

Competitive Microgrid Electricity Market Design

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ABSTRACT

The electric power grid forms the foundation for several other critical infrastructures of national importance such as public health, transportation and telecommunication systems, to thrive. The current power grid runs on the century-old technology and faces serious challenges of the 21st century - Ever-increasing demand and the need to provide a sustainable way to meet the growing demand, increased requirement of resilience against man-made and natural disasters, ability to defend against cyber attacks, increasing demand for reliable power, requirement to integrate with alternate energy generation and storage technologies. Several countries, including the United States, have realized the immediate need to modernize the grid and to pursue the goal of a smart grid.

Majority of recent grid modernization efforts are directed towards the distribution systems to be able to meet these new challenges. One of the key enablers of a fully functional Smart Grid are microgrids – subsystems of the grid, utilizing small generation capacities at the distribution system level to increase the overall reliability and power quality of the local grid. It is one of the key directions recommended by national electric delivery technologies roadmap in United States as well as policy makers for electricity delivery in many countries.

Microgrids have witnessed serious research activity in the past few years, especially in areas such as multi-agent system (MAS) architectures for microgrid control and auction algorithms for microgrid electricity transaction. However, most of the prior research on electricity transaction in microgrids fails to recognize and represent the true nature of the microgrid electricity market.

In this research, a comprehensive microgrid electricity market has been designed, taking into account several unique characteristics of this new market place. This thesis establishes an

economic rationale to the vision of wide-scale deployment of microgrids serving residential communities in near future and develops a comprehensive understanding of microgrid electricity market. A novel concept of Community Microgrids is introduced and the market and business models for electricity transaction are proposed and validated based on economic forecasts of key drivers of distributed generation.

The most important contribution of this research deals with establishing a need for a trustworthy model framework for microgrid market and introducing the concept of reputation score to market participants.

A framework of day-ahead energy market (DAEM) for electricity transaction, incorporating an approach of using the reputation score to incentivize the sellers in the market to be trustworthy, has been designed and implemented in MATLAB with a graphical user interface (GUI). Current implementation demonstrates a market place with two sellers and nine buyers and is easily scalable to support multiple market participants.

The proposed microgrid electricity market may spur the deployment of residential microgrids, incorporating distributed generation, thereby making significant contribution to increase the overall reliability and power quality of the local grid.

To my Brother

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Chapter 1

Introduction

1.1 Smart Grid and Microgrids

“The grid - which is made up of everything from power lines to generators to the meters in your home - still runs on century-old technology. It wastes too much energy, it costs us too much money, and it's too susceptible to outages and blackouts.”

“To meet the energy challenge and create a 21st century energy economy, we need a 21st century electric grid”

- President Obama

The U.S. Department of Energy, DOE, Modern Grid Strategy (previously the Modern Grid Initiative) highlights the importance of smart grid in facing the future challenges. It defines a smart grid as a grid that integrates advanced sensing technologies, control methods and integrated communications into current electricity grid – both at transmission and distribution levels [7]. Figure 1 is a pictorial representation of the vision of Smart Grid.

The seven principal characteristics expected of the fully deployed Smart Grid as identified in the Modern Grid Strategy are:

- Enable active participation by consumers

- Accommodate all generation and storage options
- Enable new products, services, and markets
- Provide power quality for the digital economy
- Optimize asset utilization and operate efficiently
- Anticipate & respond to system disturbances (self-heal)
- Operate resiliently against attack and natural disaster

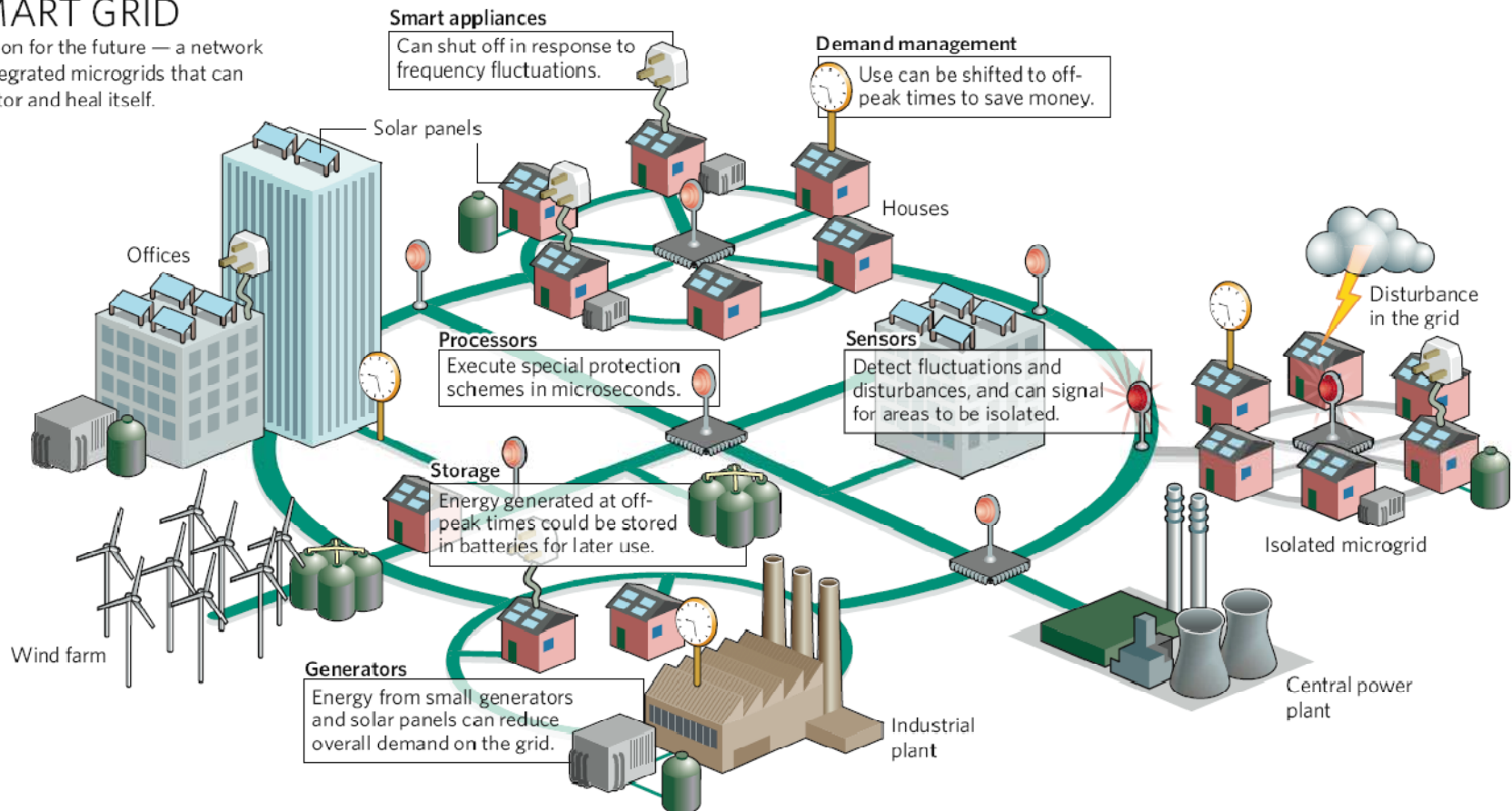
One of the key facilitators of fully functional Smart Grid will be the deployment-level of microgrids. Office of Electricity Delivery and Energy Reliability, US DOE, defines the microgrid and its scope [4] as:

“A microgrid is an integrated energy system consisting of interconnected loads and distributed energy resources which as an integrated system can operate in parallel with the grid or in an intentional island mode”.

In [1], Rahman et al have proposed the concept of Intelligent Distributed Autonomous Power System (IDAPS), a specialized microgrid. The IDAPS microgrid is aimed at intelligently managing customer-owned distributed energy resources such that these assets can be shared in an autonomous grid both during normal and outage operations, thus increasing the reliability and security of the main power grid. Figure 2 depicts an IDAPS microgrid.

SMART GRID

A vision for the future — a network of integrated microgrids that can monitor and heal itself.



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Figure 1: Smart Grid - A vision for the future

Source: "Upgrading the Grid", *Nature*, vol. 454, PP. 570-573, July 2008

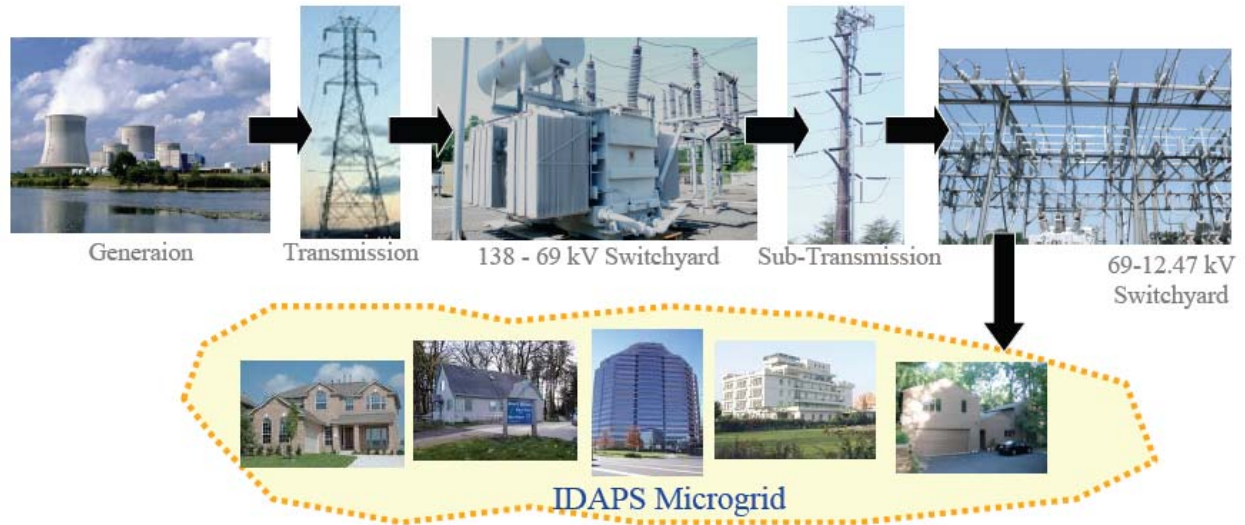


Figure 2: IDAPS Microgrid

Source: Presentation on "Intelligent Distributed Autonomous Power Systems (IDAPS)", *IEEE PES Annual General Meeting, Tampa, Florida, Jun 27, 2007*

With ubiquitous deployment of residential and commercial microgrids in sight, we envision a new market for electricity transaction among microgrid participants.

This thesis extends the concept and scope of IDAPS microgrid

- In *concept* by defining *IDAPS Community Microgrids*
- In *scope* by introducing *Reputation Score*-based microgrid electricity market

1.2 Thesis Statement

The objective of this research is to design a competitive microgrid electricity market. We design and implement a framework of Day-Ahead Energy Market (DAEM), enabling Reputation Score-based electricity transaction among IDAPS community microgrids.

1.3 Organization of the thesis

This thesis is organized as follows:

Chapter 2 - We report a comprehensive review of prior research in the related areas

Chapter 3 - We present our motivation for our research and state our research objectives

Chapter 4 - We propose the market and business models for electricity transaction in microgrids and validate our proposals using LBNL's DER-CAM (an economic model for customer adoption of distributed generation)

Chapter 5 - We introduce the concept of Reputation Score for microgrid market participants. We discuss our motivation and objective of the proposal. We conclude by discussing the reputation score computation algorithm

Chapter 6 - We present the overview of the bidding process and discuss Reputation Score-based electricity transaction algorithms. We introduce a key concept of Quality of Demand in this chapter and discuss how we incorporate this concept in the transaction algorithms

Chapter 7 - We present a comprehensive framework of Day-Ahead Energy Market (DAEM) for microgrids with a discussion of every feature proposed in this market

Chapter 8 - We discuss the implementation of the Day-Ahead Energy Market (DAEM) for microgrids in MATLAB with a Graphical User Interface (GUI)

Chapter 9 - We discuss the conclusions drawn by this thesis and outline our research contributions. Further, we suggest future work in this field.

Chapter 2

Related Work

In this chapter, we present our survey on prior research done in the related fields. Section 2.1 identifies prior economic research in customer adoption of distributed generation. The concept and research on several application contexts of Reputation Management Systems (RMS) are presented in section 2.2. Prior work on electricity transaction platforms and algorithms is then presented in section 2.3. We conclude the chapter with section 2.4, where we identify the knowledge gaps in the research done up to this point.

These knowledge gaps have driven our research reported in this thesis and presents very clear context of our work.

2.1 Customer Adoption of Distributed Generation

Customer adoption of distributed generation is the key for ubiquitous deployment of microgrids. Lawrence Berkeley National Laboratory (LBNL) has done pioneering work in analyzing customer adoption of distributed generation through their tool, Distributed Energy Resources Customer Adoption Model (DER-CAM). DER-CAM's objective is to minimize annual energy costs for a modeled site, including utility electricity and natural gas costs, amortized capital costs for distributed generation (DG) investments, and maintenance costs for installed DG equipment [12]. LBNL has performed extensive research under various economic and microgrid scenarios [12], [13], [14], [15], [16], [17], [18], [19]. However, we noticed the lack of prior work in analyzing customer adoption for microgrids comprising residential customers.

2.2 Reputation Management Systems (RMS)

2.2.1 Introduction to RMS and Application Contexts

The primary motivation and generic definition of Reputation Management System (RMS) [53] arises from the need in distributed networks and online communities to create a communication framework similar to traditional social relationships.

Establishing a mechanism to ensure cooperation among the participation entities and to isolate their selfish behavior is of paramount importance for the very survivability and scalability of the network.

RMS can be viewed as a cooperation enforcement solution in different types of communities. The three primary functions of a reputation management system applied to any context are:

- Evaluation of behavior of participating entities
- Detection of misbehavior of participating entities
- Reaction to misbehavior of participating entities

The design and deployment of a Reputation Management System has many facets – The application context, type and nature of participating entities, the nature of the communication framework, the threat model for communication, underlying network model and topology are some of them. When Reputation Management Systems do not adapt to issues specific to nature of network, their effectiveness measured by their accuracy (correct identification) and promptness will be compromised and the primary purpose of implementing a RMS might be defeated.

Further, in all application contexts, it is also very important to assess the benefit of using a RMS and the Cost of using such a system in terms of communication overhead, computational complexity etc.

Every network has a specific nature. In order to understand the complexity of implementing RMS, let us consider some examples:

- A wireless sensor network has a specific issue of dynamically changing network conditions which as a consequence causes node behavior to vary both spatially and temporally [33], [32] and [38]. In addition, say, limitations on battery power of sensors might restrict the amount of communication overhead.
- In P2P e-commerce communities, the primary issue is that the nodes or the participating entities (virtual peers on the Internet) may never have interacted with each other before. Further, the identity of the node is easy to change and poses the cheating problem highly prevalent in P2P e-commerce communities [34], [35], [37] and [40].
- The case of vehicular ad hoc networks presents us with a very different set of requirements. The underlying network is extremely dynamic in nature, lacking any kind of centralized trust authority. Ascertaining the availability, accuracy and reliability of the collected data presents a serious challenge [36]. Further such networks have an extremely small life-time and an effective RMS should take that in to account.
- The fields of e-service and e-business employing Service Oriented Architectures (SOA) have the primary issue of being able to manage the reputation of services which are offered by a service provider. A reputation score needs to be assessed based on the user's context and the server's context. Thus, a comprehensive context-aware RMS is expected in such systems [39].

2.2.2 RMS in Ad-Hoc Wireless Sensor Networks [33], [32], [38]

Nodes in an ad hoc network perform key functions such as packet forwarding and hence, cooperation among them is critical for the very existence of the ad hoc network. Reputation Management Systems have been proposed to enforce cooperation among the nodes.

Application of traditional RMS to ad hoc networks would yield poor results in terms of the performance metrics, since it does not take into account the dynamic network conditions. The local and network-wide conditions (such as traffic activity and physical channel conditions) could have a huge impact on the node behavior and such behavior or the causes of it (accuracy of misbehavior detection) are not captured by traditional RMS, which operates homogeneously across space and time.

[33] Reports first work in proposing Adaptive Reputation Management Systems (ARMS), one which would adapt to dynamically changing network conditions in an ad hoc network.

Dynamic network conditions in an ad hoc network have to be taken in to account in order to be called a Robust RMS. When dynamic network conditions are neglected, the efficiency of the RMS is reduced, both in terms of reduced accuracy of detection and promptness of identification. It could lead to falsely identifying a cooperative node as a misbehaving node (For example: If physical channel conditions at a given time are not favorable to transmission, it would reduce the node's throughput and thus a non-adaptive RMS might classify a node as misbehaving).

Thus, the problem is to understand the need for an adaptive RMS and propose one that would take in to account the dynamic network conditions, both in space and in time (all nodes in an ad hoc network might not face similar traffic conditions at all times).

2.2.3 RMS in Peer-To-Peer (P2P) e-commerce communities [34], [35], [37], [40]

We refer to the nodes in this network model as participants, parties or merchants.

Peer-To-Peer (P2P) e-Commerce Communities (ECC) are characterized by the following features and challenges [34], [35]:

- The P2P participants in this model may have never interacted before
- Identity of the participant and his/her relevant information is very easy to modify
- Prone to cheating with merchants resorting to unfair trade practices and conspiring to make profits
- A group of participants may conspire to provide dishonest feedback in an attempt to enhance the reputation value of the conspiring members
- Malicious peers may spread untrustworthy files in the network
- A large P2P network provides an Anonymous and Open platform and may be misused by spreading viruses and Trojan horses
- Storage of reputation information in a P2P network is an issue which needs consideration. Two primary approaches may be taken. Local and Global storage. Global storage provides a more comprehensive analysis of reputation of a certain participating node.
- The integrity of the reputation information is by far the most important characteristic that directly reflects the quality and reliability of the RMS. There are two levels of integrity protection:
 - Integrity of reputation evaluation
 - Integrity of reputation information during/after storage and retrieval

In view of the fundamental characteristics/challenges of the P2P network listed above, there is a strong motivation for the merchants to offer poor services abandoning the identity when he/she earns a bad reputation. This is the primary challenge for the RMS in

this context. It is very critical for the scalability and the very survivability of such a network, to implement a reputation management system in order to help build trust among the participating peers.

Prior work on P2P RMS suggests that most of the current systems are unable to let merchants keep up the honest motive for long periods of time. Several P2P RMS systems have been proposed in the literature:

P2Prep [41] is primarily a supplementary protocol to be added to the current P2P protocol, in which the participant's reputation information or score is shared among the peers

EigenTrust [42] introduces the concept of belief and addresses the issue of conspiring by exchanging the belief information among the peers

PeerTrust [43] deals with the issue of dishonest feedback and introduces the concepts of dependability factor and environmental factor and lays emphasis on feedback encouragement when computing the degree of trust.

Other related works pertain to creation of a trust matrix model based on trust group, a long-term incentive mechanism for sellers in the RMS.

Many of the existing RMS for P2P networks suffer from inherent deficiencies such as those listed below:

- Topology relationship among peers has not been fully accounted for while evaluating dishonest feedback issues.
- Most of the proposed RMSs treat the Sellers (Merchants) and the Buyers (Customers) equally. However, there is an inherent difference in the roles being played and must be accounted for.
- Conspiring set of people is often referred to as the Inner Circles. Most of the RMSs do not treat the problem of Inner Trust Circles with the emphasis that the concept deserves.

- Many models and the associated simulations consider the number of trades performed by each of the participating peer to be approximately range between 50 and 100. However, in practice, this number may be very small. In view of this, many simulations may be considered to be skewed in terms of their results.
- The state-of-the-art RMSs are expected to differentiate between Trade-Trust and Feedback-Trust. However, most of the proposed RMSs fail to clearly distinguish in their treatment of both of these parameters. It would result in an incorrect representation of the trust score of the peers.
- Traditionally, security mechanisms have been proposed in literature to provide protection against malicious users of the network, by means of cryptography, authentication, access control, digital signatures etc. However, since a P2P network is open in nature, the peers need to be protected from misleading information provided by the other participants in the network. Traditional security mechanisms fail to achieve this goal. A Robust RMS is expected to adopt adaptive trust model to encourage co-cooperativeness among selfish peers and minimize the risk from malicious service providers. Incorporating a dedicated server to monitor such malicious activities is one possible solution to address this issue [40].
- Most of the RMSs are designed, with primarily eBay as the fundamental example of an e-commerce community. However, it is a pure Customer-to-Customer (C2C) business model and comprises of just one such online business community. There is a lack of integrated RMS model which would work equally well for a suite of the e-commerce communities as B2B, B2C as well as C2C.
- In associating peer reliability based on trust, most of the RMSs do not collectively take in to account the quantum of trade, trade frequency and trade time.
- Most of the proposed RMSs do not effectively counter the issue of Reputation Deception and Rating Fraud, achieved by malicious users by means of recommendation paths.

In [34], the authors propose a RMS model composed of the reference model, a directed graph of feedback relationship (DGFR) and a protocol for the management of transaction among peers within an e-Commerce Community. Their model provides for the possibility for different pairs of peers with different trust values between them at different times. This provision is the uniqueness of the proposed model.

2.2.4 RMS in Vehicular Ad Hoc Networks [36]

Vehicular ad hoc networks are characterized by highly dynamic network conditions, lacking any kind of centralized authority providing trust information of peers. The primary objective of the participating vehicles in a vehicular ad hoc network is to co-operate with each other in locating resources, after establishing trustworthiness, under the above mentioned highly dynamic conditions. The two primary challenges in this application context are:

- Accuracy of peer provided data/information
- Reliability of the data aggregated in a distributed manner
- Availability of the information or the participating vehicles at all times, because of the highly dynamic nature of the network.

In [36], the authors propose a RMS for vehicular ad hoc networks that enables the participating devices/vehicles to quickly adapt to fast changing local network conditions and provides a robust bootstrapping method for establishment of trust relationships where only a few peers exist a priori.

The authors take in to account the two aspects of trust while assigning a reputation values and establishing trust relationships– Co-cooperativeness between the peers and accuracy of peer provided information. An epidemic data exchange protocol has been used in the proposed scheme which included reputation and agreement to ensure higher reliability of data and to enhance cooperation. It is to be noted that in order to ascertain the quality,

relevance and reliability of the data being exchanged, it is critical to dynamically build and maintain reputations in order to make reliable trusting decisions.

2.2.5 RMS in context-aware distributed systems [39]

In context-aware distributed systems, it is often required to assign reputation to the services per se in addition to the reputation values for the entities offering the services. In this research framework, the user and the service provider exchange their context information during service request to the intermediary/broker that hosts them. When this intermediary or broker sends the reputation of the service to a user, reputation information is gathered from its local database and the databases of the neighboring brokers, aggregates the databases and provides reputation value to the user, primarily based on context similarity between the user's context and the reputation context. Thus, the name "Context-Aware". We consider this a special classification of RMS since, the reputation is computed, stored and shared with respect to the context of the services, unlike all other RMSs which typically associate reputation scores just to the participating entities, totally unrelated to the user's context.

The proposed context-aware distributed reputation management system (C-DRMS) designs the RMS with respect to not only the service, but also user's/peer's preferences. That is, reputation value is determined by user's feedback and preferences (after the service is being utilized).

2.2.6 RMS in Microgrids

Microgrids consisting of Distributed Energy Resources (DERs) are an emerging research area. Since such a network/community can be considered static for all practical purposes, the RMS should be able to give reputation score to all of the participating units based on their long-term (and permanent) transaction history.

No prior research work has been reported in this area.

2.3 Electricity Transaction in Microgrids

In this section, we will discuss the prior research in the area of electricity transaction in microgrids.

For over a decade, the proposed use of multi-agent systems (MAS) to address challenges in power engineering has been reported in several IEEE transactions and conference papers [25]. Authors in [25] and [26] provide one of the most comprehensive insights in this field clearly defining concepts, approaches and technical challenges in addition to recommending technologies, standards and tools for building multi-agent systems in the context of power engineering applications. A multi-agent system simulation of IDAPS has been reported in [3].

Operation of a Multi-agent System for Microgrid Control has been proposed in [27], in which, the authors propose a classical distributed algorithm based on the symmetrical assignment problem for the optimal energy exchange between the production units of the Microgrid and the local loads, as well the main grid.

It is to be noted that this work can be understood as the prior research which gets closest to the market operation component that has been proposed in this thesis.

Significant aspects of the market operation proposal in [27] are:

1. Grid is a market participant
2. Market model follows a traditional demand-driven supply approach, where loads announce their demand in advance (equivalent to load forecasting, which is extremely difficult in small microgrids)
3. The generation units may adjust their set points - for DG technologies adjusting generations offers may be unrealistic

4. The fundamental assumption of the market model is to *minimize operational cost of the microgrid*

4. The authors implicitly assume the availability of base-load prediction of the microgrid - This assumption may not be appropriate in the microgrid scenario

The author's primary focus in [27] has been on MAS implementation and they do not address all the real challenges in the context of the future microgrid electricity markets.

Setting of Market Clearing Price (MCP) in Microgrid Power Scenario has been proposed in [22], in which, the authors propose a traditional MCP system, wherein the lowest price is obtained at the point of intersection of aggregated supply and demand curves. Further, the proposed market model consists of a day-ahead energy market (DAEM) and a real-time energy market, mimicking the wholesale electricity market. The authors discourage a free market where prices are determined by supply and demand dynamics and favor a uniform market clearing system where prices are determined, again by the classical Locational Marginal Pricing (LMP) algorithm. Traditionally, LMP is used in wholesale electricity market, which includes the cost of congestion arising out of transmission constraints.

Using LMP in MCP calculation for small distributed generators may not be fair to the loads participating in the market. We believe that this may not be the best possible approach for microgrid electricity markets.

A Market-based multi-agent system (MAS) framework for microgrids has been proposed in [24], in which, the primary emphasis of the paper was on the MAS framework based on BDI (belief, desire, intention) architecture., matching the generators with loads. The authors do not consider the dynamic pricing mechanism required to handle the energy resources optimally. The proposed MAS architecture may be a means of implementation of the microgrid energy market, but it does not present or discuss the primary market model for microgrids.

Distributed coordination of microgrids using bilateral contracts has been proposed in [24], in which, the authors propose using bilateral contracts in favor of market-based approach to electricity transaction within a microgrid. The paper studied four types of auction methodologies that may be used to implement the bilateral contracts between generators and loads: First-price sealed bid, Vickrey, English and Dutch auctions.

2.4 Knowledge Gaps

Most of the prior work done on microgrid electricity markets fall into one of two broad categories:

- Attempts to directly use concepts and best practices from wholesale electricity markets
- Emphasis on MAS implementation aspects

We identified the following four knowledge gaps in the prior research:

Knowledge Gap # 1:

A comprehensive understanding of the microgrid electricity market is much needed, which takes into account several characteristics of this new market place:

- Establish the prospect of existence of microgrid markets in imminent future based on economic, regulatory and policy frameworks
- A holistic view of smart grid deployment and its impact on the future of microgrids
- Scope the of the microgrid market
- Constraints and dynamics of the microgrid market
- Nature of market participants
- Market model
- Business model for the participants

Knowledge Gap # 2:

IDAPS microgrid concept [1] envisioned a new market for electricity transaction among customers. However, the authors identified lack of business model that can attract entrepreneurs and end-users.

Knowledge Gap # 3:

Lack of a trustworthy model framework for market participants.

Knowledge Gap # 4:

Lack of a comprehensive framework of energy market for electricity transaction among customers.

The research reported in this thesis used the above identified knowledge gaps to define its research objectives outlined in section 3.2.

Chapter 3

Research Objectives

In this chapter, we present the motivation that has driven us towards our research goals in section 3.1. Section 3.2 clearly states our research objectives.

3.1 Motivation

Figure 3 summarizes the factors that inspire our research

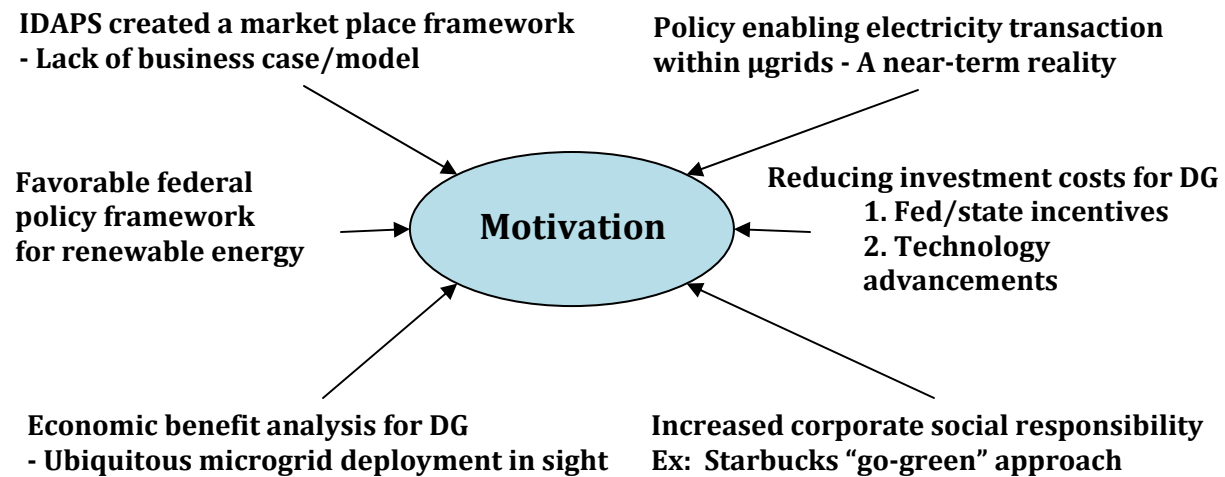


Figure 3: Motivation for our research

In section 2.4, we identified four fundamental knowledge gaps in the prior research in the microgrids and they form the basis of our research pursuit.

The four knowledge gaps are:

- Lack of a comprehensive understanding of the microgrid electricity market, which takes into account several unique characteristics of this new market place.
- IDAPS microgrid concept [1] envisioned a new market for electricity transaction among customers. However, the authors identified lack of business model that can attract entrepreneurs and end-users.
- Lack of a trustworthy model framework for market participants.
- Lack of a comprehensive framework of energy market for electricity transaction among customers.

3.2 Research Objectives

The goal of this research is to propose and implement a comprehensive microgrid energy market. This energy market is expected to serve as a platform for transaction of electricity between distributed generation (DG) sources and local demand. The work is primarily focused on microgrids serving residential customers. Much of the work done in this research is with an economic perspective.

Our goal may be broken down into the following six clearly stated research objectives:

- To establish an economic rationale to our vision of wide-scale deployment of microgrids serving residential communities in imminent future
- To develop a comprehensive understanding of microgrid electricity market
- To define market and business models for electricity transaction
 - Introducing the concept of IDAPS *Community Microgrids*
 - Validation of market/business models based on economic forecasts of key drivers of DG
- To propose a trustworthy model framework for market participants
 - Establishing a need for a trustworthy model in microgrids
 - Introducing the concept of reputation score to market participants
- To propose a framework of day-ahead energy market (DAEM) for electricity transaction
- To implement the proposed framework of day-ahead energy market (DAEM)

Chapter 4

Market and Business Models for Electricity Transaction in Microgrids

In this chapter, we present our first contribution of this thesis by introducing the novel concept of *IDAPS Community Microgrids*. Section 4.1 defines an IDAPS community microgrid and discusses the rationale behind the proposal. Section 4.2 defines our market model for electricity transaction and identifies the market participants. We use the Virginia Tech Electric Service distribution circuit in Blacksburg, Va, as a model for the distribution network topology of interest. We then propose a viable business model for the market participants in electricity transaction in section 4.3. We conclude the chapter by validating the economic rationale for our proposals of market and business models using DER-CAM.

4.1 The Concept of IDAPS Community Microgrids

4.1.1 Background on IDAPS Microgrid concept

Rahman et al. proposed the concept of a specialized microgrid - *Intelligent Distributed Autonomous Power System (IDAPS)* [1]. The key characteristics of an IDAPS microgrid are:

- The IDAPS Supply-Driven-Demand Management
- The IDAPS Multi-Agent System (MAS) framework
- Control and communication overlay architectures
- IDAPS Web Services

The authors in [1] envisioned a new market for electricity transaction among customers but identified lack of business model that can attract entrepreneurs and end-users for the envisioned market.

This thesis *extends the concept and scope of IDAPS microgrid*

- In concept by defining *IDAPS Community Microgrids*
- In scope by introducing *Reputation Score*-based electricity transaction framework

Our work fills the knowledge gap by proposing market and business models which can attract entrepreneurs and end-users to *embrace* and *adopt* the envisioned market for electricity transaction among residential customers.

This chapter discusses the extension of IDAPS microgrid concept and sets a platform to introduce another novel concept of reputation-score based electricity transaction framework in Chapter 7.

4.1.2 Defining IDAPS Community Microgrids

In this section, we present our first contribution of this thesis by introducing the novel concept of *Community IDAPS Microgrids*.

The residential load profile data averaged over approximately 700 homes has been provided to us by Dominion Power, Virginia. This Utility company uses three standard sizes of transformer installation to supply power in residential areas:

- 25 kVA: ~ 3 customers
- 50 kVA: ~ 5 customers
- 100 kVA: ~ 9 customers

Based on this data, **we define basic community microgrids of the following sizes:**

- **μgrid-3** ~ 3 customers (25 kVA)
- **μgrid-5** ~ 5 customers (50 kVA)
- **μgrid-9** ~ 9 customers (100 kVA)

For example, **μgrid-3** is microgrid of 3 homes (who would be typically connected to a 25 kVA transformer, for the purpose of power supply from the main grid). By defining **μgrid-3** to be a **community microgrid**, we mean, that these three homes come together; pool up investment (say, in a proportion of A:B:C) for distributed generation and **set-up a common DG facility** for their community (of size 3 in this case). The location of this common DG facility may be in the backyards of one of the homes or more likely, as we envision, in common community land.

At first, the proposal may seem unrealistic but such common *community assets* are everywhere around us - For example, in a commercial building of say, 20 floors, we would have an average of 6 elevators. But no one **owns** them. Elevators are a common facility for the building owners.

Electricity supply from the DG installation may be categorized as basic and critical infrastructure and in this perspective, a community-approach towards DG installations may not be as difficult to envision, comprehend and accept.

In the case of community microgrids, energy generated by the DG installation is owned by the three stake holders in the same proportion as their investment (A:B:C).

There are several benefits of setting up community microgrids, some of which are listed below:

- Reduced investment cost (\$/kW) – Economies of scale
- Reduced installation costs
- Reduced O&M costs
- Efficient after-sales service from DER equipment manufacturer
- Single contact point for main grid
- Retain the beautiful facades of your homes!

By an IDAPS community microgrid, we mean that each of the community microgrids is a specialized microgrid with characteristics as defined in [1].

The rationale for such a definition of an IDAPS community microgrid and how it may be used in establishing market and business models will be explained in the following sections.

4.2 The Market Model for Electricity Transaction

We first assume that the community microgrids defined in section 6.1 are IDAPS microgrids. As a consequence, we assume the IDAPS Multi-Agent System (MAS) is in place as described in [1].

A realistic market structure which would enable electricity transaction among IDAPS community microgrids in terms of geographical trading zone and market participants is shown in Figure 4.

Figure 5 depicts the market topology and IDAPS Multi-Agent System (MAS) at work.

Market Participants:

The proposed market model for electricity transaction identifies the market participants as community microgrids (μ grid- X ; $X = 3, 5$ or 9) - Electricity transaction occurs **among** IDAPS community microgrids.

We will explain this in further detail: For example, μ grid-5 (a community microgrid of size 5) has a community DG installation.

There are three cases when this microgrid may have energy up for sale in the market:

1. One or more of the owners of the microgrid decides to sell his *share* of energy (owing to his share of investment in the DG facility) as a means of making profit.
2. All the owners consume their share of energy from the DG installation and ALL the owners decide to sell excess energy generated by the DG installation to make profit.
3. The primary purpose of this DG installation is to make profit, in which case, ALL of the energy generated by the facility is always up for sale in the market.

In any of the three cases described above, the excess energy generated by this installation will be made available for sale through a bidding process.

Again the bidders (buyers) may be from another IDAPS community microgrid or residential customers from the same microgrid μ grid-5 (who may have consumed their share of energy and are in need of more energy).

In effect, market participants are:

1. Sellers (Community DG installations)
2. Buyers - Category 1: Residential customers
3. Buyers - Category 2: Environmentally conscious commercial enterprises such as Starbucks.

However, it must be noted that all of the market participants must be in the trading zone of approximately 1 mile radius. This geographical zone makes sense since, the primary goal of DG is to cater to the needs of **local** consumers and that distribution needs to be kept simple.

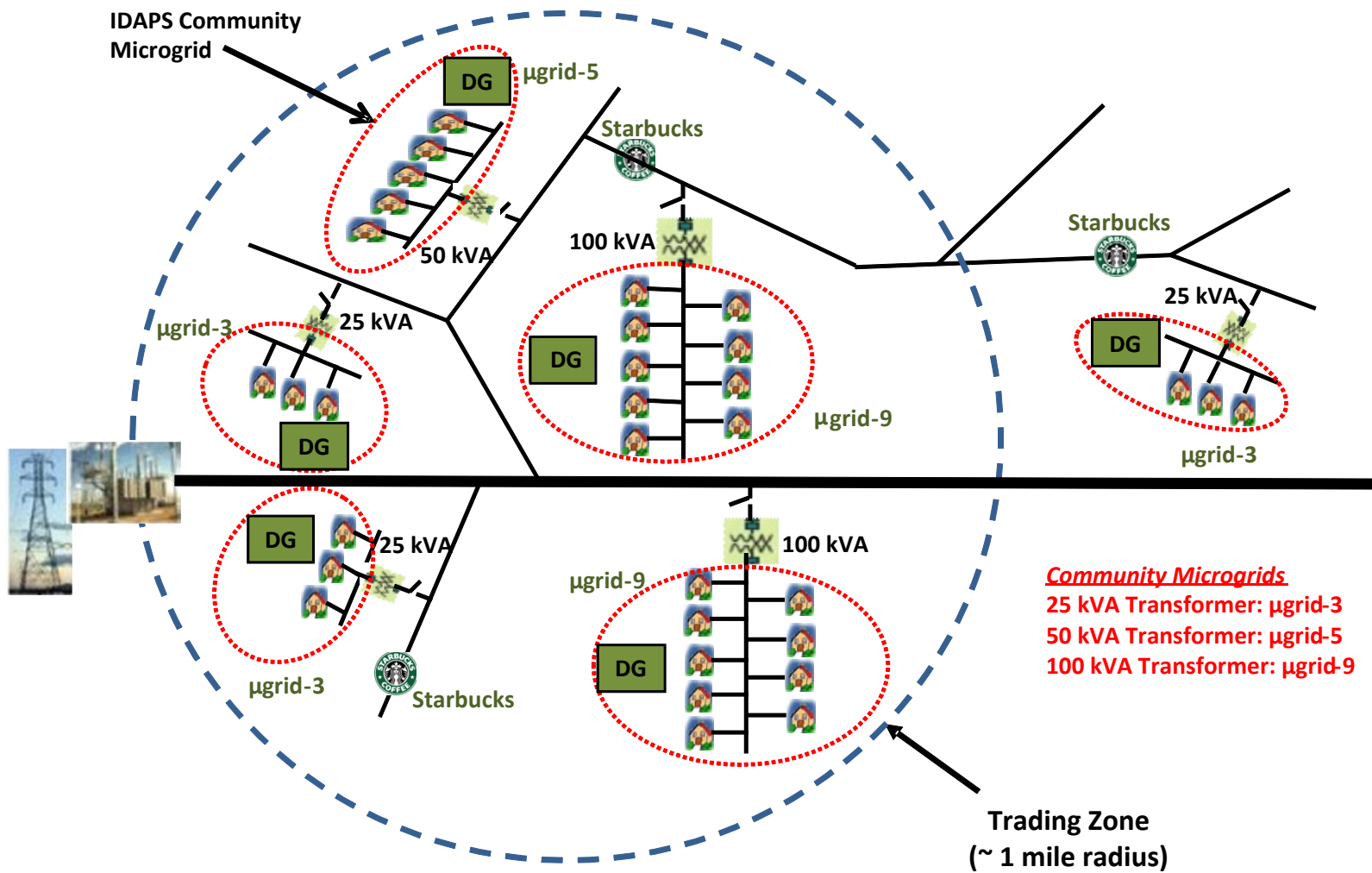


Figure 4: The proposed market model

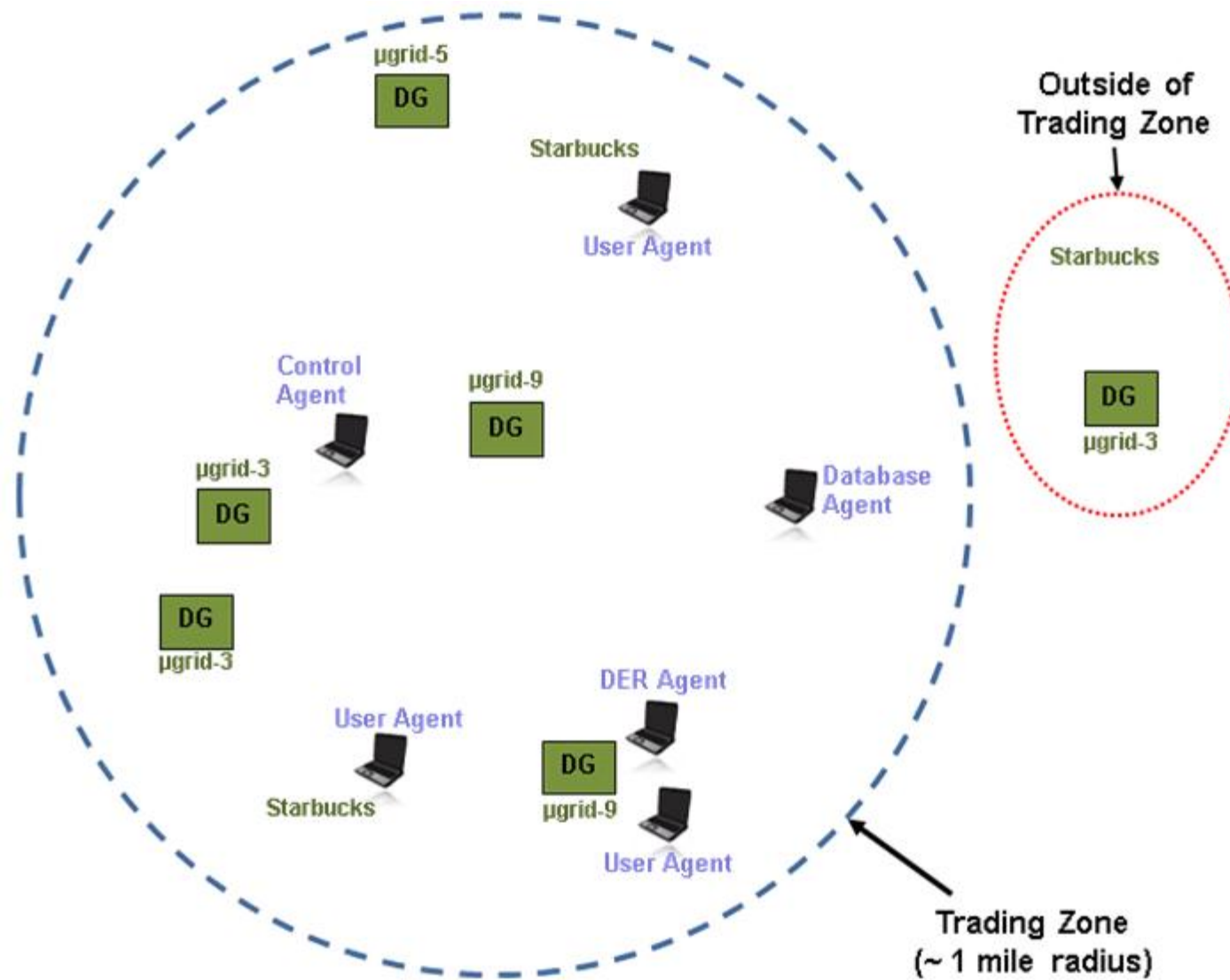


Figure 5: The topology of the proposed market model

4.3 The Business Model for Electricity Transaction

4.3.1 What *Drives* DG Installations?

For the market for electricity transaction to exist, there has to be a compelling business model for sellers and incentive for buyers.

In order to understand the business model for the market participants, it is important to first answer the following fundamental questions:

1. In the first place, why would anyone invest in DG installations?
2. What should be the *optimal* capacity of the DG installation?

Although we know of several benefits of DG installation [2], [6], [7], we consider the case of purely economic benefit driving DG installations and we make a compelling case for such installations based on Utility data (residential load profiles) and an established and proven tool, DER-CAM (Distributed Energy Resource-Customer Adoption Model) developed by Lawrence Berkeley National Laboratory (LBNL) [12][13][14][15][16][17][18][19].

The answers to the questions raised above are provided by our analysis of:

1. Utility provided residential load profiles
2. Using DER-CAM as a validation tool

4.3.2 The Business Model

For the Seller:

We now propose the business model which will be validated by our analysis in section 6.4. Based on the residential load profile for microgrids on sizes 3, 5 and 9, the DER-CAM tool is run to obtain:

1. The *optimized* DG technology selection
2. The *optimized* DG generation capacity
3. The *optimized* DG operating schedule

A microgrid of size 'n1' (n1=3, 5 or 9) installs an *optimized* capacity (as recommended by the DER-CAM tool with residential load profile input provided by the Utility data) for a microgrid of size 'n2' (n2 = 3, 5 or 9) and typically, n2 > n1.

For example:

An IDAPS community microgrid, μ grid-3, installs a recommended optimized capacity for a microgrid, μ grid-N (N typically, but not necessarily greater than 3).

For the Buyer:

It is rational to expect that the buyer will transact in the market ONLY if he/she gets an economic benefit (reduction in his/her electricity bill) - We assume other benefits of using DG supply are ignored by the buyer. This would mean, the buyer will participate in the bidding process only if the market stabilizes the prices of transacted electricity BELOW the grid price for every hour of transaction.

4.4 Market and Business Model Validation using DER-CAM Tool

4.4.1 Validation Methodology

The methodology we would follow to validate the market/business models is the following:

Step # 1: Understand the key drivers of customer adoption of distributed generation

Step # 2: Understand the economic forecasts (published by leading energy consulting companies) for the above identified key drivers

Step # 3: Create operating scenarios based on economic forecasts for DER-CAM tool

Step # 4: Create case studies for microgrids of various sizes (using residential load profile data provided by Utility Company)

Step # 5: For each case study, consider all possible operating scenarios outlined in Step#3, and run DER-CAM simulation tool

Step # 6: In all combinations of operating scenarios and case studies, consolidate the following results:

1. Percentage savings due to distributed generation over a “Do-Nothing” case
2. Percentage of energy demand met on-site

If the results of Step#6 always show a “positive savings”, there is indeed a compelling case for customer adoption and that forms the “nucleus” of the existence of such electricity transaction markets in imminent future. In this manner, our proposed market model would be validated.

Step # 7: In all combinations of operating scenarios and case studies, consolidate the following results:

1. Percentage of excess energy available for sale if a microgrid of size 'n1' (n1=3, 5 or 9) installs an optimized capacity (as recommended by the DER-CAM tool with residential load profile input provided by the Utility data) for a microgrid of size 'n2' (n2 = 3, 5 or 9) and typically, $n2 > n1$.

If the results of Step#7 always show “excess energy”, this is indeed the closest form of validation to our proposed business model for the seller.

We do not claim that this business model provides an optimum threshold for the DG capacity installation. However, this methodology demonstrates a serious potential in the business model and is looked upon as getting as close to validation as possible.

4.4.2 Validation Results

Market Model Validation:

We realize there are significant uncertainties affecting customer adoption of distributed generation.

We first frame the uncertainties by identifying the key drivers of customer adoption and our case studies incorporate uncertainties related to them:

- Utility tariffs
- Natural gas prices
- Solar PV turnkey costs
- Cost of capital
- Greenhouse gas regulations (Carbon tax)
- Economic benefits arising out of policies designed to promote renewable energy

Figure 6 shows the pictorial representation of what we identified as key drivers of customer adoption of distributed generation.

We assessed market trends and the underlying significant economic uncertainties affecting the customer adoption of distributed generation in residential microgrid scenarios. We considered a time-frame of 5 years, 2010-2015, throughout our analysis. Based on the market trends, we defined our case studies and operating scenarios for the purpose of validation.

Figure 7 shows the summary of case studies and operating scenarios that we created for the purpose of validation as described in the seven steps outlined in section 6.4.1.

We conducted 154 simulations of DER-CAM tool based on the operating scenarios created as described above. The results of simulation are shown in figure 8. It shows the consolidated results for *Percentage savings due to distributed generation over a “Do-Nothing” case*. By “Do-Nothing case”, we mean the customer does NOT install DG. It is to be noted that, in all combinations of operating scenarios and case studies, there are positive savings, and therefore forms a compelling case for customer adoption of distributed generation in residential microgrids.

For the same set of simulations, we show the percentage of energy demand met on-site, if distribution generation is adopted. Figure 9 shows consolidated results for Percentage of energy demand met on-site, for all sizes of microgrids (3, 5, 9, 25, 50, 75 and 100 homes) and under the considered economic uncertainties.

Business Model Validation:

As discussed in section 4.3.2, we considered microgrids of various sizes (n_1), installing an optimized capacity (as recommended by the DER-CAM tool with residential load profile input provided by the Utility data), for a microgrid of size n_2 . Sample results have been shown in figures 10 and 11. Several simulations were conducted although two sample, representative simulation results have been displayed.

Figure 10 shows a sample result of a case where μ grid-3 installed a DG capacity optimized for μ grid-9 with an objective to sell excess power to neighboring customers, under current utility tariff scenario.

Figure 11 shows a sample result of a case where μ grid-9 installed a DG capacity optimized for μ grid-25 with an objective to sell excess power to neighboring customers, under a 40% increase in utility on-peak tariff scenario.

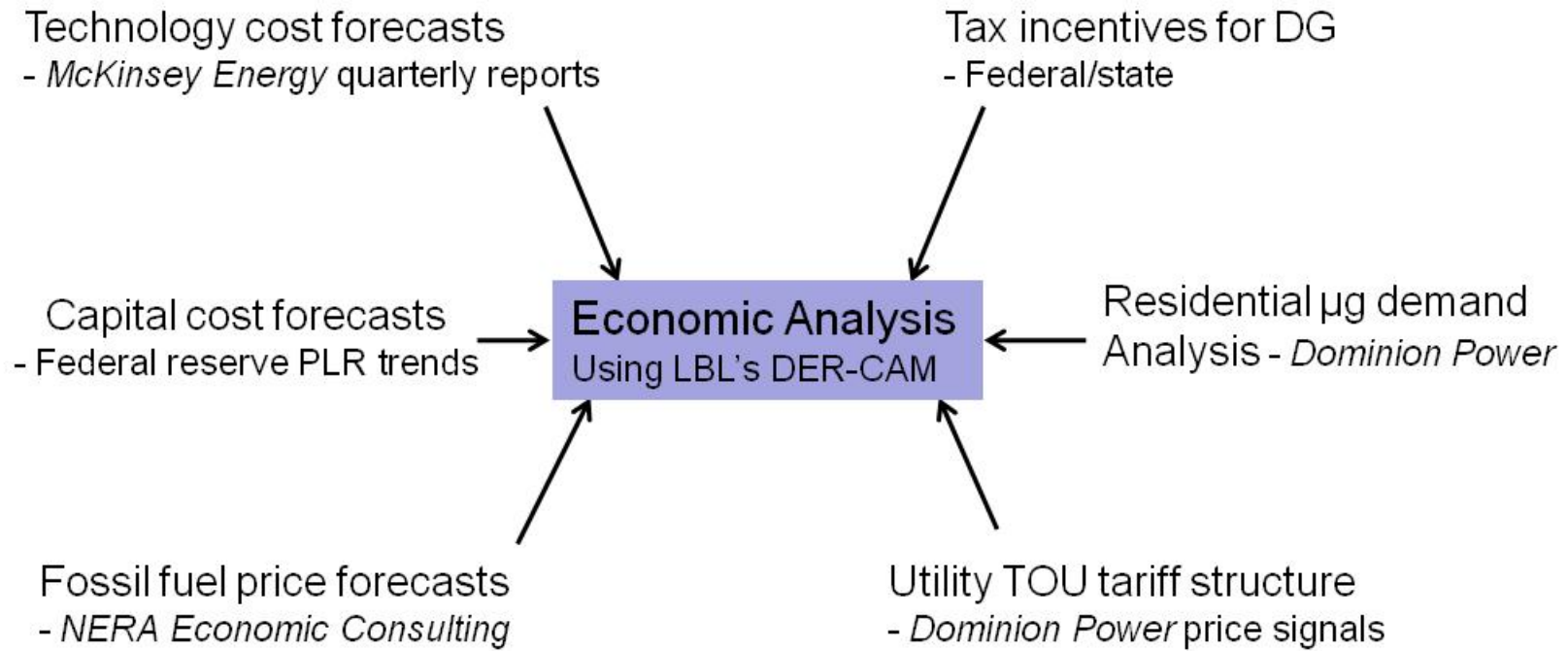


Figure 6: Key drivers of customer adoption of distributed generation

OPERATING SCENARIOS AND SENSITIVITY ANALYSIS

| Case Study | Scenario category | Scenario Code | Scenario Description |
|----------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|----------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| MICROGRID SIZE - 'N' Microgrid size of 'N' houses in a residential neighborhood [N = 3, 5, 9, 25, 50, 75, 100] | Utility Tariff Structure | Current TOU tariff | In this scenario, the customer buys all of its electricity from the disco at an established tariff structure |
| | | +20-onpeak; +40-offpeak | In this scenario, the customer buys all of its electricity from the disco at specified premium on current established tariff structure |
| | | +40-onpeak; +80-offpeak | In this scenario, the customer buys all of its electricity from the disco at specified premium on current established tariff structure |
| | Natural Gas Tariffs | +10NG | Customers face natural gas prices that are 10% higher than the current market price |
| | | +20NG | Customers face natural gas prices that are 20% higher than the current market price |
| | PV Turnkey Costs | -25PV | 25% decrease in turnkey costs of PV, compared to current costs |
| | | -50PV | 50% decrease in turnkey costs of PV, compared to current costs |
| | | -75PV | 75% decrease in turnkey costs of PV, compared to current costs |
| | Cost of Capital | +25IntRate | 25% increase in interest rate than the current rate |
| | | -25IntRate | 25% decrease in interest rate than the current rate |
| | Carbon Tax | \$50 per ton of carbon => \$0.05/Kg | A carbon tax of \$0.05/Kg levied on emissions |
| Each of these 11 scenarios will be run for microgrid sizes of: 3, 5, 9, 25, 50, 75 and 100 houses in a residential neighborhood | | | |
| Number of case studies = 7 Number of simulations per case study = 11*2 Total number of simulation cases = 7*22 = 154 | | | |

Figure 7: Summary of case studies and operating scenarios

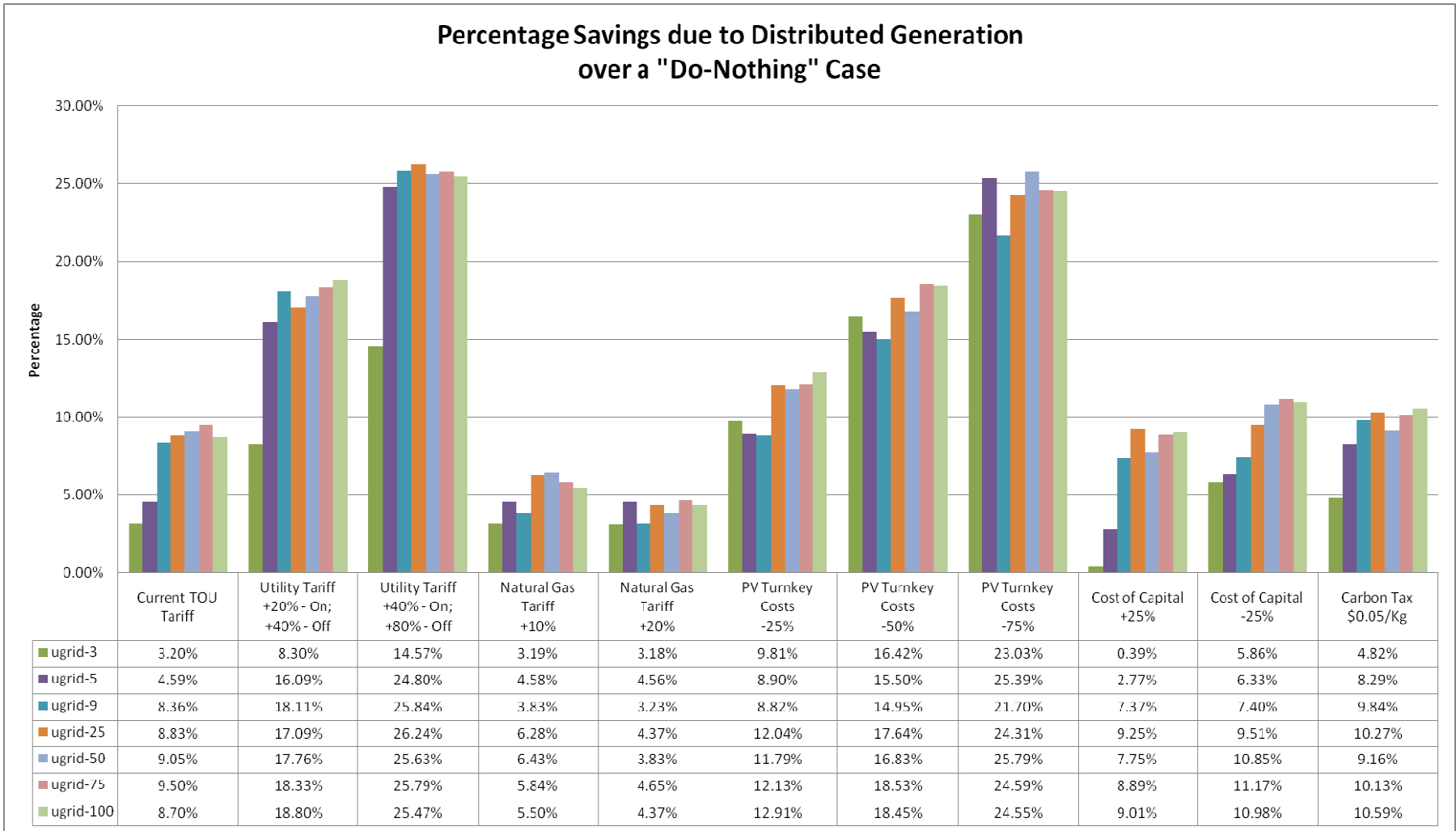


Figure 8: Percentage savings due to distributed generation over a "Do-Nothing" case

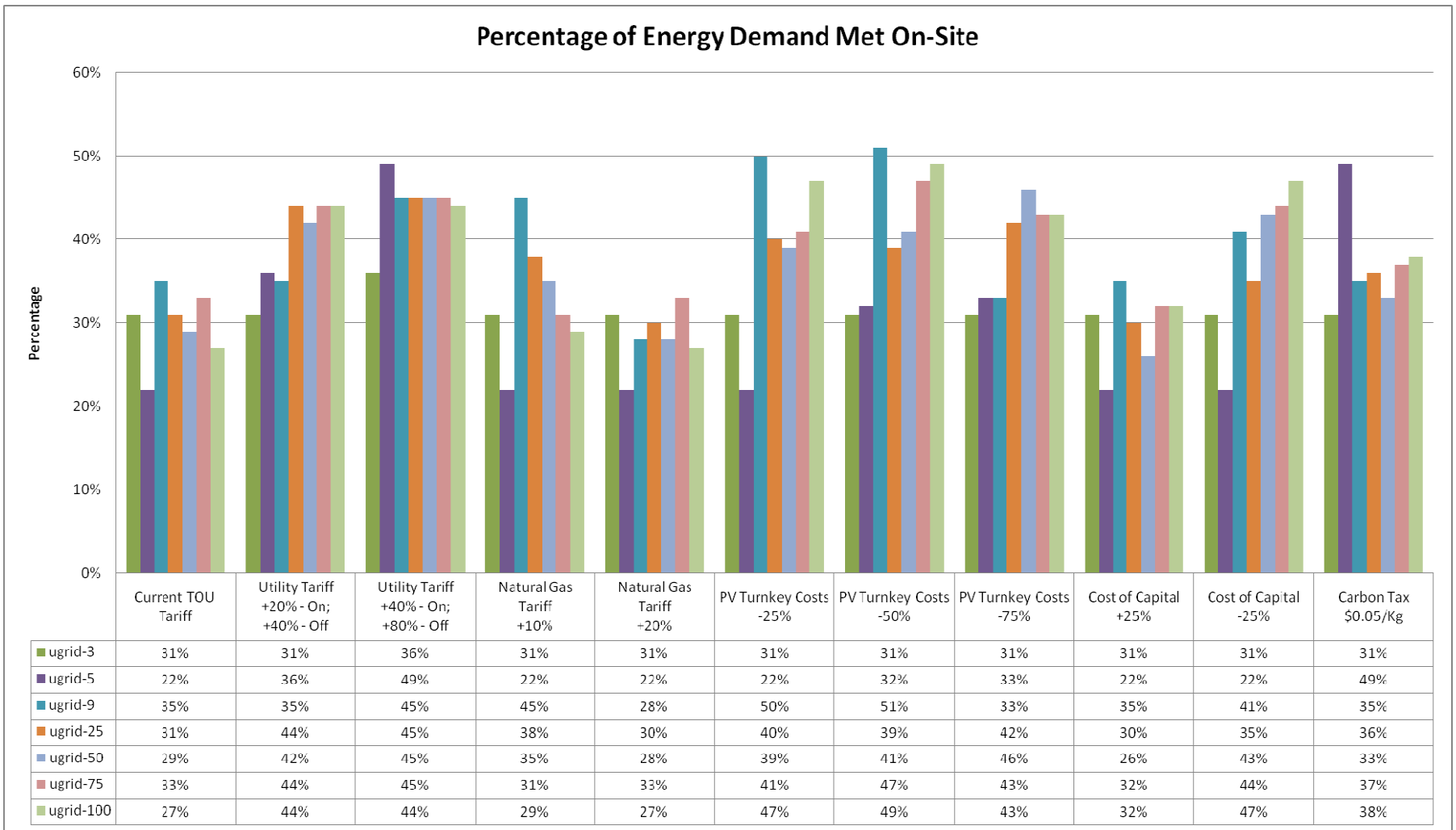


Figure 9: Percentage of energy demand met on-site due to distributed generation

ugrid-3 installs a DG capacity suggested for ugrid-9 with an objective to trade energy with its neighbors
 Peakday hourly averages over summer and winter seasons are displayed
 Scenario considered: Current Tariff Scenario

E_{trade} = Energy available for trading

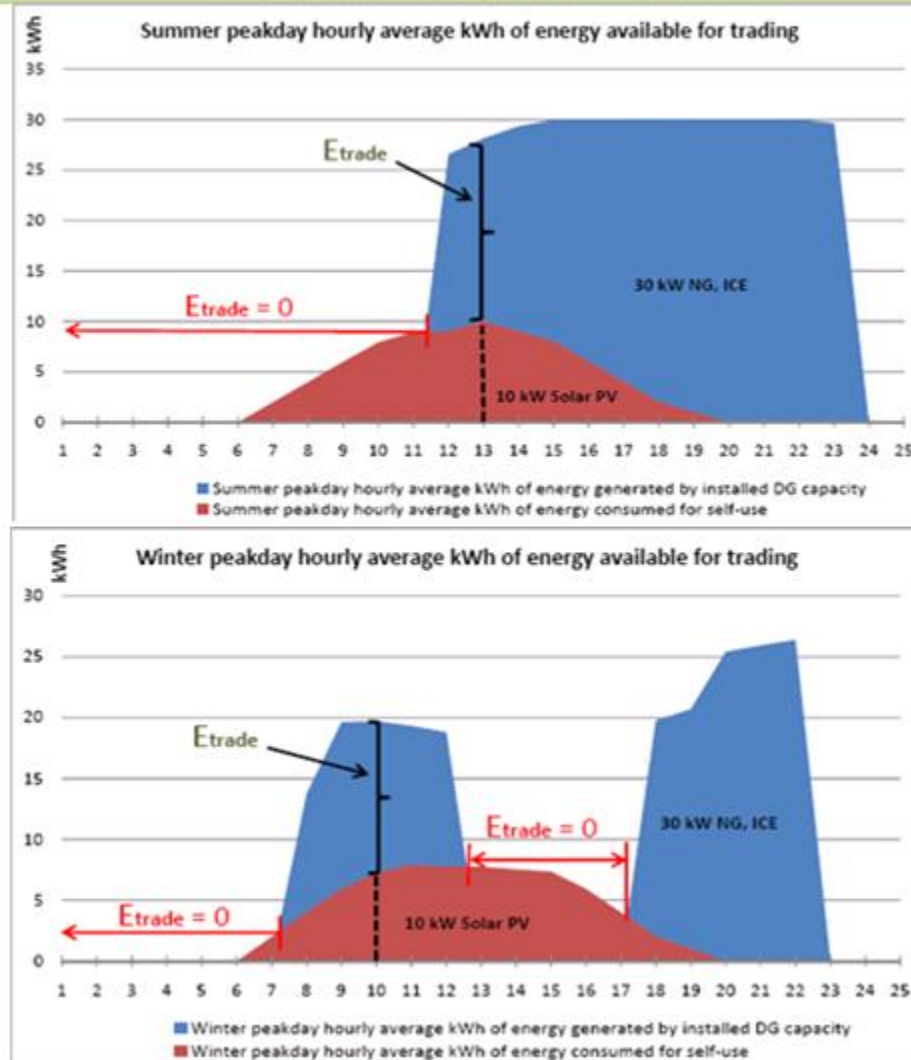


Figure 10: Sample result of a case where μ grid-3 installed a DG capacity optimized for μ grid-9, under current utility tariff scenario

ugrid-9 installs a DG capacity suggested for ugrid-25 with an objective to trade energy with its neighbors
 Peakday hourly averages over summer and winter seasons are displayed
 Scenario considered: 40% Increase in Utility On-Peak Tariff

E_{trade} = Energy available for trading

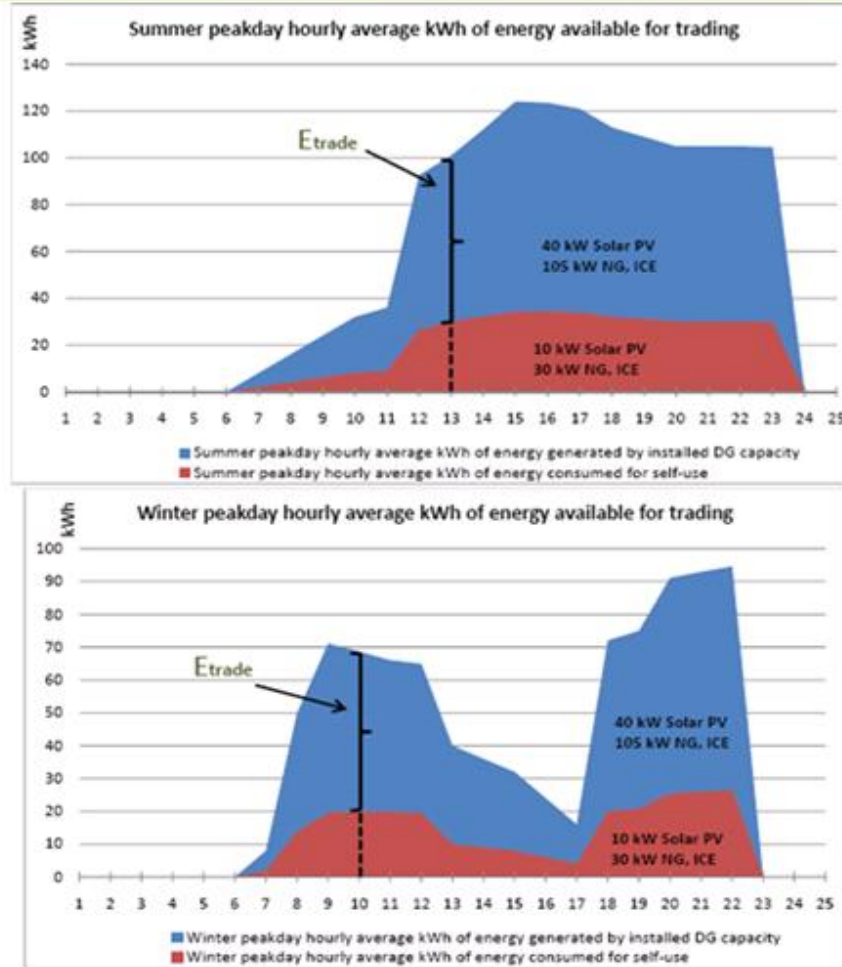


Figure 11: Sample result of a case where μ grid-9 installed a DG capacity optimized for μ grid-25, under a 40% increase in utility on-peak tariff scenario

Chapter 5

Introducing Reputation Score for Microgrid Market Participants

In this chapter, we present our second contribution of this thesis - Introducing reputation score to microgrid market participants.

Section 5.1 presents the concept of reputation score. The motivation for such a proposal is presented in sections 5.2. We then discuss the proposed components that determine the reputation score in section 5.3. In section 5.4, we present the algorithm to compute the reputation score of the market participants. We conclude the chapter by describing the results of sensitivity analysis of initial assignment of Reputation Score on long-term accumulated score in section 5.5.

5.1 The Concept of Reputation Score

The primary motivation and generic definition of *Reputation Management System* (RMS) arises from the need in distributed networks and online communities to create a communication framework similar to traditional social relationships.

Establishing a mechanism to ensure cooperation among the participation entities and to isolate their selfish behavior is of paramount importance for the very survivability and scalability in many distributed networks. RMS can be viewed as a cooperation enforcement solution.

The three primary functions of a reputation management system applied to any context are:

- Evaluation of behavior of participating entities
- Detection of misbehavior of participating entities
- Reaction to misbehavior of participating entities

The following are some of the examples of RMS application contexts

- Wireless sensor networks
- Vehicular ad-hoc networks
- P2P e-commerce communities
- E-service and e-business employing Service Oriented Architectures (SOA)

Reputation score is just one component of a reputation management system. We believe that a complex reputation management system is redundant in the context of microgrids and a strong trustworthy model for transactions can be formed by introducing and using reputation score alone.

5.2 Motivation

The recent restructuring of the electric utility market resulted in the deployment of small, independent customer-owned Distributed Energy Resources (DERs), which are typically alternate energy systems. These DERs supply excess generated power to critical loads within a localized geographical community at the feeder level. A small group of several such DERs forms what is called a Microgrid. It is one of the key directions recommended by the policy makers drafting roadmaps for the distribution of electricity in open markets.

We foresee ubiquitous deployment of microgrids in near future for several reasons:

- Policy decisions towards this restructured, open-market competition in electric utility market in many countries
- Requirement of increased robustness and resilience in the electric grid in emergency conditions (by means of a contingency achieved through the existence of microgrids serving critical loads)
- Emphasis on clean and Green energy generating technologies worldwide (achieved through alternate and renewable energy sources deployed as DERs)
- Technology advancements providing efficient sources of energy (such as photovoltaics and wind turbines) at an affordable cost

With such a large-scale deployment of microgrids in sight, there is a strong motivation for a mechanism for organizing, managing, controlling and dispatching the customer-owned DERs in microgrids. In this new market for electricity transaction among customers participating in the microgrid network, establishing a trustworthy model for participating entities is important for the success and scalability of such networks. This control mechanism within a microgrid should incorporate a reputation score based system so that customers can differentiate between different levels of service versus the price demanded by the generation sources. We discuss this further in section 6.1.

5.3 Components of Reputation Score

We first define a Reputation Score that would be associated to each of the participating DERs. The reputation score would take in to consideration the following qualifying fields/attributes of the respective DERs:

1. Reliability of the equipment used by the DER

Reliability of the equipment used by the DER in generating power is a very important factor that needs to be associated with the reputation score.

Reliability of the equipment may be considered to be inversely proportional to the outage time of DER. We propose reliability of the equipment to be computed based on empirical outage time of DER and accumulate score related to this field, averaging over long periods of time. Two important attributes are associated:

- Outage duration
- Time of outage (peak hour/off hour)

This is because; outage during peak-hours should have a heavier down-weight on reputation score than outage during off-peak hours.

Summary:

Field: Reliability of equipment

Attributes: Outage time; Outage duration

2. Capacity Factor

Some DERs may claim higher generation capacity for several reasons: lack of reasonable estimation, selfishness and malicious intent (to disrupt microgrid calculations of ability to

serve critical loads). This can be quantified by means of empirical calculation of Capacity Factor (CF), which is seen as the measure of performance averaged over a period of time.

$$\text{Capacity Factor (CF)} = \frac{\text{Actual Energy Produced (kWh)}}{\text{Rated Energy (kWh)}}$$

This would enable the IDAPS to accurately predict the total generation capacity of the microgrid.

Summary:

Field: Capacity factor

3. Generation Schedule Violation

Some DERs may violate financially binding, generation schedule assigned by the IDAPS eMKT due to selfishness and greed to demand higher prevailing energy prices. To deter DERs from violating the contracts, this field has been included in the reputation score computation.

Summary:

Field: Generation Schedule Violation

4. Transaction-based customer rating

The highly successful transaction-based customer rating methodology followed by several e-trading communities such as eBay is proposed as one of the contributing factors to the reputation score.

Summary:

Field: Transaction-based customer rating

Table 1 summarizes the components of reputation score.

| No. | Field | Attributes |
|------------|-----------------------------------|--------------------------------------------------------------------------------------------|
| 1 | Reliability of equipment | <ul style="list-style-type: none"> • Outage time • Outage duration |
| 2 | Capacity factor | Capacity factor |
| 3 | Generation Schedule Violation | Generation Schedule Violation |
| 4 | Transaction-based customer rating | Transaction-based customer rating |

Table 1: Components of Reputation Score

The *fields* of reputation score are computed using the overlay communication infrastructure of the IDAPS microgrid (which includes actuators and sensors), without any need for additional infrastructure.

5.4 Reputation Score Computation Guidelines

Before we discuss the reputation score computation guidelines, the following are to be noted:

1. Reputation score is associated only with generation sources or sellers of power in the microgrid market (DERs). We eliminate the need for a reputation score for buyers through a simple pre-payment gateway for transaction of power. More on this in section 6.1.2.
2. Reputation score represents trustworthiness of the seller (through a long-term and permanent transaction history of the seller).
3. The framework of proposed day-ahead energy market (DAEM) provides clear incentives for sellers with higher reputation score, through an in-built market mechanism of providing first bidder selection opportunity, which in turn results in higher revenues.
4. When a new seller registers with the market, he/she starts with a reputation score of 80, which corresponds to a reputation score band, **S2**. Based on the transaction history, the reputation score is scaled up or down. In the long run, the reputation score or equivalently, the reputation score band level would represent the *true* trustworthiness of the seller. Starting with a medium reputation score band level ensures that new market entrants are not penalized for entering the market *late* or in other words, to reduce the significance of first-mover advantage.
5. The range of the reputation score is: $[0, 100+)$. There are no upper or lower limits since this score is an accumulator function.
6. We define four discrete Reputation-Score-Bands, based on the reputation score (RS):
 - **S1**: $RS \geq 100$
 - **S2**: $80 \leq RS < 100$
 - **S3**: $50 \leq RS < 80$
 - **S4**: $RS < 50$

7. Reputation-score-bands directly map to bidding price bands which are recommended to buyers - discussed further in section 6.4.

The following guidelines to reputation score computation are proposed:

Guideline 1:

Every seller is assigned a reputation score of 80 upon entering the market, based on the score break-up shown in Table 2:

| Field | Attributes | Reputation Score |
|-----------------------------------|--------------------------------------------------------------------------------------------|-------------------------|
| Reliability of equipment | <ul style="list-style-type: none"> • Outage time • Outage duration | 20/25 |
| Capacity factor | Capacity factor | 20/25 |
| Generation Schedule Violation | Generation Schedule Violation | 20/25 |
| Transaction-based customer rating | Transaction-based customer rating | 20/25 |
| Total | | 80/100 |

Table 2: Guidelines for initial assignment of reputation score

This is unlike the trustworthiness model implemented in eBay, where a new entrant has an entry-level barrier and has to build his/her reputation before they enjoy the benefits of being trustworthy sellers.

Guideline 2:

| Field | Determining Factor | Reputation Score |
|----------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------|------------------|
| Reliability of equipment | For every hour of no-outage report: Off-peak | +2/24 |
| | For every hour of no-outage report: On-peak | +5/24 |
| | For 1 hour outage during off-peak | -5/24 |
| | For 1 hour outage during on-peak | -10/24 |
| Capacity factor, CF , averaged over 24-hour transactions. CF_{AVG} = Long-term average of Capacity Factor | If, $CF > 90\% \times CF_{AVG}$ | +5/24 |
| | If, $CF \leq 90\% \times CF_{AVG}$ | -2/24 |
| | If, $CF \leq 75\% \times CF_{AVG}$ | -5/24 |
| | If, $CF \leq 50\% \times CF_{AVG}$ | -10/24 |
| Generation Schedule Violation | For every off-peak hour honor generation schedule | +5/24 |
| | For every on-peak hour honor generation schedule | +15/24 |
| | For every off-peak hourly generation schedule violation | -5/24 |
| | For every on-peak hourly generation schedule violation | -15/24 |
| Transaction-based customer rating, averaged over 24-hour transactions | 5-star customer rating | +5/24 |
| | 4-star customer rating | +2/24 |
| | 3-star customer rating | -1/24 |
| | 2-star customer rating | -2/24 |
| | 1-star customer rating | -3/24 |

Table 3: Guidelines for updating reputation score

It is to be noted that reputation score of sellers gets updated after every the DAEM generation/dispatch schedule gets executed (T+1). Further the transaction-based customer feedback is anonymously submitted by the buyers. This anonymous feedback feature coupled with RS being assigned only to sellers will eliminate the notorious “revenge-feedback” problem of eBay.

Guideline 3:

Based on the updated reputation score of each of the sellers, a reputation score band is computed using the following score mapping:

- **S1:** $RS > 100+$
- **S2:** $80 \leq RS < 100$
- **S3:** $50 \leq RS < 80$
- **S4:** $RS < 50$

S1 would mean highest reputation score band level while S4 is the lowest reputation score band.

Further, In order to improve the defined reputation score in this context, several new fields may be added and the number of attributes to each field may be expanded.

5.5 Sensitivity Analysis of Initial Reputation Score on Long-Term Accumulated Score

We claim that initial assignment of high reputation score does not have any significant impact on the long-term accumulated reputation score. It is thus critical to justify our assignment of a higher reputation score to new market entrants, in order to keep the entry-level barrier to a minimum.

We have performed sensitivity analysis of our proposed reputation score computation guidelines described in the previous sections.

The methodology of our analysis is as follows:

1. Every DER or seller in the market has certain *long-term characteristics* in terms of the four components of the proposed reputation score:

- **Reliability of equipment**
- **Capacity Factor**
- **Generation schedule violation**
- **Transaction-based customer feedback**

We consider these characteristics as *stochastic processes* occurring with a certain probability of failure in adhering to the guidelines.

2. We then simulate failure of a DER in adhering to the specified guidelines, under the characteristics of the DER (in terms of probability of occurrence of failure).

3. The research uses a simulation time of 10000 hours or equivalently about 417 days of transactions.

4. We then conduct two case studies, which are described below, to study the long-term accumulated reputation score under various scenarios of initially assigned reputation score.

Case Study 1:

In this case study, we use the following characteristics of the DER:

| Field | Probability of failure |
|--------------------------------------------------------------|-------------------------------|
| Probability of failure of equipment | 0.1 |
| Probability of failure in meeting Capacity factor guidelines | 0.1 |
| Generation Schedule Violation | 0.01 |

We then simulated failures in every hour with a probability association described above and repeated the simulations for 10000 hours of transactions. The consolidated results are shown in Figure 12. The initial reputation scores used in this case study are: 0, 20, 40, 60, 80, and 100.

It is interesting to note that stochastically, all of these initial reputation scores lead to the same reputation score band for the seller - In this case the highest reputation score band of S1. Or in other words, the initial assignment does not have any significant impact on the long term reputation score of this seller. It can be understood that the long term reputation score of the seller is purely determined by the characteristics of the DER, in terms of its probabilities of failures.

It can also be noted that after about 6000 hours (or equivalently about 250 days), the reputation score of the seller reaches the highest reputation score band, under all initial assignments of the score.

Case Study 2:

In this case study, we use the following characteristics of the DER:

| Field | Probability of failure |
|--------------------------------------------------------------|-------------------------------|
| Probability of failure of equipment | 0.14 |
| Probability of failure in meeting Capacity factor guidelines | 0.14 |
| Generation Schedule Violation | 0.02 |

We then simulated failures in every hour with a probability association described above and repeated the simulations for 10000 hours of transactions. The consolidated results are shown in Figure 13. The initial reputation scores used in this case study are: 0, 20, 40, 60, 80, and 100.

Again, it is interesting to note that stochastically, all of these initial reputation scores lead to the same reputation score band for the seller - In this case the lowest reputation score band of S4. Or in other words, the initial assignment does not have any significant impact on the long term reputation score of this seller. It can be understood that the long term reputation score of the seller is purely determined by the characteristics of the DER, in terms of its probabilities of failures.

Corollary of this study:

The most important corollary of this study is the new set of guidelines in terms of probabilities of failure to stay competitive in the market. The sellers are expected to strive to curtail their failures within the numbers specified in the case studies to maintain a good reputation score.

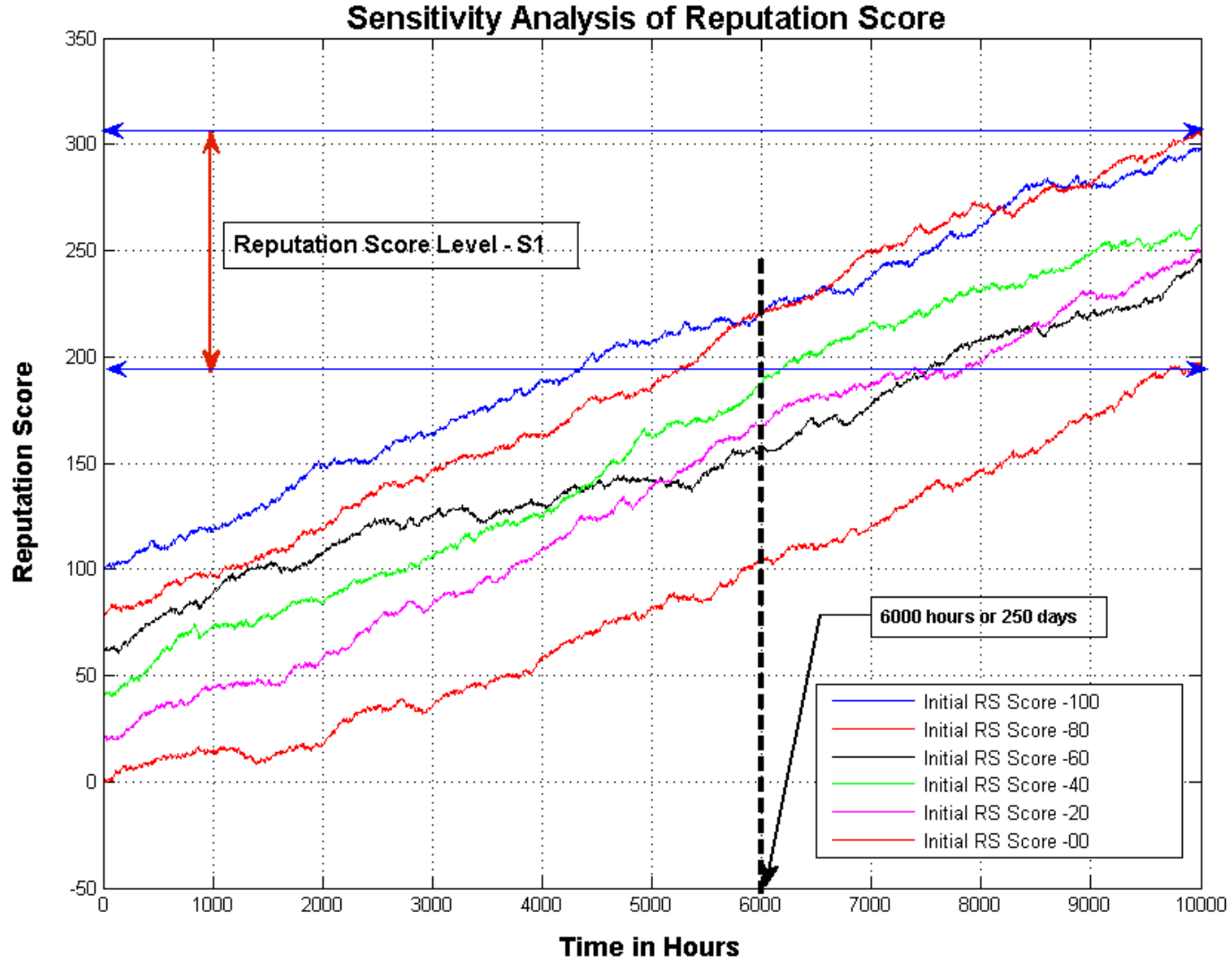


Figure 12: Sensitivity analysis of reputation score - Case study 1

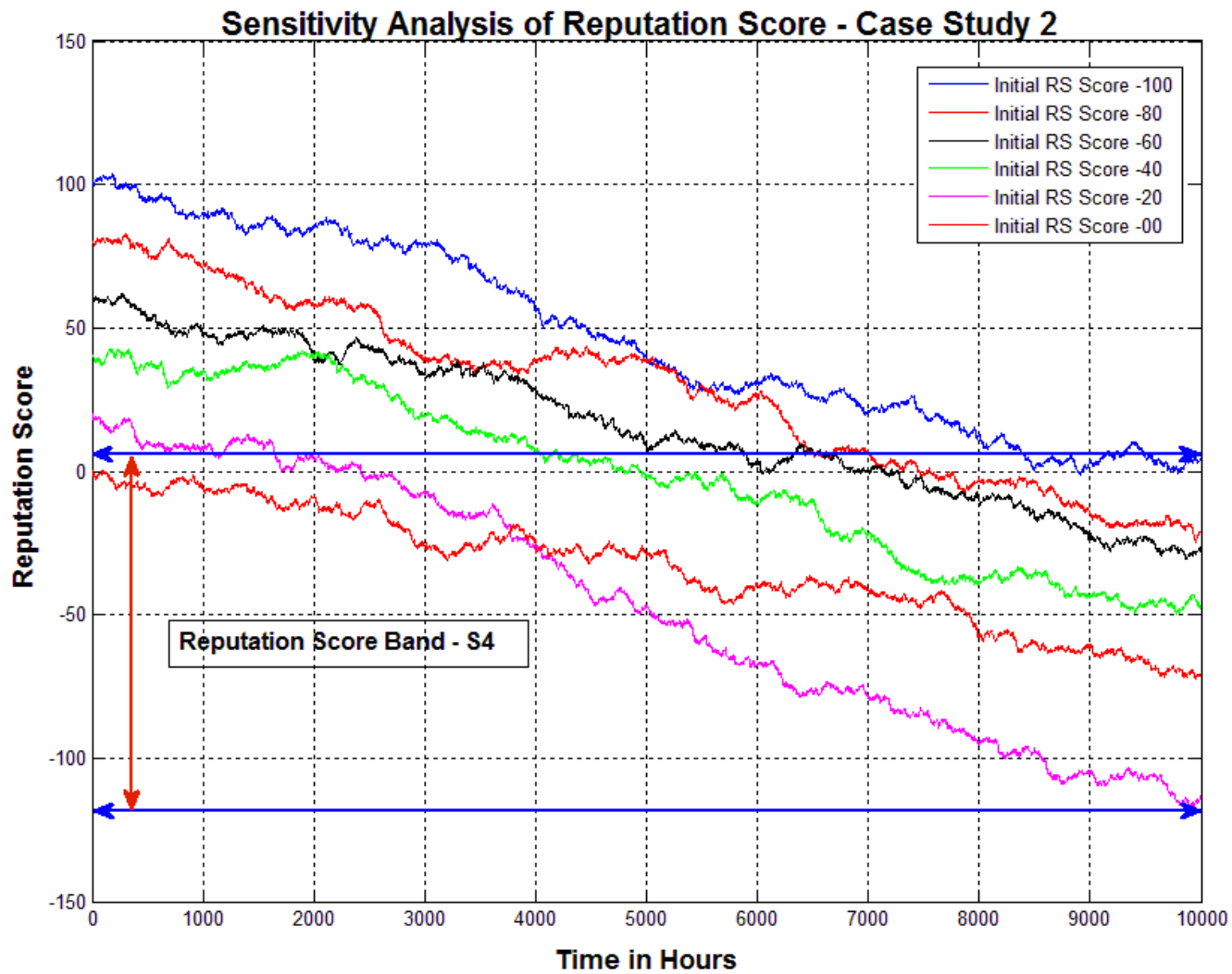


Figure 13: Sensitivity analysis of reputation score - Case study 2

Chapter 6

Reputation Score-Based Electricity Transaction Algorithms

In this chapter, we propose the framework of Day-Ahead Energy Market (DAEM). Section 6.1 carries an interesting discussion on how wholesale markets differ from the microgrid electricity markets and clearly links these differences to rationalize our approaches in proposing the DAEM. Section 6.2 describes the overview of the bidding process in DAEM. The sell-side and buy-side algorithms which are incorporated in the IDAPS eMKT, which is a clearing house for the DAEM are proposed in sections 6.3 and 6.4.

6.1 Understanding Microgrid Electricity Market

It is critical to understand the fundamental differences between wholesale electricity market and the microgrid electricity market. We believe there are two differences of paramount importance described below.

6.1.1 Core Approach: Supply-Driven-Demand Fulfillment

In wholesale electricity markets the power generators competitively sell to retailers, the system requiring the demand for electricity be known apriori or can be forecasted (a very good estimate). Based on this “known” demand, the generators “adapt” their generation offers matching the supply with the demand (electricity being a commodity which cannot be stored easily). In contrast, in a microgrid, due to its sheer micro-size, demand can change so instantaneously and neither the demand can be “known” apriori nor can it be forecasted [1].

To explain this point, consider a microgrid size of three residential customers: The behavior of a single customer in the microgrid (say, deciding to turn on the clothes dryer at some instant of time) will have a peak showing up on the microgrid load profile at that time, which cannot be forecast by any of the existing forecasting tools.

Furthermore, even if load forecasting was possible (which is not the case), since the generators in a microgrid market are small, they cannot “adapt” to the “known demand” by adjusting their generation offers. The generation of DG facilities cannot be as professionally “controlled” as in case of commercial power plants. If DGs are renewable based (which we envision most of them to be), the generation is dependent on so many external factors, adapting generation offers is just not a possibility.

Therefore, any system proposed for microgrid market thus, MUST use an approach different from that in the wholesale market.

We follow a market approach proposed in [1], which is a **supply-driven-demand model**. In this model, as the name suggests, *supply drives the demand*, unlike in conventional school of thought, where *demand drives the supply*.

This would mean, the loads are assumed to be deferrable and interruptible and will bid for power ONLY when the generator publishes the hourly generation offers. The rationale behind such a scenario to be assumed practical is that, buyer of power in the microgrid market (wishing to run a load such as a dishwasher) CAN wait when the grid price signal is too high for him/her to be willing to use electricity from the grid in that hour. The incentive for the buyer's *demand to be driven by the local supply* is purely economic in nature and thus the DAEM that we present in this chapter would stabilize to be an *efficient market* where the prices are determined by market forces (sellers, demand and the number of buyers).

6.1.2 Reputation Score-based approach to Microgrid Market

The second fundamental difference between the wholesale electricity market and the microgrid electricity market pertains to the nature of *market participants*.

In wholesale market, the market participants are generators (huge commercial power plants) and retail buyers (again huge corporations or utility companies).

In microgrid market scenario, the market participants are again generators (residential customer installations or community microgrid installations) which are of micro-size (anywhere between 5 kW and 5 MW[2][7][6]), and buyers (residential customers).

What differentiates the two sets of market participants? Wholesale market participants are too big to be *untrustworthy*, while microgrid market participants are at the core-level, individuals and thus the market needs a mechanism which enforces a *trustworthy* behavior. We believe that just the presence of such a mechanism in the market would serve as a huge deterrent for selfish, untrustworthy and greedy behavior.

It is this simple observation in differences in the nature of market participants that has driven us to towards the primary contribution of this thesis – Proposal of a DAEM for electricity transaction among IDAPS community microgrids, which has at its heart, a built-in mechanism of ensuring, enforcing and rewarding *trustworthy* behavior of the market participants. This is achieved by associating a reputation score for each of the sellers (or micro-generators), which is dependent on several factors, the details of which were discussed elaborately in Chapter 5.

When the IDAPS eMKT component of the DAEM generates financially binding, day-ahead generation/dispatch schedule, the buyers make immediate payment (using mechanisms such as automatic account deduction) to the sellers through third-party payment gateways. This aspect ensures that buyers do not default on payments to the sellers for the power transacted through the DAEM, thus eliminating the need for a reputation score for buyers.

6.2 Overview of Bidding Process

We now propose the overview of the bidding process that takes place on IDAPS eMKT platform of our DAEM.

In our proposal of the DAEM for microgrids, there are two sellers (with different reputation scores) and nine buyers. The implementation details are provided in Chapter 9. Before we discuss further, it is important to note that the proposal in no way limits itself to the above mentioned market participants. The model demonstrates all novel concepts that have been introduced in this thesis through the implementation scenario represented by 2 sellers and nine buyers.

After the day-ahead hourly generation offers (DAHGO) are submitted by the two sellers in the market, the platform seeks day-ahead hourly demand bids (DAHDB) from the nine buyers. The IDAPS eMKT then conducts matching of DAHGO and DAHDB and publishes a financially binding summary of generation and dispatch schedules for the two sellers.

For every hour, the bidding **is conducted first for the seller with a higher reputation score**. All the buyers who have published the DAHDB participate in the bidding for this seller. Matching of the seller's DAHGO and the DAHDB for all the buyers is completed at this stage. Then, for the same hour, bidding for the seller with the lower reputation score is conducted. The buyers who participate in this bidding session are those who were not bid winners in the first stage. Matching of this seller's DAHGO and the qualified second stage bidders is then conducted. These two bidding sessions complete the process for 1 hour. The process repeats for all the 24 hours.

6.3 The Sell-Side Algorithm

In this section, we first discuss our thought process that led us to the sell-side algorithm that would be described later.

6.3.1 Sell-Side Algorithm Development Approach

In this section, we first discuss our thought process that led us to the sell-side algorithm that would be described in 6.3.2.

We first make an assumption that the buyer wants all or none of the requested energy block. The rationale behind this assumption is that the residential customers request energy for using their appliances such as dish washer, dryer or television, each of which has a manufacturer specified power rating. It is logical to assume that a residential customer would like to use an appliance for a certain amount of time. If the seller is unable to provide the energy for that purpose, it is reasonable to assume that buyer would not like to buy from that seller.

Next step is to identify what the goal of the seller should be.

The following are the options for the seller:

- Choose the bidder with maximum *bid value*?
- Maximize total *revenue* in hour 'h'?
- Maximize total *profit* in hour 'h'?

Let us look at two simple examples which clarify the differences in the options presented, above:

Example 1

- Total energy available for sale in hour 'h' = 20 kWh;
- Assume only 2 bidders; Assume operating cost = 0.04 \$/kWh
- Bidder1: Bids for 5 kWh @ 0.20 \$/kWh
- Bidder2: Bids for 17 kWh @ 0.09 \$/kWh
- Notice, the seller can choose only one bidder because of our assumption
- Bidder1: Revenue = \$1; Profit = \$0.80
- Bidder2: Revenue = \$1.53; Profit = \$0.85 (Bid 2 < ½ * Bid1)
- Whom should the seller sell to – Bidder1 or **Bidder2**?

It is to be noted from this example that although Bidder 2 has bid-price of less than half of what Bidder 1 has bid, it still makes sense for the Seller sells to Bidder 2, since he gains a more overall profit than he would do by selling to Bidder 1. However, note that revenue gained by selling to Bidder 1 is less than what he would gain by selling to Bidder 2.

Example 2

- Total energy available for sale in hour 'h' = 20 kWh;
- Assume only 2 bidders; Assume operating cost = 0.04 \$/kWh
- Bidder1: Bids for 5 kWh @ 0.20 \$/kWh
- Bidder2: Bids for 17 kWh @ 0.07 \$/kWh
- Notice, the seller can choose only one bidder because of our assumption
- Bidder1: Revenue = \$1; Profit = \$0.80
- Bidder2: Revenue = \$1.19; Profit = \$0.51 (Notice revenue is higher)
- Whom should the seller sell to – **Bidder1** or Bidder2?

It is to be noted from this example that although Bidder 1 brings an overall profit greater than what Bidder 2 would and it makes sense for the Seller to sell to Bidder 1. However, note that revenue gained by selling to Bidder 2 is greater than what he would gain by selling to Bidder 1. So what?

Seller's Objective?

Based on the examples above, we came up with this simple, intuitive objective of the seller:

- Sell-side algorithm is based on maximizing seller's net profit in hour 'h'
- Consequently, seller may sell to multiple bidders in hour 'h', by optimizing his/her net profit

6.3.2 Sell-Side Algorithm

In order to achieve the objective of the seller, the following combinatorial logic-based algorithm is proposed:

The algorithm outlines, below is used to pick a set of bidders from all bidders who would bring maximum profit for the seller in that hour of transaction.

Algorithm Variables:

Energy available for sale = E

Number of buyers in the market = m

Energy-Price pairs submitted by the bidders: $\{E_i, P_i\}$

Reserve price of seller = cost of operation = C

Step # 1: Create all possible combinations of bidders:

$$\text{Set of all possible bidder combinations} = \{(m \text{ Choose } i)\}, i = 1, 2, 3 \dots m$$

This represents the set of all possible bidder combinations.

Step # 2: For each of the possible bidder combination formed above, we now inspect for *valid combinations*. By valid combinations, we mean, only those combinations whose net energy requirement (sum of the energy requirements of the constituent bidders) is less than or equal to the energy available for sale.

Step # 3: We then create a profit vector; the net profit generated by each valid combination of bidders.

Step # 4: We finally choose the maximum element of the profit vector and identify the associated bidder combination as the set of bidders which the seller should sell to in order to maximize his/her profit for that particular hour.

This algorithm will ensure that there does not exist any other combination of bidders who would provide the seller with more profit than identified by the four-step algorithm given above.

To illustrate the algorithm results graphically, let us consider two cases:

Case 1: Seller does not publish any Buy-It-Now price or none of the buyers opt to buy electricity from seller at Buy-It-Now (BIN) price.

Figure 12 shows the scatter plot identifying profit obtained in all valid combinations for a particular run of the algorithm. It identifies a 489 valid number of bidder combinations (from a total of 1023 possible bidder combinations). It then plots each of the profit vector element Vs the valid combinations. It chooses the bidder combination which yields maximum hourly profit.

Case 2: Seller publishes a Buy-It-Now price AND one of the bidders opts to buy electricity from seller at Buy-It-Now (BIN) price.

Figure 13 shows the scatter plot identifying profit obtained in all valid combinations for a particular run of the algorithm. It identifies a 115 valid number of bidder combinations (from a total of 255 possible bidder combinations). The plot also shows the \$ amount gained by the seller who opted to buy at BIN price. It then plots each of the profit vector element Vs the valid combinations. It chooses the bidder combination which yields maximum hourly profit.

Scalability of the algorithm:

As discussed in the previous section, the IDAPS eMKT uses combinatorial logic to perform the hourly matching of generation offer and demand bids, in order to maximize the seller's profit. Combinatorial logic may be time consuming. However, step#2 in the algorithm above eliminates a good percentage of bidder combinations using simple additive function, thereby selecting only *valid combinations* (only those bidder combinations whose sum of the energy requirements is less than or equal to the energy available for sale) to enter combinatorial computation stage.

In addition, in our future work section of this thesis, we proposed using a parallel computing facility since the day-ahead algorithm is an **embarrassingly parallel problem**. This is because; the bidder selection algorithm for a particular hour is totally independent of the remaining 23 hours in the day. Therefore, the algorithm can be run on a 24-core cluster computing facility such as the one at Advanced Research Institute, Virginia Tech.

Because of our elimination process and the parallel nature of the algorithm, we claim that the algorithm and consequently the software design are very much scalable.

Sell-Side (DER Agent) GUI

(c) Center for Energy and The Global Environment, ARI

Available Energy for Sale in hour 'h' - DER Specifications

Energy for Sale (kWh)
42

Click to Run DER algorithm

Summary of the results of sell-side (DER) algorithm

| Total number of bidders | Number of qualified bidders | Number of bid winners |
|-------------------------|-----------------------------|-----------------------|
| 10 | 10 | 5 |

| Disqualified bidder No | Price-Energy pairs of winning bidders | | |
|------------------------|---------------------------------------|---------------|--------------|
| | Bidder No | Price (¢/kWh) | Energy (kWh) |
| | 2 | 8 | 14 |
| | 3 | 7.5 | 20 |
| | 4 | 40 | 2 |
| | 6 | 80 | 1 |
| | 9 | 24 | 5 |

| | |
|------------------------------------------------------------------------------|-----------|
| Total energy sold in the bidding process (in kWh) | 42 |
| Unsold energy after bidding process (in kWh) | 0 |
| Total profit for DER from this bidding process (in \$) | 5.42 |
| DER algorithm bid processing time (in seconds) | 0.0130046 |
| Maximum profit (in \$) that can be gained by the DER, given the current bids | 5.42 |
| Total no of combinations of qualified bidders possible | 1023 |
| Total no of valid combinations of qualified bidders | 489 |

Profits - All valid bidder combinations

| | Profit Vector |
|---|---------------|
| 1 | 0.2000 |
| 2 | 1.1200 |
| 3 | 1.5000 |
| 4 | 0.8000 |
| 5 | 0.0300 |

Energy Buyers (User Agents) Participating in the Bidding Process

| | | | | | |
|--------------|-------------------|-----------------|---------------|------------------|-----------------|
| User Agent 1 | Price (¢/kWh) 4 | Energy (kWh) 5 | User Agent 6 | Price (¢/kWh) 80 | Energy (kWh) 1 |
| User Agent 2 | Price (¢/kWh) 8 | Energy (kWh) 14 | User Agent 7 | Price (¢/kWh) 6 | Energy (kWh) 20 |
| User Agent 3 | Price (¢/kWh) 7.5 | Energy (kWh) 20 | User Agent 8 | Price (¢/kWh) 14 | Energy (kWh) 4 |
| User Agent 4 | Price (¢/kWh) 40 | Energy (kWh) 2 | User Agent 9 | Price (¢/kWh) 24 | Energy (kWh) 5 |
| User Agent 5 | Price (¢/kWh) 3 | Energy (kWh) 1 | User Agent 10 | Price (¢/kWh) 6 | Energy (kWh) 15 |

Scatter Plot of Profit in each of the valid bidder combinations

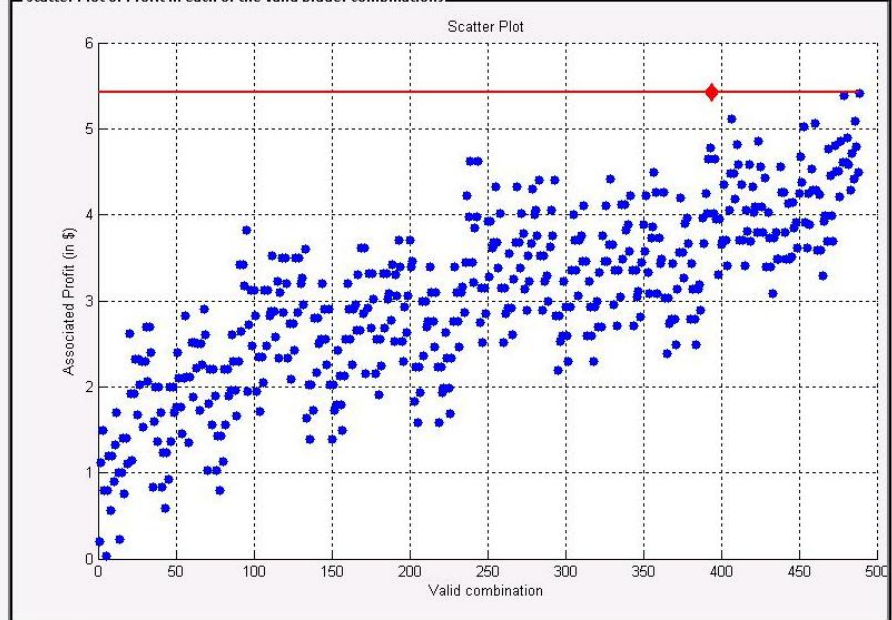


Figure 14: Scatter plot of profits obtained in all valid combinations of bidders

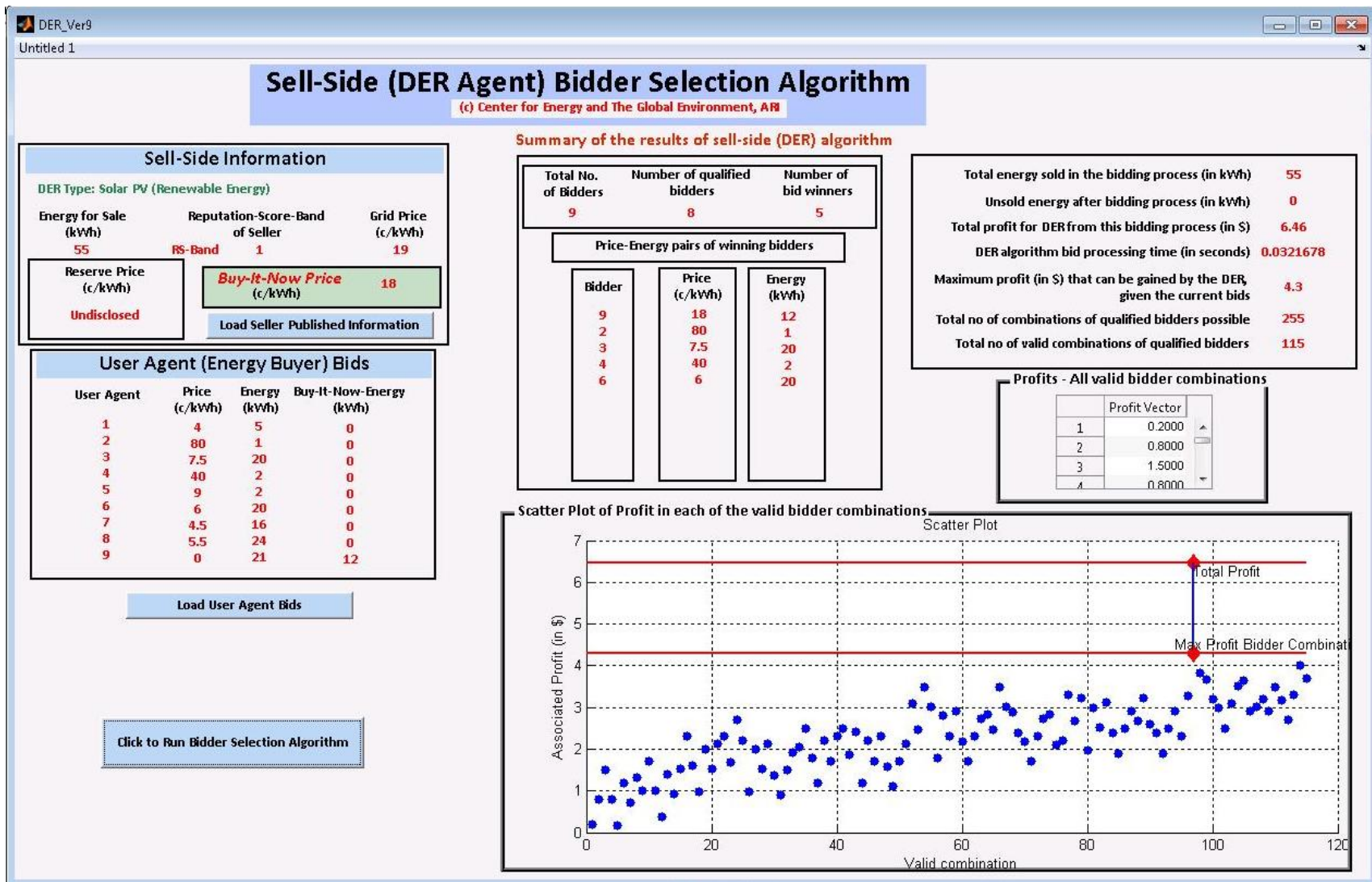


Figure 15: Scatter plot of profits obtained in all valid combinations of bidders, with a Buy-It-Now bidder

6.4 The Buy-Side Algorithm

6.4.1 Bidding Price-Band Recommendation Tool

On the buy-side, we have provided a tool for the buyer by means of which he can get a recommendation of bidding price band. This forms one of the important contributions of this thesis and will be discussed in detail in this section.

Figure 14 shows the screenshot of the tool embedded in the Buyer screen.

The screenshot shows a web-based tool titled "Seller Preference and Bidding Price Band Recommendation Tool". It contains the following elements:

- A text input field for "Please enter the bidding hour (1 - 24):" with the value "4" entered.
- A text input field for "Please enter the level of quality of your current demand: Level" with the value "4" entered. Below this field, it says "Level 1 = Highest Priority" and "Level 4 = Lowest Priority".
- A button labeled "Recommend a bidding price band".
- A table showing the "Recommended price band in which you may bid":

| Minimum (c/kWh) | Maximum (c/kWh) |
|-----------------|-----------------|
| 0 | 0 |

Figure 16: Screen shot of bidding price-band recommendation tool

6.4.2 Introducing the key concept of *Quality of Demand*

Representative examples of non-critical loads or equivalently, *deferrable or interruptible loads* which the buyer may intend to use are listed below:

- Water heating
- Clothes drying
- PHEV
- Space cooling/heating
- Optional lighting (50%)
- Television
- Other appliance-based end uses

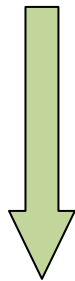
Suppose there is a load which the buyer wants to run by purchasing electricity using IDAPS eMKT. We believe, buyer's *demand* for using that particular load has two dimensions:

1. Need

2. *Quality of demand*

The intention to use may be termed as *need*. Now, how *badly* the buyer wants the load to run may be qualified as *Quality of Demand*. Although it is difficult to quantify this concept of Quality of Demand (QoD), it is not as difficult for the buyer to intuitively classify his/her QoD in to four discrete levels: From Level 1 (Highest QoD) through Level 4 (Lowest QoD).

- **Q1:** Highest QoD
- **Q2**
- **Q3**
- **Q4:** Lowest QoD



Four discrete QoD -Levels:

Decreasing order of QoD of the buyer -
It is a very subjective classification.

Buyer's, hourly, QoD-level is used as an input to the bidding price band recommendation tool.

It is important to understand that this classification of QoD is subjective and may be different for different customers and may also differ for the same customer at different times, moods, seasons etc. For example, at the time of Super bowl, the QoD for television as a load may be considered to be of the highest order (Level-1) for many people. However, the same load (television) may have a QoD of lowest order (Level 4) at 10 AM on any typical weekday.

As a corollary, we can state that the buyer's objective will be to pay an amount which is determined based on the reputation score band of the seller (or equivalently, the *trustworthiness* of the seller) AND corresponding to the buyer's *real need* (Need and QoD) and this price will not typically exceed that of the grid at that hour.

This is the primary goal of the algorithm behind the bidding price band recommendation tool.

The buyer's hourly, QoD-level (Q1 or Q2 or Q3 or Q4) is used as an input to the bidding price band recommendation tool.

The tool asks for the buyer's QoD for that hour (or equivalently, for the load he/she intends to use in that hour), pulls out the seller's reputation score band level from the eMKT and determines a bidding price band for the buyer. It is just a recommendation tool - The buyer may over-ride the recommendation and specify a final bid price based on his/her own rationale.

6.4.3 Defining Bidding Price Bands

We have defined Bidding-Price-Bands based on Grid Price Signal (P_G) using a top-down method versus a bottom-up approach.

We define four discrete Bidding-Price-Bands:

- **B1:** $[0.95 \cdot P_G, 0.85 \cdot P_G]$
- **B2:** $[0.85 \cdot P_G, 0.75 \cdot P_G]$
- **B3:** $[0.75 \cdot P_G, 0.60 \cdot P_G]$
- **B4:** $[0.60 \cdot P_G, 0.40 \cdot P_G]$

It is important to note the following:

1. The choice of bidding price band *quotients* is not by any rule and can be said to be arbitrary in our implementation.
2. In our choice of the quotients, the bands are NOT uniformly spaced.
3. These quotients can be easily modified in the software

In addition to the four discrete price bands defined above, two special cases have been identified:

Special Price Band 1: Go-Green-Price-Band

A **Go-Green-Price-Band, BG**, has been defined for environmentally conscious commercial enterprises like Starbucks (falling in the same microgrid vicinity), who may be interested in long-term contracts:

- **BG***: $[0.95 \cdot P_G, 5 \cdot P_G]$

**It is not expected that residential customers would opt to bid in BG band*

Special Price Band 2: Out-of-Band-Price Bidding

Buyers may bid at a buyer-specified price lower than the lower limit of the price band for the corresponding reputation-score-band. However the chances of winning the bid may be low in such cases.

The rationale for such an option is that it enables a seller to be able to sell even when the demand is very low (especially since the market follows the IDAPS supply-driven-demand model).

6.4.4 Discussion on factors that dominate price band recommendation

In this section, we discuss the relation between QoD, Reputation score band of the seller, Grid Price signal and Bidding price bands.

The bidding price band recommendation tool uses the relationship depicted in Table 4, below:

| Reputation Score Band of Seller | User Specified QoD | Recommended Bidding Price Band | Decision Dominating Factor |
|---------------------------------|--------------------|--------------------------------|----------------------------|
| S1 | Q1 | B1 | RS, QoD |
| | Q2 | B2 | QoD |
| | Q3 | B3 | QoD |
| | Q4 | B4 | QoD |
| S2 | Q1 | B2 | RS |
| | Q2 | B2 | RS, QoD |
| | Q3 | B3 | QoD |
| | Q4 | B4 | QoD |
| S3 | Q1 | Do-Not-Bid | RS |
| | Q2 | B3 | RS |
| | Q3 | B3 | RS, QoD |
| | Q4 | B4 | QoD |
| S4 | Q1 | Do-Not-Bid | RS |
| | Q2 | Do-Not-Bid | RS |
| | Q3 | B4 | RS |
| | Q4 | B4 | RS, QoD |

Table 4: Factors that dominate price band recommendation

An interesting analysis follows:

The dominating factor in recommending a bidding price band can be any of the following:

1. A combination of Reputation Score Band (RS) of the seller and QoD of the buyer

2. Reputation Score Band (RS) of the seller alone

3. QoD of the buyer alone

This can be observed in the last column of the Table 4.

We will now give examples of each case:

Case 1: A combination of Reputation Score Band (RS) of the seller and QoD of the buyer

It is the simplest of all the three cases.

Consider a seller with highest reputation score band (S1). Further assume that the buyer has a current QoD of highest level (Q1). Now, since, the QoD is of highest order AND the seller is trustworthy of highest level, the tool assumes that the supplier is able to supply power at the quality (defined by the attributes of reputation score) demanded by the buyer. Hence, it recommends a price band of 85% to 95% of the prevailing grid price.

In this case, both the QoD and RS were dominating factors in deciding the bidding price band recommendation.

Case 2: Reputation Score Band (RS) of the seller alone

Consider a seller with highest reputation score band (S2). Further assume that the buyer has a current QoD of highest level (Q1). Now, since, the QoD is of highest order BUT the seller has a RS of Level-2, the tool assumes that the seller may NOT be able to supply power at the quality (defined by the attributes of reputation score) demanded by the buyer. The tool then downgrades the **price band that the seller commends**. Hence, it recommends a price band, B2, which is 75% to 85% of the prevailing grid price. The rationale is to why pay more when the seller is not able to meet buyer's expectations, although the buyer's need is of highest order.

In this case, only RS was a dominating factor in deciding the bidding price band recommendation.

There is another special case where the tool recommends that buyer *Do-Not-Bid* for the seller. This is when the RS of the buyer is two levels down from the QoD level of the buyer. The rationale is that the seller may not be able to satisfy buyer's requirement in the first place, so reduction in price band may not serve the primary purpose of the buyer.

Case 3: QoD of the buyer alone

Consider a seller with highest reputation score band (S2). Further assume that the buyer has a current QoD of highest level (Q3). Now, since, the QoD is of lower order ALTHOUGH the seller has a RS of Level-2, the tool assumes that the buyer's need is not of all that importance as commended by the seller. The tool again downgrades the ***price band that the buyer's requirement suffices***. Hence, it recommends a price band, B3 (same level as the QoD), which is 60% to 75% of the prevailing grid price. The rationale is to why pay more when the buyer's *real demand* is not of as higher level as the seller is able to provide.

In this case, only QoD was a dominating factor in deciding the bidding price band recommendation.

Chapter 7

Framework of Day-Ahead Energy Market (DAEM) for Microgrids

In this chapter, we discuss the implementation of the framework of Day-Ahead Energy Market (DAEM). In section 7.1, we discuss certain aspects of Smart Grid deployment and what it means for Microgrids. This integrated understanding of the Smart Grid and potential impacts it may have on microgrid markets is incorporated into the design of the DAEM. Section 7.2 defines the scope of the proposed market. Market assumptions are put forward in section 7.3. We then propose the architecture of our DAEM design clearly identifying the market participants in section 7.4. The time-line of the DAEM, which is in-line with the PJM wholesale market, is presented in section 7.4.

7.1 Smart Grid and what it means for Microgrids

There are two aspects of Smart Grid deployment which would have a significant impact on the future microgrid markets:

- Dynamic pricing of electricity supplied by grid
- Reduced availability of power supply from the grid

Both of the above aspects are demand response strategies likely to be deployed as a part of Smart Grid implementation.

The concept of *reduced availability of power supply from the grid* is a new paradigm for the future and to the best of our knowledge, has not been discussed in literature.

In this section, we explain the criticality of the problem of peak demand reduction and the appropriate demand response strategies that utilities may very likely implement. We then analyze its impact on the future microgrid markets.

This analysis would lead us to an understanding of why and how some of the features are incorporated in the proposed day-ahead energy market for microgrids.

7.1.1 What is the Smart Grid?

According to United States DOE's modern grid initiative [7], an intelligent or a smart grid integrates advanced sensing technologies, control methods and integrated communications into the current electricity grid. Successful Smart Grid deployment would require [8]:

- Dynamic optimization of the current power resources and grid operations
- Comprehensive implementation of demand response tools
- Consumer participation by empowering end users through better information on their consumption patterns

7.1.2 Importance of Peak Reduction

In order to understand the importance of peak reduction, we will consider the load factors on the generation and distribution systems in the current power grid with respect to the percentage of the time in a year. Figure 15 shows the hourly loads as a fraction of the peak sorted from the highest to lowest versus the utilization in percentage of time in a year.

It is interesting to note from the figure, that in the current power grid, 25% of distribution assets and 10% of the generation assets are utilized 5% of the times in a year (approximately 440 hours). Which means 100s of billions of dollars of investment is helping to serve just 5% of the time in a year.

This clearly demonstrates that peak reduction is of paramount importance and would be the first meaningful step in making the Grid *Smarter*.

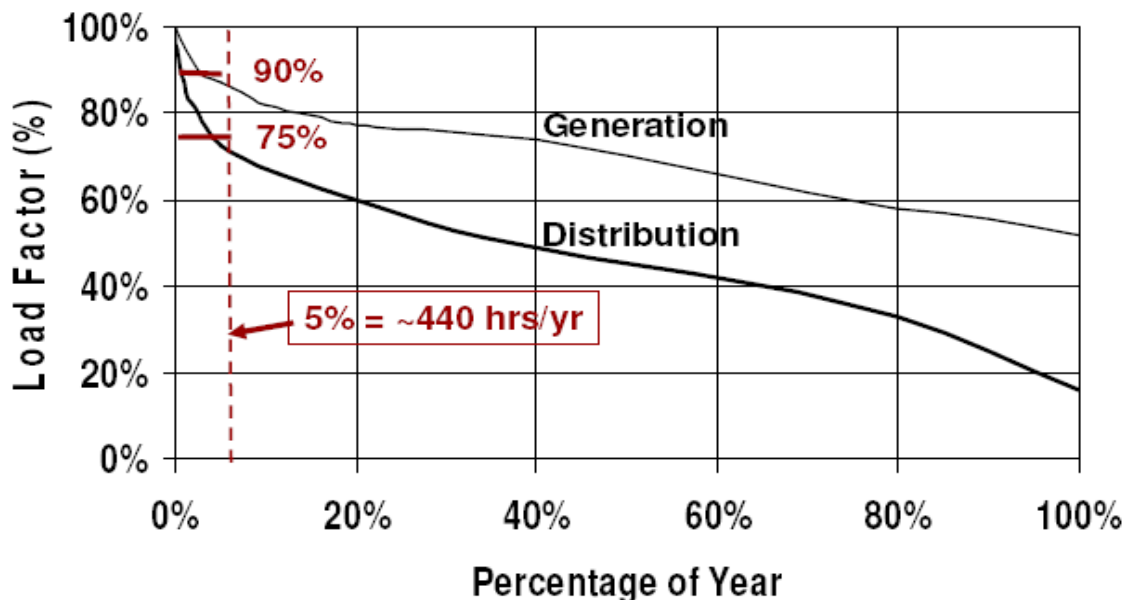


Figure 17: Hourly loads as a fraction of the peak versus the utilization in % of time in a year
Source: Presentation by Dr Steven Chu, Secretary of Energy, United States DOE

The above discussion of the utilization of generation and distribution assets applies to the current power grid scenario.

To add to the woes of the current power grid, the introduction of Plug-In Hybrid Electric Vehicles (PHEV) in the automobile market would pose serious challenges at the distribution level [2]. With the increased penetration level of PHEVs in the market, the authors in [2] have predicted new load peaks and identified that in some cases these peaks may exceed distribution transformer capacity.

In the light of the above discussion, we need to answer a very fundamental question:

- Is our grid really ready to handle high penetration level of PHEVs?

We believe that peak reduction would be one of the critical components of the overall solution to make our grid smarter and to be able to handle high penetration level of PHEVs at the distribution circuit-level.

That brings us to the next logical step of identifying the tools and approaches that can be used to reduce peak demand.

7.1.3 How can we achieve peak reduction?

We believe a four pronged approach is vital to achieve reduction in peak demand:

7.1.3.1 Empowering the consumers

Getting the consumers to *participate* by giving them the incentives and tools to manage their usage pattern, thus eliminating energy wastage, may be identified as the first step. The success of empowering the consumers relies heavily on educating them. Until now, consumers had very little or no *information* about their usage patterns and their role could be best described as *passive*. In the proposed next generation grid, consumers have to play a very *pro-active* role for the results to have any meaningful impact on the goals.

This reminds us of the very early days of electricity supply when consumers were needed to be educated on the possible applications of electricity! Below is a small story on its history.


| | |
|-----------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|  | <p>Marketing Electricity for the Home!</p> <p>In the early days of electricity, few people had anything other than electric lights. The most popular appliances were electric fans and electric irons. Most people didn't have the money—or inclination—to bring other electric gadgets into the home!</p> <p>Women, like those assembled here, flocked to see demonstrations of how electricity could change their lives. Often sponsored by power companies and manufacturers, exhibitions showed how everyday tasks, such as making a typical breakfast of bacon and eggs, could be revolutionized by electricity.</p> <p>Source: http://ieeeghn.org/wiki/index.php/Marketing Electricity for the Home</p> |
| <p>Courtesy: Library of Congress, Theodor Horydczak Collection.</p> | |

Figure 18: Marketing electricity for the home

As Joseph Rigby, CEO of Pepco Holdings, rightly puts it: “The smart grid will only work to the extent that customers win”.

7.1.3.2 Dynamic Pricing

Let us delve a little more deeply into the importance of peak reduction discussed in section 7.1.2. Typically, the generation units which are used for less than 5% of the time in a year are gas combustion turbines. Due to very high input fuels costs for such generating units, the concept of economic dispatch dictates that they be dispatched only during the peak demand time. They are idle for the rest of 95% of the time of the year which means hundreds of billions of dollars are sitting idle.

In a nutshell, the *real costs* of electric delivery are variable and are much higher during peak demand hours of the year [9]. Although there are variations in *real costs* of electric delivery which are directly proportional to the nature of demand, regulatory control of the Utilities prevents these real costs to be reflected in the *retail prices* of electricity. In essence, today's retail prices and real costs of electricity delivery can be said to be uncorrelated.

At best, current retail prices can be said to be *immune* to the nature and variability of the demand.

So what?

This lack of correlation between the *costs* and *prices* has several serious consequences:

Electricity is a commodity. The fundamental attribute of the price of any commodity, which is its *scarcity*, is totally unaccounted for in this model. When scarcity of a commodity is unaccounted for, it directly results in the *wastage* in the usage of the commodity. There are absolutely no incentives for the consumer to reduce or defer his/her demands. There is no customer participation in this model.

Dynamic Pricing, as the name suggests is a practice in which the customers receive “price signals”. These price signals are dependent on the peak demand and therefore are correlated with the fundamental attribute of the commodity, its scarcity. Now, the customer, equipped with more information (price signal information) will now *actively control* his/her demand based on this information - Primarily because he/she now has an *incentive* in doing so - A clear, simple, economic incentive!

There are two basic forms of dynamic pricing:

- Real Time Pricing (RTP)
- Time-Of-Use (TOU) Tariffs

In RTP, the hourly price of electricity is directly correlated to the corresponding price in wholesale electricity market. This is applicable for large customers and is not suitable for individual home owners, because of their small size.

A more appropriate form of dynamic pricing for individual customers is TOU tariffs under which the price bands for different hourly bands in a day, for a given season, are defined. Typically TOU price bands are defined as Off-Peak, Mid-peak and On-Peak. Under TOU tariffs, the consumers have an incentive to save on their electric bill by reducing their

consumption during On-peak price signal from the grid, which in turn reduces the overall peak demand.

Thus, the dynamic pricing model is certainly an invaluable tool towards our goal of reducing the peak demand.

7.1.3.3 Reduced availability of power supply from the grid

Consumer education coupled with dynamic pricing serves as an effective tool for reducing peak demand. To further reduce the peak demand, Utilities have applied other forms of demand response tools such as Critical Peak Pricing (CPP), Interruptible tariffs and Direct Load Control (DLC).

We envision another form of demand response (DR) strategy, which is reduced availability of supply from the grid, to be employed by the Utilities. In this DR approach utilities *restrict* the availability of supply to consumer's facility/home by a certain kWh amount, during periods of peak demand. The consumer is free to utilize the available energy in a manner which suits him/her. This would be a paradigm shift in DR approaches - *Rationing of power supply* - which the consumer has never had to experience before. We foresee the implementation of this strategy in imminent future, under scenarios where price elasticity of demand is low, that is, increase in price of electricity alone may not be sufficient to achieve the desired level of reduction in peak demand. Furthermore, this DR strategy may be more applicable for residential customer base than others.

It is to be noted that, this strategy is different from DLC strategy, where the utility directly controls specific loads on the consumer side.

7.1.3.4 Holistic Approach to Demand Response

The fourth stage is a holistic approach to the problem of reducing peak -demand. This is the hypothetical case of full-fledged deployment of demand response tools, where all customers are expected to participate and there are no regulatory or market barriers [10]

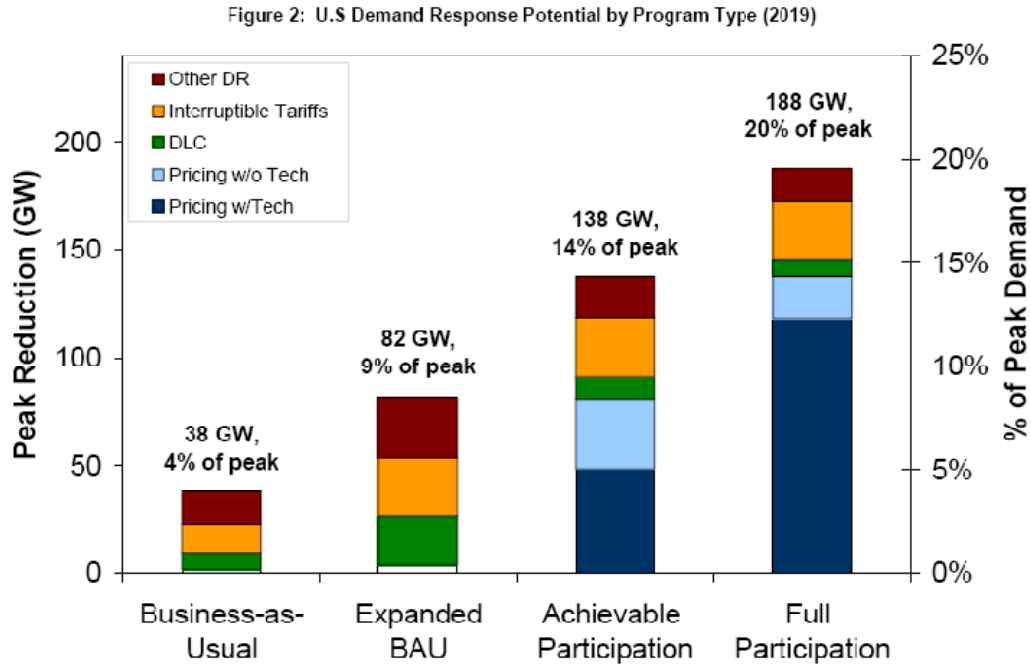


Figure 19: U.S Demand Response potential by program type

Source: <http://www.ferc.gov/legal/staff-reports/06-09-demand-response.pdf>

7.1.4 Implications of Demand Response Strategies on Microgrids

In the previous section, we noted the importance of reducing the peak demand and also investigated the DR strategies likely to be employed in our endeavor towards deployment and realization of a Smart Grid.

Two of the DR strategies have an impact on future microgrid markets:

- Dynamic Pricing
- Reduced availability of power supply from the grid

With TOU tariffs clearly in sight, the hourly grid price signal (a consequence of dynamic pricing of delivered electricity), will have significant impact on the price of DER-generated electricity transacted within microgrids. Any viable microgrid market proposal should take this into account.

We recognize and incorporate the role of hourly grid price signal in our proposed DAEM model.

Second, the prospect of reduced *availability* of power supply from the grid in periods of peak demand would be one of the most important factors in deciding the price of electricity traded in the microgrid market. There would be a serious upward pressure on the trading price since the primary source (the main grid) is at certain times unable to match the local demand, thus rationing its supply.

It is interesting to note that this DR strategy adds a totally new dimension to the microgrid market - Serving as a *primary market* at certain time periods. Microgrids thus have a major role to play in the reliability and security of the main power grid.

In the Day-Ahead Energy Market that we propose and implement in this thesis, this aspect of smart grid deployment forms one of our key assumptions.

7.2 Scope of the DAEM

The supply of electricity by the Utility companies, which in turn buy power in the wholesale electricity market, will continue to be a primary source of power for *most of the non-critical periods* for the residential customers. We envision the proposed DAEM to be either a secondary or tertiary market, working “behind the grid” most of the time. During the peak demand periods, the proposed DAEM has a serious potential of being the primary market for residential customers.

7.2.1 DAEM as a tertiary market

Given the net-metering policies of the federal and the state governments, the individuals or communities investing in distributed generation (primarily renewable energy sources such as small-scale solar PV or wind) have a fantastic offer of buy-back by the grid at a price higher than the grid supply prices. However, it is to be noted that there is a cap on such buy-back policies, which decide on the maximum power, grid is obliged to buy from such distributed generation installations. It should also be recognized that these policies are subject to change.

The proposed DAEM would then be a platform for such DG installations to sell the *excess power* (generated power minus power sold back to the grid) to residential customers who are geographically located closer to the generation units (approximately 1 mile radius).

This is the context in which the proposed DAEM would be a tertiary market.

7.2.2 DAEM as a secondary market

In states where net-metering policies have not passed the law or where the cap on buy-back policy is too low to count towards the return on investment (ROI) of DG installations, our proposed DAEM could serve as a rewarding platform for the sellers.

This is the context in which the proposed DAEM would be a secondary market.

7.2.3 DAEM as a primary market

As discussed in section 7.1, the Demand Response strategy of reducing the *availability* of power supply from the grid in periods of peak demand adds a totally new dimension to the microgrid market.

In this context the primary source of power would be the proposed DAEM and in this context, it is a *primary market*.

7.3 Assumptions of the DAEM Model

The market model has the following underlying assumptions:

1. The primary objective of this thesis is to create an *efficient, competitive and non-discriminatory* power market.

The DAEM framework is a neutral, unbiased platform and as such is an “external” component of the electricity transaction process. The framework assumes the role of a market regulator.

2. The grid is not a market participant. That means buying from the grid and selling to it is out of scope of this market model.

As discussed in section 7.1, the proposed market is a primary, secondary or a tertiary market, with transactions with the grid being out of scope.

3. The seller’s objective (Individual or a community microgrid DG installation) is purely economic. Seller’s approach to the bidding process is to maximize the hourly profit.

The market does not consider any other direct or indirect benefit that may accrue to the seller such as the overall microgrid’s contribution to the reliability and security of the main power grid and the impact of reducing carbon emissions due to renewable nature of installed DG.

4. The buyer’s objective (residential customer) is purely economic and the only benefit gained by participating in the DAEM is to reduce the electricity bill. As a consequence, it is assumed, the buyers will bid for an amount less than the grid price signal for that hour, under normal power grid operation and under unrestricted supply from the main grid.

Under reduced *availability* of power supply from the grid in periods of peak demand, the price of electricity traded in the DAEM will purely be based on supply-demand dynamics.

The market does not consider any other direct or indirect benefit that may accrue to the buyer such as the overall microgrid's contribution to the reliability and security of the main power grid and the impact of reducing carbon emissions due to renewable nature of installed DG.

4. The buyers bidding for a certain amount of energy require all or none of it.

The rationale behind this assumption is that the residential customers request energy for using their appliances such as dish washer, dryer or television, each of which has a manufacturer specified power rating. It is logical to assume that a residential customer would like to use an appliance for a certain amount of time. If the seller is unable to provide the energy for that purpose, it is reasonable to assume that buyer would not like to buy from that seller.

6. DAEM uses the supply-driven-demand model, which is a core feature of IDAPS microgrid

The rationale behind this assumption is that the load forecasting of residential customers on the scale of a microgrid of 25, 50 homes is very difficult to achieve. Thus, we assume demand from buyers is deferrable and interruptible and that the generation drives the demand.

7.4 DAEM Timeline

The following timeline is incorporated in to the proposed DAEM:

| | |
|------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|
| Day 0: 12:00 - 17:00 hours | IDAPS Power Exchange receives day-ahead hourly generation offers (DAHGO) from all the sellers (in our case, two sellers). |
| Day 0: 17:00 - 21:00 hours | IDAPS Power Exchange receives day-ahead hourly demand bids (DAHDB) from all the buyers (in our case, nine buyers). |
| Day 0: 21:00 - 22:00 hours | IDAPS Power Exchange is closed for evaluation and “matching” of generation offers and demand bids. |
| Day 0: 22:00 hours | IDAPS Power Exchange posts the eMKT summary of financially binding day-ahead, hourly “matching” of generation offers and demand bids. |
| <u>Day 1</u>: 00:00 - 24:00 hours | Actual transfer of power from the seller to the buyer takes place. |

Table 5: The proposed DAEM timeline

The rationale behind the time line is that it fits the lifestyle of residential customers who have been allotted a bidding duration of 5 hours starting 5 PM in the evening up to 9 PM in the night, the time at which they are home.

We also made the timeline very similar to that of the PJM Day Ahead Market Time Line

The following Pie-chart depicts the time-line graphically:

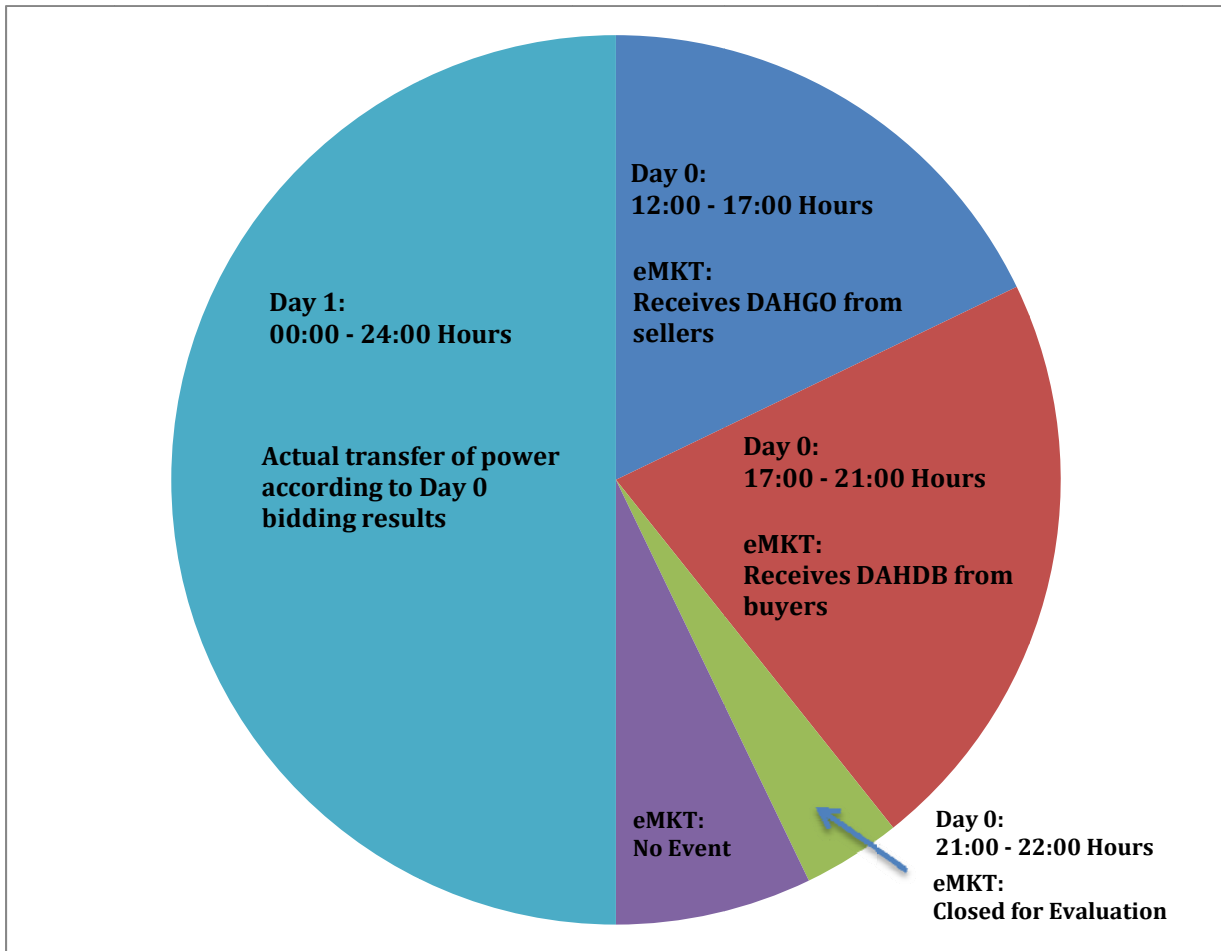


Figure 20: Pie-chart of the proposed DAEM timeline

7.5 Architecture of DAEM Design

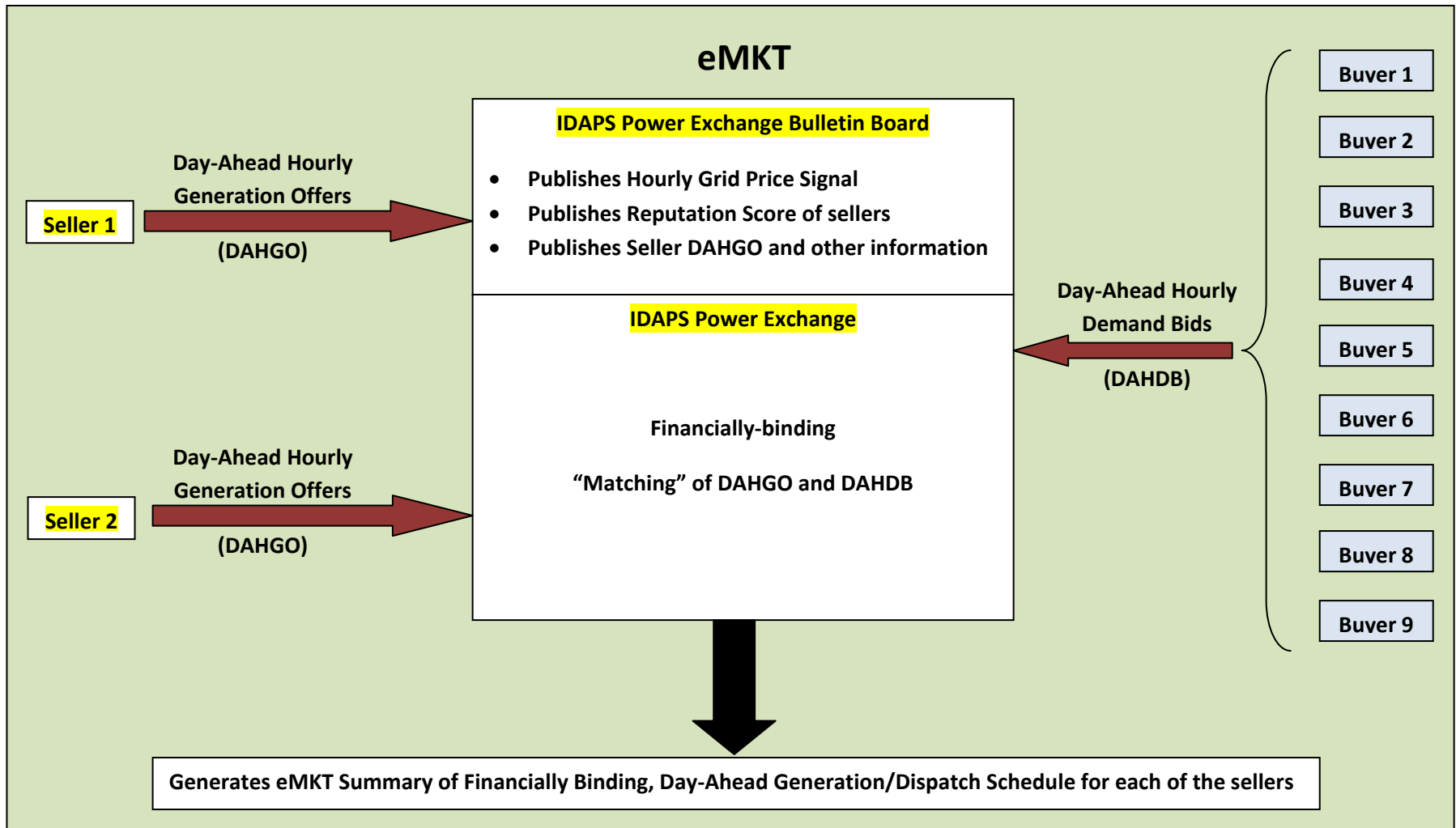


Figure 21: Architecture of DAEM design

7.6 Spot Market for Microgrids

In this chapter, we discussed the architecture of the proposed DAEM for microgrids. We also addressed some of the smart grid deployment issues and how they may affect future microgrid markets.

In this context, we would like to mention that although a day-ahead market is appropriate and suitable for the microgrid market participants, an ancillary real-time spot market may also be required under certain circumstances.

Suppose a seller participating in the DAEM violates the financially binding generation/dispatch schedule generated by the IDAPS eMKT (for several reasons such as breakdown of equipment, intentional violation), the market would penalize by reducing the reputation score or equivalently the trustworthiness of the seller. We have proposed and established built-in reactive measures for such incidents.

However, from a buyer's perspective, for whatever reason, he/she does not have power for that hour.

This scenario sets a context for the requirement of a real-time spot market, wherein, under unforeseen circumstances, the buyers are able to purchase power in real-time, albeit at much higher prices than in the DAEM. Such a spot market would ensure buyers would not face a black-out.

The proposal of a competitive, real-time spot market for microgrids is out of scope of this thesis and is suggested as future extension of our current research.

Chapter 8

Implementation of the Day-Ahead Energy Market (DAEM) for Microgrids in MATLAB

In this chapter, we discuss the implementation of the framework of Day-Ahead Energy Market (DAEM). Section 8.1 lists the components of the DAEM software. Seller software component is discussed in section 8.2. The Bulletin Board and Buyer software components are discussed in sections 8.3 and 8.4 respectively. We conclude the chapter with section 8.5 by describing the details IDAPS eMKT software component along with a discussion of the final results.

8.1 Components of DAEM Software

First, we list all the components of the DAEM software implemented using MATLAB Graphical User Interface (GUI). We then discuss each of the components in detail.

| | | |
|------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Market Participants | GUI Components for Sellers [Sellers submit Day-Ahead hourly Generation Offers] | Seller1_DAHGO Seller2_DAHGO |
| | GUI Components for Buyers [Buyers submit Day-Ahead hourly Demand Bids] | Buyer1_DAHDB Buyer2_DAHDB Buyer3_DAHDB Buyer4_DAHDB Buyer5_DAHDB Buyer6_DAHDB Buyer7_DAHDB Buyer8_DAHDB Buyer9_DAHDB |
| IDAPS Power Exchange (eMKT) | GUI Component for Bulletin Board [Bulletin Board with DAHGO along with other seller-related information] | IDAPS_BulletinBoard |
| | GUI Component for IDAPS eMKT: Day Ahead Power Transaction Exchange Board [Core Engine for matching DAHGO and DAHDB] | IDAPS_eMKT |
| | GUI Component for customer feedback of transactions [Used to update reputation score of each seller after Day1 transactions] | IDAPS_RS |

Table 6: Components of DAEM software

8.2 Seller Software Component

8.2.1 Introduction

A “Seller” is a direct market participant and is typically a DG installation who is participating in the market to sell excess energy generated by the DG site. As stated in the assumptions in section 7.2, the seller’s objective (Individual or a community microgrid DG installation) is purely economic. Seller’s approach to the bidding process is to maximize the hourly profit.

In our implementation, there are two sellers in the market. However, the software can be easily scaled to include multiple sellers.

Sellers will need to first register with the IDAPS eMKT in order to be able to transact electricity on the platform. The registered details of the two sellers with the IDAPS eMKT are shown in Table 6.

| Seller # | Seller ID | DER Type | Reputation Score Band | Max. Hourly Energy (kWh) |
|-----------------|------------------|-----------------------------|------------------------------|---------------------------------|
| Seller 1 | 22203-uG1-001 | 50 kW Solar PV Power Plant | Level - 1 (Highest) | 19.29 |
| Seller 2 | 22203-uG1-002 | 75 kW Fuel Cell Power Plant | Level - 3 (Lower) | 31.55 |

Table 7: Details of the two registered sellers in IDAPS eMKT

Seller ID format is has been designated as the zip code followed by the “microgrid number” in the area with the given zip code followed by the seller in the same geographical area:

Seller ID: Zipcode-uG#-xxx

All the sellers start the transactions on the IDAPS eMKT platform with the highest level of reputation score band (Level 1). The reputation score of each seller gets updated at the end of transactions on Day 1 (pre-determined by the DAEM on Day 0). The reputation score band evaluation and updates takes place on the unbiased, neutral, IDAPS eMKT platform.

This updated reputation score band will be broadcast to all the buyers on the BulletinBoard software component for all transactions occurring on Day 2, which will be described in a later section.

Maximum Available Hourly Energy (kWh):

To be consistent with the proposed business model for sellers, the following seller investment characteristics have been preloaded in IDAPS eMKT platform.

Seller 1: DG capacity to serve the demand in a 3-home microgrid (based on Utility load data for 3 homes) = **19.29 kWh**

Seller 2: DG capacity to serve the demand in a 5-home microgrid (based on Utility load data for 5 homes) = **31.55 kWh**

It must be noted that seller may over-ride all values in the corresponding seller screen.

8.2.2 Seller Screen

Seller 1 submits the Day-Ahead Hourly Generation Offers (DAHGO) using the software component shown in Figure 21.

| | Energy (kWh) | Reserve Price (c/kWh) | Buy-It-Now Price (c/kWh) | Grid Price Signal (c/kWh) | Grid Availability (kWh) |
|----------------------------|--------------|-----------------------|--------------------------|---------------------------|-------------------------|
| Day 1: 00:00 - 01:00 Hours | 19.2900 | 4 | 13.5000 | 15 | 100 |
| Day 1: 01:00 - 02:00 Hours | 19.2900 | 4 | 13.5000 | 15 | 100 |
| Day 1: 02:00 - 03:00 Hours | 19.2900 | 4 | 13.5000 | 15 | 100 |
| Day 1: 03:00 - 04:00 Hours | 19.2900 | 4 | 13.5000 | 15 | 100 |
| Day 1: 04:00 - 05:00 Hours | 19.2900 | 4 | 13.5000 | 15 | 100 |
| Day 1: 05:00 - 06:00 Hours | 19.2900 | 4 | 13.5000 | 15 | 100 |
| Day 1: 06:00 - 07:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 100 |
| Day 1: 07:00 - 08:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 100 |
| Day 1: 08:00 - 09:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 100 |
| Day 1: 09:00 - 10:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 100 |
| Day 1: 10:00 - 11:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 100 |
| Day 1: 11:00 - 12:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |
| Day 1: 12:00 - 13:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |
| Day 1: 13:00 - 14:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |
| Day 1: 14:00 - 15:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |
| Day 1: 15:00 - 16:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |
| Day 1: 16:00 - 17:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 5 |
| Day 1: 17:00 - 18:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 5 |
| Day 1: 18:00 - 19:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 5 |
| Day 1: 19:00 - 20:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 5 |
| Day 1: 20:00 - 21:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 5 |
| Day 1: 21:00 - 22:00 Hours | 9.6450 | 4 | 21.6000 | 24 | 5 |
| Day 1: 22:00 - 23:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |
| Day 1: 23:00 - 24:00 Hours | 9.6450 | 4 | 13.5000 | 15 | 100 |

Figure 22: Seller Day-Ahead Hourly Generation Offers (DAHGO)

Grid Price Signal (c/kWh):

The seller first obtains the hourly grid price signal for Day1: 00:00 hours to 24:00 hours from the IDAPS eMKT by clicking on the button “Get Grid Price!”

Grid Availability (kWh):

The seller also obtains the hourly grid *availability* for Day1: 00:00 hours to 24:00 hours from the IDAPS eMKT by clicking on the button “Get Availability”

Energy (kWh):

The seller enters the hourly energy available for sale in this column.

Reserve Price (c/kWh):

Reserve Price is a base-price of the seller. This feature lends itself to the eBay online market place. Buyer bids less than this value are automatically disqualified from the bidding process in the eMKT. It should be noted that the reserve price is an undisclosed amount to buyers (buyers cannot view the reserve price of the sellers).

Reserve Price feature has been provided primarily to serve as protection for seller against colluded buyers. For example, consider a case where the market size is small; say a microgrid of 5 homes with two sellers. The buyers in all probability would then *personally* know each of the two sellers. The buyers may then collude against a particular seller (or against both the sellers), *pre-decide* and group-submit very low bids, knowing very well, that the seller(s) *has* to sell the published hourly energy and that the eMKT is a financially binding obligation on seller to sell that energy. Reserve Price acts as a seller-defense against such colluding practices.

Reserve price also adds *uncertainty* in buyer's bidding price decision phase, since the buyer knows there is a reserve price but does not know the actual reserve price amount.

We believe, eventually, the market would stabilize to become an *efficient market* and the hourly energy price determined purely by the demand-supply-reputation equilibrium.

Buy-It-Now Price (c/kWh) - BIN price:

This feature also lends itself to the eBay online market place. The seller may specify an hourly "Buy-It-Now" price. By doing so, the seller in effect is offering to sell energy at a *fixed price*, if the buyer opts to buy it at BIN price. The buyers then have the convenience to buy energy at a known price and not participate in the bidding process. If any buyer opts to buy energy at BIN price, the eMKT ensures that the seller is obliged to sell energy to that buyer.

It is rational to expect that BIN price, if specified by a seller, will be on higher side and closer to the grid price signal for that hour. The preload seller data feature suggests 90% of grid price signal for that hour as BIN price.

However, in practice, we expect the market BIN price to stabilize based on a % of grid price signal Vs reputation score band of the seller.

It is interesting to note that the seller's hourly profit may or may not be greater than the maximum possible profit for the hour, in case a buyer opts to buy at a fixed BIN price.

8.3 Bulletin Board Software Component

8.3.1 Introduction

BulletinBoard software component is a part of the IDAPS eMKT and as the name suggests, it only carries information: The day-ahead hourly generation offers (DAHGO) published by the two sellers, other seller related information such as seller ID, DER Type and more importantly the reputation score band of the sellers along with the hourly grid price signals. This information is used by the buyers in determining the day-ahead hourly demand bids (DAHDB). BulletinBoard is not a direct participant in the market.

8.3.2 BulletinBoard Screen

Figure 22 shows a snapshot of the BulletinBoard screen, populated with information.

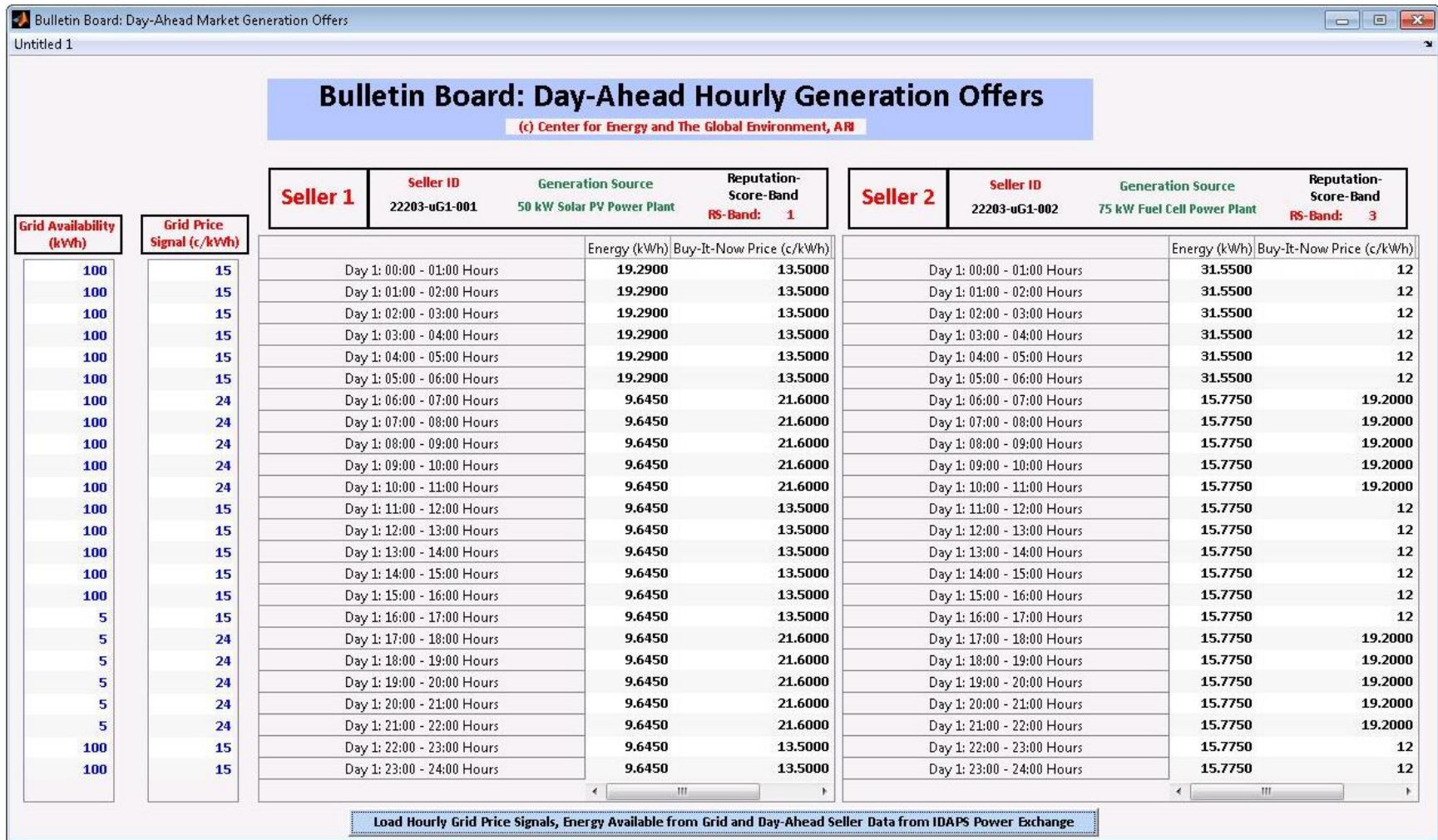


Figure 23: Snapshot of BulletinBoard screen

Note that for each seller, the seller ID, generation source and reputation score band are published along with the seller's day ahead hourly generation offers.

As mentioned in section 8.4.2.2, the reserve price of the sellers is not published and shall remain undisclosed to the buyers for the entire duration of transaction.

With the aid of the BulletinBoard, all the buyers have complete knowledge about:

- The sellers participating in the market that day
- Each of the seller's hourly generation offers and BIN Price, if any
- Each of the seller's reputation score
- Each of the seller's related information (seller ID and generation source)

Buyers can then make an informed decision to aid their submission of day-ahead hourly demand bids (DAHDB).

8.4 Buyer Software Component

8.4.1 Introduction

A "Buyer" is a direct market participant and is typically a residential customer who is participating in the market to buy energy sold by the seller. As stated in the assumptions in section 8.2, the buyer's objective is purely economic and the only benefit gained by participating in the DAEM is to reduce his/her electricity bill. As a consequence, it is assumed, the buyers will always bid for an amount less than the grid price signal for that hour (under normal power grid operation).

In our current implementation, there are nine buyers in the market. However, the software can be easily scaled to include increased number of buyers.

Buyers will need to first register with the IDAPS eMKT in order to be able to transact electricity using the platform.

8.4.2 Buyer Screen

Buyers submit the Day-Ahead Hourly Demand Bids (DAHDB) using the software component shown in Figure 23.

Buyer 1: Hourly Demand Bids in Day-Ahead Market
 (c) Center for Energy and The Global Environment, ARI

Seller Preference and Bidding Price Band Recommendation Tool

Please enter the bidding hour (1 - 24):

Please enter the level of quality of your current demand: **Level**
 Level 1 = Highest Priority
 Level 4 = Lowest Priority

Recommend a bidding price band

Recommended price band in which you may bid

| | Energy (kWh) | Final Bid (c/kWh) | BIN Energy (kWh) |
|----------------------------|--------------|-------------------|------------------|
| Day 1: 00:00 - 01:00 Hours | 4.1900 | 8 | 0 |
| Day 1: 01:00 - 02:00 Hours | 4.0100 | 8 | 0 |
| Day 1: 02:00 - 03:00 Hours | 4.0700 | 8 | 0 |
| Day 1: 03:00 - 04:00 Hours | 4.3900 | 8 | 0 |
| Day 1: 04:00 - 05:00 Hours | 4.5100 | 8 | 0 |
| Day 1: 05:00 - 06:00 Hours | 4.8500 | 8 | 0 |
| Day 1: 06:00 - 07:00 Hours | 5.2500 | 8 | 0 |
| Day 1: 07:00 - 08:00 Hours | 5.8300 | 8 | 0 |
| Day 1: 08:00 - 09:00 Hours | 6.0200 | 8 | 0 |
| Day 1: 09:00 - 10:00 Hours | 6.2700 | 8 | 0 |
| Day 1: 10:00 - 11:00 Hours | 6.3800 | 8 | 0 |
| Day 1: 11:00 - 12:00 Hours | 6.2900 | 8 | 0 |
| Day 1: 12:00 - 13:00 Hours | 5.9000 | 8 | 0 |
| Day 1: 13:00 - 14:00 Hours | 5.7000 | 8 | 0 |
| Day 1: 14:00 - 15:00 Hours | 5.5200 | 8 | 0 |
| Day 1: 15:00 - 16:00 Hours | 5.4100 | 8 | 0 |
| Day 1: 16:00 - 17:00 Hours | 5.7000 | 8 | 0 |
| Day 1: 17:00 - 18:00 Hours | 6.2400 | 8 | 0 |
| Day 1: 18:00 - 19:00 Hours | 6.5600 | 8 | 0 |
| Day 1: 19:00 - 20:00 Hours | 6.3900 | 8 | 0 |
| Day 1: 20:00 - 21:00 Hours | 6.2800 | 8 | 0 |
| Day 1: 21:00 - 22:00 Hours | 6.0200 | 8 | 0 |
| Day 1: 22:00 - 23:00 Hours | 5.7100 | 8 | 0 |
| Day 1: 23:00 - 24:00 Hours | 5.2100 | 8 | 0 |

Buyer-DAHDB Successfully Published!

Figure 24: Buyer Day-Ahead Hourly Demand Bids (DAHDB)

Using the bidding price band recommendation tool

Using the bidding price band recommendation tool provided in the buyer screen, the buyer enters the hourly energy demand and final bid prices. If the buyer is interested in buying energy from the seller at a fixed price demanded by the seller (in the form of Buy-It-Now Price), the buyer may do so by entering the amount of energy he/she intends to purchase at that price in the column “BIN Energy (kWh)”, for a particular hour. By entering a certain amount of energy as *BIN Energy*, the seller is obligated to buyer by that amount of energy.

Load previous bid settings

We have provided an option for the buyer to load existing demand data in the current buyer screen. The demand data has been taken from real load profile data from a Utility for a microgrid of a small size (3 residential customers). This data has been scaled to obtain an hourly load profile for a single residential customer. We thought, this data is as close to being real as possible.

To capture variations in load profile from buyer to buyer (among the nine buyers incorporated in the software), nine sets of hourly load profile data have been obtained by taking the Utility data for a typical week-day, week-end and peak-day for the three months of January, February and March.

8.5 IDAPS eMKT Software Component

8.4.1 Introduction

IDAPS eMKT software component is a part of the IDAPS Power Exchange, which is a neutral, unbiased platform to conduct transactions. IDAPS eMKT is not a direct participant in the market. The core algorithms in the eMKT determine the financially binding matching of the day-ahead hourly generation offers (DAHGO) and the day-ahead hourly demand bids (DAHDB). On the IDAPS eMKT screen, press the “Click to Run Financially Binding Matching of DAHGO and DAHDB” button to run the main program.

Central Idea of the IDAPS eMKT software component:

For every hour, the bidding is conducted first for the seller with a higher reputation score. All the buyers who have published the DAHDB participate in the bidding for this seller. Matching of the seller’s DAHGO and the DAHDB for all the buyers is completed at this stage. Then, for the same hour, bidding for the seller with the lower reputation score is conducted. The buyers who participate in this bedding session are those who were not bid winners in the first stage. Matching of this seller’s DAHGO and the qualified second stage bidders is then conducted. These two bidding sessions complete the process for 1 hour. The process repeats for all the 24 hours.

Execution Time:

The software takes about 12 minutes on an Intel Core 2 Duo CPU operating at 2.8 GHz (4 GB RAM) to complete the matching of DAHGO and DAHDB for 24 hours.

Outputs:

It has buttons for two outputs:

1. Summary of financially binding, day-ahead generation/dispatch schedule for Seller 1
2. Summary of financially binding, day-ahead generation/dispatch schedule for Seller 2

8.4.2 IDAPS eMKT Screen

Figure 24 shows a snapshot of the IDAPS eMKT screen.

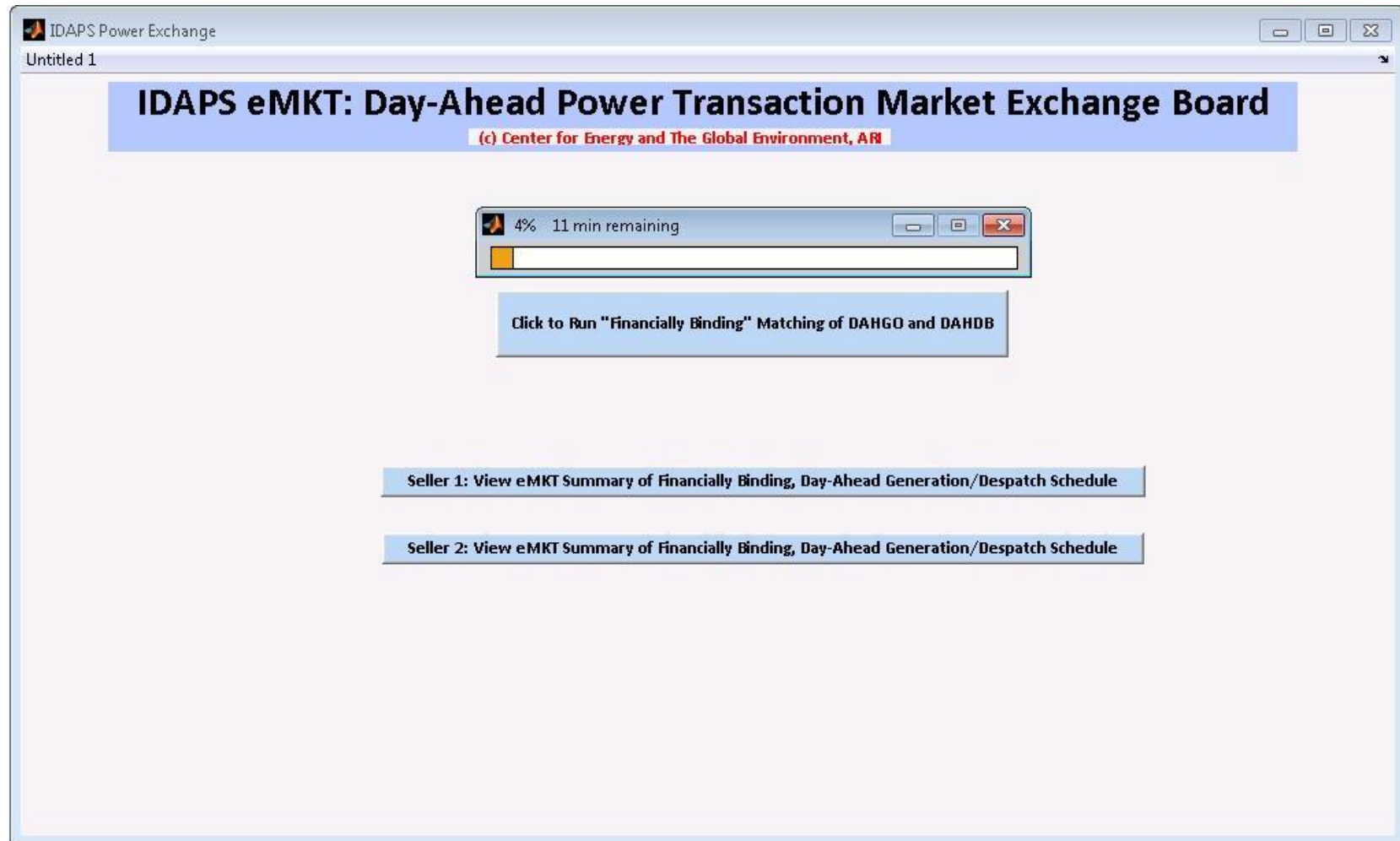


Figure 25: Screen shot of IDAPS eMKT - Day-Ahead Power Transaction Market Exchange Board

Discussion of Outputs of IDAPS eMKT

The summary of financially binding, day-ahead generation/dispatch schedules for the two sellers output by the IDAPS eMKT software in excel format are comprehensive. To interpret the results, it must be noted that the results for sellers 1 and 2 must be looked at in comparison.

Two worksheets are generated for each seller ($x = 1, 2$):

1. eMKT-Summary-Seller-x - Tabular form of the results
2. eMKT-Summary-Seller-x-Schedule - Graphical form of the results

Table 7 shows the summary data of financially binding, day-ahead generation/dispatch schedule for seller 1.

Figure 25 shows the graphical form of the summary data of financially binding, day-ahead generation/dispatch schedule for seller 1.

Table 8 shows the summary data of financially binding, day-ahead generation/dispatch schedule for seller 2.

Figure 26 shows the graphical form of the summary data of financially binding, day-ahead generation/dispatch schedule for seller 2.

| Seller 1: eMKT Summary of Financially Binding, Day-Ahead Generation/Dispatch Schedule | | | | | | | | | | | | |
|----------------------------------------------------------------------------------------------|--------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|---------------------------|------------------------------|
| Hour Details | Hour# | Buyer1 (kWh) | Buyer2 (kWh) | Buyer3 (kWh) | Buyer4 (kWh) | Buyer5 (kWh) | Buyer6 (kWh) | Buyer7 (kWh) | Buyer8 (kWh) | Buyer9 (kWh) | Profit (in \$) | % Energy Sold |
| Day 1: 00:00 - 01:00 Hours | Hour 1 | 4.19 | 3.05 | 3.22 | 3.67 | 0 | 0 | 0 | 2.58 | 2.51 | 1.61 | 99.64 |
| Day 1: 01:00 - 02:00 Hours | Hour 2 | 4.01 | 2.95 | 3.12 | 3.66 | 0 | 0 | 0 | 2.51 | 2.37 | 1.56 | 96.53 |
| Day 1: 02:00 - 03:00 Hours | Hour 3 | 4.07 | 2.96 | 3.11 | 3.78 | 0 | 0 | 0 | 2.56 | 2.38 | 1.78 | 97.77 |
| Day 1: 03:00 - 04:00 Hours | Hour 4 | 4.39 | 3 | 3.16 | 0 | 0 | 0 | 3.62 | 2.61 | 2.4 | 1.57 | 99.43 |
| Day 1: 04:00 - 05:00 Hours | Hour 5 | 4.51 | 3.1 | 3.21 | 0 | 2.81 | 0 | 0 | 2.74 | 2.49 | 1.58 | 97.77 |
| Day 1: 05:00 - 06:00 Hours | Hour 6 | 4.85 | 3.48 | 3.34 | 0 | 0 | 0 | 4.47 | 3.15 | 0 | 1.59 | 100.00 |
| Day 1: 06:00 - 07:00 Hours | Hour 7 | 4.25 | 0 | 3.54 | 0 | 3.77 | 0 | 0 | 3.73 | 2.94 | 1.62 | 99.69 |
| Day 1: 07:00 - 08:00 Hours | Hour 8 | 4.83 | 4.22 | 3.88 | 4.3 | 0 | 0 | 0 | 0 | 0 | 1.63 | 99.69 |
| Day 1: 08:00 - 09:00 Hours | Hour 9 | 6.02 | 3.95 | 4.15 | 4.55 | 0 | 0 | 0 | 0 | 0 | 1.61 | 96.79 |
| Day 1: 09:00 - 10:00 Hours | Hour 10 | 6.27 | 3.55 | 4.29 | 3.99 | 0 | 0 | 0 | 0 | 0 | 1.58 | 93.83 |
| Day 1: 10:00 - 11:00 Hours | Hour 11 | 6.38 | 3.32 | 4.24 | 0 | 0 | 0 | 0 | 0 | 3.34 | 1.55 | 89.58 |
| Day 1: 11:00 - 12:00 Hours | Hour 12 | 6.29 | 3.15 | 4.11 | 0 | 2.84 | 0 | 0 | 2.58 | 0 | 1.66 | 98.34 |
| Day 1: 12:00 - 13:00 Hours | Hour 13 | 4.9 | 3.03 | 4.06 | 0 | 0 | 0 | 0 | 2.47 | 3.11 | 1.65 | 96.27 |
| Day 1: 13:00 - 14:00 Hours | Hour 14 | 4.7 | 2.92 | 3.96 | 0 | 0 | 0 | 0 | 2.36 | 2.91 | 3.97 | 92.53 |
| Day 1: 14:00 - 15:00 Hours | Hour 15 | 4.52 | 2.83 | 3.85 | 0 | 0 | 0 | 0 | 2.3 | 2.83 | 1.54 | 89.84 |
| Day 1: 15:00 - 16:00 Hours | Hour 16 | 4.41 | 2.93 | 3.78 | 0 | 0 | 0 | 0 | 2.34 | 2.75 | 1.53 | 89.22 |
| Day 1: 16:00 - 17:00 Hours | Hour 17 | 4.7 | 3.26 | 3.93 | 0 | 0 | 0 | 0 | 2.54 | 2.82 | 1.62 | 94.61 |
| Day 1: 17:00 - 18:00 Hours | Hour 18 | 6.24 | 3.82 | 4.3 | 0 | 0 | 0 | 0 | 2.98 | 0 | 1.59 | 89.89 |
| Day 1: 18:00 - 19:00 Hours | Hour 19 | 6.56 | 4.23 | 4.55 | 0 | 0 | 0 | 0 | 3.46 | 0 | 1.72 | 97.46 |
| Day 1: 19:00 - 20:00 Hours | Hour 20 | 6.39 | 4.31 | 4.45 | 0 | 0 | 0 | 0 | 3.73 | 0 | 1.72 | 97.87 |
| Day 1: 20:00 - 21:00 Hours | Hour 21 | 6.28 | 4.2 | 4.37 | 0 | 0 | 0 | 0 | 3.73 | 0 | 1.69 | 96.32 |
| Day 1: 21:00 - 22:00 Hours | Hour 22 | 0 | 4.06 | 4.17 | 4.06 | 0 | 0 | 0 | 3.58 | 3.29 | 1.64 | 99.33 |
| Day 1: 22:00 - 23:00 Hours | Hour 23 | 4.71 | 3.73 | 3.82 | 0 | 0 | 0 | 0 | 3.23 | 1 | 1.50 | 90.67 |
| Day 1: 23:00 - 24:00 Hours | Hour 24 | 4.21 | 3.34 | 3.49 | 3.34 | 0 | 0 | 0 | 2.84 | 0 | 1.57 | 94.45 |
| Total profit gained by Seller-1 in the DA Market in \$ | | | | | | | | | | | 41 | |

Table 8: Summary data of financially binding, day-ahead generation/dispatch schedule for seller 1

Seller 1: Financially Binding, Day-Ahead Energy Generation/Dispatch Schedule

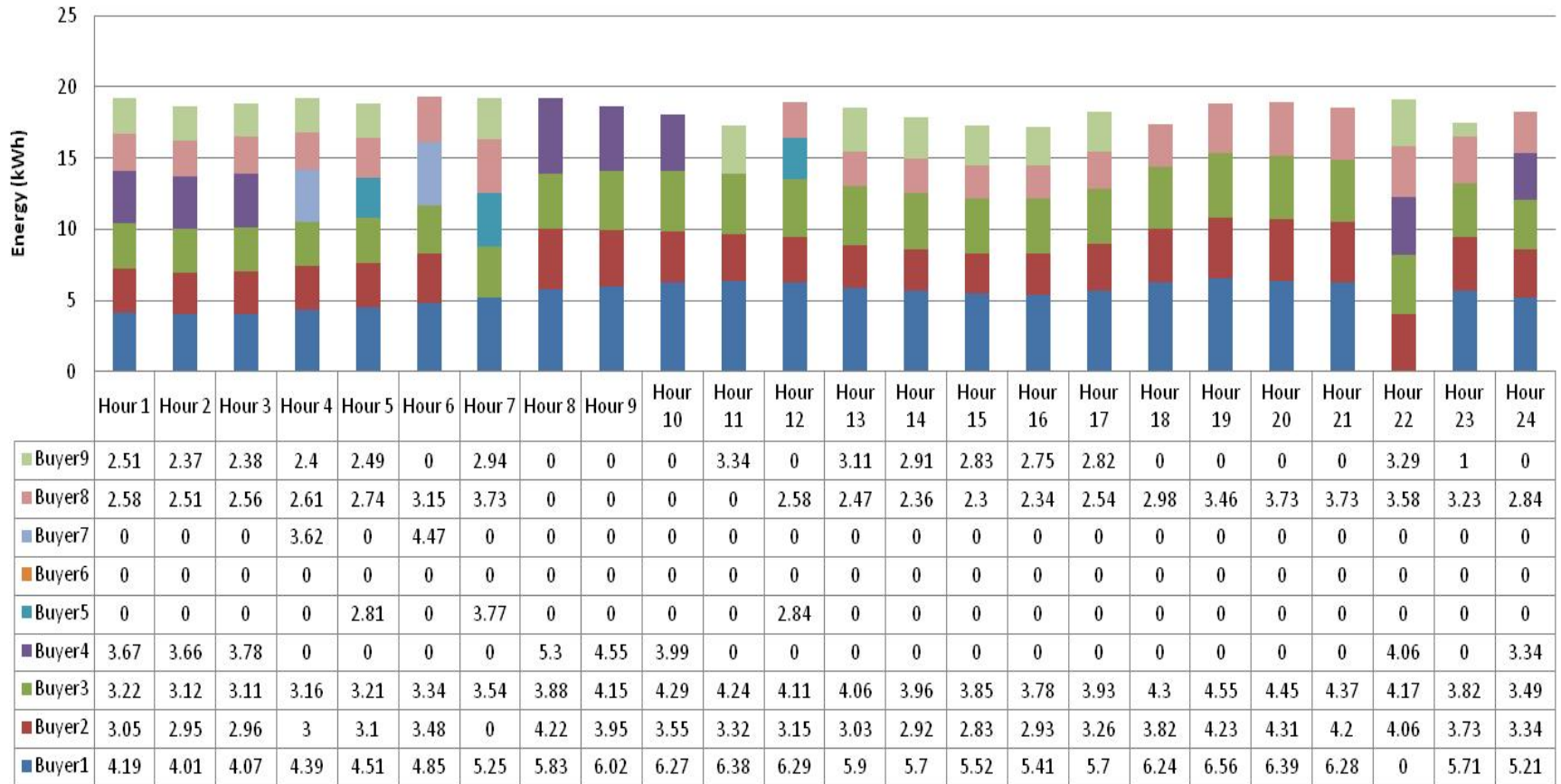


Figure 26: Graphical summary of financially binding, day-ahead generation/dispatch schedule for seller 1

| Seller 2: eMKT Summary of Financially Binding, Day-Ahead Generation/Dispatch Schedule | | | | | | | | | | | | |
|----------------------------------------------------------------------------------------------|---------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|----------------|---------------|
| Hour Details | Hour# | Buyer1 (kWh) | Buyer2 (kWh) | Buyer3 (kWh) | Buyer4 (kWh) | Buyer5 (kWh) | Buyer6 (kWh) | Buyer7 (kWh) | Buyer8 (kWh) | Buyer9 (kWh) | Profit (in \$) | % Energy Sold |
| Day 1: 00:00 - 01:00 Hours | Hour 1 | 0 | 0 | 0 | 0 | 2.65 | 3.18 | 3.55 | 0 | 0 | 0.5 | 29.731 |
| Day 1: 01:00 - 02:00 Hours | Hour 2 | 0 | 0 | 0 | 0 | 2.58 | 3.2 | 3.41 | 0 | 0 | 0.49 | 29.128 |
| Day 1: 02:00 - 03:00 Hours | Hour 3 | 0 | 0 | 0 | 0 | 2.63 | 3.2 | 3.55 | 0 | 0 | 0.5 | 29.731 |
| Day 1: 03:00 - 04:00 Hours | Hour 4 | 0 | 0 | 0 | 3.96 | 2.68 | 3.21 | 0 | 0 | 0 | 0.56 | 31.22 |
| Day 1: 04:00 - 05:00 Hours | Hour 5 | 0 | 0 | 0 | 4.09 | 0 | 3.31 | 3.89 | 0 | 0 | 0.63 | 34.784 |
| Day 1: 05:00 - 06:00 Hours | Hour 6 | 0 | 0 | 0 | 4.55 | 3.19 | 3.44 | 0 | 0 | 2.63 | 0.83 | 43.772 |
| Day 1: 06:00 - 07:00 Hours | Hour 7 | 0 | 3.97 | 0 | 4.03 | 0 | 3.71 | 4.06 | 0 | 0 | 1.07 | 56.323 |
| Day 1: 07:00 - 08:00 Hours | Hour 8 | 0 | 0 | 0 | 0 | 3.94 | 4.15 | 4.17 | 3.79 | 3.24 | 1.25 | 64.311 |
| Day 1: 08:00 - 09:00 Hours | Hour 9 | 0 | 0 | 0 | 0 | 3.66 | 4.18 | 4.32 | 3.35 | 3.48 | 1.17 | 60.19 |
| Day 1: 09:00 - 10:00 Hours | Hour 10 | 6.27 | 0 | 0 | 0 | 3.22 | 4.02 | 3.52 | 0 | 0 | 1.01 | 53.978 |
| Day 1: 10:00 - 11:00 Hours | Hour 11 | 0 | 0 | 0 | 3.61 | 3.01 | 3.72 | 3.18 | 2.74 | 0 | 0.98 | 51.537 |
| Day 1: 11:00 - 12:00 Hours | Hour 12 | 0 | 0 | 0 | 3.35 | 0 | 3.43 | 2.94 | 0 | 3.25 | 0.76 | 41.109 |
| Day 1: 12:00 - 13:00 Hours | Hour 13 | 0 | 0 | 0 | 2.91 | 2.72 | 3.25 | 2.65 | 0 | 0 | 0.64 | 36.545 |
| Day 1: 13:00 - 14:00 Hours | Hour 14 | 0 | 0 | 0 | 2.74 | 2.63 | 3.12 | 2.52 | 0 | 0 | 0.61 | 34.897 |
| Day 1: 14:00 - 15:00 Hours | Hour 15 | 0 | 0 | 0 | 2.68 | 2.59 | 2.97 | 2.51 | 0 | 0 | 0.6 | 34.073 |
| Day 1: 15:00 - 16:00 Hours | Hour 16 | 0 | 0 | 0 | 2.72 | 2.64 | 2.96 | 2.54 | 0 | 0 | 0.61 | 34.422 |
| Day 1: 16:00 - 17:00 Hours | Hour 17 | 0 | 0 | 0 | 2.96 | 2.88 | 3.14 | 2.86 | 0 | 0 | 0.66 | 37.528 |
| Day 1: 17:00 - 18:00 Hours | Hour 18 | 0 | 0 | 0 | 3.49 | 3.39 | 3.47 | 3.36 | 0 | 3.02 | 0.99 | 53.027 |
| Day 1: 18:00 - 19:00 Hours | Hour 19 | 0 | 0 | 0 | 4.05 | 3.87 | 3.88 | 3.64 | 0 | 3.42 | 1.11 | 59.778 |
| Day 1: 19:00 - 20:00 Hours | Hour 20 | 0 | 0 | 0 | 4.01 | 3.95 | 3.96 | 3.83 | 0 | 3.56 | 1.14 | 61.204 |
| Day 1: 20:00 - 21:00 Hours | Hour 21 | 0 | 0 | 0 | 4.34 | 3.94 | 3.88 | 3.68 | 0 | 3.47 | 1.14 | 61.204 |
| Day 1: 21:00 - 22:00 Hours | Hour 22 | 6.02 | 0 | 0 | 0 | 3.81 | 3.73 | 3.43 | 0 | 0 | 1.07 | 53.851 |
| Day 1: 22:00 - 23:00 Hours | Hour 23 | 0 | 0 | 0 | 3.81 | 3.44 | 3.43 | 3.33 | 0 | 0 | 0.79 | 44.406 |
| Day 1: 23:00 - 24:00 Hours | Hour 24 | 0 | 0 | 0 | 0 | 3.07 | 3.12 | 3.04 | 0 | 2.6 | 0.68 | 37.496 |
| Total profit gained by Seller-2 in the DA Market in \$ | | | | | | | | | | | 20 | |

Table 9: Summary data of financially binding, day-ahead generation/dispatch schedule for seller 2

Seller 2: Financially Binding, Day-Ahead Energy Generation/Dispatch Schedule

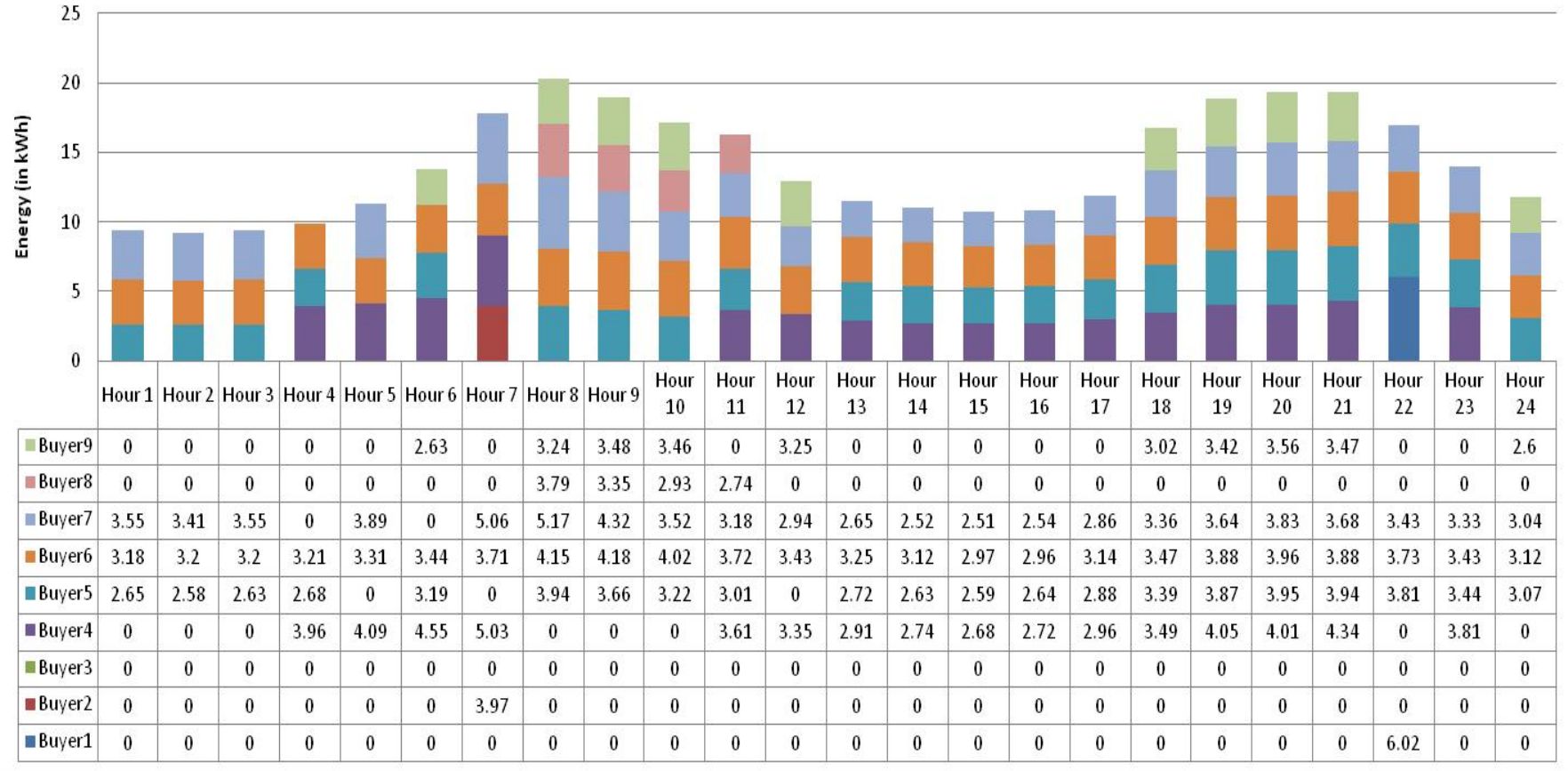


Figure 27: Graphical summary of financially binding, day-ahead generation/dispatch schedule for seller 2

The following points are to be noted:

1. Since, Seller 1 has been assigned a higher reputation score, the eMKT schedules Seller 1's bidding session first, for every hour. The number of bidders are therefore 9 for this bidding session.

2. The number of bidders participating in Seller 2's bidding session would depend upon the winners of bidding session 1. Again, this may vary by hour.

3. The chart has to be read like this:

Hour 1: Bidding session for seller 1

Participating bidders: Buyers 1 through 9

Winning bidders: {1, 2, 3, 4, 8 and 9}

Hour 1: Bidding session for seller 2

Participating bidders: Buyers {5, 6 and 7}

Winning bidders: {5, 6 and 7}

4. It may not always happen that all buyers will win the bids (from seller 1 and seller 2)

4. Total profit gained by Seller-1 in the DAEM is: \$41, while that gained by Seller 2 in the DAEM is: \$20

6. Percentage of energy sold (with respect to their DAHGO) by each of the sellers is noted in the last column in both of the seller's summary tables. Please note that these values are low for Seller 2, primarily because, bidding occurred for seller 2 after the bidding session of seller 1.

7. Percentage of energy sold information may be used by the sellers to either decrease their reserve price or increase their reputation score.

Chapter 9

Conclusions and Future Work

9.1 Conclusions and Contribution

In this thesis, a competitive microgrid electricity market has been designed and implemented. A comprehensive framework of Day-Ahead Energy Market (DAEM), enabling Reputation Score-based electricity transaction among IDAPS community microgrids has been proposed.

We believe, the following are the contributions of this thesis:

- We established an economic rationale to our vision of wide-scale deployment of microgrids serving residential communities in imminent future and presented a comprehensive understanding of microgrid electricity market.
- We defined market and business models for electricity transaction in microgrids and validated market/business models based on economic forecasts of key drivers of DG.
 - Introduced the concept of IDAPS *Community Microgrids*

- We perceived the need and established a strong motivation to introduce reputation score in the context of microgrids. We developed a trustworthy model framework for market participants.
 - Established a need for a trustworthy model in microgrids
 - Introduced the concept of reputation score to market participants

This is perhaps one of the most significant contributions of this thesis.

- A bidding price-band recommendation tool for the buyer has been designed and implemented. It helps the buyer decide on a price which he may bid based on: The current grid price signal, current availability of power from grid, reputation score of the seller, and the quality of current demand of the buyer.
 - Introduced the concept of *quality of demand* for the buyer
- We designed and implemented a framework of day-ahead energy market (DAEM) for electricity transaction in microgrids.
 - Introduced the approach of using the reputation score to incentivize the sellers to be trustworthy

9.2 Future Work

Future work is suggested along the following lines:

- The current implementation of IDAPS eMKT uses MS Excel, both as a back-end database as well as a tool for reporting financially binding, generation dispatch schedule.

As the first future research area, the IDAPS eMKT system may be deployed in client-server architecture mode. The server would run webservice to exchange data and information in the universal XML format. Such a deployment could be incorporated in to an IDAPS microgrid multi-agent system implementation.

- The second research area which may be of interest is to run the IDAPS eMKT on a cluster computing facility, such as the one available at ARI. In a DAEM, the bidding for each of the 24 hours is independent of the other and it turns out to be a classical parallel computing problem. This would result in a drastic cut-down of execution time of core program which generates the generation/dispatch schedule after matching the DAHGO and DAHDB.
- The third area of research is adding new components to determine reputation score of sellers in the market. Our current proposal of the components of reputation score is made flexible and scalable, leaving the possibility of improving the robustness of the score wide open.
- The last and the most ambitious research work could creating a full-fledged IDAPS microgrid test-bed at Advanced Research Institute (ARI), with the following components:
 - Simulated distributed generators (Solar PV, WTG, IC engine and PEM Fuel Cell)
 - MAS implementation of IDAPS microgrid

- IDAPS microgrid market design as proposed in this thesis, which is implemented using webservices and XML technologies

A cost-effective implementation of the integrated IDAPS microgrid is to use netbooks for DGs, MAS agents and market participants and ARI cluster computing facility as the IDAPS eMKT server.

- Security in IDAPS microgrid operation and the proposed microgrid electricity market have not been addressed in this thesis and can be a very interesting research field to work on.

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