MARKET-BASED DECISION GUIDANCE FRAMEWORK FOR POWER AND ALTERNATIVE ENERGY COLLABORATION

by

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DEDICATION

This is dedicated to my wife Manar, my son Yazeed, my daughter Lama, my mother Norah, and to the memory of my father Rasheed for their love, support, patience, and encouragement.

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TALBLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

MARKET-BASED DECISION GUIDANCE FRAMEWORK FOR POWER AND ALTERNATIVE ENERGY COLLABORATION

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With the introduction of power energy markets deregulation, innovations have transformed once a static network into a more flexible grid. Microgrids have also been deployed to serve various purposes (e.g., reliability, sustainability, etc.). With the rapid deployment of smart grid technologies, it has become possible to measure and record both, the quantity and time of the consumption of electrical power. In addition, capabilities for controlling distributed supply and demand have resulted in complex systems where inefficiencies are possible and where improvements can be made. Electric power like other volatile resources cannot be stored efficiently, therefore, managing such resource requires considerable attention.

Such complex systems present a need for decisions that can streamline consumption, delay infrastructure investments, and reduce costs. When renewable power resources and the need for limiting harmful emissions are added to the equation, the search space for decisions becomes increasingly complex. As a result, the need for a comprehensive decision guidance system for electrical power resources consumption and productions becomes evident.

In this dissertation, I formulate and implement a comprehensive framework that addresses different aspect of the electrical power generation and consumption using optimization models and utilizing collaboration concepts. Our solution presents a two-prong approach: managing interaction in real-time for the short-term immediate consumption of already allocated resources; and managing the operational planning for the long-run consumption.

More specifically, in real-time, we present and implement a model of how to organize a secondary market for peak-demand allocation and describe the properties of the market that guarantees efficient execution and a method for the fair distribution of collaboration gains. We also propose and implement a primary market for peak demand bounds determination problem with the assumption that participants of this market have the ability to collaborate in real-time. Moreover, proposed in this dissertation is an extensible framework to facilitate C&I entities forming a consortium to collaborate on their electric power supply and demand. The collaborative framework includes the structure of market setting, bids, and market resolution that produces a schedule of how power components are controlled as well as the resulting payment. The market resolution must satisfy a number of desirable properties (i.e., *feasibility*, *Nash equilibrium*, *Pareto optimality*, and *equal collaboration profitability*) which are formally defined in the dissertation.

Furthermore, to support the extensible framework components library, power components such as utility contract, back-up power generator, renewable resource, and power consuming service are formally modeled. Finally, the validity of this framework is evaluated by a case study using simulated load scenarios to examine the ability of the framework to efficiently operate at the specified time intervals with minimal overhead cost.

CHAPTER 1: Introduction

1.1 The Problem: Motivation and Background

Energy consumption has been increasing steadily in the recent past and is also expected to continue to increase furthermore in the future [1]. Moreover, distributed generation has become a mainstream power generation source to provide localized power to areas where more power is needed [2]. A large number of companies have already adopted cleaner energy sources due to stricter regulations over carbon emissions and environmental pollutants [3]. Other companies are considering adopting similar measures (such as acquiring photovoltaic (PV) systems, or wind turbines) in a trend toward being more sustainable enterprises [4].

The paradigm of energy consumption and production has also seen some vital shifts. Previously power consumers are becoming power producers. Houses can be outfitted with photovoltaic systems or wind turbines or any other type of alternative energy resource [5]. These homes have been able to reduce their power consumption during peak-demand periods and in certain instances are able to provide power back to the grid.

Moreover, with the introduction of deregulated energy markets [6], there has been an increase in the number of entities that consume power and produce power, added to that, the combination of alternative energy resources options and smart grid technologies. In this dissertation, I develop methods where units which supply and demand power can collaborate and interact among themselves in an optimal fashion by designing market-based decision guidance frameworks and their associated mechanisms to enhance in the best ways possible such collaboration. More specifically, I propose how to develop such methods for both the run-time environment when units have certain resources which are about to be consumed such as peak-demand bounds as well as the planning of various power components for future consumption or generation of power.

Different Commercial and Industrial (C&I) organizations or units within these organization may have some autonomy on power consumption or generation decisions. In addition, power consuming services that are being operated by these units may vary in importance and urgency (see Figure 1.1). For example, services like water heating may require large amounts of electricity to run but it can also tolerate less than the maximum power and its operation often can be delayed depending on factors set by energy managers. However, services such as office lighting or computer servers may not tolerate shortages or delay in the supply of power.

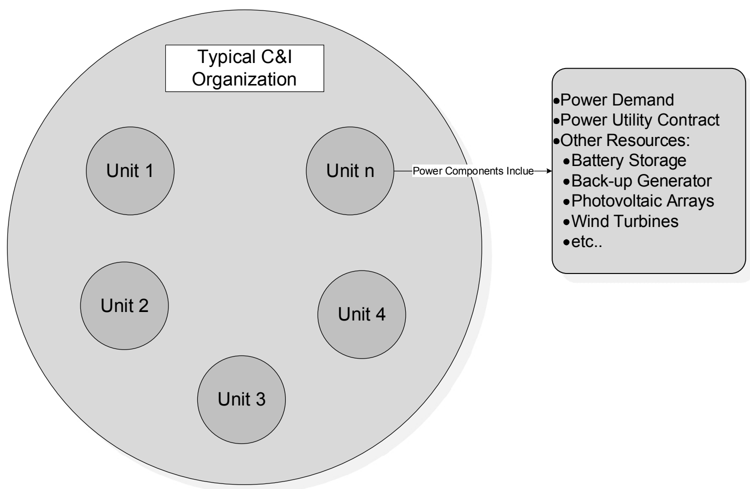

Figure 1.1: Typical Organization Structure

Some organizations may consider alternative energy sources to try to address their long term power needs to deal with rising costs or consider other means of supplying power. Certain units' locations could be suitable for photovoltaic power systems installations, but their consumption time-frame may not align well with their resources' performance, time, or variability. Other units, however, may need power more consistently forming a trend but lack the ability to deploy such alternative energy sources.

With an increasingly complex environment, organizations are left with many alternatives as to how to satisfy their power demand. There are small consumers of electricity who have little negotiation leverage over their power rates with power companies, and there are large consumers with substantial leverage over the procurement prices of their electrical power needs. To illustrate such complexity, consider an organization with multiple units where units have bilateral contracts with electrical power providers over their peak-demand energy requirements. To reduce the overall organization's peak demand, units within the organization may collaborate to share their peak-demand bounds using market mechanisms instead of resorting to cost-prohibitive spot when unused peak-demand bounds or non-critical loads may exist in other units. This can be enhanced by knowing the value that units associate to running their services. Another example could be the formation of a consortium between multiple organizations to reduce their peak-demand needs by utilizing their loads variability and employing their volume negotiating power.

Considering all these complexities, it becomes obvious that there is a benefit and a room for improvement that results from the interaction of power supply and demand entities. The problem that is being addressed here is how to better manage the interaction of power consuming and power producing units. There are mainly two aspects to this interaction: real-time use of already allocated resource, and the operational planning of the use of different power resources. In real-time interaction, an issue like how to best organize a secondary market for participating units that is transparent and have a sustainable added value to its participants is of great importance. The process of how to optimally operate the market within different time-frame considerations that are applicable to the nature of the market is also necessary for the effective operation of the market. Finally, the benefits that result from such interaction need to be distributed among participants in a fair and efficient fashion to motivate participants to better provide more accurate information that would not affect their gains from the participation.

On the longer run, collaboration between entities is important for the optimal operational planning of the use of different resources. To achieve such collaboration, many questions need to be addressed. For example, an efficient and transparent coalition formation is required to the stability of a consortium. While units want to achieve maximum benefit by joining a coalition, there is a decision of what is the best coalition given the units' different available resources. Assuming the coalition is determined, there is also the question of how to optimally plan such that every unit's benefit is maximized. A primary market mechanism needs to formalized where units can fairly and transparently participate in the market without an extensive overhead management cost. Figure 1.2 provides a summary of the taxonomy of the array of problems that are addressed in this dissertation.

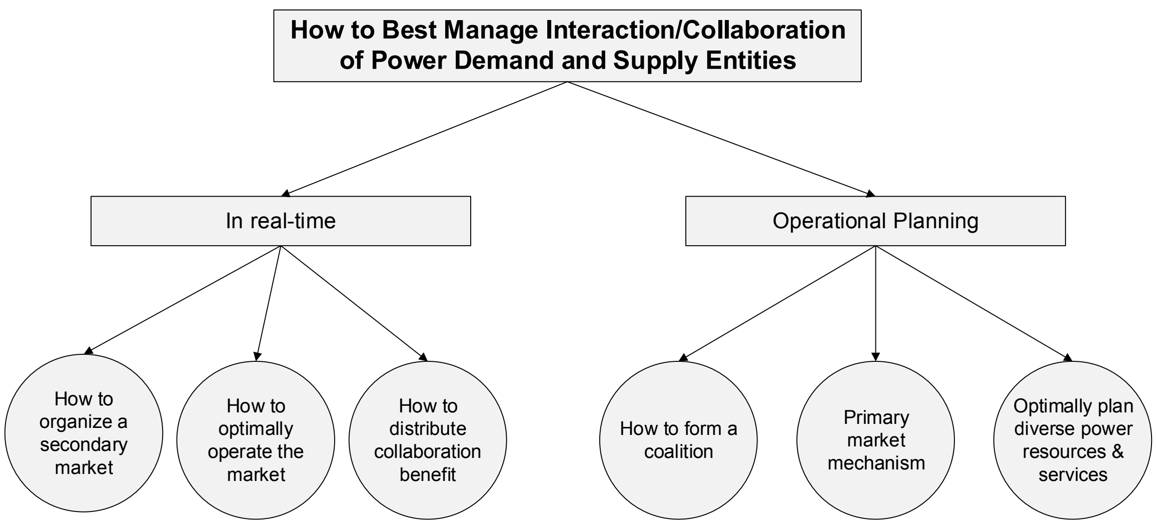

Figure 1.2: Summary of Contributions

1.2 Research Challenges

The deregulated energy market has transformed energy market and introduced the concept of increased competitiveness in once a monopolistic utility companies environment. Smart grid technologies also enabled accurate measurements of the quantity and time consumption. There have been numerous efforts on how to best structure the market to increase competitiveness which consequently results in a more fair price discovery model and ultimately lower costs to the consumer. Demand Response (DR) techniques deal with the reactions of energy customers to changes in supply and the cost of providing it. However, the problem of how to create a secondary market to distribute already available resources was not addressed. Moreover, these techniques may have addressed how to optimally react to demand and price changes of getting power, the question of how to distribute the benefit of collaboration among participating entities has not been explored. Moreover, the idea of how units can collaborate to plan future consumption in a primary market while taking into consideration the ability of collaboration in real-time to address changes in supply and demand has not been previously explored. The concept of how gains or reductions in cost from collaboration can be distributed among nits of a coalition is not a trivial problem as the impact on a unit of the coalition differ according to its size and order of joining such coalition.

While there has been many work on the operational planning of the power needs of an organization, the idea of forming a consortium where some organizations power components may complement other organizations while simultaneously improving the overall welfare of the consortium without negatively affecting the benefit of any single organization as a result of joining the consortium has not been explored. The literature covers many phases of the power life cycle starting from power generation, transmission, and ending with the actual consumption of electrical power. Various solutions aim to optimize individual parts of the electric power life cycle while not taking into consideration the overall effects of such decisions on the combined utility of all other decisions.

Energy markets use either historical data or inferred information about the utility of running a specific service. Stakeholders are rarely consulted on the actual benefit (or utility) or running a specific service. This process is either considered costly or infeasible especially in large organizations or in a consortium of organizations. Such information are generally abstracted as an overall benefit. Providing this information is vital to the determination of the value of running such services. Our approach takes into consideration such hurdles and tries to as easily as possible model such information and streamline the process of updating it.

Furthermore, most existing models aim to either improve efficiency or simply just cut demand as means of reducing cost. However, There haven been no comprehensive decision-guided market-based models, up to our knowledge, that describe market design and resolution from the macro and micro level.

1.2.1 Energy Management Decisions Complexity

To provide a perspective on the energy management decisions complexity, consider a typical Commercial and Industrial (C&I) organization's energy portfolio as depicted in Figure 1.3. This organization have various options to satisfy its power demand. Utility contract with a power company is usually a common part of any organization's energy supply options options. This utility power contract typically specifies the rate that the cost of power is to be calculated which usually has two parts. The first part is the cost of total kWh quantity that an organization consumes over the a certain billing period. The other part is the cost of peak demand which, if exceeded, penalty rates apply which could affect the entire contractual period. In other words, if the chosen peak demand is exceeded even for a very short time (e.g., 30 minutes), it could affect the cost per kW over the entire term of the contract. To reduce peak demand cost, an organization may adopt cleaner power resources such as photovoltaic (PV) systems or wind turbines to either reduce their peak demand or be more resilient from interruptions of the main grid. However, these resources are susceptible to certain environmental conditions (e.g., the activity of wind, or sunshine). To mitigate this variability, some organization may invest in resources such as local back-up generator or battery storage unit. However, operating these resources may incur higher variable cost than other types of resources. There is also the question of what is the optimal time to charge, discharge, or keep the battery storage unit idle. Operating the back-up power generator can be expensive but at certain times it could be a cost effective choice due to the higher cost of using other resources. Some organizations also may have the the ability to form a microgrid for different purposes (e.g., reducing peak demand, enhancing reliability, reducing capital costs, etc.). It is also possible that certain power loads that these organizations operate are not urgent or necessary in what is collectively termed as *deferrable loads*. This term simply means that these loads can be deferred up to a certain extent without much effect on the organization's utility. There are also curtailment contracts which are signed with the power company. These contracts involve reducing consumption when the overall grid is experiencing heavy load upon receiving a signal from the power company. This agreement entails, in return, reduced costs or rebates when power consuming organizations comply.

From all these alternatives, even a single organization has so many options when it comes to making power supply and demand decisions. It is also not an easy task to determine the effects of a single decision without a comprehensive framework that enables an organization to manage its power supply and demand needs in an optimal fashion.

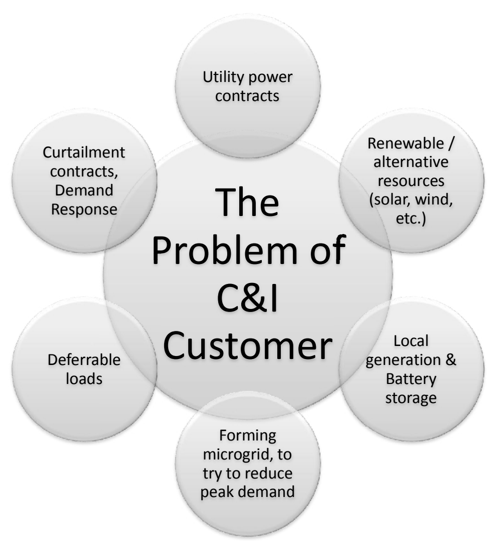

Figure 1.3: Power Energy Management Complexity

1.2.2 Need for Collaboration

To make the problem more concrete consider a scenario depicted in Figure 1.4. In this example there are two units. Unit 1 has three power resources: a power contract, an alternative energy resource, and a curtailment contract. Unit 2 has three power resources as well: a power contract, a local backup generator, and supports deferrable loads. If each unit was to act separately, It would evaluate its power demand and power supply then make decision that keep its costs at minimum while satisfying its power needs. Now consider the ability for these two units to collaborate. When unit 1 , for example, faces an excess demand, it may use unit's 2 resources if unit 2 is not experiencing high power demand during the same time period. The opposite is also true if unit 2 , for example, would experience excess demand, instead of curtailing important demand, it could use unit's 1 local backup generation temporarily until that demand is satisfied. This scenario poses an important question: how can a unit decide and then manage such an exchange of resources and how each unit is rewarded fairly for such collaboration.

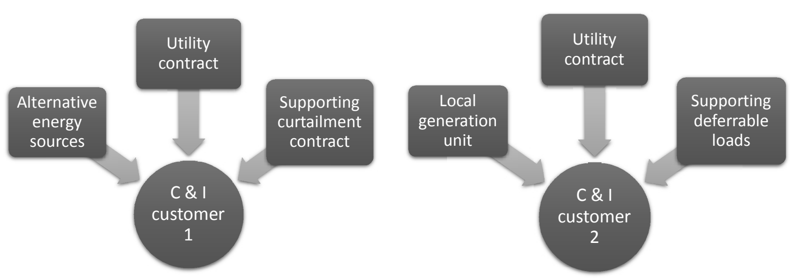

Figure 1.4: Need for Collaboration

In another scenario, even within the same C&I organization, there maybe units that have already acquired certain resources (e.e., peak demand bound)as depicted in Figure 1.5. Such units may encounter the possibility for the need to shed some power when their peak demand bounds are to be exceeded. Energy managers who are supposed to react usually have no insight of what is an important power load and what is not. Moreover, units or department within the C&I organization have no incentive to reduce their peak demand consumption because they typically don't pay for it. A solution would involve setting a peak demand bound for each unit. However, at certain times, units or departments may not have that much demand to reach their pre-determined peak demand bound. It is also possible that this unit can afford to shut down a service if another unit or department needs to run a more important service in lieu of a payment instead of that unit incurring significant peak demand overage costs or resorting to spot market.

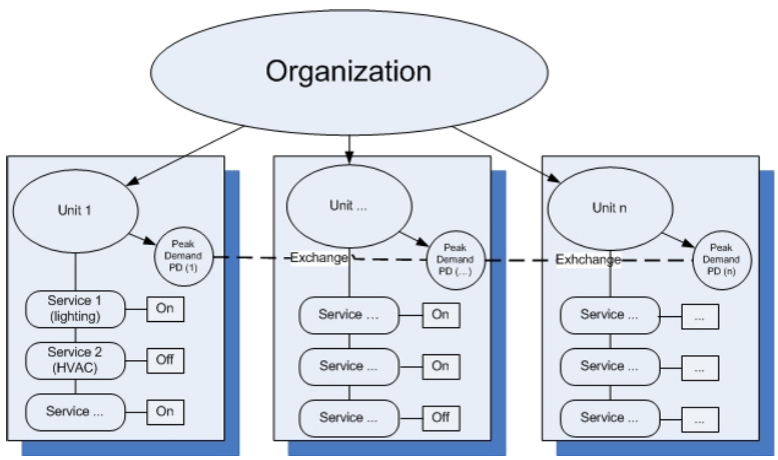

Figure 1.5: Peak-Load Demand Problem

1.3 Thesis Statement & Summary of Key Contributions

In order to support collaboration and interaction among power demand and supply entities, it is possible to develop a decision guidance market-based framework to support optimal collaboration among them:

- **Peak demand operation and determination** (i.e., secondary market for the optimal collaboration on peak demand bounds, primary market for optimal determination of peak demand, and fair distribution of collaboration benefits).

- **For operational planning** (i.e., the formation of a coalition modeling various power components, optimal planning of a coalition).

The main contributions of my dissertation are as follows:

1. I developed a secondary peak-load allocation market framework designed to incentivize organizational units of Commercial and Industrial (C&I) customers to reduce their peak demand. The market mechanism requires units' bids to indicate the value they associate with power consuming services, and the power requirement for these services. The market resolution produces a service and payment allocation, i.e., determination of power services operation schedule and the payments that the units need to make or receive as part of exchange of peak demand bounds resulting of the market resolution. The market mechanism is based on decision optimization, and guarantees the formally defined properties of *Pareto* optimality, *Nash* equilibrium and fairness.

2. I proposed a primary market-based mechanism for organizational units of C&I power consumers or organizations participating in a consortium to reduce their peak demand power bounds. The market mechanism requires participants' bids to indicate the value they associate with power needed to run various services, and the power quantity required for these services over a specified time horizon. The market resolution produces peak demand allocation, i.e., determination of the peak demand bounds and the associated cost that the units need to pay as part of the market resolution. The global peak-demand bound is then derived by optimizing individual participants' peak demand bounds. The market mechanism is based on decision optimization, and guarantees the formally defined properties of *Pareto* optimality, *Nash* equilibrium and benefit distribution fairness.

3. I proposed an extensible decision guidance framework to facilitate Commercial and Industrial entities forming a consortium to collaborate on their electric power supply and demand in order to streamline their consumption and reduce their costs. The collaborative market framework includes the structure of market setting, participants'

bids, and a market resolution which produces a schedule of how power components are controlled as well as the resulting payment to be made by market participants. I also defined four properties that the market resolution must satisfy, namely, *feasibility*, *Pareto*-optimality, *Nash* equilibrium, and *equal collaboration profitability*. Furthermore, we develop a market resolution algorithm, based on a formal optimization model and prove that it satisfies the desirable market properties.

4. To support the extensible framework, I formally modeled various classes of commonly utilized power components (e.g., power contract, back-up power generator, renewable resource, battery storage unit, and power consuming service). The modeling of the components formally defines the cost, revenue, intrinsic value, constraints, and control actions for every component class.

5. I implemented the extensible decision guided framework to facilitate Commercial and Industrial entities forming a microgrid consortium to collaborate on their electric power supply and demand. I developed the optimization models using OPL and Java. Furthermore, I conducted a case study experiments using simulated loads which conforms to typical consumption patterns and random input parameters to validate that the implemented system is feasible to operate efficiently within required time constraints.

1.4 Dissertation Organization

This dissertation is organized as follow:

- Chapter 2: Related work
- Chapter 3: Secondary market design for peak-demand allocation
- Chapter 4: Primary market design for peak-demand bounds
- Chapter 5: Electrical power consortia: decision support based on market optimization

- Chapter 6: Power demand and supply components
- Chapter 7: Consortia market optimization implementation and case study
- Chapter 8: Conclusions and future work

CHAPTER 2: Literature Review

This chapter provides a related work overview of the state of art in the areas necessary to develop a decision guidance framework that studies power resources, markets, and collaboration. The first section present an overview of the deregulated power markets. The second section describes microgrids and decision guidance management systems (DGMS). The third section provides an overview of the coalitional games and the surplus value distribution methods.

2.1 Deregulated Power Markets

There has been an extensive work on deregulated electricity markets and their competitive characteristics [7]. Most of the work is concerned with different parts of market design, mainly, the relationship between power generation companies and wholesale companies. Different approaches to the use of auctions in electric markets has been investigated, e.g.,in [8–13]. They discuss in detail how such markets should be designed to account for buyers and sellers of electric power. Although there has been some work that tries to address large consumers power procurement optimization by evaluating different procurement options [14], they fall short from addressing internal power distribution optimization. There is also some effort to control peak demand and reduce overall consumption by using physical improvements [15] and load scheduling [16], however, the idea of designing a decision guidance framework for the power components modeling and collaboration has not been addressed.

Furthermore, such concepts have been employed in other fields like computational systems resource distribution and wireless spectrum allocation (i.e., [17–21]). Solutions of micro-economic equilibrium have been implemented with promising results. However, the notion of using such methods to share load consumption and allocate electric power among multiple participants such as units of the same organization has not been explored. Moreover, studied electricity markets are akin to commodity markets with special characteristics, whereas our study, we need to consider the market of power components with right of use, which is more akin to options markets.

Renewable resources are becoming a significant part of the energy for a growing number of organizations. According to data from U.S Energy Information Administration [22], energy sources like wind and solar are becoming increasingly utilized as clean energy resource in recent years. If the current trend continues, which is predicted as oil prices rise, and stricter environmental standards are adopted, distributed renewable resources are expected to be a significant part of energy portfolio.

However, there is a characteristic that is shared between wind and solar based energy sources which is that it is difficult to predict their throughput over a long time horizon because they depend on either clear skies or wind activity. However, the performance of these resources can be fairly predicted over a short period of time. Hence, the need to incorporate that knowledge becomes vital for the decisions on the limit of energy consumed by a certain organization.

Power markets has been the focus of a great deal of research. There have been numerous efforts to deal with reducing power consumption costs either through improving technological efficiency or through market supply and demand mechanisms. An extensive body of work was directed to dealing with the reduction of power consumption from the demand side by changes in prices in an area that is termed as Demand Response (DR) [23]. This approach has been used broadly with large power consumers to cut or curtail demand when power generation and transmission networks are about to be overloaded. The participants are motivated by being promised financial incentives if they comply. Demand response entails changing the consumers normal consumption patterns in response to changes in prices, or in order to qualify for a certain incentive payment. Such DR programs are categorized into two broad groups: Price-based, and Incentive-based. Price-based methods include the use of time-of-use (TOU) rates, real-time pricing (RTP), and critical peak pricing (CPP).

Whereas, Incentive-based methods uses techniques such as: direct load control (DLC), interruptible/curtailable (I/C) service, demand bidding/buyback (DB), emergency demand response programs (EDRP), capacity market programs (CMP), and ancillary services market programs (ASMP). These methods are summarized in [24].

There has been attempts to create a real-time pricing market where participant place bids at every considered time slot. The idea proposes a model for collaboration between customers of a power company where participants place bids that correspond to benefits gained from running household appliances. It also considers a mix auxiliary power sources such as batteries and plug-in hybrid electric vehicles (PHEV). Through simulated loads, the results indicated an overall stabilization of power consumption curve over the considered time span compared to flat-rate and other schemes and resulted in the reductions of peak-demand consumption. While such solution is promising, it does not consider the dynamics and the cascading effects of power components planning for units of an organization or a consortium of organizations where certain resolution and payment exchange must be determined at each time interval while optimizing for the entire time horizon. It also doesn't propose a fair mechanism to sharing the extra benefit of collaboration versus working alone [25].

Optimizing the planning of the utilization of resources has been extensively studied in an area collectively named *Unit Commitment Problem* [26–31]. This area addresses the problem of finding the most optimal and cost effective operational planning of power resources (e.g., nuclear, thermal, renewable). While this approach is very effective for the day-ahead planning of power supply procurement given a predicted demand, it doesn't address the demand side aspect of the of the power generation and consumption.

2.2 Microgrids and Decision Guidance Systems

Microgrids [32,33] has been gradually introduced to the traditional grid. Microgrids provide localized power and can operate autonomously from the traditional grid which provides more reliability and reduces the risks of disruptions of the traditional grids. It also help reduce the loss from transmission networks and can adapt to various power resource types. It also provides the capability of responding to changes in demand dynamically. Figure 2.2 provides an overview of a typical microgrid installation. As can be seen in the figure, microgrids can adopt a wide variety of power resources such as, wind, photovoltaics, conventional generation, energy storage, and other services that consume or produces power.

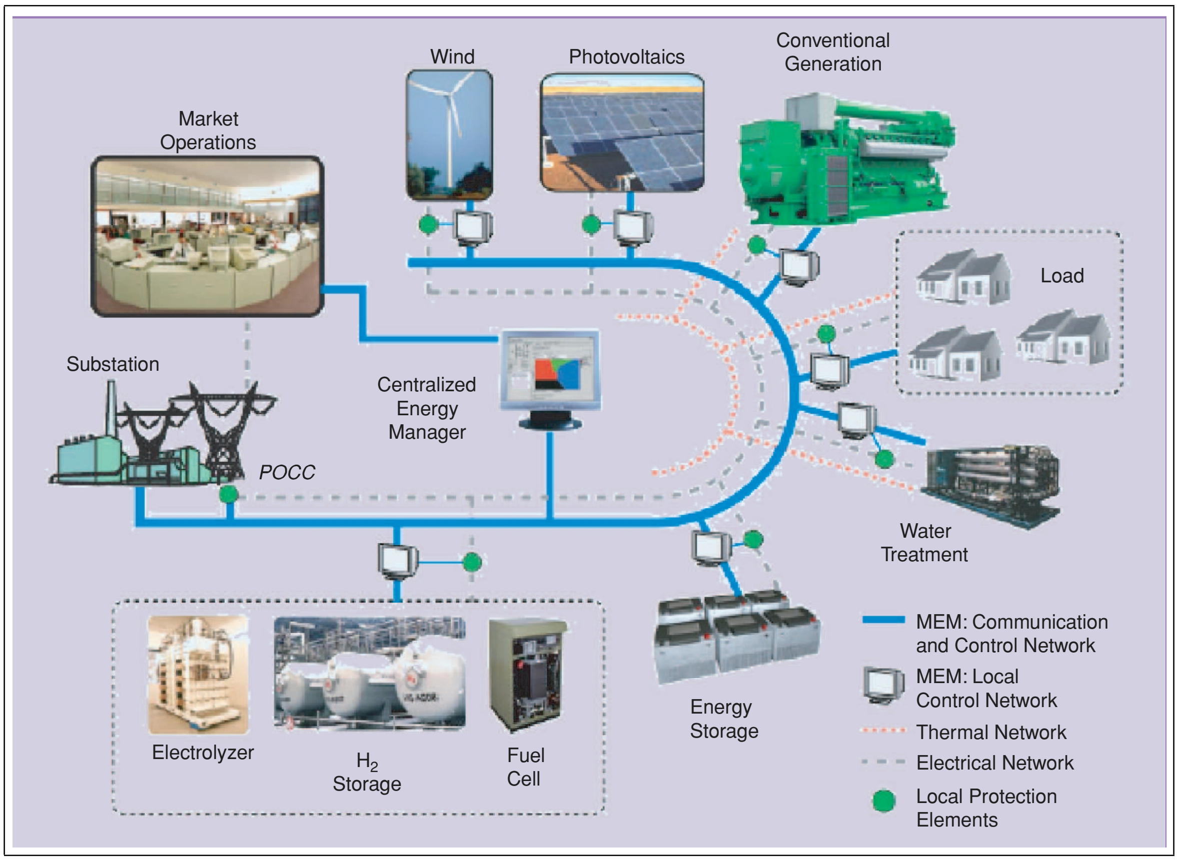

Figure 2.1: Typical Microgrid Power Components (source: GE Global Research)

In a microgrid, power loads usually vary in sensitivity and urgency. There are loads can afford reduction in power and there also loads that can delayed or rescheduled. Smart microgrids provide the means to control loads which optimize their operation. This is usually achieved by the help of an energy manager.

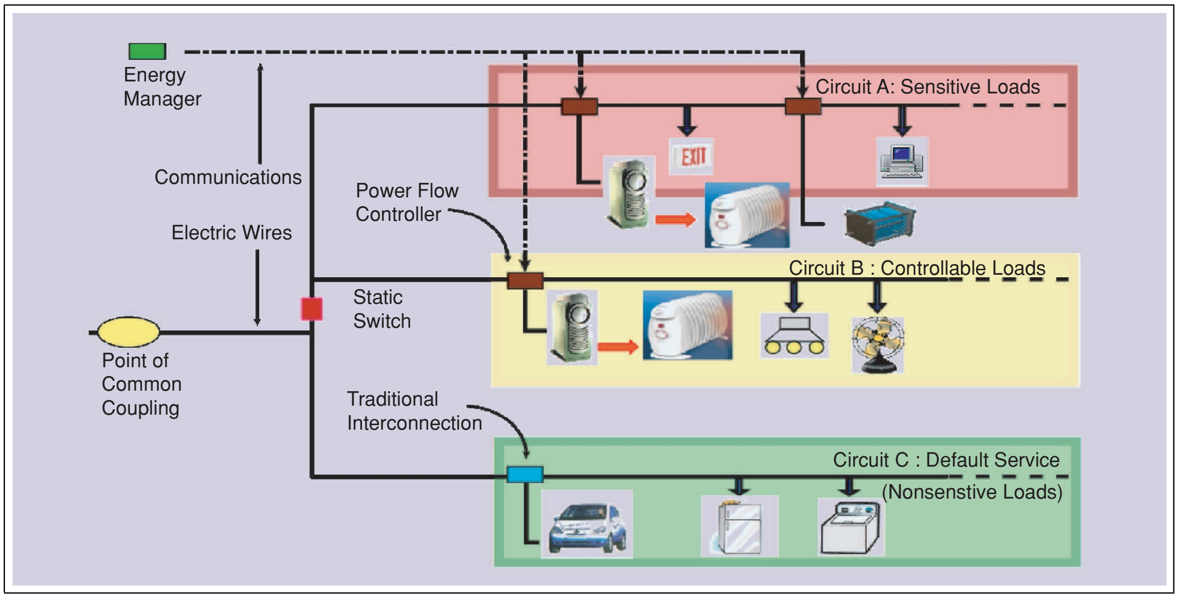

Figure 2.2: Example of Power Loads in a Microgrid (source: CERTS)

Decision support system can be defined as a computer application that support complex decision making and problem solving [34]. Model-based support systems usually consist of three components: formulation, solutions, and analysis. Mixed Integer Programming (MIP) has greatly contributed to widespread use of these types of decision support systems. A recent iteration which provides a comprehensive framework for data acquisition, learning, simulation and prediction, and decision optimization was proposed by Brodsky and Wang in [35]. This DGMS describes what such a system would intuitively consist of. The data acquisition process gathers data from data sources such as a database. The data is then analyzed for learning and certain useful views are created. The DGMS may also rely a domain knowledge that help enhance the learning. The simulation and prediction component facilitate scenarios such as what-if analysis. The decision optimization then gives actionable recommendation based on specific optimization models [36–38].

2.3 Coalitional Games & Surplus Value Distribution

In game theory , players usually form coalition for its perceived added value compared to working to acting individually [39]. A common method to calculate the marginal contribution of a player to a coalition is called *Shapley Value* [40]. Given a set of players, N of coalition, and a value function v, the *Shapley Value* is defined as:

$$\phi_i(N, v) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|! \, (|N| - |S| - 1)! \, [v(S \cup \{i\}) - v(S)]$$

Shapley value also defines a number of axioms and provides proves a proof that these axioms are satisfied. The axioms include:

1. Efficiency: This axiom simply means that the sum of all players *Shapley* values should be exactly equal to the added collaboration value that the coalition get by collaborating.

2. Symmetry: If players i and j are interchangeable with respect to a game v, then $\phi_i(v) = \phi_j(v)$. It means that if two players give the same value to the coalition across all possible coalition orders, then they should get the same *Shapley* value distribution.

3. Additivity: Additivity means if there are two independent v, and w games, then the *Shapley* value of the two games combined must be equal to the sum their separate *Shapley* values, i.e., $\phi(v + w) = \phi(v) + \phi(w)$

4. Dummy Player: This concept means if a player i has no added value to any sucoalition of grand coalition then its *Shapley* value must be equal to zero, i.e., if $v(S \cup i) - v(s) = 0$ for all $S \subset N$, then $\phi_i(v) = 0$.

Shapley Value requires determining the value of all possible orders of subcoalitions not containing payer i then comparing it with the value with palyer i added to the subcoalition. Clearly, this methods is computationally very expensive (NP-Complete) especially when the underlying value function v is based on a MILP optimization problem. There has been attempts for a linear approximation of the Shapley Value [41–45], however such approximations include randomness and require a big computational budget of MILP optimization when considering the feasibility of executing a market at short time intervals.

Another important concept in cooperative games is called the Core which measures the willingness of and stability of participants to form a grand coalition as opposed to forming smaller subcoalitions that maximizes their value. A payoff vector x of a coalitional game of N players and a value function v is considered to be in the *core* if and only if:

$$\forall S \subseteq N, \sum_{i \in S} x_i \geq v(S)$$

Determining the *core* of a reasonably sized coalition is also computationally expensive (NP-Complete). A value function of an MILP type would make calculating possible payoffs for all possible coalitions values computationally infeasible. Due to the computational complexity of determining both the *Shapley* value and the *core* membership (NP-Complete), some authors suggested these complexities serve as a barrier to participants manipulating their bids' orders, or breaking away from the grand coalition [46].

CHAPTER 3: Secondary Market Design for Peak-Demand Allocation

In this chapter, we propose a Peak-Demand Allocation Market framework designed to incentivize organizational units of Commercial and Industrial (C&I) organizations to reduce their peak demand consumption. The market mechanism requires units' bids to indicate the value they associate with power services, and the power requirement for these services. The market resolution produces a service and payment allocation, i.e., determination of power services that are to be running and the payments that the units need to make or receive as part of the exchange of the peak demand bounds. The market mechanism is based on decision optimization, and guarantees the formally defined properties of *Pareto* optimality, *Nash* equilibrium and fairness.

3.1 Introduction

Power demand is increasing and so is the cost of procuring it. Power generation companies are reluctant of making large capital investments that expand the capacity which could even make future costs to customers greater. Power companies prefer consistent streamlined consumption which help maximize their returns. Short spikes in power consumption affects their bottom line by requiring higher capital investment and making it more costly to generate and distribute power.

Typically, the cost of electric consumption of Commercial and Industrial (C&I) customers comprises of two factors: amount of kWh of power consumed; and the maximum peak-demand (kW) that an organization reaches during a specific contractual consumption period. This peak-demand constitutes a significant part of the electric consumption cost because exceeding this peak limit even for a short period in the past could cause the cost of electricity to increase significantly. Therefore, C&I customers are motivated to reduce their peak demand.

However, individual units within the C&I organization usually have little to no motivation to reduce their peak-demand. To address this problem, the focus of this chapter is to develop an optimization-based market mechanism that would incentivize organizational units to reduce their peak demand.

Consider George Mason University (GMU) as an example of such a C&I customer. GMU comprises of different units (e.g. schools, departments, centers, etc.). These units need to operate certain services (e.g. water heating, lighting, ventilation and air-conditioning (HVAC), etc.) which require electric power. The electric supplier (Dominion Virginia Power) provides power to GMU according to an agreed upon contract which specifies the terms on which Dominion provides power. More specifically, it states the price per kWh of consumption and an additional cost component for each peak-demand bracket reached during the contractual consumption period. As a result, the higher peak-demand is, the higher the cost will be. GMU has an energy manager who is responsible for predicting and setting the maximum consumption anticipated at any given time interval. In normal conditions, the energy manager tries to predict the demand for each time interval and account for contingencies when setting the peak-demand for a building or a service. Once these limits are set, GMU's energy management system (EMS) takes over the control of its power consumption. When the overall maximum peak-demand load is about to be exceeded, the energy manager faces the responsibility of "load shedding", i.e, shutting down some services to avoid exceeding the preset peak demand bound. Therefore, little evaluation of the services to be shut down is made. Moreover, units benefiting from the services are rarely consulted to determine the real value of the services being shut down.

The question that is addressed here is whether we can deploy a market based mechanism in which units have an incentive to reduce their peak-demand consumption, thereby, minimizing the overall peak-demand load of a C&I customer and associated costs.

The idea of our proposed market framework is that each organization unit of a C &I

customer can separately run its services by utilizing its pre-assigned peak-demand budget which will result in the total value for each unit and the entire organization. Alternatively, units can exchange their pre-assigned peak-demand budget, in lieu of monetary compensation, which also results in the total value (of acquired value of running services plus or minus the monetary compensation). The idea is that the exchange of the peak demand budget may result in a higher total organizational value than what could be achieved in the original allocation. The question our framework resolves is (1) how to maximize the overall organizational added value (Δ) by exchanging the peak peak demand budget, and (2) how to fairly distribute this Δ among organizational units. More specifically, the contributions are as follows:

First, we propose and formally define a Peak Load Allocation Market (PLAM) framework. The idea is to divide an organization into units where each unit has a fixed peak demand budget. The demand budget represents the right which a unit has to consume up to the specified demand budget. For every power consumption time interval, the unit automatically submits a bid, which indicates the services it needs to run, the benefit value of each service and its power requirements. The market resolution mechanism produces a Service and Payment Allocation (SPA) for each unit, indicating which of its services will be running, and the payment that the unit needs to make or receive depending on whether it consumes additional power or contributes a portion of its peak demand. We also identify desirable properties of market, namely *Pareto optimality*, *Nash equilibrium* and *fairness* which are defined formally in this next section.

Second, we develop a formal optimization model to decide on the selection of services to run that maximizes the global organization benefit while ensuring feasibility, i.e., that the total power consumption will not exceed the total peak demand budget. We also implement a prototype optimization system using the CPLEX's Mixed Integer Linear Programming (MILP) solver.

Third, we propose a method to *fairly* distribute the added collaboration organization benefit Δ among the units. To design the method, we propose and advocate an underlying principle of *equal profitability* as a proxy of *fairness*, and show how to determine the payments that the units need to make or receive as part of the exchange, in order to satisfy the *equal profitability* principle. The resulting market resolution method is also guaranteed to satisfy the *Pareto* optimality and *Nash equilibrium* properties.

Finally, we conduct an initial experimental study on the time complexity of the proposed algorithms which demonstrates that it is feasible to resolve the market fast enough for each power consumption time interval, and that the algorithms scale well with the increase in the number of units and services supported, and combinations of both small and large peak demand budgets.

This chapter is organized as follows: In the second section, we describe our framework named Peak Load Allocation Market (PLAM). We also formally define the problem, and describe some desirable properties that our market must satisfy. In section three, we explain how we arrive at global optimal solution to our proposed market. In section four, We describe the market resolution and the different conditions in which the added Δ benefit is distributed fairly according to different units' contributions. In the fourth section, We implement our solution and show time and space complexity of implementing our market along with some initial experimentation. Finally, we briefly discuss our conclusions.

3.2 Peak Load Market Framework

In this section we describe the formal model and explain the major parts of our solution. We also formulate the optimization problem. We begin by describing the model formally.

To facilitate market mechanisms, we divide continuous time into operational time intervals, e.g., of 30 minutes each, and assign kilowatts (kW) an integer number to each interval. We denote by $T = \{1, \cdots, N\}$ a set of time intervals in the time horizon considered. We assume that units of the organization have the ability add, delete, or update service details up until the market executes.

We denote by $U = \{u_1, \ldots, u_i\}$ that set of organizational units (e.g., departments) that are autonomous in decisions on power usage and budget. Every unit has a set of power consuming services. Every service s consumes a certain amount kw$[s]$ of electrical power measured in kilowatt (kW). Each service s that needs to run have a measurable amount of benefit B$[s]$ which indicates the value added to the unit by running that service. In monetary terms, $B_u[s]$ can be viewed as the amount of money that the unit running service s is willing to receive in lieu of service s (i.e., to not have service s running for a given time interval). Each unit consumption is bound by a peak-demand budget limit PD$[u]$ measured in kilowatt (kW).

Consider the Peak Load Allocation Market (PLAM) diagram depicted in Figure 3.1.

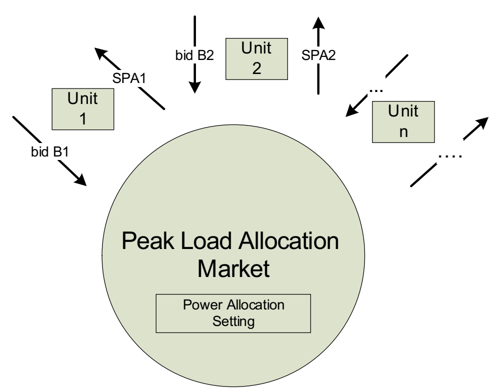

Figure 3.1: Peak Load Allocation Market Framework

Every unit u submits to the market its bid B_u, which indicates, for each of its services s, the benefit $B_u[s]$ of s, as well as the amount of power kw$[s]$ necessary to run s.

More formally, we define Power Allocation Setting (PAS) as a tuple:

$$P = \langle U, S, s, \mathrm{kw}, \mathrm{PD} \rangle$$

where:

- $U = \{1, \cdots, n\}$: is a set of units.

- S: is a set of (power consuming) services.
- s: $U \to 2^S$ is a function that associates a set of services $s(u)$ with each unit $u \in U$.
- kw: $S \to \mathbb{R}$, is a function that gives the amount of power $\mathrm{kw}(s)$ required to run service $s \in S$.
- PD: $U \to \mathbb{R}$, is a function that gives the peak-demand bound $\mathrm{PD}(u)$ "owned" by unit $u \in U$.

We assume that at every time interval, the Peak Load Allocation Market (PLAM) stores the associated Power Allocation Setting (PAS) as depicted in Figure 3.1.

At every interval, every unit $u \in U$ submits a bid B_u for power allocation, and receives back the Service & Payment Allocation SPA_u from the market. We now formally define the bids and the Service & Payment Allocation (SPA).

A bid B_u for unit $u \in U$ is a function $B_u : s(u) \to \mathbb{R}$ where $B_u(s)$ is the benefit for unit u received by running service $s \in s(u)$

A Service Payment Allocation (SPA) for unit $u \in U$ is a pair:

$$\langle \mathrm{ON}_u, \mathrm{PAY}_u \rangle$$

where:

- PAY_u is the payment that is to be received by unit u (note that $\mathrm{PAY}_u < 0$ means the unit u pays to the market).
- $\mathrm{ON}_u : s(u) \to \{0, 1\}$ is a function that indicates, for every service $s \in s(u)$, whether it will be on, ie., (1) or off, i.e., (0).

Given Power Allocation Setting PAS P, a set of bids $\{B_1, \cdots, B_n\}$, and a set of Service & Payment Allocations $\{\mathrm{SPA}_1, \cdots, \mathrm{SPA}_n\}$, we define the following:

- $\text{ServiceBenefit}[u] = \sum_{\substack{s \in s(u) \wedge \\ \text{ON}_u(s)=1}} B_u(s)$ is the service benefit achieved by unit u.
- $\text{TotalBenefit}[u] = \text{ServiceBenefit}[u] - \text{PAY}_u$ is the total benefit achieved by unit $u \in U$ by participating in the market.
- $\text{TotalBenefit} = \sum_{u \in U} \text{TotalBenefit[u]}$ is the total organizational benefit achieved by all units in U.

We now define a number of desirable properties of the Peak Load Allocation Market framework.

Property 1: Feasibility.

Given PAS P and bids$\{B_1, \cdots, B_n\}$, we say that $\{\text{SPA}_1, \cdots, \text{SPA}_n\}$ is *feasible* if:

$$\sum_{\substack{s \in S \wedge \\ \text{ON}(s)=1}} \text{kw}(s) \leq \sum_{u \in U} \text{PD}(u)$$

i.e., the Peak Load Allocation Framework is feasible, *if* it always returns a feasible

$$\{\text{SPA}_1, \cdots, \text{SPA}_n\}$$

for any given PAS P and bids $\{B_1, \cdots, B_n\}$.

Property 2: Pareto Optimality.

Given a PAS P and bids$\{B_1, \cdots, B_n\}$, we say that $\{\text{SPA}_1, \cdots, \text{SPA}_n\}$ is Pareto optimal if:

1. it is feasible

2. there does not exist a feasible $\{\mathrm{SPA}'_1, \cdots, \mathrm{SPA}'_n\}$ such that

$$(\forall u \in U) \quad \mathrm{TotalBenefit}'[u] \geq \mathrm{TotalBenefit}[u]$$

and

$$(\exists u \in U) \quad \mathrm{TotalBenefit}'[u] > \mathrm{TotalBenefit}[u]$$

where $\mathrm{TotalBenefit}'[u]$ is the total benefit under SPA'_u. In other words, no other Service & Payment Allocation can increase the the benefit of a unit without reducing the benefit of another unit.

Similarly, we say that Peak Load Allocation Market framework is Pareto-optimal if it always returns a Pareto-optimal $\{\mathrm{SPA}_1, \cdots, \mathrm{SPA}_n\}$, i.e., for any PAS P and bids $\{B_1, \cdots, B_n\}$.

Property 3: Nash Equilibrium.

We say that Peak Load Allocation Market satisfies the Nash Equilibrium property if for every PAS P and bids $\{B_1, \cdots, B_n\}$, the Peak Load Allocation Market returns allocations $\{\mathrm{SPA}_1, \cdots, \mathrm{SPA}_n\}$ such that no unit can get a higher total benefit by quitting the coalition. That is, for every $u \in U$:

$$\mathrm{StandAloneBenefit}[u] \leq \mathrm{TotalBenefit}[u]$$

where $\mathrm{StandAloneBenefit}[u]$ is the maximum benefit that can be achieved by unit u by running its services within its peak demand budget. That is,

$$\begin{aligned} \mathrm{StandAloneBenefit}[u] = \max_{\mathrm{ON} \in (s[u] \rightarrow \{0,1\})} \quad & \sum_{s \in s(u)} B_u(s) \\ \text{subject to} \quad & \sum_{\substack{s \in s(u) \wedge \\ \mathrm{ON}(s)=1}} \mathrm{kw}(s) \leq \mathrm{PD}(u) \end{aligned}$$

In the next sections, we propose a Peak Load Allocation Market (PLAM) framework that satisfies the previously mentioned properties, as well as, the property of *fairness* to be defined.

3.3 Optimizing Global Benefit

Here we will be using a service configuration function

$$\text{ON} : S \rightarrow \{0, 1\}$$

to denote, for each service $s \in S$, whether it will be on (1) or off (0). To implement the Peak Load Allocation Market, we need to be able to allocate peak demand bounds optimally among any subset W of units U. We formulate this optimization problem here.

Given

1. PAS $A = \langle U, S, s, \text{kw}, \text{PD} \rangle$
2. bids $\{B_1, \cdots, B_n\}$
3. a subset W of U
4. a service configuration ON

the service configuration value $V(A, W, \text{ON})$ for $W \subseteq U$ is defined as the total benefit achieved by running all services of W that are on, that is,

$$V(A, W, \text{ON}) = \sum_{u \in W} \text{SerivceBenefit}[u]$$

where

$$\text{ServiceBenefit}[u] = \sum_{\substack{s \in s(u) \wedge \\ \text{ON}(s)=1}} B(s)$$

Given PAS A, we say that a service configuration ON is *feasible* if the total kW consumption of all turned on services is bound by the total peak-demand, that is,

$$\sum_{\text{ON}(s)=1} \text{kw}(s) \leq \sum_{u \in W} \text{PD}(u)$$

Given (1) Power Allocation Setting A and (2) a subset W of U, Optimal Service Value $O(A, W)$ is the maximum value $V(A, W, \text{ON})$ among all *feasible* service configurations ON, that is,

$$\begin{aligned} O(A, W) = \max_{\text{ON} \in (s_W \to \{0,1\})} & \quad V(A, W, \text{ON}) \\ \text{subject to} & \quad \sum_{\substack{s \in S_W \wedge \\ \text{ON}(s)=1}} \text{kw}(s) \leq \sum_{u \in W} \text{PD}(u) \end{aligned}$$

where $S_W = \{s \in S \mid (\exists u \in W)\ s \in s(u)\}$. An optimal ON configuration is a solution to the above.

3.4 Resolving Peak Load Allocation Market (PLAM)

Given the Power Allocation Setting A and bids $\{B_1, \cdots, B_n\}$, the resulting consortium collaboration benefit Δ is as follows:

$$\Delta = O(A, U) - \sum_{u \in U} O(A, \{u\})$$

We are faced with the question of how to *fairly* distribute the added consortium collaboration benefit Δ among the consortium's participants. We propose a equal profitability of Peak Load Allocation Market mechanism as follows. Given the consortium's collaboration benefit Δ, we decide on its distribution $\Delta_1, \cdots, \Delta_n$ among n units, i.e.,

$$(\forall u \in U) \;\; \Delta_u \geq 0 \;\text{ and }\; \sum_{u \in U} \Delta_u = \Delta$$

In this section we discuss how to *fairly* distribute the collaboration benefit Δ. Given a distribution $\Delta_1, \cdots, \Delta_n$ of Δ, the Peak Demand Allocation Market resolution gives the Service & Payment Allocation $\langle \text{ON}_1, \text{PAY}_1 \rangle, \cdots, \langle \text{ON}_n, \text{PAY}_n \rangle$ as follows. Let service configuration ON be the result of the Service Value optimization discussed in Section 2. Then:

For every

$$u \in U = \{1, \cdots, n\} \;,$$

$$\text{ON}_u : \; s[u] \rightarrow \{0, 1\}$$

is defined by $\text{ON}_u(s) = \text{ON}(s) \quad \forall s \in s[u]$.

To decide on PAY_u, note that the collaboration benefit increase Δ_u for u is:

$$\Delta_u = \text{ServiceBenefitIncrease}[u] - \text{PAY}[u] \;,$$

where

$$\text{ServiceBenefitIncrease}[u] = \sum_{\substack{s \in s(u) \,\wedge \\ \text{ON}(s)=1}} B_u(s) - O(P, \{u\})$$

Therefore,

$$\text{PAY}_u = \sum_{\substack{s \in s(u) \,\wedge \\ \text{ON}(s)=1}} B_u(s) - O(A, \{u\}) - \Delta_u$$

The only remaining part to complete the Peak Load Allocation Market framework is to design a mechanism for a *fair* distribution $\Delta_1, \cdots, \Delta_n$ of the Total Benefit Δ. We propose the following distribution based on the principle of *equal profitability* for each unit as follows.

Given a distribution $\Delta_1, \cdots, \Delta_n$ of Δ, we define the profit of unit u as

$$\text{Profit}[u] = \frac{\Delta_u}{O(A, \{u\})}$$

Equal profitability means

$$\text{Profit}[1] = \text{Profit}[2] = \cdots = \text{Profit}[n] = p$$

that is,

$$p = \frac{\Delta_1}{O(A, \{1\})} = \cdots = \frac{\Delta_n}{O(A, \{n\})}$$

Therefore,

$$\Delta_1 = p \cdot O(A, \{1\}), \cdots, \Delta_n = p \cdot O(A, \{n\})$$

Because $\Delta_1 + \cdots + \Delta_n = \Delta$,

$$p\big(O(A, \{1\}) + \cdots + O(A, \{n\})\big) = \Delta$$

and thus p can be computed by:

$$p = \frac{\Delta}{O(A, \{1\}), \cdots, O(A, \{n\})}$$

Finally, $\Delta_1, \cdots, \Delta_n$ can be computed by:

$$\Delta_1 = p \cdot \Delta, \cdots, \Delta_n = p \cdot \Delta$$

3.5 Implementation & Initial Experimental Study

For the purposes of evaluation, we implemented the model using *OPL* (see Listing 3.1 and generated four sets of an increasing number of units and services using *Java*. The main objects of our model are units and services, and their attributes are illustrated in Figure 3.2.

```
tuple unit{
   key string unitId;
   float unitBudget;
 };

tuple service{
  key string serviceId;
  key string serviceUnitId;
  float serviceBenefit;
  float kw;
};

{unit} Units=...;
{service} Services=...;

dvar boolean serviceRun[Services];
float totalUnitsBudget = sum(u in Units) u.unitBudget;
dexpr float unitUtility [ u in Units]= sum (s in Services: u.unitId == s.
    serviceUnitId) s.serviceBenefit * serviceRun[s];
dexpr float totalUtility= sum (s in Services)s.serviceBenefit * serviceRun[s];
dexpr float unitKw [u in Units]= sum(s in Services: u.unitId == s.serviceUnitId)
     s.kw * serviceRun[s];
dexpr float totalKw = sum(s in Services)s.kw * serviceRun[s];

maximize totalUtility;
```

```
constraints {
  forall (u in Units) u.unitBudget >= unitKw[u];
  totalKw <= totalUnitsBudget;
};
```

Listing 3.1: Peak Load Allocation Market OPL Implementation

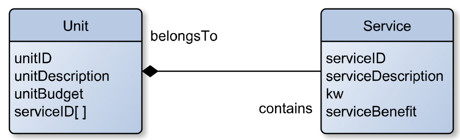

Figure 3.2: Class Diagram

We use *IBM's ILOG CPLEX* Mixed Integer Linear Programming (MILP) solver . The model communicates with *CPLEX* through IBM's *Concert* Application Program Interface (API). The execution flow of the program is shown in the flowchart depicted in Figure 3.3.

We start the execution of the model by generating units and services data. For each unit, we calculate the base benefit bound by each unit's individual peak demand budget and add all units' base benefits together to determine the overall base benefit. After that, we compute the overall optimal peak demand distribution and determine the overall benefit and each optimal unit's power allocation. The Δ benefit can be easily computed as the difference between the total optimal individual unit's benefits bound by their respective peak demand budget and the overall optimal benefit of all unit combined. Finally, we determine each unit's contribution to the Δ and distribute payments accordingly.

To test our market framework, we populate our model with four data sets of sample units and services with varying peak-demand budgets, benefits and service power needs.

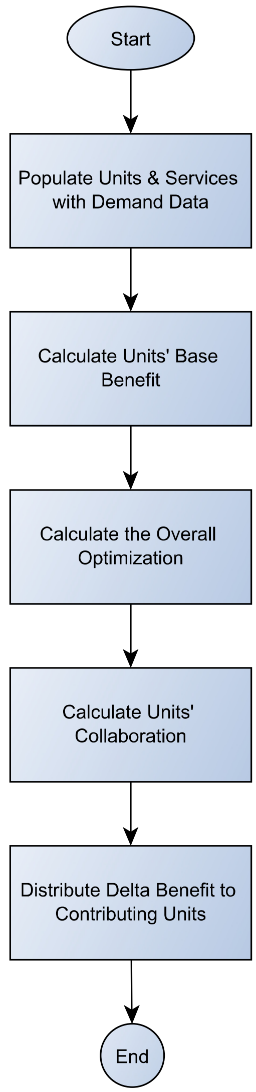

Figure 3.3: Execution Flow Chart

The first data set consists of ten units and each unit contains six services. The second, third, and fourth, sets consist of a hundred, five hundred, and a thousand units respectively while each unit contained ten services. We assume that the benefit of running each service is consistent by normalizing that benefit into monetary value. Sample unit's data are shown in Table 3.1.

Table 3.1: Sample Unit Data

Service ID	Unit ID	Benefit	Consumption in (kw)
0	0	6	25
1	0	5	20
2	0	4	20
3	0	3	15
4	0	2	15
5	0	1	10

The initial calculation of individual optimization against the overall optimal optimization is presented in Figure 3.4. As can be seen from the figure, some units had to give up some of their peak-demand budget to other units that presented higher benefit demand for it.

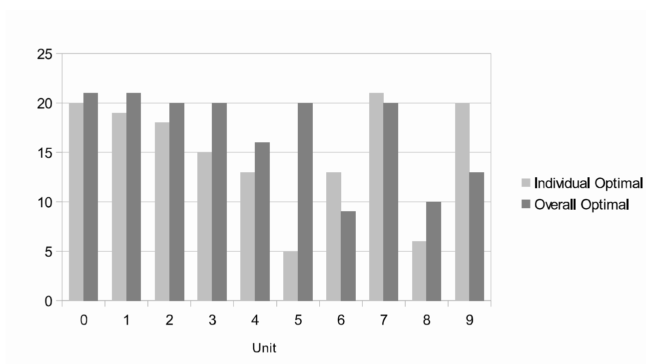

Figure 3.4: Individual Vs. Optimal Power Allocation

We can also notice from the chart that there are units that were assigned more power than their initial demand budget allowed while others had part of their demand budget assigned to other units. The total budget is allocated such that the highest benefit yielding services are given priority.

After both individual and the overall benefits are determined. We compute each unit collaboration to the consortium. Each unit's contribution is captured in Table 3.2.

Table 3.2: Individual Units' Collaboration

Unit	Contribution
0	1
1	2
2	2
3	3
4	2
5	5
6	2
7	2
8	2
9	4

As can be seen from the table, all the units have a positive contribution value (greater than zero) which means that these units will receive part of the added Δ benefit according to the *equal profitability* principle described in Section 4. Since the Δ gain in this set was (20.0), the corresponding Δ distribution for each unit is captured in Table 3.3.

After the Δ distribution is derived, each unit's payment can be easily calculated using the payment function explained in Section 4 which is depicted in Table 3.4. Negative payment indicates the unit is receiving monetary compensation, while positive payment indicates that the unit is giving out payment.

After conducting the experiments using the data sets mentioned earlier, we found that our implementation performed well above expectations despite the fact that the optimization variables were boolean (see Table 3.5). In addition, we noticed that Δ benefit increased

Table 3.3: Units' Δ Distribution

Unit	Δ Share
0	1.19
1	1.25
2	1.32
3	1.58
4	1.83
5	4.75
6	1.83
7	1.13
8	3.95
9	1.19

Table 3.4: Units' Payment

Unit	Payment
0	-0.19
1	0.75
2	0.68
3	3.42
4	1.17
5	10.25
6	-5.83
7	-2.13
8	0.05
9	-8.19

as the number of units and services increased which further demonstrate the value of such collaboration market framework.

The tests were performed on a moderate specification workstation (2.0 GHz dual core processor, and 4 GB RAM). The maximum optimization run-time for a test of 1,000 units and 10,000 services took a little more than a minute which is quite reasonable if we expect the market to execute over short intervals (30 minutes).

Table 3.5: Test Data Showing Δ Benefit Obtained and Optimization Time

# Units	# Services	Δ Benefit	Optimization Time(in seconds)
10	60	20	0.29
100	10,00	449	5.23
500	5,000	2,214	32.19
1,000	10,000	4,471	66.34

3.6 Conclusions

We proposed Peak Load Allocation Market framework that incentivizes organizational units of Commercial and Industrial customers to reduce their peak demand consumption. The market described units' bids elicitation as well as the resolution of the market as well as the service and payment allocation. Moreover, we formally defined the market and constructed an optimization model that satisfies desirable properties, i.e, *Nash* equilibrium, *Pareto* optimality and *equal profitability*. After running multiple experiments, the proposed market resulted in an increase in the overall benefit of an organization based on the generated test data sets.

Our approach is designed for organization where operation of different units is greatly independent. Whereas in an organization where units' consumption is interrelated, a global scheduling optimization to achieve the global benefit may work better.

CHAPTER 4: Primary Market Design for Determining Peak-Demand Bounds

In this chapter, we propose a market-based mechanism for organizational units of Commercial and Industrial power consumers or companies in a consortium to reduce their peak power demand. The market mechanism requires participants' bids to indicate the value they associate with power needed to run various services, and the power quantity requirement for these services over a time horizon. The market resolution produces peak demand allocation, i.e., determination of the optimal peak demand bound and the associated cost that the units need to pay for the that bound. The global peak-demand is then derived by optimizing individual participants' peak demand. The market mechanism is based on decision optimization, and guarantees the formally defined properties of *Pareto* optimality, *Nash* equilibrium and benefit distribution fairness.

4.1 Introduction

In the previous chapter, we investigated the optimal distribution of an already chosen peak demand (PD) among participating organization's units. In this chapter, we focus on the problem of the determination of the PD of all units for a primary market purposes apriori. We try to determine the optimal PD to be contracted based on the projected costs and benefits of such a decision.

Typically, the cost of electric consumption by Commercial and Industrial (C&I) customers comprises of two factors: amount of kWh of power consumed; and the maximum peak-demand (kW) that an organization reaches during a specific contractual consumption period. This peak-demand constitutes a significant part of the electric power consumption cost because exceeding this peak even for a short period in the past could cause the cost of electricity to increase significantly. Therefore, C&I customers are motivated to reduce their peak demand.

However, individual units within the C&I organization, which often have autonomy on cost decisions, have little to no motivation to reduce their peak-demand. Therefore, many advantages such as purchasing power collaboratively that could reduce the cost due to economies of scales may not be realized. It could also be more beneficial to individual units to decide on their short term peak demand power internally instead of resorting to exceeding a peak demand limits set by a power company and incur higher penalties. To address this problem, the focus of this paper is to develop an optimization based market mechanism that would incentivize participating units to decide on peak demand limits which maximize their benefit by increasing their overall utility and reducing their cost.

Consider George Mason University (GMU) as an example of such a C&I customer. A university usually comprises of different units (e.g. schools, departments, centers, etc.). These units require some services (e.g. lighting, heating, ventilation and air-conditioning (HVAC), etc.) which require electric power to operate. An electric utility company, Dominion Virginia Power, supplies power to the university according to a signed contract which specifies its terms. More specifically, it states the price per kWh of consumption and an additional cost component for each peak-demand bracket reached during the contractual consumption period. As a result, the higher peak-demand is, the higher the cost will be. The university has an energy manager who is responsible for predicting and setting the maximum consumption anticipated at any given time interval. In normal conditions, the energy manager tries to predict the demand for each time period and account for contingencies when setting the peak-demand for a building or a service. Once these limits are set, the university's energy management system (EMS) takes over the control of its power consumption. When the overall maximum peak-load is about to be exceeded, the energy manager faces the responsibility of "load shedding", i.e., shutting down some services as to not exceed the preset peak demand bound. However, little evaluation of the services to be shut down is made. Moreover, the units benefiting from the services are rarely consulted to determine the real value of the services being shut down.

Therefore, unit can choose higher peak-demand bound to avoid exceeding the peak-demand bound, but effectively it will paying for a peak-demand that it rarely reaches. On the other hand, a unit can choose a lower peak-demand bound and then will continuously be exceeding this peak-demand and will be paying higher fees. The purpose of our proposed market framework is that each unit of a C&I organization or any member of a consortium can separately run its services by choosing its own peak-demand budget, which will result in the total value for each unit. Alternatively, units can collaboratively determine their collective peak-demand budget, in lieu of monetary benefit, which also results in the total value (of services plus an extra benefit). The idea is that the exchange of the peak demand budget may result in a higher total value than what could be achieved in the original allocation. The question our framework resolves is (1) how to determine the peak-demand for each participating member, then (2) how to maximize the overall organizational value by collaboratively selecting the peak demand limit, and (3) how to fairly distribute Δ among organizational units. More specifically, the contributions of this paper are as follows:

First, we propose and formally define a Peak-Load Demand Market framework. The idea is to create a market or a consortium of players where units of an organization or other organizations who have autonomy on decisions pertaining to power. The demand budget represents the right which a unit has to consume up to the specified power bound. Each unit submits a bid, which indicates the services it would like to run, the utility value of each service and the power requirements over a fixed time horizon, e.g., one year. The market resolution mechanism produces a Peak Demand Allocation for each unit, and the payment that each unit needs to make. We also define a set of desirable properties of the peak demand market, namely *Pareto* optimality, *Nash* equilibrium and the benefit distribution fairness defined formally in the paper.

Second, in order to support market resolution, we develop and implement a formal optimization models to decide on the selection of services to run that maximizes the global organization benefit while ensuring feasibility, i.e., that the total power consumption for each unit does not exceed the peak demand limit.

Third, based on the optimization model, we develop a market resolution algorithm that guarantee that the satisfaction of the properties of *Pareto* optimality and *Nash* equilibrium as well as the property of fair benefit distribution, defined formally in the paper.

Finally, we conduct an initial experimental study on the time and space complexity of the proposed algorithms which demonstrate that it is feasible to resolve the market fast enough for a potentially large pool of participants, and that the algorithms scale well with the increase in number of units and services supported.

This chapter is organized as follows: In the second section, we describe our framework named Peak-Load Demand Market. We also formally define the problem, and describe some desirable properties that our market must satisfy. In section three, we explain how we arrive at global optimal solution to our proposed market. In section four, we describe the market resolution and a methodology in which the added Δ benefit of collaboration is distributed fairly proportional to different units' contributions. In the fifth section, we implement our solution using IBMs Optimization Programming Language (OPL) and show time and space complexity of implementing this market along with initial experimentation. Finally, we briefly discuss our conclusions and results.

4.2 Primary Peak-Load Demand Market Framework

In this section, we describe a formal model and explain the major components of our solutions. We also formulate the optimization problem. We begin by describing the model formally. To facilitate market analysis, continuous time is divided into discrete time intervals i.e., $T = \{1, \cdots, N\}$ (e.g., hourly time intervals for 1 month). We denote by $U = \{u_1, \ldots, u_i\}$ a set of units (e.g., departments in an organization or companies in a consortium) that have the ability to make decisions of power usage and budget. Every unit u has a set of power consuming services. At each time interval $t \in T$, every service s of every unit u consumes a certain amount $kw_u(t, s)$ of electrical power measured in kilowatts (kW).

Every one of these services also has measurable amount of utility or benefit $v_u(t, s)$ to its corresponding unit u which indicates the value added to the unit by turning on that service. In monetary terms, $v_u(t, s)$ can be viewed as the amount of money that the unit running the service s is willing to receive in lieu of service s (i.e., to not have service s running for a given time interval). Every unit's consumption is bound by a peak-demand budget limit PD_u measured in kilowatts (kW). For every peak-demand power level (PD) there is a corresponding peak-demand cost ($P(PD)$) function which is set the by the electric power providers as part of the contract price schedule. Consider the Peak-Load Demand Market (PLDM) framework, depicted in Figure 4.2. Every unit $u \in U$ submits to the market its bid d_u, which indicates, for every service which the unit operate, the value of turning on that service as well as the amount of power necessary to run the service at every time interval.

More formally, we define a Power Allocation Setting (PAS) as a tuple:

$$PAS = \langle U, S, s, P \rangle$$

where:

- $U = \{1, \cdots, n\}$ is a set of units.
- S is a set of (power consuming) services.
- $s : U \to 2^S$ is a function that associates services to their respective units such that $(\forall\, u_1, u_2)\ (u_1 \neq u_2) \to s(u_1) \cap s(u_2) = \emptyset$.
- $P : \mathbb{R} \to \mathbb{R}$ is the peak demand price function (i.e., $P(PD)$ is the price of peak demand allocation PD.

A bid $d_u = \langle kw_u, v_u \rangle$ is pair for every $u \in U$, where:

- $kw_u : T \times s(u) \to \mathbb{R}$ is a function that gives at each time interval $t \in T$ the power needed to run service $s \in s(u)$.

- $v_u : T \times s(u) \to \mathbb{R}$ is a function that gives at each time interval $t \in T$ the value or benefit received from running service $s \in s(u)$.

A market resolution produces a Peak Demand Allocation (PDA) for unit $u \in U$ which is a pair

$$\langle PD_u, C_u \rangle$$

where $PD_u \in \mathbb{R}$ is the bound on power demand allocated to u , and $C_u \in \mathbb{R}$ is the cost (in dollars) that u needs to pay for PD_u . Given PD_u for unit u, the unit can use the power to accommodate its services within its own PD_u and decide on function:

$$ON_u : T \times s(u) \to \{0, 1\}$$

which indicates, for each time interval $t \in T$ and service $s \in s(u)$, whether the service runs, i.e., $ON_u(t, s) = 1$, or not, i.e., $ON_u(t, s) = 0$.

Given PDA $\langle PD_u, C_u \rangle$ for unit $u \in U$, the unit's total value V_u is defined by:

$$V_u = \max_{\mathrm{ON}_u} \sum_{\substack{t \in T \wedge \\ s \in s(u) \wedge \\ ON_u(t,s)=1}} v_u(t, s)$$

subject to:

$$(\forall t \in T) \sum_{\substack{s \in s(u) \wedge \\ ON_u(t,s)=1}} kw_u(t, s) \le PD_u$$

The total benefit for u, denoted B_u, is defined as its optimal value minus its cost, i.e.,

$$B_u = V_u - C_u$$

We say that a function ON_u is feasible with respect to PDA $\langle PD_u, C_u \rangle$ if the constraint that total power at every time interval is less than the peak demand bound is satisfied.

We assume that for the time interval in the horizon under consideration, the Peak-Load Demand Market (PLDM) stores the associated Power Allocation Setting (PAS) as depicted in Figure 4.1. We now define a number of desirable properties of the Peak-Load Demand Market (PLDM).

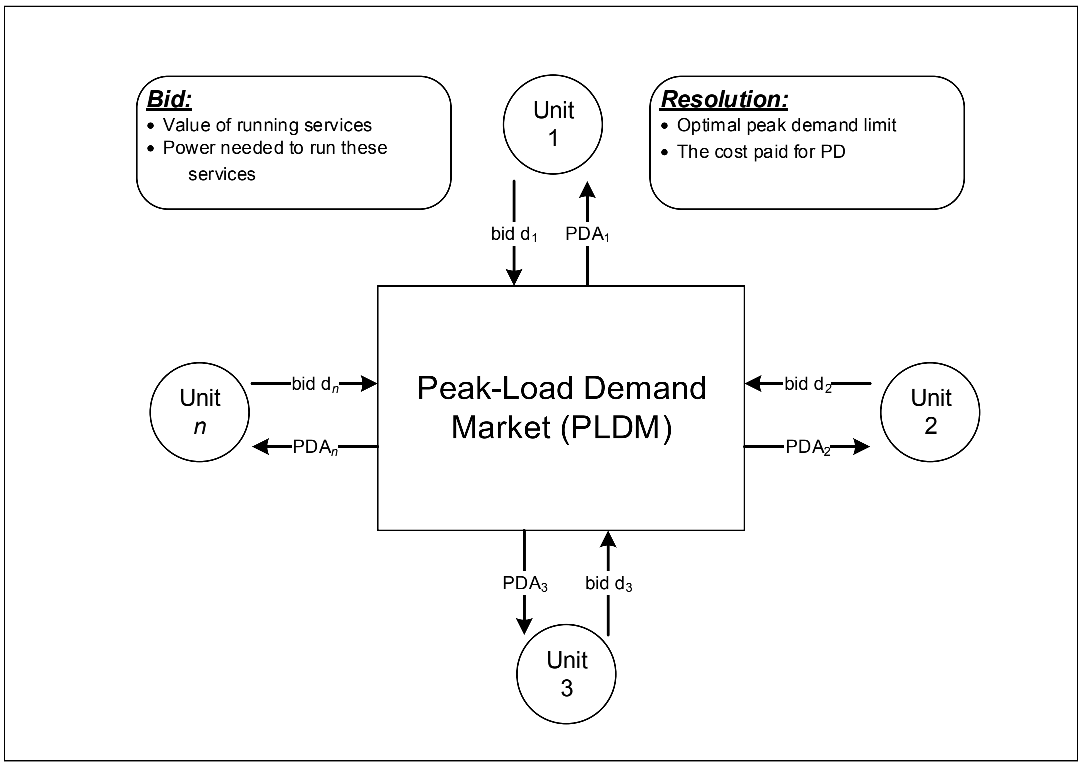

Figure 4.1: Peak-Load Demand Market

Property 1: *Pareto* Optimality.

Given a PAS P and bids $\{d_1, \cdots, d_n\}$, we say that $\{PDA_1, \cdots, PDA_n\}$ are Pareto optimal if there does not exist a set of PDA allocations $\{PDA'_1, \cdots, PDA'_n\}$ such that

$$(\forall u \in U) \quad B'_u \geqslant B_u$$

and

$$(\exists u \in U) \quad B'_u > B_u$$

where B'_u is the total benefit under PDA'_u . In other words, no other peak demand allocation can increase the benefit of a single unit without reducing the benefit of other units. Similarly, we say that Peak-Load Demand Market framework is *Pareto* optimal if, for every *PAS P* and bids $\{d_1, \cdots, d_n\}$, it always returns a *Pareto* optimal $\{PDA_1, \cdots, PDA_n\}$.

Property 2: *Nash* Equilibrium.

We say that Peak-Load Demand Market satisfies the *Nash* equilibrium property if for every *PAS P* and bids $\{d_1, \cdots, d_n\}$, the Peak Load Demand Market returns allocations $\{PDA_1, \cdots, PDA_n\}$ such that no unit can get a higher total benefit by quitting the coalition. That is, for every $u \in U$:

$$B'_u \leqslant B_u$$

where B'_u is the maximum benefit that can be achieved by unit u by running its own services within its optimal peak demand budget. That is,

$$B'_u = \max_{ON_u, PD_u} \sum_{\substack{t \in T \wedge \\ s \in s(u) \wedge \\ ON_u(t,s)=1}} v_u(t,s) \; - \; P(PD_u)$$

subject to:

$$(\forall t \in T) \sum_{\substack{s \in s(u) \wedge \\ ON_u(t,s)=1}} kw_u(t,s) \leq PD_u$$

4.3 Optimizing Consortium's Utility

Here we use a service configuration function

$$ON : T \times S \to \{0, 1\}$$

to denote, for each service $s \in S$ and time point $t \in T$, whether it will be on (i.e., $ON(t, s) = 1$) or off (i.e., $ON(t, s) = 0$). To implement the Peak-Load Demand Market, we need to allocate peak demand bounds optimally among any subset W of units U. We formulate this optimization problem as the following:
Given:

- Power Allocation Setting (PAS) $A = \langle U, S, s, P \rangle$.
- a set $D = \{d_1, \cdots, d_n\}$ of bids.
- a subset W of units U, and
- a service configuration ON.

The service configuration value $X(A, D, W, ON)$ is defined as the total utility achieved by running all services of W that are on. That is,

$$X(A, D, W, ON) = \sum_{u \in W} V_{u,ON}$$

where

$$V_{u,ON} = \sum_{\substack{t \in T \wedge \\ s \in s(u) \wedge \\ ON_u(t,s)=1}} v_u(t, s)$$

Given (1) Power Allocation Setting A, (2) a set of bids $D = \{d_1, \cdots, d_n\}$, and (3) a subset W of U, the optimal peak demand for each unit is optimal value that this subset of unit can achieve, i.e.,

$$(\forall u \in W) \quad PD_u \in \underset{\substack{ON \in (T \times S \to \{0,1\}),\\ (\forall u \in W)(PD_u \in \mathbb{R})}}{\arg\max} X(A, D, W, ON) - P(\sum_{u \in W} PD_u)$$

subject to:

$$(\forall t \in T)\ (\forall u \in W) \sum_{\substack{s \in s(u) \wedge \\ ON_u(t,s)=1}} kw_u(t, s) \leq PD_u$$

The optimal service value $O(A, D, W)$ is defined as the maximum value $X(A, D, W, ON)$ among all feasible service configurations ON, that is,

$$O(A, D, W) = \max_{ON \in (T \times S \to \{0,1\})} X(A, D, W, ON)$$

subject to:

$$(\forall t \in T)\ (\forall u \in W) \sum_{\substack{s \in s(u) \wedge \\ ON_u(t,s)=1}} kw_u(t, s) \leq PD_u$$

We say that a service configuration function ON, and peak-demand bounds PD_u , for every $u \in W$, are optimal, if they are a solution to the above optimization problem. Using this modular representation, we can derive the optimal benefit value for any subset W of U.

4.4 Resolving Peak-Load Demand Market

By resolving a peak-load demand market we mean coming up with power demand allocations which are the the optimal peak-demand bounds that should be selected by each unit and their associated costs that needs to be paid, i.e.,

$$PDA = \{(PD_1, C_1), \ldots, (PD_u, C_u)\}$$

Given the Power Allocation Setting A and bids $D = \{d_1, \cdots, d_n\}$, the global collaborative optimal value is

$$V = O(A, D, U)$$

The optimization problem for finding $O(A, D, U)$ gives optimal peak demand bounds PD_u, for every $u \in U$. The cost of procuring these peak-demand bounds is

$$C = P(\sum_{u \in U} PD_u)$$

Thus, The benefit achieved by the collaboration is the total value of the optimal solution minus the cost of the peak demand, i.e.,

$$B = V - C$$

Whereas, the optimal value for each $u \in U$ operating individually, i.e., without collaboration is

$$V'_u = O(A, D, \{u\})$$

The cost of peak demand to each unit $u \in U$ operating individually is

$$C'_u = P(PD'_u)$$

where PD'_u is an optimal peak demand for u . Therefore the benefit B'_u for each unit $u \in U$ is given by:

$$B'_u = V'_u - C'_u$$

Therefore, if the units do not collaborate, their combined benefit B' is the sum of their individual benefits, i.e.,

$$B' = \sum_{u \in U} B'_u$$

Note that the collaborative benefit B achieved when units work together can only improve the non-collaborative benefit B', when each unit acquires its own peak demand separately:

$$B \geq B'$$

The difference

$$\Delta = B - B'$$

is the collaboration added benefit. We now need to *fairly* distribute the added collaboration benefit Δ among participating units into $(\Delta_1, \ldots, \Delta_n)$, where $\Delta_u \geq 0$ for every $u \in U$.

We say that$(\Delta_1, \ldots, \Delta_n)$ is a fair distribution of collaboration benefit of Δ if, for each unit $u \in U$, all units make equal profit margin on their non-collaborative benefit, i.e.

1. $\sum_{u \in U} \Delta_u = \Delta$

2. $(\forall i, j \in U) \quad \frac{\Delta_i}{B'_i} = \frac{\Delta_j}{B'_j}$

To achieve this fair distribution $(\Delta_1, \ldots, \Delta_n)$, we must satisfy

$$\frac{\Delta_1}{B'_1} = \ldots = \frac{\Delta_n}{B'_n} = p$$

Where p is the *Equal Profit Margin.* Then,

$$(\forall u \in U) \quad \Delta_u = p \cdot B'_u$$

Therefore,

$$\Delta = \sum_{u \in U} \Delta_u = \sum_{u \in U} p \cdot B'_u = p \sum_{u \in U} B'_u = p \cdot B'$$

Thus,

$$p = \frac{\Delta}{B'}$$

Finally,

$$(\forall u \in U) \quad \Delta_u = p \cdot B'_u$$

To resolve the market, we need to find the peak demand allocation $PDA_u = \langle PD_u, C_u \rangle$ for every $u \in U$. PD_u for every $u \in U$ is obtained by solving $O(P, D, U)$ optimization problem. Therefor, we only need to compute C_u, for every $u \in U$.

From the collaboration added benefit Δ_u for every $u \in U$, we can compute its benefit B_u:

$$B_u = B'_u + \Delta_u$$

We also have the utility value of every unit V_u given which services to run from the optimal solution value of $O(A, D, U)$ optimization problem. Thus,

$$B_u = V_u - C_u$$

and so

$$C_u = V_u - B_u$$

This concludes the market resolution.

Claim: Peak-Load Demand Market guarantees the following aforementioned properties:

- *Pareto Optimality.*
- *Nash Equilibrium.*
- *Equal Profit Margin.*

Proof:

Pareto Optimality follows from the fact, $B_1 + \ldots + B_n = B$, where B is the global maximum of the consortium benefit. *Nash Equilibrium* property follows from the fact that Δ, and thus $\Delta_u \geq 0$, for each $u \in U$. *Equal Profit Margin* follows directly from the way the cost of peak demand bound is distributed.

4.5 Implementation

To evaluate our model, we implemented the optimization problem using IBM's Optimization Programming Language (OPL) which is part of IBM's ILOG CPLEX Optimization Studio. OPL is a language that is tailored to write mathematical programming (MP) and constrained programming (CP) problems. We primarily take advantage of its Mixed Integer Linear Programming (MILP) solver to provide the solution of our optimization. To better simulate this market, we created multiple units which in turn consist of multiple services 4.2. We simulate the demand of multiple services over the time horizon under study and store their kW demand and the associated utility of running the services as depicted in Table 4.1.

Table 4.1: Sample Services

Service ID	Unit ID	KW	Utility	Time Slot
1	1	100	40	1
2	1	150	50	1
3	2	400	90	1
4	2	200	45	1
5	3	300	70	1
6	3	500	55	1
7	4	100	25	1
8	4	350	30	1

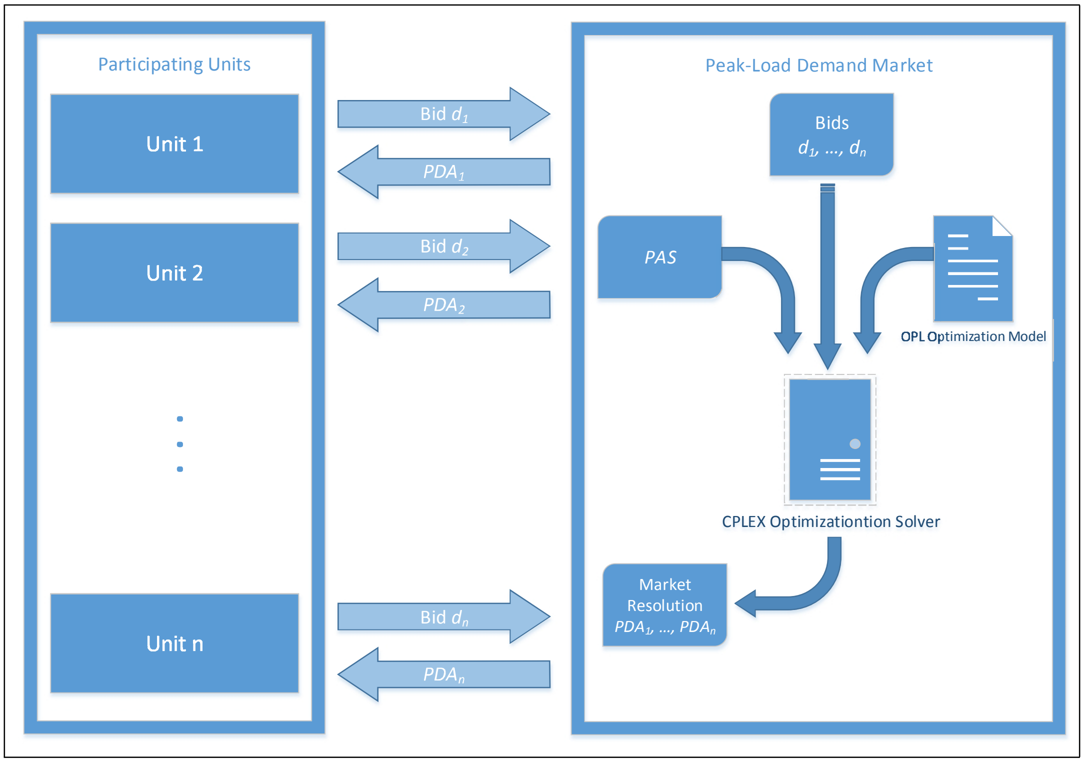

Figure 4.2: Peak-Load Demand Market Implementation

After the services data for all time intervals under consideration are acquired, optimization is conducted on each unit individually to determine their separate optimal values as if they are working alone. Table 4.2 show piece wise step function for the peak demand power price for the considered contractual time period.

Table 4.2: Peak Demand Price Function

Peak Demand in KW	Price
0-1000	KW*(0.20)
1,001-2,000	KW*(0.15)
2,001-3,000	KW*(0.13)

After the individual optimization is performed, we conduct an overall optimization assuming all units are working collaboratively. The resulting allocation specifies which services to run and at which time interval as shown in Table 4.3.

Table 4.3: Optimized Services Run Schedule

Service ID	ON	Time Slot
1	1	1
2	1	1
3	1	1
4	0	1
5	1	1
6	1	1
7	0	1
8	1	1

The benefits of working collaboratively versus working individually are compared. Then, the resulting added benefit (Δ) is calculated. Using the *Equal Profit Margin* described in resolution of peak-load demand market section, the added benefit is distributed fairly among participating units as depicted in Table 4.4.

Table 4.4: Added Benefit Distribution

Unit ID	B'_u	Δ_u
1	24	3
2	64	6
3	135	15
4	52	5

Finally, the cost for each unit is calculated by determining the benefit to each unit and finding out the cost that each unit has to make part of the market resolution. A sample of peak demand distribution and its cost to each unit is shown Table 4.5.

Table 4.5: Peak Demand Allocation

Unit ID	Peak Demand in KW	Cost
1	250	45
2	400	70
3	800	136
4	350	63

To verify the applicability of such solution to real world setting, we populated three data sets with an increasing number of participating units and their corresponding services. Although the optimization model consisted mainly of a large number of boolean decision variables, we found that the execution time was relatively fast using the multiple data sets as shown in Table 4.6. The machine used was a dual-core processor workstation, with an 8 GB RAM. ILOG CPLEX Studio was installed on the same machine where the experiments were performed. Since the market is run less frequently for specific peak demand contractual period, the emphasis to converge to an optimal solution in a very short time is not of high significance. As can be seen from the table, the largest test set of 1,000 units and 10,000 services required around 1 minute and 30 seconds to arrive at a solution. Comparing this result with previous data sets' execution time, it can be stated the time complexity is linear to the test data set size. This result is very reasonable considering the consortium's size and the overhead of managing bids.

4.6 Conclusions

We presented Peak-Load Demand Market framework which aims to make units of a power consumption consortium collaborate to reduce the cost of procuring their electricity. We

Table 4.6: Test Data Sets Size and Optimization Time

Number of Units	Number of Services	Optimization Time (in seconds)
10	60	0.32
100	1,000	8.62
500	5,000	52.91
1,000	10,000	93.11

proposed Peak-Load Demand Market framework to incentivize organizational units of Commercial and Industrial customers or units of a consortium to reduce their peak demand cost by collaboratively deciding their peak demand bound limits. The market described units bids elicitation as well as the resolution of the market and the service and peak demand allocation as well as the cost. We formally defined the market and constructed an optimization model that satisfies desirable properties, i.e, *Nash Equilibrium*, *Pareto Optimality* and *Equal Profit Margin*. After experimentation, the proposed market resulted in an increase in the overall benefit of participating organizations and reduced their cost based on randomly generated data test sets. Our approach assumes certain independence on the power loads of participating units. However, there still remain some open questions about the possibility of introducing some scheduling constraints to address issues of interrelated power loads across multiple participating units.

CHAPTER 5: Electric Power Consortia: Decision Guidance Based on Market Optimization

Proposed in this chapter is an extensible decision guidance system framework to facilitate Commercial and Industrial entities forming a consortium to collaborate on their electric power supply and demand in order to streamline their consumption and reduce their costs. The collaborative framework includes the structure of market setting, participants' bids, and a market resolution which produces a schedule of how power components are controlled as well as the resulting payment by market participants. We also define four properties that the market resolution must satisfy, namely, *feasibility*, *Pareto-optimality*, *Nash equilibrium*, and *equal collaboration profitability*. Furthermore, we develop a market resolution algorithm, based on a formal optimization model and prove that it satisfies the desirable market properties.

5.1 Introduction

There has been an ongoing trend of moving toward less reliance on conventional hydrocarbon energy resources and more adoption of cleaner alternative energy due to increased fuel costs or for organization's strive be more sustainable. This trend created a plethora of alternatives that promise to cut carbon emissions and pollutants. Commercial & Industrial (C&I) organization have a variety of power enabled services. Furthermore, they add a variety of energy and power resources including Photovoltaics, wind, storage, local back-up generation, and commercial contracts on supply of power and load curtailment.

In this context two complex questions arise: (1) how to optimaly operate available resources over time, and (2) how multiple C&I organizations can collaborate on sharing resources to minimize their costs. This chapter focuses on decision support and guidance for C&I organizations to address these two problems.

To better understand interaction and collaboration between different units, consider an illustrative scenario depicted in Figure 5.1. In this scenario multiple units (e.g., C&I organizations) have a diverse set of resources that supply power and provide multiple services that consume power at any operation time interval.

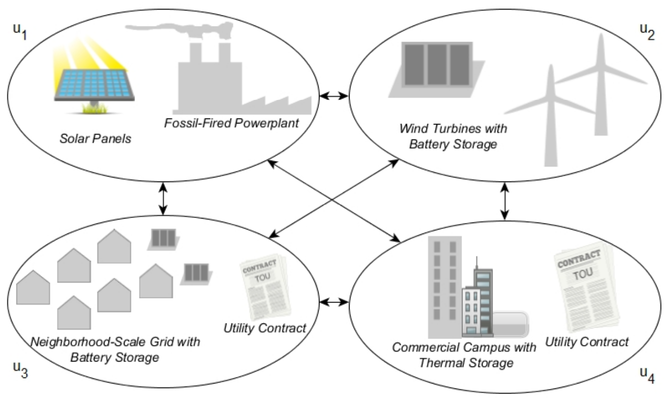

Figure 5.1: Power Loads & Resources Collaboration Example

While a utility contract with electrical power company is common, an organization can have other energy resources (e.g., photovoltaic power systems, storage batteries, backup engine generators, etc.) at its disposal. With so many alternatives, finding the optimal operation of such resources while taking into consideration the possibility of collaborating with others becomes an increasingly complex problem.

In order to model such a scenario, we must define how electrical power components (i.e., electrical power resources, or electrical power consuming services) are modeled. Furthermore, we need to describe how they behave under various conditions. In general, power components of the electrical power infrastructure can either produce power, consume power, store power, or remain idle at any given time interval over the time horizon under consideration. While power components' internal workings can be unique, we try to find common characteristics that these components share in order to generalize their modeling.

In previous chapters, we explored the idea of how units of an organization can optimally share their peak-demand bounds to achieve an overall better operational utility while fairly compensating participating units. We also optimally planned the selection of peak-demand of collaborating entities based on the projected demand over a time-horizon with the condition that units can share their peak-demand bounds during operation. Both approaches resulted in a better overall optimal value than if each player acted separately. However, this approach does not consider a range of power resources and services (e.g., photovoltaics, battery storage, backup generator, etc.), and is not extensible. Bridging this gap is the focus of this chapter.

Making decisions in an environment where the the benefit received from the operation of power consuming services and the costs of power supply and acquisition coupled with the possibility of collaboration in real-time and for future planning with other C&I units presents a complex problem. The purpose of this chapter is to introduce a decision guidance and support framework (see Figure 7.1) where C&I units that demand power, supply power, or both can collaborate to optimize the operation, supply, and acquisition of electrical power components so that they achieve a better financial and operational level.

In this chapter, we propose an extensible decision guidance system framework for market-based collaboration of power resources and services. In doing so, we create an extensible model where resources & services can be added or removed by minimally describing their attributes. More specifically, the contributions of this chapter are as follows:

First, we propose and formally define a collaborative market framework. The basic idea of this market is to create a consortium of organizational units where each unit has the freedom to make decisions related to power consumption, generation, and storage. Members of this consortium have multiple services that they need to run (e.g., lighting, HVAC, water heating, etc.) and also have various power resources (e.g., utility contract, photovoltaics, backup power generator, etc.). The members also have some expectation of the intrinsic value of running services at different levels of operation over a time horizon represented

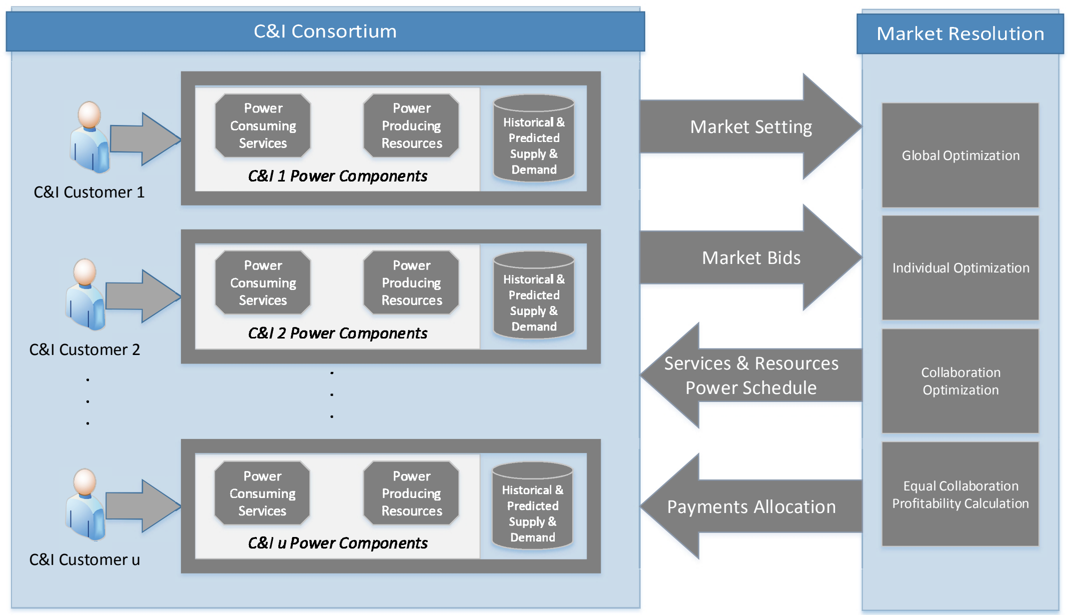

Figure 5.2: Electric Power Collaboration Decision Support Framework

as a bid that each member of this consortium submits to market. The market resolution produces a power resource allocation for each unit, and the payment that each member has to pay or receive at every time interval when the market executes. We also define four desirable properties that our market must satisfy, namely, *feasibility*, *Pareto-optimality*, *Nash equilibrium*, and *equal collaboration profitability*.

Second, in order to support market resolution, we develop and implement a formal optimization model to decide on the operation of resources to be used, and the services that are run while maintaining feasibility, i.e, the power consumed by all members of the consortium does not exceed the total power supply.

Third, we develop a market resolution mechanism based on the optimization models that guarantees the satisfaction of the defined properties of market, namely, *Pareto optimality, Nash equilibrium*, as well as the property of *equal collaboration profitability* which will be defined formally in the next sections.

This chapter is organized as follows: In the section two, we present a small example of the collaboration problem. In section three, we describe our collaborative market framework where we formally define the power market setting, market bids, market resolution and the desirable properties that our market must satisfy. In section four, we describe the market resolution algorithm and how the extra benefit that resulted from the collaboration is fairly distributed among the participants. Finally, we briefly discuss our conclusions.

5.2 Problem Example

To make the problem more concrete consider an example depicted in Figure 5.3 which has tow units. Unit 1 runs two power consuming services, water heating, and HVAC. These two services have value to their respective unit which we call intrinsic value (measured in dollar amount). By intrinsic value we mean the amount in dollars that a unit is willing to accept in lieu of shutting that service off. Unit 1 also has two types of power resources. Each power consuming service needs power to operate measured which is measured in kW. The first resource of unit 1 is a is a utility contract with a power company. This is not a power resource in itself but a right to use power based on an agreed upon terms. Utility contract typically states the rate per kWh in dollars and a maximum peak demand consumption level before incurring a penalty rate. The other resource type is a back-up power generator. Unit 2, on the other hand, has two other power consuming services: lighting, and Plug-in Electric Vehicle (PEV) charging . Unit 2 resources are Photovoltaic (PV) unit and battery power storage unit. The battery unit has controls that can be instructed at any given time interval to store power (charge), provide power (discharge), or remain idle.

Using a power resource typically incurs certain cost which can be either variable, fixed or both (e.g., acquisition cost, fuel cost, maintenance cost, etc.). If these resources are dispatched to third parties, they can generate revenue. These resources usually have certain status indicators (e.g., charge level, efficiency, etc.) which vary depending on the type of resource. Resources also have constraints that determine the feasible operation parameters depending on multiple factors including the status of the power resource. Most power consuming and producing components allow for control that affect their operation.

In a typical environment, units operate independently to satisfy their power loads. Now let's consider a scenario where unit 1 has a previously unanticipated surge in demand. Unit 1 now has many alternatives to consider. It can exceed its peak demand and incur penalty which could affect the entire contractual period. It can also arbitrarily curtail demand without giving much thought to the lost intrinsic value of the service being turned off. Unit 1 can also dispatch the battery to satisfy excess demand without considering the diminished ability of the battery to satisfy possible future demand. Now add to that the ability for multiple units to collaborate. That means if units 2 would agree to a certain compensation, unit 1 could use unit 2's back-up power generator. Choosing an alternative that maximizes the units' value becomes increasingly complex problem without a collaborative market framework.

The proposed formal market framework described in the next Section (5.3) is designed to address the problems of (1) how combined resource and service operate in an optimal fashion, and (2) How to fairly compensate each unit for enabling the usage of its resources.

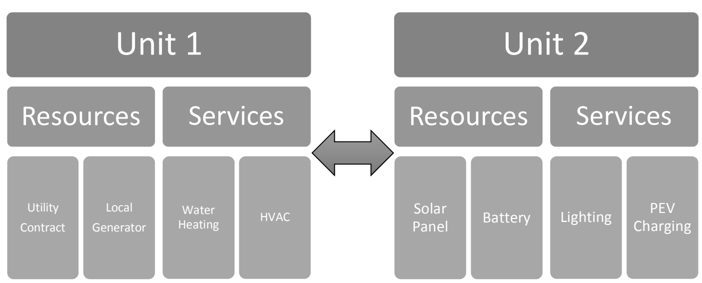

Figure 5.3: Example Problem Units' Power Components

5.3 Collaborative Market Framework

In this section we define the power market setting, market bids, and the market resolution and its desired properties. We begin by describing the power market setting (see 5.4 for an overview of the decision guided market).

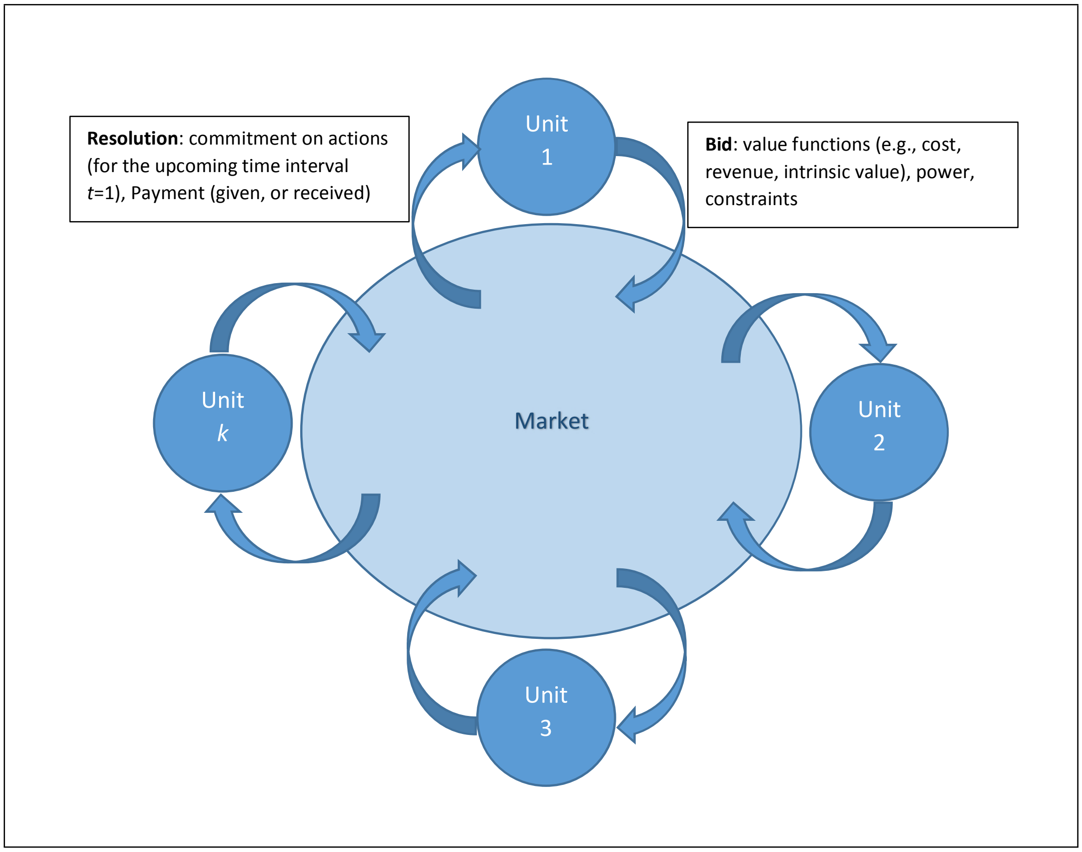

Figure 5.4: Decision Guidance Framework Overview

5.3.1 Power Market Setting

To facilitate market mechanisms, we assume that the market consist of a set of components $C = \{1, \cdots, n\}$. Power components can be in the form power producing resources such as back-up power generators, Photovotiac units, etc. They can also be in the form of power consuming services such as lighting, air conditioning, water heating, etc. The time horizon is a set of time intervals $T = \{1, \cdots, N\}$, i.e., we assume that time is divided into discrete time intervals which determine the market execution frequency. For example, a day of operation can be divided into 24 hours, i.e., $N = 24$.

A control vector $a_{i,t}$, $1 \le i \le n$, $1 \le t \le N$ represents the control actions that component i takes at time interval t. Let $\mathrm{dom}(i)$ indicate the domain of all possible control action values for component i. A vector of controls $\bar{a}_i = (a_{i,1}, \cdots, a_{i,N})$, $1 \le i \le n$, represents the control actions that component i takes over the time horizon N. The control actions for all components over the time horizon N is represented as a matrix

$$A = \begin{pmatrix} \bar{a}_1 \\ \vdots \\ \bar{a}_n \end{pmatrix} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,N} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,N} \end{pmatrix}$$

We assume that the market consists of a set of units $U = \{1, \cdots, k\}$. Each unit $u \in U$ has number of components and each component belongs to only one unit. We further assume without loss of generality that unit 1's components are $\{1, \cdots, n_1\}$, unit 2's components are $\{n_1 + 1, \cdots, n_2\}$, and so on and finally unit k's components are $\{n_{k-1} + 1\ , \cdots, n\}$. For a general notation, unit u's components are $\{n_{u-1} + 1, \cdots, n_u\}$ where $n_0 = 0$ and $n_k = n$.

The matrix of actions A can then be segmented by the participating units, i.e.,

$$A = \begin{pmatrix} A_1 \\ \vdots \\ A_u \\ \vdots \\ A_k \end{pmatrix} = \left(\begin{array}{c} \bar{a}_1 \\ \vdots \\ \bar{a}_{n_1} \\ \hdashline \boldsymbol{\vdots} \\ \hdashline \bar{a}_{n_{u-1}+1} \\ \vdots \\ \bar{a}_{n_u} \\ \hdashline \boldsymbol{\vdots} \\ \hdashline \bar{a}_{n_{k-1}+1} \\ \vdots \\ \bar{a}_n \end{array}\right)$$

where A_u, $1 \leq u \leq k$, is given by

$$A_u = \begin{pmatrix} \bar{a}_{n_{u-1}+1} \\ \vdots \\ \bar{a}_{n_u} \end{pmatrix} = \begin{array}{c} \begin{array}{ccc} A_{u1} & & \phantom{a_{n_{u-1}+1,N}} \end{array} \\ \begin{pmatrix} \mathbf{a_{n_{u-1}+1,1}} & \cdots & a_{n_{u-1}+1,N} \\ \vdots & \ddots & \vdots \\ \mathbf{a_{n_u,1}} & \cdots & a_{n_u,N} \end{pmatrix} \end{array}$$

We will denote by A_{u1} the first column of matrix A_u, i.e., the actions for the components of unit u at time interval $t = 1$ (upcoming time interval). That is,

$$A_{u1} = \begin{pmatrix} a_{n_{u-1}+1,1} \\ \vdots \\ a_{n_u,1} \end{pmatrix}$$

5.3.2 Market Bids

Every unit $u \in U$ submits a bid to the market

$$\{\langle cost_i, rev_i, intrinsicVal_i, power_i, constr_i \rangle \mid n_{u-1} + 1 \leq i \leq n_u\}$$

which gives a tuple $\langle cost_i, rev_i, intrinsicVal_i,\ power_i, constr_i \rangle$ for every component i of u where:

- $cost_i : \text{dom}(i)^N \rightarrow \mathbb{R}^+$ is a function that gives total cost of component of operating component i associated with actions $\bar{a}_i$ over the time horizon. For example, a cost of a pack-up power generator consists of the acquisition cost, fuel cost, maintenance cost, etc.

- $rev_i : \text{dom}(i)^N \rightarrow \mathbb{R}^+$ is a functions that gives the revenue of operation received (in dollars) of component i associated with control actions $\bar{a}_i$ over the time horizon, for example, dispatching the battery to a another unit in return for compensation.

- $intrinsicVal_i : \text{dom}(i)^N \rightarrow \mathbb{R}^+$ is a function that gives the intrinsic value (or utility received) of operating component i (in dollars) given control actions $\bar{a}_i$ over the time horizon. In other words, this is the value that unit u is willing to get in lieu of not operating component i.

- $power_i : \text{dom}(i) \rightarrow \mathbb{R}$ is a function that gives the power in kW that component i produces (or consumes) given the control actions $\bar{a}_i$ at any time interval. A positive value means that the component gives power while a negative value means that the component receives power.

- $constr_i(\bar{a}_i)$ is the operational constraints of component i in terms of control actions $\bar{a}_i$. For example, maximum charge rate (in kW) and maximum discharge rate (in KW) are constraints that affect the power given or received from a battery resource component.

We denote the net value of operating component i given control actions $\bar{a}_i$ by the function

$$value_i : \mathrm{dom}(i) \to \mathbb{R}^+$$

which is defined by

$$value_i(\bar{a}_i) \stackrel{\mathsf{def}}{=} intrinsicVal_i(\bar{a}_i) + rev_i(\bar{a}_i) - cost_i(\bar{a}_i).$$

The total value of all components given their control actions matrix

$$A = \begin{pmatrix} \bar{a}_1 \\ \vdots \\ \bar{a}_k \end{pmatrix}$$

is defined as

$$totalValue(A) \stackrel{\mathsf{def}}{=} \sum_{i=1}^{k} value_i(\bar{a}_i).$$

5.3.3 Market Resolution and Its Desired Properties

Definition. *A market resolution is a set*

$$\{\langle A^*_{u1}, P_u\rangle \mid 1 \leq u \leq k\}$$

where, for every $1 \leq u \leq k$:

- *A^*_{u1} is the actions control matrix at time interval 1 (upcoming time interval) for all* *components of unit u .*

- P_u *is the payment amount (in dollars) by unit u. A positive value indicates that unit u makes a payment while a negative value means that the unit receives a payment.*

We propose the following desired properties of a market resolution:

- *Feasibility*
- *Pareto-optimality*
- *Nash equilibrium*
- *Equal collaboration profitability*

which we describe next.

Intuitively, a market resolution is feasible if the actions control vector for every unit u at time interval 1 can be extended for the entire time horizon without violating unit u's constraints. More Formally,

Definition. *We say that a market resolution* $\{\langle A_{u1}, P_u\rangle \mid 1 \leq u \leq k\}$ *is feasible if, for every unit* u, $1 \leq u \leq k$, *there exists a unit's actions control matrix*

$$A_u = \begin{pmatrix} \bar{a}_{n_{u-1}+1} \\ \vdots \\ \bar{a}_{n_u} \end{pmatrix} = \begin{pmatrix} a_{n_{u-1}+1,1} & \cdots & a_{n_{u-1}+1,N} \\ \vdots & \ddots & \vdots \\ a_{n_u,1} & \cdots & a_{n_u,N} \end{pmatrix}$$

$$\textit{where} \begin{pmatrix} a_{n_{u-1}+1,1} \\ \vdots \\ a_{n_u,1} \end{pmatrix} = A^*_{u1}$$

In the definition, note that the control actions for time interval 1 are exactly those of A^*_{u1} so that each component i of u, $n_{u-1}+1 \leq i \leq n_u$ satisfies its constraints $constr_i(a_{i,1}, \cdots, a_{i,N})$.

To define the properties of *Pareto optimality* and *Nash equilibrium*, we need to define the notions of *selfValue* and *collabValue* for unit u , associated with the market resolution.

Intuitively, a *selfValue* of u is the value u can optimally achieve without collaborating with other units. More formally,

Definition. $\mathit{selfValue}_u$ =

$$
\begin{aligned}
&\max_{A_u} \quad \mathit{totalValue}(A_u) \\
&\mathit{subject\ to} \\
&(\forall i,\ n_{u-1}+1 \le i \le n_u) \quad \mathit{constr}_i(\bar{a}_i) \quad \wedge \\
&(\forall t,\ 1 \le t \le N) \sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a_{i,t}) = 0
\end{aligned}
$$

The optimal actions matrix A_u^s *is the actions matrix that gives the maximum self value under the the same constraints. That is,*

$$
\begin{aligned}
A_u^s \in \ &\arg\max_{A_u} \ \mathit{totalValue}(A_u) \\
&\mathit{subject\ to} \\
&(\forall i,\ n_{u-1}+1 \le i \le n_u)\ \mathit{constr}_i(\bar{a}_i) \quad \wedge \\
&(\forall t,\ 1 \le t \le N) \sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a_{i,t}) = 0
\end{aligned}
$$

Intuitively, given a market resolution, a collaborative value of u is the value that u can optimally achieve by extending its actions A_{u1}^* from the market resolution. More formally,

Definition. $\mathit{collabValue}_u =$

$$\max_{A_u} \ \mathit{totalValue}(A_u)$$

$$\mathit{subject\ to}$$

$$(\forall i,\ n_{u-1}+1 \leq i \leq n_u)\ \big(\mathit{constr}_i(\bar{a}_i) \wedge (a_{i,1} = a^*_{i,1})\big) \wedge$$

$$\sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a_{i,1}) = \sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a^*_{i,1}) \wedge$$

$$(\forall t,\ 2 \leq t \leq N) \sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a_{i,t}) = 0$$

where $a^*_{i,1}$ *is a component of* $A^*_{u_1}$ *from the market resolution.*

The optimal control actions matrix A^c_u is the actions matrix that gives the maximum collaborative value for each unit under the same constraints. That is,

$$A^c_u \in \arg\max_{A_u} \quad \mathit{totalValue}(A_u)$$

$$\text{subject to}$$

$$(\forall i,\ n_{u-1}+1 \leq i \leq n_u)\ \big(\mathit{constr}_i(\bar{a}_i) \wedge$$

$$(a_{i,1} = a^*_{i,1})\big) \wedge$$

$$\sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a_{i,1}) = \sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a^*_{i,1}) \wedge$$

$$(\forall t,\ 2 \leq t \leq N) \sum_{i=n_{u-1}+1}^{n_u} \mathit{power}_i(a_{i,t}) = 0$$

Intuitively, a market resolution is *Pareto optimal* if no other market resolution can increase the value of a unit without decreasing the value of another unit. More specifically,

Definition. *Pareto-ptimality: We say that a market resolution* $\{\langle A^*_{u_1}, P_u\rangle \mid 1 \leq u \leq k\}$ *is Pareto-optimal if there does not exist a market resolution* $\{\langle A'_{u_1}, P'_u\rangle \mid 1 \leq u \leq k\}$ *such that*

$$(\forall u \in U) \quad (collabValue'_u + P'_u) \geq (collabValue_u + P_u)$$

and

$$(\exists u \in U) \quad (collabValue'_u + P'_u) > (collabValue_u + P_u)$$

Definition. *Nash equilibrium: We say that a market resolution satisfies the Nash equilibrium property if no unit can get a higher value by quitting the coalition, i.e.,*

$$(collabValue_u + P_u) \geq selfValue_u$$

Nash Equilibrium guarantees that each unit can only do better by joining the consortium.

Definition. *Equal collaboration profitability of market resolution (fairness): We say that a market resolution satisfies the equal collaboration profitability property if every unit u has the same profit margin* r_u*, defined as*

$$r_u \stackrel{\text{def}}{=} \frac{(collabValue_u - P_u) - selfValue_u}{selfValue_u}$$

Note that $collabValue_u - P_u$ reflects the total value that unit u receives from the market ($collabValue$ minus the payment).

Definition. *Market-Resolution Algorithm properties: We say that a market resolution algorithm satisfies the properties of (1) Feasibility, (2) Pareto-optimality, (3) Nash equilibrium, and (4) Equal collaboration profitability, if for every market setting and market bids, it returns a market resolution that satisfies the corresponding properties.*

5.4 Market Resolution Algorithm

After we have formally defined the market resolution and its desired properties, we now present how our market resolution algorithm. We first define the global optimization upon which the control actions of the market resolution for the upcoming time interval are based(A^*_{u1}). We then optimally extend control actions for all the units for remaining time intervals to find their collaborative value and then compare it to their non-collaborative value and calculate the added benefit of collaboration (Δ). Finally we define how this added benefit is distributed in order to determine the payment (P_u) that each unit has to give or receive as part of the market resolution.

5.4.1 Global Optimization

The optimal value that the coalition can achieve which maximizes the welfare is given by the maximization

$$
\begin{aligned}
globalValue \; = \; & \max_{A} \quad totalValue(A) \\
& \text{subject to} \\
& (\forall i,\ 1 \leq i \leq n) constr_i(\bar{a}_i) \quad \wedge \\
& (\forall t,\ 1 \leq t \leq N) \sum_{i=1}^{n} power_i(a_{i,t}) = 0
\end{aligned}
$$

The control actions matrix that produces the optimal maximum total value for all components is the global control actions matrix A^g, i.e.,

$$A^g \in \arg\max_A \quad totalValue(A)$$

$$\text{subject to}$$

$$(\forall i,\ 1 \le i \le n) constr_i(\bar{a}_i) \quad \wedge$$

$$(\forall t,\ 1 \le t \le N) \sum_{i=1}^{n} power_i(a_{i,t}) = 0$$

The matrix

$$A^g = \begin{pmatrix} a_1^g \\ \vdots \\ a_n^g \end{pmatrix} = \begin{pmatrix} a_{1,1}^g & \cdots & a_{1,N}^g \\ \vdots & \ddots & \vdots \\ a_{n,1}^g & \cdots & a_{n,N}^g \end{pmatrix}$$

represents the control actions that all units combined need to make in order to achieve the optimal value over the entire time horizon. However, since our market lets units commits on at the first time interval, we are only interested in the upcoming time interval ($t = 1$) control actions. The control actions matrix A_u^g for every unit $1 \le u \le k$, is given by

$$A_u^g = \begin{pmatrix} \bar{a}_{n_{u-1}+1}^g \\ \vdots \\ \bar{a}_{n_u}^g \end{pmatrix}$$

The market resolution control actions are therefore adopted from the this global optimization, i.e.,

$$A^*_{u1} = A^g_{u1} = \begin{pmatrix} a^g_{n_{u-1}+1,1} \\ \vdots \\ a^g_{n_u,1} \end{pmatrix}$$

5.4.2 Added Collaboration Benefit (Δ)

After determining the optimal market resolution control actions, the impact on units' values for choosing this market resolution must be measured in order to compensate the units appropriately. The additional value the units collectively get by collaborating is the sum of the their collaborative values minus the sum of their non-collaborative values, i.e.,

$$\Delta = \sum_{u=1}^{k} collabValue_u - \sum_{u=1}^{k} selfValue_u$$

We assume that each unit u has a non-negative share of this Δ, i.e.,

$$\Delta = \sum_{u=1}^{k} \Delta_u \qquad , (\forall u = 1, \cdots, k) \quad \Delta_u \geq 0$$

Value difference is the value that each unit u gets by participating versus working alone, i.e.,

$$V_u = collabValue_u - selfValue_u$$

P_u is the payment that unit u makes ($P_u < 0$ means that u receives payment)

$$\Delta_u = V_u - P_u$$

Therefore,

$$P_u = V_u - \Delta_u$$

5.4.3 Added Benefit Distribution

The only remaining part is to find a *fair* methods to calculate Δ_u for each unit. We recall our defined principle of *equal collaboration profitability* which means that each unit gets a portion of the resulting added value of collaboration proportional to its standalone value, i.e.,

$$r = \frac{\Delta_1}{selfValue_1} = \cdots = \frac{\Delta_k}{selfValue_k}$$

where r is the ratio of the *equal collaboration profitability* margin. That is,

$$(\forall u \in U) \qquad \Delta_u = r \ \cdot \ selfValue_u$$

Since,

$$\Delta = \sum_{u=1}^{k} \Delta u$$

Therefore,

$$\Delta = \sum_{u=1}^{k} r \ \cdot \ selfValue_u$$

Thus,

$$\Delta = r \ \cdot \ \sum_{u=1}^{k} selfValue_u$$

Finally,

$$r = \frac{\Delta}{\sum_{u=1}^{k} selfValue_u}$$

The market resolution algorithm is summarized in Algorithm 1.

Algorithm 1 Market Resolution

Input: Market setting, Market bids

Output: Market resolution $\{\langle A^*_{u_1}, P_u \rangle \mid 1 \le u \le k\}$

Let $optCont[u] = \emptyset,\ pay[u] = \emptyset,\ V[u] = \emptyset$
Let $totalSelfValue = \emptyset,\ totalCollabValue = \emptyset$
Let $\Delta = \emptyset,\ r = \emptyset,\ \Delta[u] = \emptyset$
Solve $globalValue$
for $u \leftarrow 1$ **to** k **do**
  $optCont[u] \leftarrow A^g_{u_1}$
end for
for $u \leftarrow 1$ **to** k **do**
  Solve $selfValue_u$
  Solve $collabValue_u$
  $V_u \leftarrow collabValue_u - selfValue_u$
  $totalSelfValue \leftarrow totalSelfValue + selfValue_u$
  $totalCollabValue \leftarrow totalCollabValue + collabValue_u$
end for
$\Delta \leftarrow totalCollabValue - totalSelfValue$
$r \leftarrow \Delta / totalSelfValue$
for $u \leftarrow 1$ **to** k **do**
  $\Delta_u \leftarrow r \times selfValue_u$
  $pay[u] \leftarrow V_u - \Delta_u$
end for
return $(optCont, pay)$

Theorem. *The Market Resolution algorithm guarantees the desired market properties which are:*

- *Feasibility*
- *Pareto optimality*
- *Nash equilibrium*
- *Equal collaboration profitability*

Proof. Feasibility follows directly from A^c_u where actions of the global optimization are extended to satisfy the constraints of individual units. *Pareto optimality* follows from the fact of the collaborative maximization of the consortium value ($collabValue_u$). *Nash equilibrium* follows from the fact that $\Delta \geq 0$, and thus $\Delta_u \geq 0$ for every $u \in U$. *Equal collaboration profitability* of the added value of collaboration follows directly from the way the payment P_u and thus Δ_u is distributed. $\square$

5.5 Conclusions

This chapter introduced an extensible decision guided market-based framework where units that contain power producing and power consuming components can collaborate to increase their value and reduce their cost. This market described the market setting, market bids, and market resolution. This framework also described a number of desired properties that the market resolution algorithm must satisfy.

This up to our knowledge is the first attempt to model a generic electric power collaboration market framework with multiple players that is also extensible. In the next chapter, we formally model commonly used power components which has been briefly discussed in this chapter.

CHAPTER 6: Power Demand and Supply Components

In the previous chapter we proposed an extensible decision support system framework to facilitate Commercial and Industrial (C&I) entities forming a consortium to collaborate on their electric power supply and demand. In this chapter, we model common power components and provide their mapping to the concepts explained in the previous chapter.

6.1 Introduction

In the previous chapter, we presented a general market framework. Defined in the market framework were market setting, market bids, and market resolution. More specifically, The bids included the definitions of the functions of cost, revenue, intrinsic value, and power, i.e.,

$$\bar{a}_i, \mathrm{cost}_i, \mathrm{rev}_i, \mathrm{intrinsicVal}_i, \mathrm{power}_i, \mathrm{constr}_i$$

. In the following sections, commonly utilized power components such as renewable resources, battery storage units, backup generators, utility contracts, and power consuming services are discussed in details where the functions of the general model are mapped to specific classes of resources and the actions that units may take depending on the type of power component is also formally modeled.

6.2 Power Components Modeling

The controls actions that each power component take vary based on its type. In this section, a mapping between the general framework and specific types of commonly used power components is explained. To begin, the market consists of a set of units U and a set of components C such that each component i belong to exactly one unit u. The time horizon

T under consideration is a set of discrete time intervals (in hours) that a typical operational day has, i.e., $T = \{1, \cdots, N\}$ where $N = 24$ which means 24 hours a day with interval length. intervalLenght $= 1$ means that each time interval and an hour long. Although the planning of operation is modeled over the entire time horizon. The market resolution occurs only for the upcoming time interval, i.e., $t = 1$. For every power component, there are only two possible ways in which power flows. kw$[i][t]$ value can be positive which indicates that the component is supplying power or negative which indicates that the component is receiving power. It also can be equal to zero which indicates an idle and a turned off power component.

6.2.1 Utility Power Contract

Utility contract represents the most commonly used resource in C&I organizations. The utility contract is not a resource in itself but a right to use power at an agreed upon terms. These terms of use (TOU) usually state the cost of using drawing power from power company utility which typically consist of two components: The quantity of kWh consumption at specific billing period, and the peak demand charge which measure the maximum rate of power consumption at any giver time interval.

Controls:

The control of the contract is typically handled through the energy management system at every time interval $t \in T$ for every contract component i, of how much power should be used from the contract, i.e.,

$$\bar{a}_i = (a_{i,1}, \cdots, a_{i,N}), \text{ where } a_{i,t} = \text{kw}[i,t] \text{ and } \text{dom}(i) = \mathbb{R}^+$$

Cost:

For every contract power component i, the cost composition is as follows:

$$\text{cost}_i = \sum_{t=1}^{N} \text{conCost}[i,t] \text{ where,}$$

- $\text{conCost}[i,t] = \text{quantityCost}[i,t] + \text{demandCost}[i,t]$

- $\text{quantityCost}[i,t] = \text{kw}[i,t] * \text{quantityCostPerKw}(\text{kw}[i,t])$

- $\text{demandCost}[i,t] = \text{kw}[i,t] * \text{demandCostPerKw}(\text{kw}[i,t])$

The quantityCost and demandCost can be any type of function that returns the rate per kW of consumption. Typically these function are represented as piece-wise or step-wise linear functions. For example, the quantity kWh consumption cost per kW can be as follow:

$$\text{quantityCostPerKw}(x) = \begin{cases} 12¢ & : 0 < x \leq 3000 \\ 10¢ & : 3000 < x \leq 6000 \\ 8¢ & : x > 6000 \end{cases}$$

Whereas, the peak demand cost per kW can be:

$$\text{demandCostPerKw}(x) = \begin{cases} 1.50\$ & : 0 < x \leq 1000 \\ 3.00\$ & : 1000 < x \leq 2000 \\ 6.00\$ & : x > 2000 \end{cases}$$

Constraints:

The only operational constraint on the contract power component is that the total kW consumption at any time interval t must not exceed the that contract peak demand bound, i.e., $\text{constr}_i(\bar{a}_i) : (\forall\ i,t)\ \text{kw}[i,t] \leq \text{peakDemand}[i]$. The other constraint is an integrity constraint which limits the power used from the contract to a positive or zero value, i.e.,

$$\text{constr}_i(\bar{a}_i) : (\forall\ i,t)\ \text{kw}[i,t] \geq 0$$

which mean we can only draw power from the contract and cannot supply power back using the contract power component.

Revenue:

Since this resource cannot be committed to third party, the revenue of this component is always equal to zero, i.,e.,

$$\text{rev}_i(\bar{a}_i) = 0$$

.

Intrinsic Value:

The organization typically does not get any direct value from using the utility power, therefore, the intrinsic value of this component is always equal to zero, i.e.,

$$\text{intrinsicVal}_i(\bar{a}_i) = 0$$

Power:

The power at every time interval for this type of components is the identity matrix of controls, i.e.,

$$\text{power}_i(a_{i,t}) = \text{kw}[i, t]$$

6.2.2 Battery Storage Unit

The battery storage is a special type of power component because it can consume power, supply power, or remain idle, i.e., for every battery power component i and any time interval t, i.e., $\text{kw}[i, t] = +, -,$ or 0.

Controls:

Each unit needs to decide how to control their batteries at every time interval t. The controls for the battery can be either discharge, charge, or keep the battery idle. It also needs to decide how much kW should supplied from the battery or drawn from it, i.e.,

$$\bar{a}_i = (a_{i,1}, \cdots, a_{i,N}), \text{ where,}$$

$$a_{i,t} = (\text{batFlag}[i, t], \text{kw}[i, t])$$

where $\text{batFlag}[i,t] \in \{\text{“charge”}, \text{“discharge”}, \text{“idle”}, \text{“commitToMarket”}\}$ and $\text{kw}[i,t] \in \mathbb{R}$.

Cost:

The cost of operating a battery storage unit is the sum of the cost of depreciation and maintenance cost, i.e.,

$$\text{cost}_i = \text{batDeprCost}[i] + \text{batMaintCost}[i] \text{ where,}$$

- Depreciation cost is the cost of using the battery by cause of wear. Typical battery storage units have a number design charge/discharge cycles, i.e., $\text{battCycles}[i]$ before they are considered inefficient and need to be replaced by new battery storage unit. The depreciation cost of a battery is result of multiplying the used cumulative charge/discharge cycles of the battery, i.e., $\text{battCummulative}[i] = \sum_{t=1}^{N} |kw[i]|$ divided by kW power for a cycle, i.e, $\text{battCycleKw}[i]$ to get the number of cycles used. This result is also divided by the number of battery design cycles times the new battery cost, that is $\text{batDeprCost}[i] = (\text{battCummulative}[i] \div \text{battCycleKw}[o]) \div \text{battCycles}[i] \times \text{newBatCost}[i]$.

- Maintenance cost is the cost of the part of annual maintenance cost of the battery $\text{batAnnualMaintCost}[i]$ times the duration of operation as part of the year, i.e., $\text{batMaintCost}[i] = (\text{batAnnualMaintCost}[i] \div 365 \div 24) * (N \times \text{intervalLength})$

Revenue:

If the unit actions controls decides to commit this resource to a third party, the revenue is the total revenue of a component over the time horizon, i.e.,

$$\text{rev}_i(\bar{a}_i) = \sum_{t=1}^{N} \text{rev}[i,t], \text{ where}$$

$$\text{rev}[i,t] = \begin{cases} \text{mktPmt}[i,t] & \text{batFlag} = \\ & \text{``cmmitToMarket''} \\ 0 & \text{otherwise} \end{cases}$$

Intrinsic Value:

An organization typically does not gain from the operation of the battery storage unit in itself and therefore its intrinsic value is zero, i.e.,

$$\text{intrinsicVal}_i(\bar{a}_i) = 0$$

Constraints:

The constraints of the battery storage that guarantees operational integrity include the following:

$$\text{constr}_i(\bar{a}_i) : (\forall\ i,t)\ \text{maxDisRt}[i] \leq \text{kw}[i,t] \leq \text{maxChgRt}[i] \wedge$$

$$\text{kw}[i,t] \leq \text{currentChg}[i,t] \wedge \text{currentChg}[i,t] \leq \text{batCap}[i] \text{ where,}$$

- The discharge power amount must not exceed the maximum discharge rate, i.e., $(\forall t \in T)\ \text{kw}[i,t] \geq \text{maxDisRt}[i]$

- The charging power amount must not exceed the maximum charge rate, i.e., $(\forall t \in T)\ \text{kw}[i,t] \leq \text{maxChgeRt}[i]$.

- For the first time interval, $t = 1$, The discharge amount cannot exceed the battery initial charge at the beginning of the first time interval, i.e., $\text{kw}[i,1] \leq \text{batInitialCharge}[i]$. For the remaining time intervals, $\{2,\cdots,N\}$, the discharge amount cannot exceed the current charge, i.e., $(\forall t \in \{2,\cdots,N)\}\ \text{kw}[i,t] \leq \text{currentChg}[i,(t-1)]$, where, $(\forall t \in T)\ \text{currentChg}[i,(t+1)]\text{currentChg}[i,t] - \text{kw}[i,t]$.

- The battery current charge must not exceed the battery capacity, i.e.,

$$(\forall t \in T)\ \mathrm{currentChg}[i,t] \leq \mathrm{batCap}[i]$$

Power:

The power at every time interval for the battery is the power that the battery produces as a result of committing the battery or the power consumed to charge the battery. Therefore, the power for the battery is the identity matrix of the power part of the controls, i.e.,

$$\mathrm{power}_i(a_{i,t}) = \mathrm{kw}[i,t]$$

6.2.3 Renewable Resource

Renewable resources (e.g., Photovoltaic systems, and wind turbines) has been increasingly adopted recently as part of organization move to be more energy sustainable. The output power of these components cannot be controlled. However, their performance depends of on environmental factors such as sunshine or wind activity. The output from these component is represented as the predicted power generated over a time horizon, i.e., $\mathrm{predOut}[i,t]$ in kW.

Controls:

Renewable resources typically do not receive control actions except for emergency shut off. Therefore renewable power components control actions are null, i.e.,

$$\bar{a}_i = (a_{i,1}, \cdots, a_{i,N}) = \emptyset$$

Cost:

Since renewable resources typically do not use fuel to produces power, their operational cost consist of the depreciation cost and maintenance cost, i.e.,

$$\mathrm{cost}_i = \mathrm{renCost}\ \text{where,}$$

- $\text{renCost}[i] = \text{renMaintCost}[i] + \text{renDeprCost}[i]$ where,
- $\text{renMaintCost}[i] = (\text{renAnnualMaintCost}[i] \div 365 \div 24) * (N \times \text{intervalLength})$
- $\text{renDeprCost}[i] = (\text{renNewCost}[i] \div 365 \div 24) * (N \times \text{intervalLength})$

Revenue:

The renewable power component is not usually committed to third party therefore the revenue generated from this resource equal to zero, i.e.,

$$\text{rev}_i(\bar{a}_i) = 0$$

Intrinsic Value:

The operation of this type of component does not yield any intrinsic value for the respective unit, therefore, the intrinsic value is equal to zero, i.e.,

$$\text{intrinsicVal}_i(\bar{a}_i) = 0$$

Power:

The power generated from this component can only be the predicted output from this resource, i.e.,

$$\text{power}_i(a_{i,t}) = \text{kw}[i,t] = \text{predOut}[i,t]$$

Constraints:

The only operation constraint that this component have is that the power used cannot exceed the power generated, i.e.,

$$\text{constr}_i(\bar{a}_i) : (\forall\ i,t)\ \text{kw}[i,t] \leq \text{predOut}[i,t]$$

6.2.4 Back-up Power Generator

Backup power generators differs from other power resources in terms of cost and availability. Certain large power generator may require time to ramp up and usually require a minimum output power. These generators require fuel for their operation. They typically have an efficiency function of fuel consumption depending the amount of power drawn from these back-up power resources. This function can be usually defined as piece-wise linear function or step function which gives the the fuel needed per kW of output power, i.e., for every back-up power generator component i, $\text{genEff}[i] : \mathbb{R} \to \mathbb{R}$.

Controls:

Units can decide whether to use the back-up power generator or not at every time interval t. They also need to determine at which kW level this resource should operate, i.e.,

$$\bar{a}_i = (a_{i,1}, \cdots, a_{i,N}), \text{ where,}$$

$$a_{i,t} = (\text{genFlag}[i,t], \text{kw}[i,t])$$

where $\text{genFlag}[i,t] \in \{\text{“turnOn”}, \text{“turnOff”}, \text{“cmmitToMarket”}\}$ and $\text{kw}[i,t] \in \mathbb{R}$.

Cost:

The cost of operating back-up generator component includes the cost of fuel, depreciation cost, and maintenance cost, i.e.,

$$\text{cost}_i = \text{genTotalFuelCost}[i] + \text{genDeprCost}[i] + \text{genMaintCost}[i], \text{ where,}$$

- The fuel cost per component per time interval is calculated by the total kW generated times the efficiency times the fuel cost, i.e., $\text{genTotalFuelCost}[i] = \sum_{t=1}^{N} \text{genFuelCost}[i,t]$, where, $\text{genFuelCost}[i,t] = \text{kw}[i,t] \times \text{fuelCost}[i,t] \times genEff[i](\text{kw}[i,t]) \times \text{kw}[i,t]$

- The depreciation cost is the result of sum of the kW generated divided by mean time to failure times the price to replace it with a new generator, i.e., $\text{genDeprCost}[i] =$

$\sum_{t=1}^{N} \mathrm{kw}[i,t] \div \mathrm{genMTTF}[i] \times \mathrm{genNewCost}[i]$

- The maintenance cost is the portion of the annual maintenance cost that covers the market intervals optimized, i.e., $\mathrm{genMaintCost}[i] = (\mathrm{RenAnnualMaintCost}[i] \div 365 \div 24) * (N \times \mathrm{intervalLength})$

Revenue:

If the unit actions controls commit this resource to a third party, the revenue is the total revenue of this component over the time horizon, i.e.,

$$\mathrm{rev}_i(\bar{a}_i) = \sum_{t=1}^{N} \mathrm{rev}[i,t], \text{ where}$$

$$\mathrm{rev}[i,t] = \begin{cases} \mathrm{mktPmt}[i,t] & \mathrm{genFlag} = \\ & \text{“cmmitToMarket”} \\ 0 & \text{otherwise} \end{cases}$$

Intrinsic Value:

The unit may get utility value from using the power generated by the back-up power generator to run a service, but the intrinsic value of operating the back-up generator is equal to zero, i.e.,

$$\mathrm{intrinsicVal}_i(\bar{a}_i) = 0$$

Power:

The power generated from the back-up power generator is precisely the identity matrix of the kW part of the controls, i.e.,

$$\mathrm{power}_i(a_{i,t}) = \mathrm{kw}[i,t]$$

Constraints:

The operational constraint of the back-up power generator is that the output power must not exceed the generator's capacity, i.e.,

$$\text{constr}_i(\bar{a}_i) : (\forall\, i, t)\ \text{kw}[i, t] \leq \text{genCap}[i]$$

6.2.5 Power Consuming Service

Power consuming components are the services that units operate as part of the demand for power (e.g., HVAC, lighting, or heating). The bids for these power consuming services consist of two parts: the amount of power required to run a service at any time interval, i.e., predKW$[i, t]$, and the value received by the unit if this service is turned on, i.e., predValue$[i, t]$

Controls:

Units typically can decide to turn on or turn off a power consuming service, i.e.,

$$\bar{a}_i = (a_{i,1}, \cdots, a_{i,N}), \text{ where,}$$

$$a_{i,t} = \text{serFlag}[i, t]$$

where serFlag$[i, t] \in \{$"turnOn", "turnOff"$\}$. Although some power services can have other controls besides turning on or off a service, we consider these as discrete parts of the load where the unit can satisfy any part of that service loads.

Cost:

In typical scenario, there is no power related cost that results from the operation of services other than the cost supplying power, i.e.,

$$\text{cost}_i = 0$$

Revenue:

The operation of a power service does not yield any power related revenues, i.e.,

$$\text{rev}_i(\bar{a}_i) = 0$$

Power:

The power for each power consuming service is the kW required to run that service it is turned on, i.e.,

$$\text{power}_i(a_{i,t}) = \begin{cases} \text{predKW}[i,t] & \text{serFlag} = \\ & \text{“turnOn”} \\ 0 & \text{serFlag} = \\ & \text{“turnOff”} \end{cases}$$

Intrinsic Value:

The intrinsic value of a consuming service is the sum of the utility received from turning on that service (in dollars amount), i.e.,

$$\text{intrinsicVal}_i(\bar{a}_i) = \sum_{t=1}^{N} \text{intrinsicVal}[i,t], \text{ where}$$

$$\text{intrinsicVal}[i,t] = \begin{cases} \text{predValue}[i,t] & \text{serFlag} = \\ & \text{“turnOn”} \\ 0 & \text{serFlag} = \\ & \text{“turnOff”} \end{cases}$$

Constraints:

The only operational constraint that services have is that the power supplied must be equal to the power needed if the service is turned on, otherwise it should be zero. This is controlled by the action controls taken by the respective unit. Therefor, there are no constraints on the power consuming services level, i.e.,

$$\text{contr}(\bar{a})_i = \emptyset$$

6.3 Common Modeling

In order to maintain a stable power supply. There is a balance constraint which guarantees that the sum of supply and demand at any give time intervals equals to zero, i.e., $(\forall t \in T)\ \sum_{i=1}^{N} \text{kw}[i,t] = 0$. This constraint is required to maintain the integrity of the grid and provide stable operation.

6.4 Conclusions

This chapter provided the formal modeling of commonly used power components and their mapping to the extensible framework. The modeling included the definition of the action controls, cost, revenue, intrinsic value, power, and constraints. The modeled component types are utility power contract, battery storage unit, renewable resource, back-up power generator, and power consuming service.

In the next chapter, an implementation of these types of power components is provided using and optimization language and case study analysis is conducted to verify the viability of the modeling with reasonable problem size that simulates a real-world scenario.

CHAPTER 7: Consortia Market Optimization Implementation & Case Study

In this chapter, we implement the extensible decision guided framework. We also implement the optimization models using an optimization programming language. Furthermore, we conduct case study experiments using randomly generated simulated data to validate that the implemented system is feasible and is able to operate efficiently within required time constraints.

7.1 Introduction

In the previous chapter, we proposed a decision guided framework (depicted again in Figure 7.1) where we described generic power components and discussed how collaboration optimization can be achieved. We also formally defined a number of power components bids. In this chapter however, we implement this extensible framework with common classes of power components (e.g., renewable resource, battery storage, backup power generator, power contract, and power consuming service). The aim is to implement a decision guided system where C&I units that demand power, supply power, or both can collaborate to optimize the operation, generation, and acquisition of electrical power components so that they achieve a better financial and operational level.

In the next sections, we implement an extensible decision guided system framework for market-based collaboration of power resources and services. In doing so, we create a library of power components which can be power producing resources or or power consuming services that can be added or removed by minimally describing their parameters. More specifically, the contributions of this chapter are as follows:

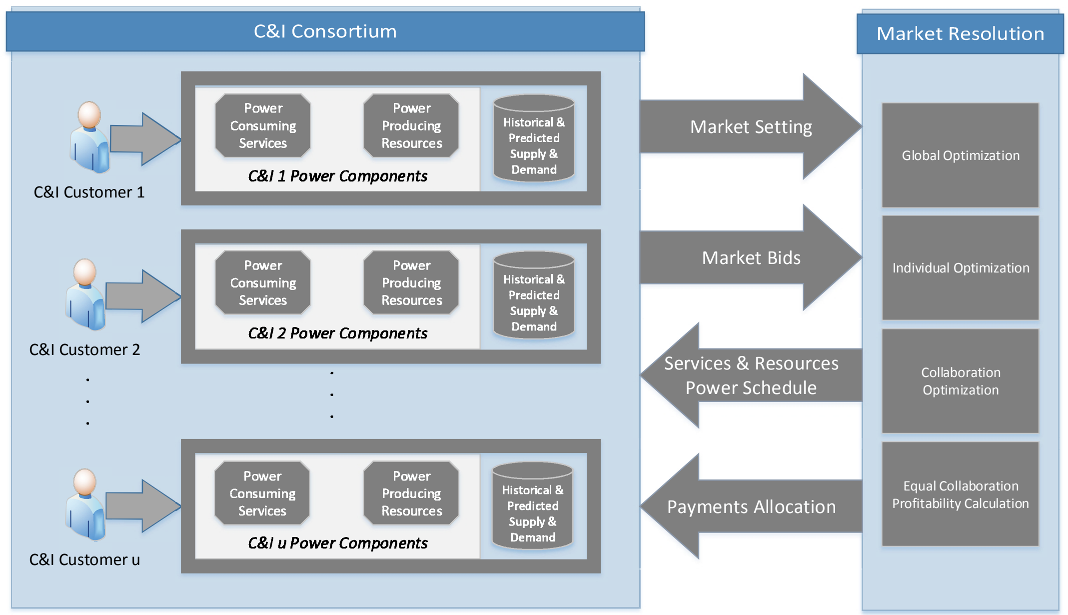

Figure 7.1: Electric Power Collaboration Decision Guidance Framework

First, we implement a collaborative market framework. The basic idea of this market is to create a consortium of organizational units where each unit has the freedom to make decisions related to power consumption, generation, and storage. Members of this consortium have some services that they need to run (e.g., lighting, HVAC, water heating, etc.) and also have some power resources (e.g., utility contract, photovoltaic array, backup power generator, etc.). The members also have some expectation of the intrinsic value of running services at different levels of operation over a time horizon represented as a bid that each member of this consortium submits to market. The market resolution produces a power resource allocation for each unit, and the payment that each member has to pay or receive.

Second, in order to support market resolution, we implement formal optimization models using Optimal Programming Languages (OPL) to decide on the operation of resources to be used, and the services that are run while maintaining feasibility, i.e, the power consumed by all members of the consortium does not exceed the total power supply.

Third, we implement a library of power components (e.g., power contract, back-up power generator, renewable resource, battery storage unit, and power consuming service) using OPL and Java. We also describe the parameters, cost and intrinsic value calculations, and the operational constraints of these components.We guarantee the implemented optimization models guarantee the satisfaction of the properties of: *Pareto optimality, Nash equilibrium*, as well as the property of *equal collaboration profitability.*

Fourth, we conduct a case study experiments with multiple randomly simulated data set sizes and show that this market has a computational and time complexity that is reasonable for the purpose of executing this market at the predetermined time intervals.

This chapter is organized as follows: In the second section, we describe our implementation of the collaborative market framework and its components. In section three, we conduct case study experiments and show our results of the market resolution. Finally, we give a brief conclusion.

7.2 Microgrid Consortia Market Design

As depicted in implementation design overview Figure 7.2, the system consists of a database which stores historical consumption patterns and future predicted supply and demand. This data can be used to generate appropriate bids for the participating units. It also consist of a JAVA application which abstract the design of the various components which were formally explained the previous chapter and also facilitate the communication between the optimization models and the communication with ILOG CPLEX Solver engine.

We first describe the general components variables and parameters. Then, we describes how the cost of operating resources is derived. Furthermore, we describe the components constraints based on their types.

In this section, we describe the implementation details of five power components:

- Back-up generator
- Battery storage unit
- Utility power contract

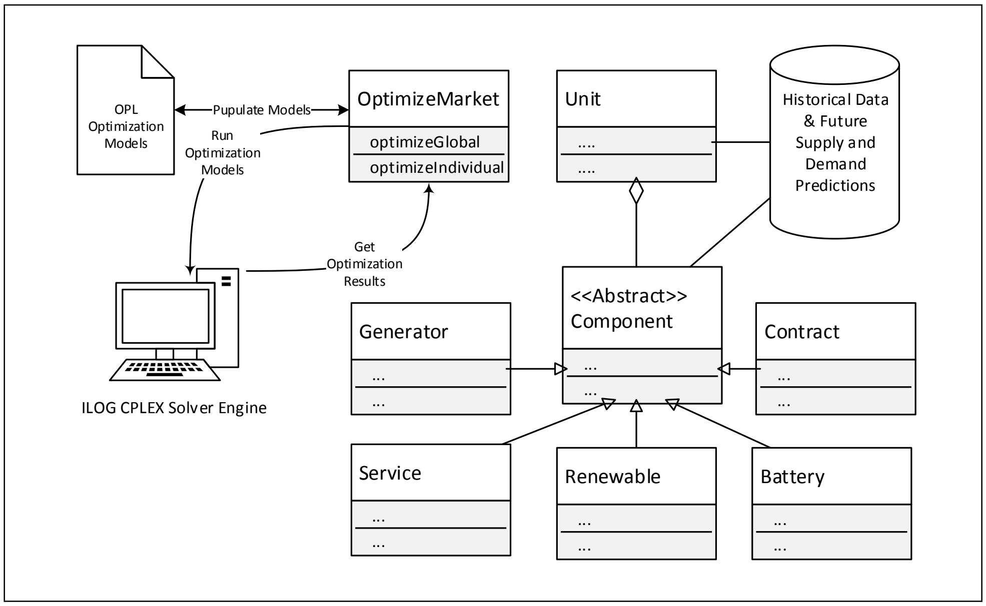

Figure 7.2: Microgird Collaboraiton Optimization Market Implementation

- Renewable resource
- Power consuming service

7.2.1 Back-up Power Generator

Backup power generators are commonly used in large organizations. Their main purpose is usually to provide power to essential services in case of a power outage. Backup power generators are generally more expensive to operate over extended periods of time due to their higher relative cost variable compared to other power sources. However, at certain situations, backup power generators can provide power at a competitive cost even when there are no power outages at peak demand times. Generators share common parameters such maximum capacity, generator efficiency function, new generator cost, generator's annual maintenance cost, and the generator's mean time to failure. These parameters are modeled in Listing 7.1

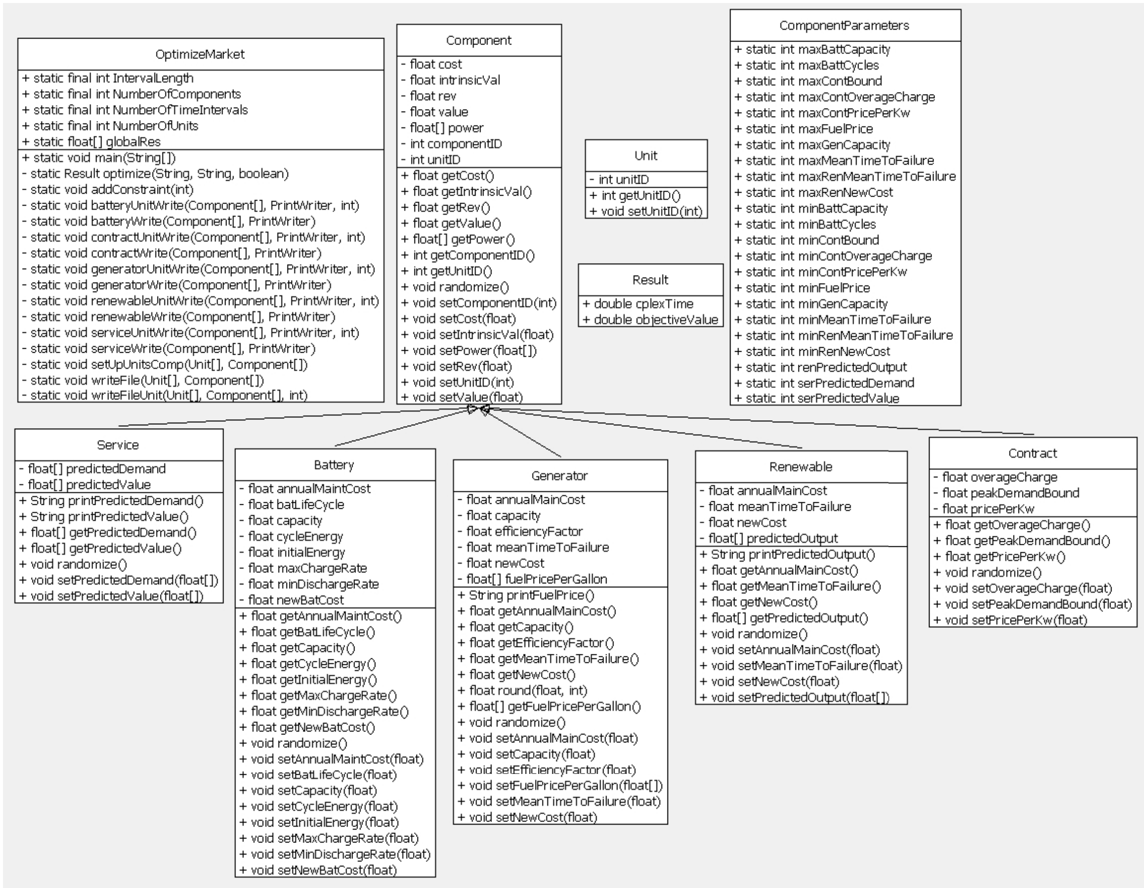

Figure 7.3: Collaborative Power Market Optimization Class Diagram

```
{unitComp} GenerationUnitCompPairs = ...;
float genCapacity[GenerationUnitCompPairs] = ...;
float fuelPrice[GenerationUnitCompPairs][timeHorizon] = ...;
float genEfficiency[GenerationUnitCompPairs]=...;
float newGenCost[GenerationUnitCompPairs]=...;
float genAnnualMaintCost[GenerationUnitCompPairs]=...;
float genMTTF[GenerationUnitCompPairs] = ...; // Generator Mean Time To Failure
    in hours
dvar float+ genKW[GenerationUnitCompPairs][timeHorizon];
dvar boolean genUseFlag[GenerationUnitCompPairs][timeHorizon];
```

Listing 7.1: Back-up Generator Parameters and Decision Variables

There is the fixed cost of acquiring a generator. In addition, there is the cost of fuel given the amount of power being drawn multiplied the efficiency factor for the specific generator. The last part of the cost is the variable cost of operating the generator which includes maintenance cost is given by a function. These cost parts calculations are captured in Listing 7.2.

```
dexpr int genUsedIntervals[uc in GenerationUnitCompPairs]= sum (t in timeHorizon
    ) genUseFlag[uc][t];
dexpr float genFuelCost[uc in GenerationUnitCompPairs][t in timeHorizon]=
    fuelPrice[uc][t] * genEfficiency[uc] * genKW [uc][t];
dexpr float genTotalFuelCost[uc in GenerationUnitCompPairs] = sum(t in
    timeHorizon) genFuelCost [uc][t];
dexpr float genMaintCost[uc in GenerationUnitCompPairs] = genAnnualMaintCost[uc]
     * intervalLength * noTimeIntervals / (365*24);
dexpr float genDeprCost [ uc in GenerationUnitCompPairs]= newGenCost[uc] *
    genUsedIntervals[uc] * noTimeIntervals / genMTTF[uc]; // Running Intervals
dexpr float genTotalCost[uc in GenerationUnitCompPairs] = genTotalFuelCost[uc] +
     genMaintCost[uc] + genDeprCost[uc];
```

Listing 7.2: Back-up Generator Cost Calculation

Back-up power generator Constraints as depicted in 7.3 which include the constraint that the power being generated at any time interval must be less than the maximum generation capacity of the back-up generator. It also sets the flag of whether the generator is used at any time interval or not for the purpose of determining the operating generator intervals for the calculation of the depreciation cost.

```
forall (uc in GenerationUnitCompPairs, t in timeHorizon) genKW[uc][t] <=
    genCapacity[uc];

forall (uc in GenerationUnitCompPairs, t in timeHorizon) {
    (genUseFlag[uc][t] == 0) => (genKW[uc][t] == 0.0);
    (genKW[uc][t] >= m) => genUseFlag[uc][t] == 1;
```

Listing 7.3: Back-up Generator Operational Constraints

7.2.2 Battery Storage Unit

A battery storage unit typically holds a maximum charge measured in kW as depicted in Listing 7.4. It also has an initial starting charge measured in kW. The is initial charge that battery contain at before the first time interval starts. The battery also has other parameters which determines its performance such as the maximum discharge rate and the maximum charge rate.

```
{unitComp} BatteryUnitCompPairs = ...;
float batCapacity[BatteryUnitCompPairs] = ...;
float batInitialEnergy [BatteryUnitCompPairs]=...;
float batMinDischargeRateKW[BatteryUnitCompPairs]= ...;
float batMaxChargeRateKW[BatteryUnitCompPairs]=...;
dvar float+ batCurrentCharge [BatteryUnitCompPairs][1..noTimeIntervals+1];
dvar float batKW[BatteryUnitCompPairs][timeHorizon];
float cycleEnergy[BatteryUnitCompPairs] = ...; // single cycle life energy
```

Listing 7.4: Battery Storage Unit Parameters and Decision Variables

Furthermore, the battery unit has other information related to cost such as the battery annual maintenance cost, new battery replacement cost and maximum energy charge/discharge cycles before the battery is considered unreliable and needs to be replaced. This involves measuring the cumulative charge and discharge over all time intervals under consideration as depicted in Listing 7.5.

```
float batAnnualMaintCost[BatteryUnitCompPairs] = ...;
float newBatCost[BatteryUnitCompPairs] = ...;
float batLifeCycles[BatteryUnitCompPairs] = ...; // battery design number of
    lifecycles
dvar float+ cumChargeDischarge[BatteryUnitCompPairs][1..noTimeIntervals+1];
dexpr float cumCycles[uc in BatteryUnitCompPairs][t in 1..noTimeIntervals+1] =
    cumChargeDischarge[uc][t] / cycleEnergy[uc];
dexpr float batMaintCost[uc in BatteryUnitCompPairs] = batAnnualMaintCost[uc] *
    intervalLength * noTimeIntervals / (365*24);
dexpr float batDeprCost [ uc in BatteryUnitCompPairs]= newBatCost[uc] *
    cumCycles[uc][noTimeIntervals+1] / batLifeCycles[uc];
dexpr float batCost[uc in BatteryUnitCompPairs] = batMaintCost[uc] + batDeprCost
    [uc];
```

Listing 7.5: Battery Storage Unit Cost Related Calculation

The battery storage unit operational constraints include constraint that the charge or discharge amount at any time interval should not exceed the the maximum or the minimum charge/discharge specification rates. It also sets the current battery charge for the first time intervals to initial battery charge at the beginning of the time horizon. It also sets the charge current charge for the next interval as the existing current charge plus or minus the power taken or supplied by the battery from the previous interval.

```
forall (uc in BatteryUnitCompPairs, t in timeHorizon) batKW[uc][t] >=
    batMinDischargeRateKW[uc];
forall (uc in BatteryUnitCompPairs, t in timeHorizon) batKW[uc][t] <=
    batMaxChargeRateKW[uc];
forall (uc in BatteryUnitCompPairs) batCurrentCharge [uc][1] == batInitialEnergy
     [uc];
forall (uc in BatteryUnitCompPairs, t in timeHorizon) batCurrentCharge[uc][t
    +1]== batCurrentCharge[uc][t]- batKW[uc][t];
forall (uc in BatteryUnitCompPairs, t in timeHorizon) batCurrentCharge[uc][t+1]
    <= batCapacity[uc];
forall (uc in BatteryUnitCompPairs) {cumChargeDischarge[uc][1] == 0.0;
        forall (t in timeHorizon) {
                   cumChargeDischarge[uc][t+1] == cumChargeDischarge[uc][t] +
                                         abs(batKW[uc][t]) * intervalLength;}}
```

Listing 7.6: Battery Storage Unit Operational Constraints

7.2.3 Electrical Power Utility Contract

The third type of power components to be modeled is a utility power contract. This contract is not a resource in itself but a right to use a resource at an agreed upon terms. The terms usually specifies the price per kW of consumption and the cost of the maximum peak demand bound measured in kW. It also details the penalty charge for exceeding the peak demand bound and the price per kW above the peak demand. The power contract operational constraint simply states the power used from the contract power component must be less than the peak demand bound at each time interval. These information are detailed in Listing 7.7.

```
{unitComp} ContractUnitCompPairs = ...;
```

```
float conPeakDemandBound[ContractUnitCompPairs]=...;
float conPricePerKW [ContractUnitCompPairs]= ...;
float conOveragePerKW [ContractUnitCompPairs]= ...;
dvar float+ conKW [ContractUnitCompPairs][timeHorizon];
dexpr float conCost[uc in ContractUnitCompPairs][t in timeHorizon]= conKW[uc][t]
     * conPricePerKW [uc];
dexpr float conTotalCost [uc in ContractUnitCompPairs] = sum (t in timeHorizon)
    conCost[uc][t];
forall (uc in ContractUnitCompPairs, t in timeHorizon)conKW[uc][t] <=
    conPeakDemandBound[uc];
```

Listing 7.7: Power Utility Contract Parameters, Costs, and Constraints

7.2.4 Renewable Resource

The fourth type of power components is a renewable resource. The renewable resource does not have to provide a constant current of electricity and its performance depends on outside environmental factor (e.g., sunshine or wind activity). Therefore, the predicted output over the time horizon is provided and can also be updated at each time interval before the market execution. Although most renewable resources do not need fuel, their operation incurs cost (i.e., fixed cost, maintenance cost). The renewable resource's only operational constraint is that the power used from it cannot exceed the power being produced by the renewable resource. The modeling of the renewable resource is captured in Listing 7.8.

```
{unitComp} RenewableUnitCompPairs = ...;
float predictedOutput[RenewableUnitCompPairs][timeHorizon]=...;
float newRenCost[RenewableUnitCompPairs]=...;
float renMTTF[RenewableUnitCompPairs] = ...; // Renewable Mean Time To Failure
    in hours
dvar float+ renKW [RenewableUnitCompPairs][timeHorizon];
```

```
float renAnnualMaintCost[RenewableUnitCompPairs] = ...;
dexpr float renMaintCost [uc in RenewableUnitCompPairs]= renAnnualMaintCost[uc]
    * intervalLength *noTimeIntervals / (365*24);
dexpr float renDeprCost [ uc in RenewableUnitCompPairs]= newRenCost[uc] *
    intervalLength * noTimeIntervals / renMTTF[uc];
dexpr float renTotalCost [ uc in RenewableUnitCompPairs]= renMaintCost[uc] +
    renDeprCost[uc];
float renAnnualMaintCost[RenewableUnitCompPairs] = ...;
dexpr float renMaintCost [uc in RenewableUnitCompPairs]= renAnnualMaintCost[uc]
    * intervalLength *noTimeIntervals / (365*24);
dexpr float renDeprCost [ uc in RenewableUnitCompPairs]= newRenCost[uc] *
    intervalLength * noTimeIntervals / renMTTF[uc];
dexpr float renTotalCost [ uc in RenewableUnitCompPairs]= renMaintCost[uc] +
    renDeprCost[uc];

forall (uc in RenewableUnitCompPairs, t in timeHorizon) renKW [uc][t] <=
    predictedOutput[uc][t];
```

Listing 7.8: Renewable Resource Parameters, Cost, and Constraints

7.2.5 Power Consuming Service

The last type of power components is a power consuming service. Participants of the market submit their power needs for the power consuming services that requires electrical power to run and the value that they associate with running these services. This intrinsic value indicates the monetary payment that a unit is willing to take in lieu of turning off that service assuming that the unit has enough electricity to power it. Typically, running a service does not incur any power related costs besides the cost of the power needed to operate it. The owners of the power service have the ability to revise their services power needs and their respective values before each market execution. The modeling details of the service power component is captured in listing 7.9.

```
{unitComp} ServiceUnitCompPairs = ...;
dvar boolean serFlag [ServiceUnitCompPairs][timeHorizon];
float serPredictedDemand[ServiceUnitCompPairs][timeHorizon]=...;
float serPredictedValue[ServiceUnitCompPairs][timeHorizon]=...;

dexpr float serIntrinsicValue[uc in ServiceUnitCompPairs][t in timeHorizon]=
    serPredictedValue[uc][t] * serFlag[uc][t];
dexpr float serTotalIntrinsicValue [uc in ServiceUnitCompPairs]= sum (t in
    timeHorizon) serIntrinsicValue[uc][t];
dexpr float serKW [uc in ServiceUnitCompPairs][t in timeHorizon]=
    serPredictedDemand[uc][t] * serFlag[uc][t];
```

Listing 7.9: Power Consuming Service Parameters, Intrinsic Values, and Constraints

7.3 Case Study

To ensure the validity of our proposed framework. We constructed multiple data sets with randomly generated instantiations of the classes of components listed in the previous section. The purpose of this study is to test whether the system with a reasonable size is able to arrive at resolution within the market resolution time constraints. These data sets vary in size with in terms of the number of participating units and the number of power components within each unit. To accurately model the operational setting. The data was randomly generated following a typical daily consumption profile as depicted in Figure 7.4. This is a typical profile for residential and office consumption pattern. Figure 7.5 provides a sample of the value differences that each unit get under the different optimization models (i.e., global, standalone, and collaborative) after conducting the simulation. Note that market global value does not reflect the market resolution and does not include the payment. The global value is a result of an optimization that produces the maximum value of all units components combined.

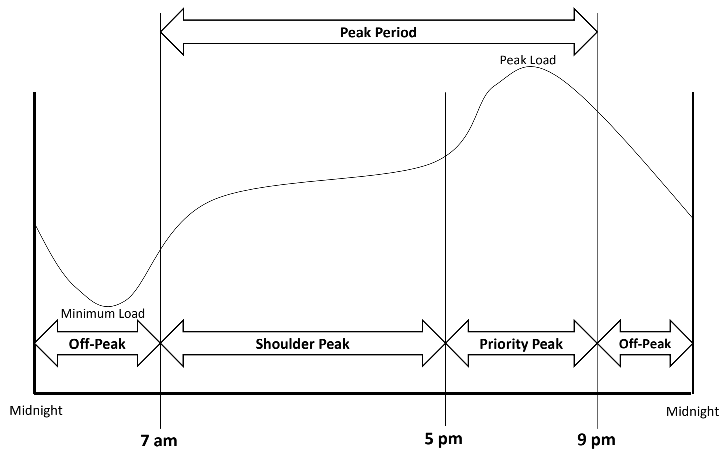

Figure 7.4: Typical Daily Consumption Pattern

Prepared randomly generated test data sets were successively run to test the system feasibility of operating the market under realistic time constraints. The number in intervals in the prepared data sets was 24 with an interval length of 1 which corresponds to normal 24 hours a day with the market executing at one hour intervals. The run time of the test data was within acceptable operation time constraint. Summary of the average run time of the market is depicted in Figure 7.6.

Throughout the simulation over 24 intervals, the market produced a resolution with payment allocations for all participating unit that resulted in a better collaborative value than the standalone value. Figure 7.7 shows the market resolution's collaborative value minus the payment versus the standalone value over a 24 hours interval simulation. The market always produces a resolution that is better than or equal the standalone value over all time intervals.

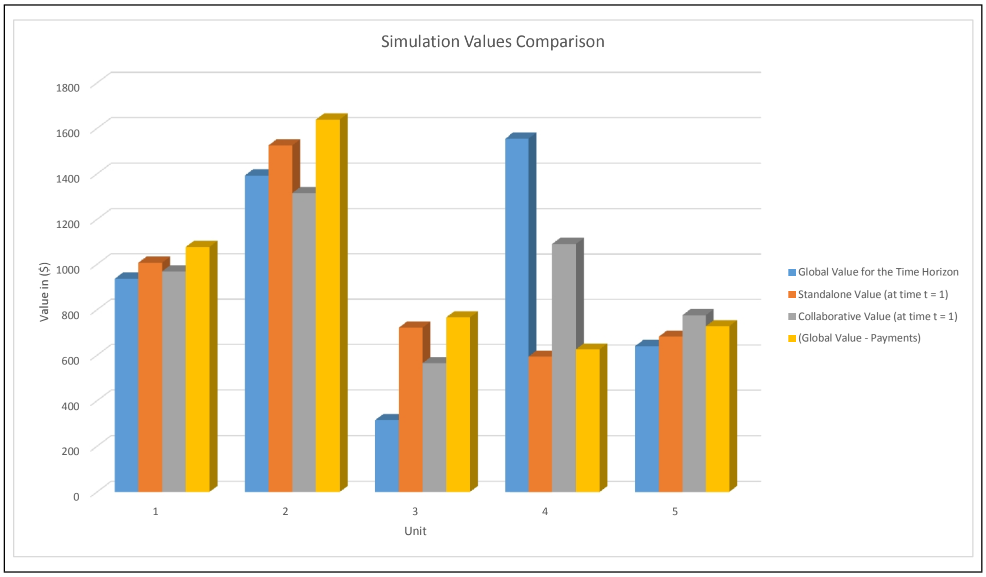

Figure 7.5: Units Value Comparison

To validate that the consortium market implementation is feasible to execute at the market time constraints, two testing cases were constructed. The first test case involved randomly generated loads that conforms to a typical day load profile for residential and office setting with a probability distribution functions that introduces variation within that profile. This typical daily load profile hand a peak and an off-peak periods. The off-peak period starts from 9 am to 7 pm in the morning. The peak periods ranges from 7 am to 9 pm with the highest demand occurring between 5 pm and 9 pm. A total of 12 data set sizes ranging from the lowest configuration with 10 units and a 100 components up to 1000 units and 10000 components where each test configuration has a sample size of 10 randomly generated data sets. The maximum data set of 1000 units and 10000 components had around 44,000 binary decision variables and close to 100,000 real and integer decision variables. The same size configuration was used to generate completely random data that didn't conform to the daily consumption profile to measure the efficiency of the branch and bound and branch and cut of the Mixed Integer Linear Program (MILP) Solver. These experiments were conducted using IBM's ILOG CPLEX Solver. The testing was performed

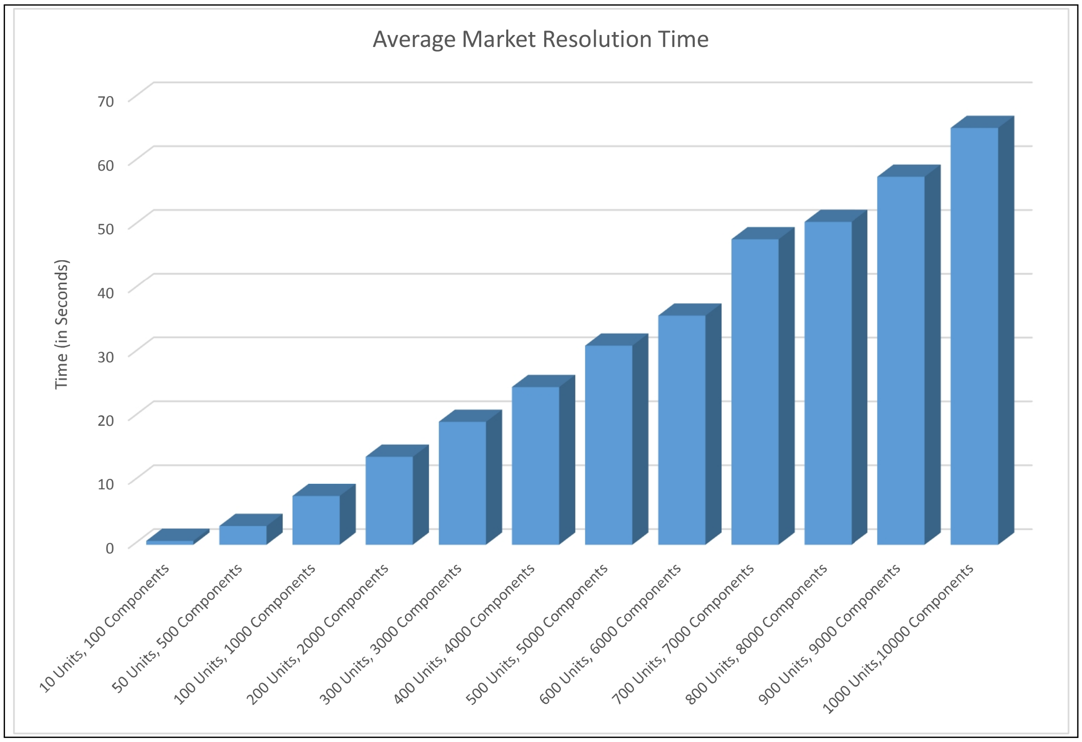

Figure 7.6: Market Resolution Average Runtime

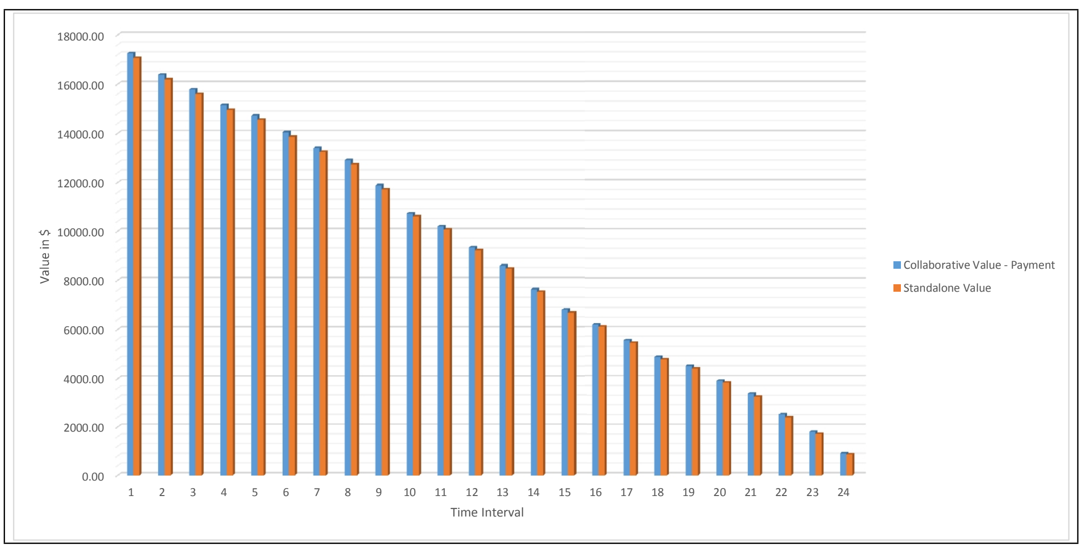

Figure 7.7: (Collaborative Value - Payment) Vs. Standalone Value

on 2.5 GHz workstation with a dual core processor and 16 GB RAM. The total resolution time which included the total of global optimization, sum of individual units' self value optimization, and sum of individual collaboration optimization was measured. The mean resolution time for the maximum data set was around 157 seconds with an upper and lower bounds of 2 seconds which proves that this market is in fact feasible to run in short interval periods. The experiment results are captured in Table 7.1 for the typical daily profile and in Table 7.2 for the random daily profile. Depicted in Figure 7.8, the mean resolution time of the typical daily profile versus the random load are compared. Both showed very close resolution mean time as the number of units and components increased. It can also be noticed from the graph that mean resolution time increased linearly as the the number of units and components increased which indicates a scalable solutions.

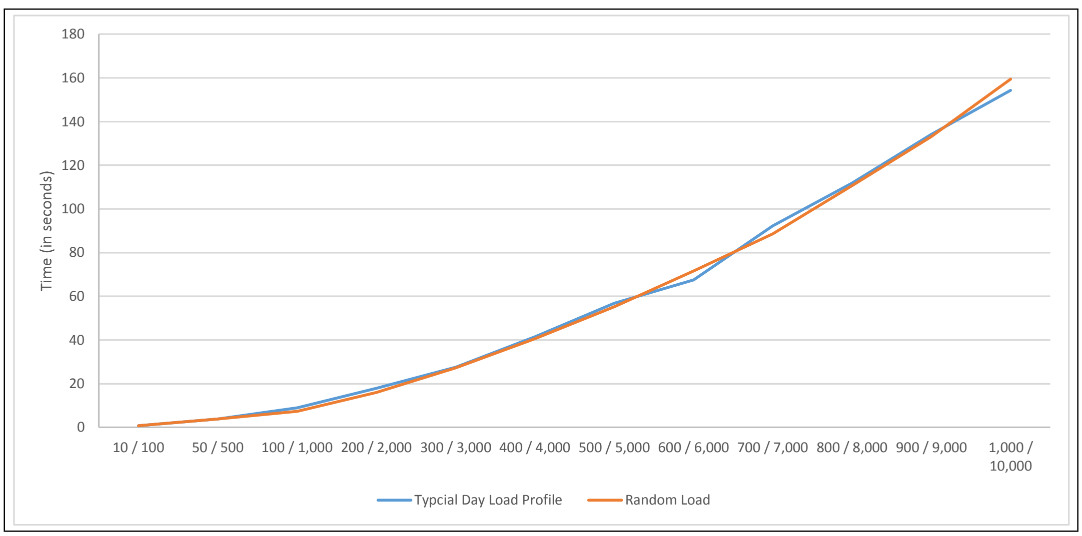

Figure 7.8: Simulation Mean Time - Typical Load Profile vs. Random Load

7.4 Conclusions

We presented an implementation of the extensible decision guided microgrid collaborative framework. Moreover, to support the extensible framework components library, power components such as utility contract, back-up power generator, renewable resource, and power consuming service have been implemented. Finally, the validity of this framework is evaluated by a case study using simulated load scenarios to examine the ability of the framework to efficiently operate at the specified time intervals with minimal overhead cost.

Table 7.1: Typical Day Profile Resolution Time

# of Units / # of Components	Mean Time (in Seconds)	Standard Error	Median	Standard Deviation	Sample Variance	Range	Min	Max	Confidence Level (95.0%)	Lower Bound	Upper Bound
10 / 100	0.81	0.04	0.74	0.12	0.01	0.30	0.69	0.99	0.08	0.72	0.89
50 / 500	3.93	0.12	3.82	0.37	0.14	1.08	3.54	4.62	0.27	3.66	4.20
100 / 1,000	8.96	0.11	8.95	0.36	0.13	1.14	8.42	9.56	0.26	8.71	9.22
200 / 2,000	17.94	0.11	18.09	0.36	0.13	1.08	17.32	18.40	0.26	17.69	18.20
300 / 3,000	27.64	0.16	27.73	0.49	0.24	1.74	26.30	28.04	0.35	27.29	27.99
400 / 4,000	41.42	0.30	41.39	0.96	0.92	2.90	40.38	43.29	0.69	40.74	42.11
500 / 5,000	56.76	0.21	56.61	0.65	0.43	2.45	55.99	58.44	0.47	56.30	57.23
600 / 6,000	67.48	0.83	66.69	2.64	6.97	7.40	64.35	71.75	1.89	65.59	69.37
700 / 7,000	92.17	1.93	91.42	6.09	37.07	20.98	86.70	107.68	4.36	87.81	96.53
800 / 8,000	111.91	0.46	111.83	1.46	2.12	4.49	109.78	114.27	1.04	110.87	112.95
900 / 9,000	134.14	0.65	133.55	2.05	4.22	6.48	131.78	138.26	1.47	132.67	135.61
1,000 / 10,000	154.36	1.24	154.13	3.91	15.29	10.77	149.81	160.58	2.80	151.56	157.15

Table 7.2: Random Load Resolution Time

# of Units / # of Components	Mean Time (in Seconds)	Standard Error	Median	Standard Deviation	Sample Variance	Range	Min	Max	Confidence Level (95.0%)	Lower Bound	Upper Bound
10 / 100	0.70	0.05	0.62	0.15	0.02	0.40	0.55	0.95	0.11	0.59	0.81
50 / 500	3.76	0.22	3.65	0.69	0.48	2.42	3.06	5.49	0.50	3.27	4.26
100 / 1,000	7.32	0.08	7.39	0.25	0.06	0.90	6.69	7.58	0.18	7.14	7.49
200 / 2,000	16.03	0.33	16.25	1.04	1.08	3.57	13.21	16.77	0.74	15.29	16.77
300 / 3,000	27.27	0.24	27.41	0.75	0.56	2.00	26.05	28.05	0.54	26.73	27.81
400 / 4,000	40.59	0.16	40.58	0.52	0.27	1.70	39.80	41.50	0.37	40.22	40.97
500 / 5,000	55.19	0.38	55.13	1.19	1.41	3.81	52.77	56.58	0.85	54.34	56.04
600 / 6,000	71.65	0.42	71.41	1.32	1.73	4.51	69.79	74.30	0.94	70.71	72.60
700 / 7,000	88.57	0.36	88.57	1.14	1.30	3.67	86.51	90.18	0.81	87.75	89.38
800 / 8,000	110.65	0.57	110.54	1.79	3.20	6.33	107.22	113.55	1.28	109.37	111.93
900 / 9,000	133.04	0.73	133.42	2.31	5.34	7.27	128.81	136.08	1.65	131.39	134.69
1,000 / 10,000	159.35	0.75	158.66	2.36	5.55	8.77	156.18	164.95	1.69	157.66	161.03

CHAPTER 8: Conclusions and Future Work

This chapter presents a summary of the research accomplished in this dissertation and also provides possible directions for future work.

8.1 Conclusions

We have highlighted the decision challenges faced by energy mangers in Commercial and Industrial (C&I) organizations in general and proposed an extensible decision guided framework for C&I organizations to collaborate on their power needs and resources. We first proposed a secondary market framework where participants can collaborate to share their resources in real-time. We defined the the market setting, participant's bids, a market resolution and described the market's resolution desirable properties. We also proposed a fair mechanism of distributing collaboration gains.

Then, we proposed a primary market where participants can decide on the acquisition of peak-demand bound with the assumption that they have the ability to collaborate later in real-time. We also, defined the market resolution, execution intervals, schedule of resources operation at every time interval, and the cost of the peak demand that result from the market resolution.

After that, an extensible decision guided framework was proposed to address different types of power components that C&I organization typically have a part of their power portfolio options. The proposed framework allowed for addition of any type of power component by minimally describing its attributes. Then, we proposed a generalized market setting, participants' bids, and a market resolution. We also defined the market properties the must satisfied and proposed a market resolution algorithm that guarantees these properties.

Finally, we implemented the decision guided system by modeling classes of commonly used power components such as power contract, renewable resource, back-up power generator, and power consuming service. We also conducted a case study experiments. The randomly generated data sets instantiated a number of power components with varying data sets sizes and simulated power demand using a typical daily consumption profile and randomly generated loads. We found that our framework operated within the time constraints proposed and produced a significant coalition gains as opposed to C&I participants working alone.

8.2 Future Work Directions

As future work, there are several aspects our framework that deserve further investigation. Examples are listed below:

- Designing framework that allows for the optimal investment of power resources given their projected demand and the projected value functions of the existing power components. This framework may account for budgeting constraint of participating organizations. I can also allow the joint investment and operation of resources.
- A more efficient and fair value distribution that takes into consideration the complexity of underlying value function and resolution time constraints.
- Gaming the market or and the possibility of the participant's collusion [47–50] can be further studied to determine if manipulating the market bids has an effect on the outcome of the market resolution or it can unfairly benefit colluding parties.
- Expanding this framework to a multi-agent system framework while taking advantage of the the concepts covered in the area of the internet of things and proposing a method of an efficient communication with a very large pool of participant, and a central market execution and settlement authority that manages the interaction (independent system operator) while taking into consideration the scalability issues of the proposed system.

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