear at the top left corner of the panel.

Objective over limiting emissions, while policies favoring minimal emissions appear near the lower left corner. Policies near the curve of the pareto front represent a more balanced performance across the two objectives. The shading in the figure represents the daily expected interruptible load requirement for each policy. As the vertical gradient of color is fairly consistent across the emissions axis, it can be inferred that for a fixed emissions level, revenue can be improved by leveraging interruptible load.

Figure 4.7 provides a closer look at the impact of interruptible load by showing the revenue impact of one additional kW of flexible load on the revenue objective, at each level of emissions, computed from the gradient in Figure 4.6. The value of flexible load is highest at lower emissions and decreases rapidly for increasing emission levels. The highest emission policies are already maximizing revenue performance, so there is little additional benefit available from interruptible load. Figures 4.6 and 4.7 illustrate the potential to quantify the inherent value of flexible load in the system through these
these control policies, which can be very difficult to ascertain \textit{a priori}. With the ability to quantify the flexibility in the system, stakeholders can make informed decisions to maximize MG benefits.

Figure 4.7: Marginal benefit of an additional kW of interruptible load on expected revenue, across the range of emissions levels. This analysis can enable better exploration of economic benefit of flexibility.

The pareto front in Figure 4.8 illustrates the trade-off between revenue and interruptible load objectives for each policy, with the colorbar now representing emission performance. Although the relationship between the two objectives is more complex relative to 4.6, the tradeoff in performance between revenue and IL is significantly weaker. For example, there exist policies that can attain high revenue performance with very low interruptible load requirements.

Additional complexity is noted as the pareto front breaks into to distinct frontiers at higher revenue levels, representing discontinuity in possible performance levels for the objectives. Further analysis of policy performance reveals that this break is attributable to the energy exchange limit set for the test microgrid, set at $50 \text{ kW/hr}$ (as noted in the
Figure 4.8: Two-dimensional representation of performance tradeoffs between interruptible load and revenue, with emission levels represented by the colorbar.

Appendix). For example, Figure 4.9 shows the pareto front obtained by re-simulating the policies under conditional of 60 kW/hr exchange limit with the main grid, showing a more consistent pareto front.

Figures 4.5, 4.6 and 4.8 provide daily expected performance without insight into variability of these performances. Analyzing the variability in these solutions can provide deeper understanding of performance consistency and trade-offs across multiple objective. The standard deviation in objective performance of policies across a 1000 day out-of-sample set is shown in Figure 4.10. The primary and secondary axes represent the variation in load and revenue objectives, respectively, while the color gradient matches variation in emissions. Policies closer to lower left corner with the darkest markers, represent most consistent performances in revenue, load and emissions objectives respectively. Consideration of Figure 4.10 illustrates that policy performances range from fairly consistent to wildly varying, and consistency in one objective generally comes at the cost of another. Specifically, there appears to be a strong trade-off
between consistency in revenue and load objectives, especially when the variation in emissions objective is low. For example, policies closer to the bottom right corner of the figure have high revenue and emissions consistency but high variability of the load objective, whereas policies with higher variation in emissions (near the lower left corner) can achieve higher stability for both revenue and load objectives.

As demonstrated, the methodology allows for crucial insights into the operational tradeoffs across the objectives which can be pivotal in decision making processes. By re-simulating the policies, without re-training, decision makers are provided information about performance and limitations across the system. Such a tool could a meaningful tool in MG design and operational planning. For example, the ability to quantify the marginal value of flexible loads, as previously demonstrated, can potentially inform development of demand response programs in microgrids.
Figure 4.10: Standard deviation of objective performances for each policy with interruptible load and revenue on the primary and secondary axes, respectively, depicting a strong tradeoff between consistency in revenue and load objective performance.

4.3.5 Policy Analysis

The EMODPS optimization results in a large and diverse set of candidate policies, shown in Figures 4.5 through 4.10. A key benefit of this framework is the ability to explore candidate policies, to analyze and compare performance based on diverse stakeholder preferences. In this Section, the candidate policies are further analyzed in this context. To structure these results, the policies are categorized into three sets based on expected objective performance, with daily expected performance and hourly characteristics explored in sections below.
Daily Expected Performance of Select Policies

The policies can be selected according to preference for performance across the three objectives. For illustrative purposes, Figure 4.11 is based on three possible sets of criteria.

- **High Revenue policies** with average revenue performance in the 70th percentile (higher than 70% of the policies).
- **Low Emission policies** with average emissions in the 30th percentile (lower than 70% of policies).
- **Balanced policies** exhibit revenue in the 40th percentile, emissions in 70th percentile and interruptible load requirement in the 30th percentile.

![Figure 4.11: Performance trade-offs across the three objectives for a selection of high revenue, balanced and low emissions policies.](image)

Figure 4.11 shows the average performance of select policies across the out-of-sample set. High revenue policies will be well suited for stakeholders with clear preference for revenue generation, however, the environmental implications of such an operation...
strategy is evident. For stakeholders with the goals of lower environmental impact, the emissions and reliability criteria provide a wide range of low emissions policies to meet this goal, with the associated sacrifice in revenue. For a more moderate daily performance, balanced policies can be explored to provide a good compromise between the revenue and emissions.

Before implementing one of these policy types for MG operation, an hourly analysis can provide better understanding of how the different policy types achieve the respective objective performance as shown in section below.

**Hourly Performance of Select Policies**

While the previous section explores expected annual policy performances, hourly information can be useful in understanding the dynamics of policy decisions, and the mechanisms by which the policies achieve their objectives under various system conditions. This section focuses on analyzing the hourly performance of the high revenue, low emission, and balanced policy types for key metrics. Hourly results for additional metrics are provided in the Appendix. Figure 4.12 compares the hourly dynamics of each of the representative policy types for three key system conditions. Each column represents a policy type; the first row depicts diurnal pattern of net-load variation in the validation set, which is the same for all policies, and subsequent rows provide a box-plot for emissions, battery use, and energy exchange with main grid, respectively. Thus, the plot shows the hourly distribution of above metrics including quartiles and outliers.

Beginning with the emissions objective, Figure 4.12 shows that the high revenue policy is generally insensitive to the emissions and focuses on revenue generation, with peak emission levels aligning with highest net-load (and thus price) hours as the policy favors local generation for storage and sale to the main grid. Conversely, the low emissions policy follows the net load curve as it prioritizes controlling emissions entirely by
Figure 4.12: Comparison of box-plots of hourly performance for various system metrics, across a representative of high revenue, low emissions, and balanced policy types, which illustrates diverse behaviors among policy types.

regulating local generation (details in Appendix). Correspondingly, the buy/sell pattern shows that lower-emission sources are leveraged from the main grid up to the limit of 50 kW/hr, undermining the revenue potential. This decision pattern also renders the policy unusable if the goal of MG is self-sufficiency.
Between these two extremes, the balanced policy shows a tendency to regulate emissions early in the day by buying power from the main grid when there is energy surplus and capacity to store in the battery. While the high revenue policy prioritizes selling throughout the day, the balanced policy tends to sell only later, when prices would tend to be higher. Battery level differences among the policies lead to differences in the use of interruptible load, which is used at much higher levels in the high revenue policy (see Appendix).

These results demonstrate the ability to deconstruct and analyze hourly decisions made by representative policies. This ability to contrast and compare decision behavior can be an effective tool in understanding trade-offs and selecting the preferred operation strategy for the system. As can also be seen from Figure 4.12, the hourly behaviour is complex and can vary from the expectation. Therefore, the ability to analyze hourly decisions \emph{a-posteriori} can elucidate performance limitations of policies. For example, analysis can be deconstructed a step further to identify specific load, wind and solar scenarios resulting in deviation from the expected behavior which can allow the operator the ability to make appropriate adjustments.

\subsection*{4.3.6 Robustness Analysis}

A realistic concern regarding the application of EMODPS control policies, is the possibility that the training data and scenarios may not completely characterize potential uncertainties. In this case, we consider unplanned scenarios of the uncertain system parameters such as system load or generation from variable renewable sources. Inaccurate characterization of wind and solar generation pattern, or lack of consensus regarding the daily load, could result in real-world scenarios that are not included in the training data during the optimization process. To address this concern, additional analysis follows to identify robust policies that perform well under a broad range of potential system characteristics.
The robustness analysis implemented in this case study is based on many-objective robust decision making (MORDM) framework as developed in [42, 63], and includes the following steps:

1. Re-evaluation of the candidate control policies across an extended uncertainty set, generated by explicit sampling outside of the initial uncertainty.
2. Comparison of performance under extended uncertainty with results under the initial training set.
3. Quantify generalization of policies across new uncertainty conditions, based on a pre-defined performance criterion. For example, daily reliability is a key measure of robust performance.
4. A final step includes a sensitivity analysis to identify key system parameters affecting policy performance

![Figure 4.13: Performance validation of the policies under Configuration 1 vs. Baseline optimization. All objectives remain fairly stable across the 1:1 line therefore the policies generalize reasonably well to increased uncertainty in wind, solar and load.](image)

**Policy Performance under Increasing Uncertainty**

To assess the robustness of solutions, the candidate policies were tested and evaluated under two additional system configurations;
Figure 4.14: Comparing performance of the policies under second configuration with baseline configuration. Revenue objective shows stability to increased uncertainty, while emissions and load objectives show less stable performance, signaled by deviation from identity line.

- Configuration 1: To test robustness to underestimation of uncertainty in the training set, uncertainty in solar and wind generation are increased by 40% and 50% respectively, while load uncertainty is increased to 15%.

- Configuration 2: Additional operational uncertainty is added to the system, with randomness added to initial battery state of charge, across the available range (40 kWs to 160 kWs). Thus, there will be scenarios in this configuration with extra energy in the system at the beginning of the day as compared to optimization conditions.

To test the policies under these new conditions, one thousand daily (24 hours) scenarios were generated under the updated parameter assumptions, using the latin hypercube (LHS) sampling method. LHS is a stratified sampling method that is known to provide significantly better coverage of the extreme cases in high dimensional sampling space, relative to a standard random sampling method [52]. The results of this analysis are shown in Figures 4.13 and 4.14.

The performance of candidate policies on revenue, emissions, and interruptible load objectives, under increasing uncertainty of wind, solar, and load scenarios is shown in Figure 4.13. Once again, performance is compared to baseline performance under the
initial uncertainty set used in training and policy selection. Examination of this figure shows that the policies perform very well under increased uncertainty for revenue and emissions objectives. The deviation of interruptible load objective performances (panel 3) shows more deviation from the identity line, indicating that while the policies continue to perform reasonably well, additional flexibility from loads is used to manage increasing uncertainty.

When the increased uncertainty in wind, solar, and load are further extended by introducing uncertainty in the initial level of stored energy each day, clear degradation in policy performance is visible across all objectives in Figure 4.14. Notably, the emissions and load objectives show significant inconsistencies, which are particularly severe in case of the interruptible load objective. It is worth noting that the inconsistent performances are sometimes improving and sometimes degrading, which is a result of variation in stored energy available at the start of the day.

**Selecting Robust Policies**

Results shown in Figure 4.14 highlight the interruptible load objective as most sensitive to unplanned increases in uncertainty. Therefore, it is worthwhile to focus on this objective as a criteria for identification of the most robust policies from within the candidate set. While the optimization stage includes a constraint requiring that any viable policy should have, on average, 90% reliable hours in a day, this may not translate to consistent reliability over all 1000 days of simulation. Indeed, it is fair to expect that there are some policies that are more or less reliable throughout the day, and given the large number of candidate policies, it is sensible to use robustness to this important criterion to further refine the policy set. To identify these more robust policies, the robustness criterion is now introduced such that 99% of the scenarios meet the 90% reliability criterion, i.e. a policy has to be reliable for more than 990 scenarios out of the 1000 to be considered robust. This differentiation is illustrated in Figure 4.15.
Figure 4.15: Daily reliable hours for a robust and non-robust policy, where primary axis represents all daily scenarios against the number of reliable hours on the secondary axis, showing that reliability constraints target average performance, with a smaller subset of scenarios that can be considered robust.

This robustness criterion can also be applied to analyze policy performance under different configurations of the system; under the baseline configuration, approximately 56% of the policies satisfied this reliability-based robustness criterion. As uncertainty is increased in renewables and system load, the percent of policies that meet the criteria declines to 32%, while only 9% of the policies satisfy the criterion when uncertainty in initial battery state is added.

These results demonstrate the resiliency of operating policies generated via the EMODPS methodology, as some policies generalize well even the system is operated outside the baseline settings. In addition, results of a robustness can be used to refine the decision makers’ policy preference. It is worth noting that it would be fairly difficult to predict robustness of solutions \textit{a priori} which limits the ability to conduct these types of analyses using traditional mathematical optimization methods, as often seen in power system operations and planning literature. With this information about policy
robustness, the natural step is to attempt to identify the factors that are influencing lack of robustness.

**Sensitivity Analysis**

The robustness analysis can be extended to explore the influence of specific system parameters on policy performance across different objectives, using a scenario discovery and factor mapping analysis[13, 63]. This is an accepted method to identify parameter ranges (or combination of parameter ranges) that lead to drop in objective performance. This methodology have been shown to be effective on non-linear interactions between model parameters, in a way that isn’t possible for some other potential approaches such as Patient Rule Induction Method(PRIM) [21], and Classification and Regression Trees(CART) [12].

For illustration purposes the sensitivity analysis has been performed on two different policies A and B. Policy-A has higher expected revenue, while Policy-B performs slightly better on emissions, and both have similar expected interruptible load requirements. The results of analysis on Policy-A are represented in Figure 4.16 as a two-dimensional projection of the 1000 scenarios, where each row represents an objective while the columns explore different parameter combinations impacting performance. Each marker represents a 24 hour scenario which is shaded blue (success) if the objective performance meets the criterion and red (failure) otherwise. For the purpose of this analysis, success/failure across each objective is set to be one standard deviation below the expected daily performance from the policy under baseline conditions.

Considering objective sensitivity across parameters ranges for Policy-A in Figure 4.16, it is clear that the revenue objective is sensitive to initial battery states as all three panels for the revenue objective perform well in regions of high initial battery state, and failures are more common at lower initial states of charge. There is also important interaction of battery and load uncertainty, with performance failures more
Figure 4.16: Combination of uncertain parameter values leading to failure for policy-A. Each dot represents a day/scenario for the policy with blue color depicting successfully meeting the performance criterion while red color meaning failure. The figures show that policy-A evolves into a high revenue policy as revenue and load objectives perform well under high uncertainty while sacrificing performance of emissions objective.

likely at load uncertainty of 10 % or higher, which are mitigated in scenarios where battery is charged at 120 kWs or higher at the beginning of the day. Overall, the revenue objective is negatively impacted by high variations in load and wind parameters, but is mitigated by high battery charge at the beginning of the day.

The interruptible load objective (bottom panel of Figure 4.16) follows a similar pattern with increased sensitivity to load and wind uncertainties. Comparing different parameter combinations, Policy-A is likely to fail at even moderate load and wind uncertainties, when combined with low initial battery charge. Similar to the revenue objective for battery states of 120 kWs or higher the extra energy in the system is able to compensate for the high wind and load variation.
In contrast, the emissions objective is highly sensitive to initial battery charge with more moderate impact from variation in wind and load parameters. The policy performs remarkably well for the objective below initial battery states of 140 kWs after which there is a significant drop, and the performance of other objectives improve markedly. This indicates that the policy gives preference to revenue and load performance, at a cost to the emissions objective. In this case, high initial battery charge generates revenue by selling excess energy to the grid, requiring increased local generation later in the day to satisfy load requirements. For comparative purposes, this sensitivity analysis is also conducted for Policy-B, showing distinctly different behaviors, despite the fact that both Policy-A and Policy-B are both ‘balanced’ policy types. For brevity, Policy-B results are included in Appendix.

The above analysis demonstrates the ability of policies to adapt, even to significantly uncertain system conditions, and to identify interactive effects that lead to poor performance. Specifically, in this case study, it is shown that revenue objectives are less sensitive to system uncertainty than emissions and interruptible load objectives, and high initial battery charge can nullify impacts of variability in load and wind parameters across all objectives. This analysis highlights the value of the EMODPS framework in this application, providing the flexibility to explore system operation across a range of candidate policies and system parameter, and the provision of greater insight into trade offs among objectives.

4.4 Conclusion

As power systems become increasingly distributed and microgrids become more common, performance expectations from stakeholders will in turn become more diverse and complex. Managing such a system with economic, environmental and societal considerations will lead to complex perspectives and trade offs that must be considered.
In this study, an EMODPS based robust decision making framework is implemented for a microgrid energy management operation to explore its ability to address many of these challenges. By directly parameterizing operating policies for the system and optimizing the parameters of those policies, the methodology can exploit the information available in larger scale system simulations. The resulting policies provide a diverse set of operating strategies, which can help quantify the inherent tradeoffs between stakeholder objectives. As these policies are parametric relationships, they enable exploration of alternative decisions based on system states, without having to re-optimize. This approach also allows detailed exploration of questions of robustness and flexibility in system operations under significant sources of uncertainty.

This ability to resimulate daily operation of the microgrid, one can comprehensively analyze the decision making process of the policies under varying system conditions. As shown in the study, this allows the exploration of the limits of the system, as well as the ability leverage individual or combined components in the system to improve performance. The robustness analysis also demonstrates the adaptability of the policies even under unplanned and highly uncertain system configurations. This analysis highlighted policies that generalized well under the unplanned scenarios, and the framework allows the system operator to analyze the impact of changing combinations of system parameters on policy performance. Finally, this framework can be used as an efficient tool for decision makers and stakeholders to not only communicate objectives, but also understand the limitations of the system which can generate a healthy dialogue and help improve stakeholder participation.

This methodology also opens up many interesting directions for future work. The flexibility of the framework allows for objective formulations other than expected performance. In fact, comparing different formulations can further help understand the nature of operational tradeoffs across the system. The key challenge of microgrid design and optimal configuration can be tackled using this framework as decision makers will be able to compare and contrast long term performances of candidate configura-
tions. The approach could also be used to test systems under islanding conditions, to better prepare control strategies. The objective of this work was to explore the applications of this framework on a test microgrid, however, future implementations could leverage more detailed underlying models for detailed network representation in a hybrid formulation. The microgrid initiative under the US Department of Energy highlights the need for tools that allow for multiobjective formulations and enhance consumer participation [74]. This framework has shown the ability to satisfy both of these goals and more.

4.5 Appendix: System Configuration

Cost parameters: \( C_{\text{gen}} = 0.25 \text{ ct/kWh}, \ C_{\text{wt}} = 1.0 \text{ ct/kWh}, \ C_{\text{pv}} = 2.0 \text{ ct/kWh}, \ C_{ES} = 0.30 \text{ ct/kWh}. \) Emissions factor: \( C_{ES} = 0.437 \text{ kg/kWh}. \) Reliability criteria: \( d_{\text{crit}} = 95\%. \) System limits: \( p_t \in [80, 200] \text{ kW}, \) \( ES_t \in [40, 160] \text{ kW}. \) Buy/Sell limits: \( e_t \in [-50, 50] \text{ kW}. \) Ramp limits: \( p_t \in [-50, 50] \text{ kW}. \)

4.6 Appendix: Formulation

The revenue objective is calculated as the expected value over \( N \) simulations of daily revenue as represented below.

\[
O_1 = -\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \left( C_{\text{gen}}(p_{i,t}) + \alpha_t(e_{i,t}) + C_{\text{wt}}(wt_{i,t}) + C_{\text{pv}}(pv_{i,t}) + C_{ES}[ES_{i,t} - ES_{i,t-1}] \right) \tag{4.2}
\]

where \( p_{i,t} \) and \( e_{i,t} \) are generation and grid exchange decisions, \( wt_{i,t} \) and \( pv_{i,t} \) are...
the wind and solar generation, and $ES_{i,t}$ is the battery storage level for simulation $i$ at time $t$. The exchange decision $e_{i,t}$ takes negative values when selling to the grid and positive when buying. $C_{gen}$, $C_{wt}$ and $C_{pv}$ are the cost for diesel, wind and solar generation while $C_{ES}$ is the battery charging/discharging costs. $a_t$ represents the real-time energy prices to buy or sell from or to the utility at time $t$.

### 4.6.1 Emissions Objective

Equation 4.3 defines the emissions objective which is the expectation of daily emissions over the $N$ simulations. The formulation assumes emissions from diesel generation and any energy bought from the grid as shown below.

$$O_2 = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \left( C_{ef}(\max(e_{i,t}, 0) + p_{i,t}) \right)$$  \hspace{1cm} (4.3)

where grid emissions are non-zero when $e_{i,t} > 0$ and $C_{ef}$ represents the carbon emissions factor.

### 4.6.2 Reliability Objective

The objective is defined as reliability in the system under consideration and is utilized to explore the limits of IL in a MG system. The structure of the objective is set to quantify load flexibility at each hour. The objective, $O_3$, is the expected percentage of hours in a day when demand response is required as shown below.
\[
O_3 = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \varphi_{i,t}
\]

\[
\varphi_{i,t} = \begin{cases} 
1, & 1 - \frac{d_{DR,i,t}}{d_{i,t}} > d_{crit} \\
0, & \text{otherwise}
\end{cases}
\quad (4.4)
\]

where \( d_{DR,i,t} \) is the hourly flexible load for simulation \( i \). This implies that any given hour in a day is considered reliable i.e. \( \varphi_{i,t} = 1 \) when \( d_{DR,i,t} \) is less than a predefined critical threshold percentage, \( d_{crit} \), of the hourly load \( d_{i,t} \). For the purpose of this study \( d_{crit} \) was set to be 0.95 which implies that at any given hour a maximum of 5 percent of \( d_{i,t} \) can be curtailed.

### 4.6.3 Optimization Formulation

The three objectives are optimized simultaneously subject to constraints defined in equations (4.5) - (4.11). The optimization problem is formulated as described below.

\[
\min_{\theta_p, \theta_e} (-O_1, O_2, -O_3)
\]

\[
p = (p_{1,i}, p_{1,i}, \ldots, p_{T,i})
\]

\[
e = (e_{1,i}, e_{1,i}, \ldots, e_{T,i})
\]

s.t.

\[
ES_{i,t+1} = ES_{i,t} + w_{i,t} + p_{i,t} + e_{i,t} + p_{i,t} - (d_{i,t} - d_{DR,i,t}), \forall i \in N, t \in T
\]

(4.5)
\[ p_{i,t} - p_{i,t-1} \leq p_{\text{rmp,up}}, \forall i \in N, t \in T \]  
\[ p_{i,t-1} - p_{i,t} \leq p_{\text{rmp,down}}, \forall i \in N, t \in T \]  
\[ P_{\text{min}} \leq p_{i,t} \leq P_{\text{max}}, \forall i \in N, t \in T \]  
\[ E_{\text{min}} \leq e_{i,t} \leq E_{\text{max}}, \forall i \in N, t \in T \]  
\[ |E_{\text{s.i},t+1} - E_{\text{s.i},t}| \leq E_{\text{chg/dischg}}, \forall i \in N, t \in T \]  
\[ E_{\text{s.min}} \leq E_{\text{s.i},t} \leq E_{\text{s.max}}, \forall i \in N, t \in T \]  

where equation (4.5) is energy balance constraint for the system dependent on battery storage levels at any time \( t \), equations (4.6) and (4.7) are the ramping constraints for the diesel generator, equations (4.8) and (4.9) are the upper and lower limits for the generator and energy exchange with the grid, equation (4.10) represents the limits on charging/discharging of the battery and equation (4.11) is the bounds on battery storage level. The formulation is solved to optimize the three objectives by finding the best set of parameters \( \theta_p \) and \( \theta_e \) for the operating policies \( p \) and \( e \).

### 4.6.4 Operating Policy Formulation

In this study cubic RBFs are implemented as the control policies described in section 4.2.2. The battery storage level and hour of the day \( t \) are the input variables representing the system state, which are then mapped to hourly diesel generation and buy/sell decisions as shown in equations (4.12) and (4.13).

\[ p_{i,t} = \sum_{j=1}^{n} w_j \left( \frac{|E_{\text{s.i},t} - c_j|}{r_j} + x_t^2 + y_t^2 \right)^3, \forall t, i \]  
\[ e_{i,t} = \sum_{j=1}^{n} w_j \left( \frac{|E_{\text{s.i},t} - c_j|}{r_j} + x_t^2 + y_t^2 \right)^3, \forall t, i \]
where \( x_t = \sin(2\pi t/T - a_1) \) and \( y_t = \cos(2\pi t/T - a_2) \). \( p_{i,t} \) and \( e_{i,t} \) are the policy-prescribed generation and buy/sell decisions at hour \( t \) for sample \( i \); \( ES_{i,t} \) is the battery storage level at a given hour; \( n \) is the number of RBFs; \( x_t \) and \( y_t \) are phase shifted \( \sin(.) \) and \( \cos(.) \) functions for cyclic representation of time; \( w_j, c_j \) and \( r_j \) are the weights, centers and radii, respectively of \( j \)th RBF associated with the generation or buy/sell decision; and \( a_1, a_2 \) are the phase shifts on \([0, 2\pi]\).

### 4.7 Appendix: Additional Results

#### 4.7.1 Detailed Hourly Analysis of Select Policies

Expanding on Section 4.3.5, the following analysis discusses hourly performance of all system metrics for a policy belonging to each policy type (high revenue, low emission and balanced).

Looking at the revenue objective in Figure 4.17, the high revenue and balanced policies show a similar diurnal trend in which revenue peaks coincide with net-load, indicating that the policies are taking advantage of high electricity prices at those hours. The major difference being the better overall performance of the high revenue policy as compared to the balanced policy. Another key difference is that the high revenue policy prioritizes revenue generation in the early hours of the day, whereas for balanced policy it is concentrated in later half. This pattern is further evident in Buy/Sell metric figures. Due to this focus on revenue generation early in the day the battery levels for high revenue policy tend be relatively lower later in the day which leads to higher requirement for interruptible load. In comparison, for the low emissions policy, the
revenue objective pattern is markedly different as the policy tends to lose revenue during peak load hours as the policy tends to buy from the grid to satisfy high load requirements. The variation in hourly revenue performance is also decidedly higher in low emissions policy, compared to the other policy types, with a strong tendency toward losses, indicating the poor revenue performance of the policy. Focusing on the emissions objective, the focus of the low emissions policy becomes evident as hourly emissions follows the same trend as the net load curve. This pattern is possible because the policy prioritizes controlling emissions entirely by regulating local generation as can be seen in Figure 4.17. As a result the policy depends on the grid for meeting load requirements, hence, undermining the revenue potential. This decision pattern renders the policy unusable if the goal of MG is self-sufficiency. An interesting byproduct of this decision behavior is the interruptible load requirement pattern. The low emissions policy requires load flexibility during hours of low local generation and battery level which do not coincide with peak load hours, instead occurring at beginning and middle of the day. As expected the high revenue policy tends to be generally insensitive to the emissions objective, with high local generation for majority of the day. The policy does tend to reduce generation for a few hours early in the day when battery levels are nearing upper limits and there is an energy surplus in the system. The balanced policy, however, tends to mimic the low emissions policy for the first few hours of the day by making similar generation and buy/sell decisions. The focus turns to revenue generation from hour 5 onward with local generation at maximum capacity and high selling pattern to the grid. However, it does attempt to reduce emissions again just before the second load peak from hours 12 to 14.
4.7.2 Sensitivity Analysis - Policy B

Continuing the discussion on sensitivity analysis, this section discusses behavior of Policy-B. Considering the results in Figure 4.18 the emissions and revenue objectives show similar behavior to the different parameter values. Both objectives markedly outperform the performance criterion. High initial battery values essentially nullify any negative impacts of load and wind variation as the density of failures reduces to zero after 120 kWs. The wind vs load figures show that high variations do negatively impact objective performance but those effects are being successfully nullified. As with Policy-A improvement in two objectives comes at the cost of the third objective. The load objective for policy-B sees high amounts of failures at all ranges of parameters. The number of failures increase for high uncertainties which is to be expected. It is evident that the objective performance has degraded in favor of revenue and emissions objective.

The policy behavior changes, such that the extra energy available at the beginning of the day is utilized to reduce local generation and sell to the grid thus improving revenue and emissions objectives. However, these changes come at the cost of high interruptible load requirements. Thus showing distinctly different behavior than Policy-A, further highlighting the value of the proposed framework.
Figure 4.17: Hourly performance of the different policy types for various system metrics. Each column outlines performance across a single policy of the respective policy type. The box-plots represent the distribution of hourly performance across the 1000 scenarios including the quartiles and the outliers.
Figure 4.18: Combination of uncertain parameter values leading to failure for policy-B. Each dot represents a day/scenario for the policy with blue color depicting successfully meeting the performance criterion while red color meaning failure. The figures show that policy-B performs well on revenue and emission objectives under high uncertainty while sacrificing performance of load objective.
CHAPTER 5
CONCLUSION

This dissertation explores modeling frameworks that support the daily operation of modern-day power system networks with the increasing complexity of supply and demand technologies. To this end, three projects are presented, each of which introduces a different approach to optimize grid operation. The first project aimed to find a framework to generate robust unit commitment and economic dispatch decisions in large scale electrical networks. A hybrid methodology is introduced, unifying statistical feature ranking with an analytical power system framework. The solution performance obtained is comparable to the state of the art analytical frameworks in literature. The methodology is highly scalable, parallelizable, and adaptable to the requirements of the system operator, thus avoiding the pitfalls of traditional approaches. The second project focuses on the daily operation of a community-owned Microgrid (MG) while considering competing stakeholder objectives. The study implements a parametric simulation-based optimization approach, called Evolutionary Multi-objective Direct Policy Search (EMODPS), to identify diverse and adaptable control strategies capable of long term daily operation without re-optimization. The framework demonstrated the benefits of pure multi-objective framework compared to other traditional approaches when considering long term operation strategies for MGs. The advantages of parametric control strategies are also explored briefly in analyzing system performance. The final project performs expands on the work in the second project by comprehensively exploring a MG energy management operation. The study demonstrates a robust decision-making framework based on EMODPS formulation to alleviate the economical, environmental, and societal challenges associated with Microgrid operation.
The framework and the parametric control strategies are shown to introduce robustness and flexibility in system operations that can react to wildly varying operating conditions. Finally, the study demonstrates that the framework can be used as an efficient tool for decision-makers and stakeholders to not only communicate expectations but also understand the limitations of the system which can generate a healthy dialogue and help improve stakeholder participation.

Overall, the dissertation introduces novel and interesting lines of questioning in energy management for power system networks that are worth exploring in greater detail in future work. Instead of following traditional assumptions about network operation. These hybrid frameworks focus on a more holistic approach to analyze system operation, which can then be followed by eliciting stakeholder preferences before selecting management actions. The frameworks introduce a much-needed dimension of explainability in power system energy management literature by allowing the ability for extensive \textit{a posteriori} analyses. These analyses demonstrated the frameworks’ ability to identify the influence of system parameters on objective performance; deconstruct the decision-making process of the parametric policies, and study system performance under highly unplanned conditions without explicit re-optimization. These qualities mark this work at the forefront of frameworks focused towards meaningful engagement with communities and stakeholders.

In addition to the contribution to existing literature, the work also opens up interesting possibilities for future lines of questioning. The work makes a strong case for exploring the value of switching from hourly decisions-making strategies that are prevalent in current literature to long-term operating policies. Such strategic decision-making approaches could lead to meaningful long-term plan-
ning that protects against catastrophic failures due to extreme scenarios. The EMODPS framework needs to be tested on real-world Microgrid to thoroughly understand the advantages and potential limitations of the approach. This type of frameworks also opens up opportunities to study interactions between public infrastructure systems such as local distribution networks and water supply networks. Such studies should lead to smarter planning and operation of public support systems in the long term.

Finally, this work pushes the boundary of existing power system literature with the hope of bringing a positive contribution to the future of electric grid operation.
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