A CUSTOMER DRIVEN ENERGY MANAGEMENT SYSTEM FOR A DISTRIBUTED ENERGY RESOURCE INSTALLATION INCORPORATING LOCAL ENERGY STORAGE AND A PHOTOVOLTAIC SOURCE

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ABSTRACT

An aging electric grid, ever-increasing load demand, and the national focus placed on the modernization of the existing grid through the Energy and Independence Security Act of 2007 are the key motivators for the work presented in this thesis. A customer-driven methodology for the operation of a customer-owned distributed energy resource installation with local energy storage is presented. The objective of the methodology is to include customer preference in the operation of the system, while maximizing the operational profit of the customer.

The methodology is comprised of a load scheduling method based on the Analytic Hierarchy Process and a heuristic scheduling technique that exchanges real and reactive power with the utility grid. The validity of the heuristic technique is verified through linear programming. Four case studies for the heuristic scheduling technique are presented, including the operational cost of the system with no energy management as a base case for comparison. The case studies are comprised of the operation of the installation when (1) only real power is available for exchange with the grid, (2) there is no available energy from the distributed energy resource, with real and reactive power exchange, and (3) there is available energy from the distributed energy resource, as well as real and reactive power exchanged with the grid. The fourth case study is a linear programming solution used to verify the operation of the first case study with respect to the heuristic scheduling technique. The most profitable operation of the distributed energy resource installation considered in this thesis resulted from the installation having the capability to exchange both real and reactive power with the grid, as well as having solar generation available.

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NOMENCLATURE

A	Pairwise comparison matrix
$A(t)$	Dynamic pairwise comparison matrix
AHP	Analytic hierarchy process
AMI	Advanced metering infrastructure
AMPL	A modeling language for mathematical computing
ARRA	American Recovery and Reinvestment Act of 2009
$c(t)$	Cost of electricity for hour t
C.I.	Consistency index
C.R.	Consistency ratio
CAM	Control actions module
CFI	Current fed inverter
$d(t)$	Load demand for hour t
DDP	Deep discharge protection
DER	Distributed energy resource
DG	Distributed generation
DIEMS	Distributed intelligent energy management system
d_k	Slope
DSM	Demand side management
EISA	Energy Independence and Security Act of 2007
EMS	Energy management system
EPRI	Electric Power Research Institute
FERC	Federal Energy Regulatory Commission
HAN	Home area network
h_k	Interval length
I	Identity matrix
LCC	Life cycle cost
LEMS	Local energy management system
LMP	Locational marginal price
LP	Linear programming
LPM	Load prioritization module
LSM	Load scheduling method
LSS	Load shedding scheme
MDD	Maximum depth of discharge
MILP	Mixed integer linear programming
$P(x_k)$	Interpolating polynomial
$p_{12}(t)$	Power flow from PV array in hour t
$p_{23}(t)$	Power flow from battery to the inverter in hour t
$p_3(t)$	Total power flow out of inverter in hour t
$p_{32}(t)$	Power flow from inverter to the battery in hour t

$p_{34}(t)$	Power flow from inverter to the grid in hour t
$p_{35}(t)$	Power flow from inverter to the load in hour t
$p_4(t)$	Total power flow out of grid in hour t
$p_{43}(t)$	Power flow from grid to the inverter in hour t
$p_{45}(t)$	Power flow from grid to the load in hour t
PCC	Point of common coupling
pchip	Piecewise cubic hermite interpolating polynomial
P_{max}	Maximum price threshold
P_{min}	Minimum price threshold
PSE	Puget Sound Energy
PV	Photovoltaic
PWM	Pulse width modulation
R.I.	Random consistency index
RPS	Renewable portfolio standard
SCUC	Security constrained unit commitment
SNL	Sandia National Laboratories
SOC	State of charge
SPS	Shipboard power system
SPWM	Sinusoidal pulse width modulation
SRP	Salt River Project
SWTDI	Southwest Technology Development Institute
TOU	Time of use
TVA	Tennessee Valley Authority
VFI	Voltage fed inverter
W	Matrix of absolute measurements
w	Principal right Eigenvector
w_k	Weight of interval length
W_x	Eigenvector of X
X	Inconsistent matrix example
Y	Dummy matrix for improving matrix consistency
Z_{inv}	Local load
δ_k	First divided difference
λ_{max}	Maximum Eigenvalue

CHAPTER 1
INTRODUCTION

1.1 Objective

The objective of this thesis is to develop an economically driven methodology for the operation of a customer-owned distributed energy resource (DER) installation with local energy storage that is interfaced with the area electric power system operated by the local utility. The primary facet of this methodology is the inclusion of customer preferences in the operational philosophy. The methodology covers demand side management in the form of load scheduling, and establishes the necessary energy flows to and from the grid that maximize the customer profit.

1.2 Motivation

An aging electric transmission system, increasing transmission congestion levels, and decline in transmission investments are necessitating the modernization of the US electric grid to handle the ever-increasing demand [1]. Currently, 20% of the electricity grid generation capacity exists solely to meet the peak demand [2]. According to the US Energy Information Administration, the total marketed energy consumption of the world is expected to increase by 44% from 2006 to 2030 [3]. The transmission system infrastructure is on average, 40 years old, and investments in transmission have declined steadily for the last 25 years [1]. As a result, the Energy Independence and Security Act (EISA) of 2007 was passed by the 110th Congress of the United States as an omnibus energy policy law which focuses on increasing energy efficiency and the availability of renewable energy [4]. Specifically, Title XIII of the EISA of 2007 – popularly termed the 'Smart Grid Initiative' – was enacted in order to modernize the US transmission and distribution grid [5]. The major functions of the Smart Grid have been defined by the US Department of Energy, (taken directly from [6]).

i. Self-healing from power disturbance events
ii. Enabling active participation by consumers in demand response
iii. Operating resiliently against physical and cyber attack
iv. Providing power quality for 21st century needs
v. Accommodating all generation and storage options
vi. Enabling new products, services, and markets
vii. Optimizing assets and operating efficiently

While the move toward the Smart Grid has gained momentum in the US – including the allocation of several billion dollars for Smart Grid projects through the American Recovery and Reinvestment Act (ARRA) of 2009 [7] – it is imperative that the Smart Grid installations targeting residential, commercial, and industrial customers provide economic justification for the end-users.

In the US, there are also state-level mandates known as Renewable Portfolio Standards (RPS) which require "electric utilities and other retail electric providers to supply a specified minimum amount of customer load with electricity from eligible renewable energy sources" [8]. Colorado was the first state to pass an RPS in 2004 [9]. As of March 2007, the RPS was updated by US House Bill No. 1281, where it currently requires that investor-owned utilities provide 20% of their retail electricity sales, and that all electric cooperatives and municipal utilities (serving at least 40,000 customers) provide 20% of their retail electricity sales from eligible renewable energy sources by 2020 in Colorado [9]. Another example of the impact of such state level mandates is the issuance of the 'Million Solar Roofs' initiative in the US state of California [10]. In the light of the Smart Grid Initiative and RPS, it is apparent that customers that install DER installations would seek to attain optimal operational profits from the installation, while the utilities to which such customers connect may potentially use the DER installations for peak shaving [11]. A customer-driven DER installation with an emphasis on maximizing consumer profit is attractive due to a combination of the formerly mentioned factors.

1.3 Scope

The scope of this thesis includes a load scheduling scheme for a DER installation that uses a guided decision-making approach that includes customer preferences. Furthermore, a heuristic technique for real and reactive power scheduling is presented. The objective of this heuristic scheduling technique is to drive the operation of the customer-owned DER toward a region of operational profit through user inputs – thus contributing to the customer-driven nature of the DER installation. The heuristic scheduling technique is assumed to be in the presence of dynamic energy pricing, where the price to buy and sell energy is the same. The day's local load demand profile, energy prices, and the energy availability of the DER are assumed to be accurate and known 24-hours ahead of time.

The scope of this thesis does not include forecasting methods of: solar availability, load profile, or energy prices. The effect of a high penetration of customer-owned DER installations on the ability of the utility to purchase energy is also not incorporated.

1.4 Literature Search

The literature search for this thesis pertains to the following: 1) Smart Grid and its enablers, 2) a discussion on the physical components of the test system, and 3) tools and methods applicable to the thesis. The tools and methods section contains information on the analytic hierarchy process (AHP), energy management systems through heuristics, linear optimization, and battery management.

1.4.1 Smart Grid

The Smart Grid has been characterized as an "integrated solution of technologies driving incremental benefits in capital expenditures, operation and maintenance expenses, and customer and societal benefits" [12]. It is making the best use of existing technologies, such as sensing, communication, and real-time monitoring, in order to improve overall system operation. The authors of [12] state that the implementation of the Smart Grid can bring positive benefits to utilities and end-users by establishing a basis from which greater, more integrated solutions can be realized. The development of demand response and residential energy management systems (EMS) on a home area network (HAN) are expected due to Smart Grid advancements, whereby in these EMSs end users are seen as both consumers and suppliers of electricity [12].

The Smart Grid is an implementation of operational philosophies and values into the existing electric infrastructure. The Smart Grid values include increased reliability and security, more economic and efficient performance, environmentally conscious practices, and increased safety for the public, as well as the service personnel working on the grid [13]. Moreover, the principal characteristics of the Smart Grid include active participation by consumers, accommodation of all generation and storage technologies in the generation portfolio, establishment of a market forum where the suppliers and customers of energy can interact, the provision for increased power quality sensing and responses, the optimization of assets to lower system losses, and power factor improvements. It will also include the self-healing of the grid, and be resilient in the face of natural and man-made disasters [13].

1.4.1.1 Enablers

Necessary advancements and implementations must be made in the area of electricity pricing, 'smart' devices, demand response, and advanced metering in order to realize the Smart

Grid on a national scale. The following discusses these necessary advancements, as well as individual examples of their application.

1.4.1.1.1 Advanced Metering Infrastructure

The advanced metering infrastructure (AMI) is a fundamental step in realizing the Smart Grid as it provides two-way communication between consumers and grid operators. AMI is the first major step in implementing the Smart Grid because AMI technologies enable communication between the consumer and the service provider, thus enabling generation and storage to be monitored and/or controlled. AMI provides a connection to energy markets, allowing direct consumer participation and communication of real time pricing. AMI can include power quality improvement through measuring and monitoring of power quality, as well as self healing due to the real time detection of system failures [14].

As of September 2009, the Federal Energy and Regulatory Commission (FERC) estimates that there are approximately 7.95 million installed advanced meters throughout the US [15]. The ARRA of 2009 has allotted the city of Houston, Texas 2.2 million smart meters [16]. According to FERC, the US state with the highest advanced meter penetration as of April, 2009 is Pennsylvania, with a penetration of 52.5% of advanced versus non-advanced installed meters [17].

1.4.1.1.2 Demand Response and Electricity Pricing

Time of use (TOU) energy pricing is a necessary step in implementing the Smart Grid, as utility rates will reflect the time of day, and season of energy use [18]. The authors of [19] used data from a generic utility in order to examine the feasibility of dynamic pricing for all consumer classes. The results show that dynamic pricing can reduce the peak demand of the system 1-9%, though greater benefits can be seen through the implementation of automated demand response systems.

As a part of the Smart Grid initiative active demand side response will play an important factor in the implementation of the Smart Grid [20]. According to [21], demand response and peak shaving are gaining momentum as Smart Grid expenditures. Demand side management (DSM) has received positive response from consumers with financial incentives in preliminary demonstrations [22]. As an example of DSM, in the US state of Colorado, 440,000 consumers of Xcel energy are participating in the "Saver's Switch" program. The program entails allowing

Xcel energy to install a switch for the central air conditioning unit that allows Xcel energy to cycle the customer's air conditioner. Customers receive a yearly $40 credit on their energy bill each year they participate in the "Saver's Switch" program [23].

Active participation by consumers in DSM allows them a measure of control over their electricity bills. One method being currently employed by several utilities is TOU pricing. For example, Puget Sound Energy (PSE) implemented TOU pricing for a short time during an energy crisis in 2000, whereby the average residential customer shifted approximately 4% of their load demand out of peak periods, translating to approximately 25,000 kWh peak demand reduction for PSE [24].

DSM and TOU pricing are necessary steps to implement the system presented in this thesis. Thus, as active participation by consumers continues to increase, and as utilities explore the implementation of new pricing schemes, the energy industry continues to move in alignment with the Smart Grid Initiative.

1.4.2 Test System Background

Solar energy has recently received a large economic boost due to the ARRA of 2009, which specifically designated $117.6 million dollars to the specific research, development, and manufacturing of solar energy technology within the US [25]. Furthermore, grid-tied solar photovoltaic (PV) applications are also on the rise in the US. The Solar Energy Industries Association reported that grid-tied PV solar installations grew 81% in 2008 over 2007, with a 2008 installation of 292 MW [26]. The current size of PV installations in the US ranges from a few kilowatt hours for residential use to the largest solar array installation in the US of 2.4 MW by FedEx Ground in Woodbridge, New Jersey [27]. The Tennessee Valley Authority (TVA) has developed a program called Generation Partners, in which increased incentive to install renewable generation is given. The program states that TVA will purchase all energy produced by renewable sources at the retail rate, in addition to an incentive of 12 cents/kWh for solar energy sources [28].

The system utilized in this thesis incorporates a typical residential level PV array and energy storage in the form of a lead acid battery which is interfaced to the grid utilizing the 'smart' inverter developed in [29]. The purpose of the inverter is to convert the DC current generated by the PV array and battery to an AC current that can be used to supply the residential

load and export power to the utility. The inverter is a DC-AC converter that can "change a DC input voltage to a symmetric AC output voltage of desired magnitude and frequency" [30]. The inverter can provide a fixed or variable output voltage at a fixed or variable frequency, by using pulse width modulation (PWM). The inverter is classified as voltage-fed (VFI) or current-fed (CFI) depending on which input value is held constant. Sinusoidal PWM (SPWM) generates the desired voltage waveform through the comparison of a reference waveform (modulating signal) which represents the desired waveform, with a high frequency triangular wave, known as the carrier wave. The "average voltage applied to the load is proportional to the amplitude of the signal (assumed constant) during," [31] the period of one triangle wave. The modulation index is defined in [30] as the ratio of the reference waveform (sine wave) amplitude to the carrier (triangular) waveform amplitude. High frequency components traveling into an AC network or load are not a major consideration when a high frequency carrier wave is implemented. The downside to a high frequency carrier wave is increased power loss due to the increased number of switches necessary per cycle.

The significance of the 'smart' inverter developed in [29] is that it is a voltage source inverter that can operate in both VFI and CFI modes, and it can also output both real and reactive power. Through the implementation of this inverter, a residential DER installation can now export both real and reactive power to the local utility. Thus, an inverter with this functionality is necessary to implement the DER installation presented in this thesis.

1.4.3 Tools and Methods

The following sections outline some of the previous research and applications of heuristic and linear optimization schemes, battery management, and applications of the AHP. Specifically, the work presented refers to the topic addressed in this thesis.

1.4.3.1 Heuristics and Linear Optimization Energy Management Schemes

Energy management refers to the control of thermal and/or electrical systems within a specified range, such as a house, commercial entity, industrial plant, or a portion of the grid, Microgrid, or Smart Grid. Energy management systems provide automated system control with the objective to reduce energy consumption and energy inefficiency. Energy management systems can be classified in a variety of ways. According to [32], a local energy management system (LEMS) is characterized by load-level management software operated by the consumer. The definition of LEMS can be further extended to include residential applications as well. The

capabilities of EMSs can include, but are not limited to, establishing operational set points for equipment, monitoring and/or controlling power flows, and the operating characteristics of generation and/or energy storage. The operational goals of the EMS can be achieved through an assortment of optimization and/or heuristic techniques such as Fuzzy ARTMAP, linear programming, mixed integer linear programming, and neural networks [11],[33,34] [39]. The operational schemes presented are narrowed to EMSs which control electrical systems.

The short-term scheduling of a PV/Battery system in a security constrained unit commitment (SCUC) is discussed in [11]. Three modes of operation are defined for PV/battery systems, specifically for non-cloudy days:

i. Charging state for battery: When system load is low, PV and/or grid will charge the battery storage
ii. Idle state of battery: PV supplies the local load directly at certain hours when both PV power and load are high
iii. Discharging state of battery: Both PV and battery supply the peak load at certain hours (like noon hours); battery supplies the evening peak load hours when the PV power is scarce and the marginal cost of grid power is high

On cloudy days when PV power is very low or nonexistent, the battery will be discharged only when there is a sufficient price gap between on- and off-peak hours. Otherwise, the battery will not be scheduled for use [11]. Furthermore, a Lagrangian relaxation algorithm that determines the charging and discharging of the battery in the grid was developed [11]. Several assumptions were made, including the representation of the batteries in the system as one aggregate battery, the battery voltage is kept constant such that the charge/discharge power curve can be assumed linear, and the PV output is known on a daily basis. Case studies were conducted on a candidate eight-bus system in [11], with six thermal units and an aggregate PV/battery. The hourly scheduling of the PV/battery is shown in [11] for an hourly load profile with two peak periods. From midnight to the early morning the battery will be charged by the grid. During the noon peak load, the PV and battery will sustain the local load, while during the afternoon peak the battery will supply the local load. The presented case study shows that the PV/battery decreases system congestion, and stabilizes hourly locational marginal prices (LMP) at lower values. The extent of these benefits is related to the size of the PV/battery units. However, the presented work does not consider selling any power to the utility. The operational method in [11] is limited by the test system's inability to operate as a possible generation source for the utility, and does not include any TOU pricing. The system presented in this thesis can both export and/or import real and reactive power to/from the electric utility grid, and includes TOU pricing.

The EMS in [33] seeks to maximize the total profit with respect to what real power is bought and sold from the grid (including lead acid battery energy storage) in a basic distributed generation (DG) structure with energy storage. The EMS has two operational modes, stable operation mode where the chief concern is battery charging management, and economic operation mode where the chief concern is the operational cost of the system. The operational mode employed in this EMS is dependent upon any surplus capacity in the battery, and weather forecasting information. The energy prices are on a TOU basis, such that periods are defined throughout the day as peak (0800-1200 h and 1800-2200 h), flat (1200-1800 h, 0-0800 h), and valley (2200-00 h). During the valley period, the grid supplies the local load and charges the battery, and throughout the peak period the system sells power to the grid. During the flat period, load is supplied by local generation and the remainder is sold to the grid. The power prediction of the PV system is forecasted through neural networks 24-hrs ahead of time. The authors of [33] do not consider the purchase or selling of reactive power, TOU pricing information is implemented that is not dynamic on an hourly basis, and the most important operational concern is either battery charging management or the operational cost of the system. Furthermore, there is no load scheduling method defined.

The authors of [34] present a multilevel optimization through Mixed Integer Linear Programming (MILP) of a PV installation with local energy storage for a residential application. The optimization is divided into the anticipation and reactive management control layers. The anticipation layer utilizes forecast information on weather conditions, load demand, and the prices for buying and selling electricity. Using that information, the optimization focuses on minimizing the difference between buying and selling electricity and also performs load scheduling on the premise that the customer is not concerned with when the load is served, as long as "the purpose to use the service is satisfied" [34]. The reactive management layer adjusts the real time operation of the system as needed when the actual operation of the system strays from the predictions made in the anticipation layer by shedding load and/or generation. When this occurs, the optimization will begin again from the current hour. If no solution exists for the new optimization, the system minimizes the energy that must be cut-off. Both the anticipation and reactive management control layers are constrained by load and generation balance, a pre-defined range on the battery state of charge (SOC), a linearized model of battery charging and discharging, a maximum limit the grid will consume, and that the total power consumed is the same as not having any load management on a daily basis. Points that are not considered in [34]

include the stipulation that only excess PV can be injected into the utility network (not from the battery), and it does not consider reactive power management.

A heuristic technique for scheduling a residential DER installation containing PV arrays and local energy storage, interfaced to the grid through a single phase voltage source inverter is presented in [35]. The principal aspect of the technique is aligned with the Smart Grid Initiative in order to provide for the customer-driven operation of the DER installation while maximizing the customer's daily profit. The technique is based on the DER installation's ability to sell specified amounts of real and reactive power to the utility grid. The technique is implemented in an algorithm that determines the operating points for the inverter for the next 24 hrs of operation based on forecasts of the residential demand, solar irradiance, and the price of real and reactive power. The validity of the technique is illustrated through an example case study, and compared with the day's operating costs of the same residence without local energy storage, and without a DER installation, where it is concluded that the residential DER installation with energy storage has the highest operating profit for the day. Reference [35] is a result of the work performed towards this thesis.

The feasibility of a residential PV array with battery storage that was interconnected to the utility grid is examined by the Salt River Project (SRP), Electric Power Research Institute (EPRI), and Sandia National Laboratories (SNL), in [36]. The operational parameters are defined such that all energy was stored when available from the PV array, and the batteries would be discharged during the peak demand of the household (approximately three hours). The PV-battery energy storage system is not capable and/or permitted to sell or supply energy back to the utility grid. The authors concluded that such an interconnection could be implemented successfully. The economic operation of [36] was analyzed by comparing the costs associated with a flat electricity rate and a three rate per 24-hr period schedule. It was found that implementing the PV system alone would decrease the annual electric bill of the residence less than the implementation of a PV system with energy storage. This reduction of economic benefit when implementing energy storage comes from the battery losses. The maximum efficiency of the flooded lead-acid batteries implemented in this system as storage is 75-80% when operated under ideal conditions, namely constant temperature, and extremely low charge and discharge rates [36]. The PV array used in [36] was designed and installed by Southwest Technology Development Institute (SWTDI). The authors of [36] developed a battery control scheme that improves battery efficiency under non-optimal operating conditions to approximately 75%. This was accomplished by using the natural solar irradiance to charge the battery to 85% SOC daily,

then discharging only during the peak demand hours. Furthermore, with the exclusion of peak demand hours during the weekend, the battery is equalized every other weekend in order to "minimize problems with sulfation and stratification" [36]. Changing the residential loading schedule to take advantage of the different electric rates available will increase the economic benefits of the system.

Reference [37] presents an operational strategy for a residential PV-battery system. The customer-driven nature of the homeowner's economic parameters is specified as an advantage to residential PV systems. However, the operational strategy assumes that the following information is known: the load characteristic of the homeowner, the generation characteristic of the PV power, and the power-leveling demand of the utility. Four modes of operation are defined as follows:

i. Off-Peak Load Period- defined by no PV power from midnight to sunrise, recharges batteries from utility
ii. Low-Insolation Period- defined by minimal PV power, the net load is supplied by utility
iii. High-Insolation Period- defined by greater PV power input than demand from late morning to middle evening. Load is supplied and stored to the batteries, if there is anything left it is sent to the utility
iv. Discharging Period- defined from late evening to midnight, where the power used from the utility is minimized by supplying the load with PV and batteries, and then just batteries

The operational mode control is determined by the operating condition pertaining to that hour. If there is no electric energy available from the PV source, it is deemed as an abnormal operating condition, and is based on the load demand of the utility. If the battery voltage is greater than its expected value when the battery should be discharging the operating condition will be considered as a normal condition and continue to discharge. If at any point the battery voltage is below a preset level, the battery must charge until that condition is no longer violated. The authors of [37] do not incorporate the buying and/or selling of real or reactive power.

1.4.3.2 Heuristics and Linear Optimization Energy Management Scheme in a Microgrid Environment

A microgrid has been defined in [38] as a "self-contained subset of the electric grid with indigenous generation (micro-sources), access to distribution assets, control, protection, and ability to serve at least one end user load in either the grid interconnected mode or an isolated (islanded) mode". As such a system is similar in nature to the Smart Grid, and in effect also has

many of the operational capabilities desired in a Smart Grid by the Smart Grid Initiative; the following section reviews a linear programming and heuristics combination for energy management within a microgrid. Specifically, [39] is applicable to this literature search because the authors present an optimization scheme of a PV-battery storage system. However, the optimization does not include the exportation of real and/or reactive power to the local utility at retail price; instead it only exports energy when the given generation of the microgrid is greater than the demand of the load, and exports to the utility grid at the avoided cost.

A combination of linear programming (LP) and heuristics was utilized in [39] in order to optimize the operating costs of a PV based microgrid with more than one generation source (renewable and non-renewable) and energy storage site. The EMS presented is distributed throughout the microgrid to define the operation of all micro-sources and assets within the microgrid and is thus named the distributed intelligent energy management system (DIEMS). However, the operational philosophies developed can apply to a microgrid consisting of only one customer-owned DER installation. The DIEMS is divided into the prediction, optimization, and online control modules. The prediction module is utilized in order to forecast the power generation of the renewable sources using neural networks. The optimization module then establishes the necessary set points for all energy sources and storage such that it minimizes the operating cost (fixed costs are not considered). The total operating cost includes the cost of generation, the cost associated with the grid, and any penalty costs incurred for under utilizing the renewable sources when available. The optimization is constrained by a maximum storage size, and the load must be met by some combination of the local generation and/or utility grid. Due to the nonlinearity of the charging rate constraint on the battery, LP alone cannot be used. However, the authors of [39] developed a heuristic approach that links the battery storage with the energy availability of the following day, assuming it is known the day before. Each optimization scheme establishes a specific storage level at the end of the day and different charging/discharging thresholds. For example, if solar irradiation levels are high on Monday, but will be low on Tuesday, then the DIEMS will store more energy on Monday. The price to sell energy is assumed to be 1/3 the price to purchase energy from the grid (estimation of the avoided cost), thus the storage saves more money than selling any excess energy to the utility.

1.4.3.3 Battery Management

The customer-owned DER installation in this thesis employs lead acid batteries. The following section reviews issues related to battery cycling, sulfation, and stratification; including their causes and mitigation techniques.

Reference [40] discusses the effects of battery cycling on lead-acid batteries that are specific to a PV application. The PV system is made substantially more expensive by the costs incurred due to the shortened life of a battery [40]. By remaining within the operational parameters of the manufacturer, the life of a battery can be notably extended. The authors of [40] state that gel type, maintenance free, lead acid batteries are the most common battery used for renewable energy applications.

Due to the characteristics of a PV system, batteries used for this application incur deep cycle discharging and irregular charging patterns on a regular basis. During battery cycling, it is important to avoid reducing the depletion of the battery to operating continuously at low states of charge. The minimum SOC is known as deep discharge protection (DDP). Operating in this state causes greater sulfation, which significantly reduces the life of the battery. Sulfation is caused by continuously exposing a flooded lead acid battery to undercharge. When a battery is charging the lead sulfate crystals are converted to lead, and if it is not fully recharged some of the lead acid crystals will remain on the battery plate. These lead acid crystals will harden over time and form a layer of insulation over the battery plate reducing the battery capacity [41]. Stratification of flooded lead acid batteries will occur if the battery is not charged adequately. The electrolyte in a flooded lead acid battery is made of sulfuric acid and water, where stratification is the effect of the heavier sulfuric acid sinking, thus making the solution almost pure water on top. Sulfuric acid is a good conductor of electricity, such that only the bottom of the battery plates in the sulfuric acid are contributing to the capacity of the battery, while the top portion of the battery plates oxidize and corrode in water, causing permanent damage [41].

Due to frequent battery cycling incurred when using batteries as a buffer for non-dispatchable energy resources, the loss of battery life caused by sulfation and stratification can be significant over time. This results in having to replace the batteries, contributing to higher costs for the customer-owned DER installation. Thus, it financially benefits the consumer to employ an energy management system which takes the operational parameters and limitations of the battery into account, so as not to reduce battery life.

1.4.3.4 Analytic Hierarchy Process

The AHP was developed by Professor Thomas L. Saaty in the 1970s as a decision making tool for complex problems [42]. The AHP structures a problem into its relevant components such that the best known alternative can be chosen with respect to the relevant criteria through pairwise comparisons. AHP is a valuable tool for complex decision making, and has an extensive range of applications. AHP is a popular decision making tool as it provides a logical way to balance the tangible aspects of engineering and the intangible value of experience. The following provides a selected review of the applications of AHP in general applications such as business and engineering, as well as selected applications in power and energy systems engineering. A sampling of applications of AHP to power and energy systems engineering as well as a comprehensive review of the application of AHP to microgrids is presented in [38].

1.4.3.4.1 General AHP Examples

AHP has a variety of applications in decision–making; the following references represent a small but eclectic subset of its applications in business, sports, government projects, political decisions, and hospital industry. Previously, the AHP has been used in order to choose appropriate contractors in project management [43]; in business, it was used to choose the best project delivery method with respect to construction, necessary designers, construction managers, and contractors [44]. The US government utilized the AHP to evaluate attack helicopters [45], and it was also used to evaluate the American-Chinese trade relationship, where it was decided that a permanent normal trade relations status with China was the best US option [46]. At the University of Virginia Health Sciences Center, AHP was used to determine that mobile robots are a better option than human based delivery systems [47]. In baseball, the New York Yankees used AHP to make the decision of signing Johnny Damon in 2005 as their center fielder in a $52 million four year contract [48]. The possible alternatives for the Yankees included keeping their current center fielders and making no changes, adding another free agent, and signing Johnny Damon. According to the model, signing Johnny Damon was the best solution with a 64.4% priority ranking. A realistic simplification of the AHP model used to determine eligible patients for organ transplants at Pittsburgh's Presbyterian Hospital is given in [46]. The eligible organ transplant candidates are analyzed with respect to family, medical history, social factors, and funding. The criteria is further decomposed to include subcriteria such as the patients time on the donor list, their social worth, psychological evaluation, physical history, and financial and emotional dependence.

AHP is used in many fields in a variety of decision-making scenarios. It is beyond the scope of this section in the thesis to list such applications.

1.4.3.4.2 AHP within Power and Energy Systems

In this sub-section, a representative sample of the application of AHP to topics related to the elements of the customer-driven setup being used in this thesis is provided. AHP has been used to choose an energy storage system with respect to efficiency, load management, technical maturity, environmental concerns, power quality, and costs [49]. These criteria were prioritized such that AHP and fuzzy logic could be utilized in a multi-criteria decision making process. The main case study presented classified power quality as the greatest priority and was able to verify equivalent rankings of energy storage technologies using both fuzzy logic and AHP.

The AHP was implemented in [50] for load forecasting. Using AHP, different forecasting solutions from methods such as regression analysis and neural network were weighted on the basis of criteria such as their applicability to the current loading situation profile, and the believability of the forecast determined by experts in the field. The combination of hard forecasting methods such as regression analysis, neural network, and production value per unit consumption, combined with expert opinion and experience provide increased accuracy in load forecasting.

The life cycle cost (LCC) for coal-fuel, hydro, nuclear, and wind power plants was calculated using the AHP in [51]. The original formulation for the LCC was the summation of the initial investment cost, cost of operation, maintenance cost, and the disposal cost. The new formulation for the LCC presented in [51] includes the addition of an environmental cost. AHP is implemented in order to weight the importance of each factor in the formulation of the LCC, thus forming a new ranking of each generation method with respect to the criteria that internalizes environmental cost of generation.

Reference [52] presents a load shedding scheme (LSS) for islanded power systems through shipboard power systems (SPS). The LSS consists of a load prioritization module (LPM) and a control actions module (CAM). It is assumed that the amount of load that must be shed has already been previously provided. The load information is provided by a dynamic database to the LPM. The load information consists of load power ratings, inrush current, harmonic injections, power factor, full load power rating, and the manpower necessary for restoration (including start-up time). Each load is divided into one of five priority levels for each mission, ranging from non-

vital to vital loads in order of increasing importance. The LSS maximizes the objective function of the SPS with respect to weighting criteria determined by the AHP, based on the concurrent missions being executed at that time. The LSS is subject to the running loads and line losses being less than or equal to the ships generation capacity during the mission(s) in question. The necessary pairwise comparisons for AHP are completed by experienced electrical engineers or ship operators.

AHP has been implemented for scheduling maintenance on power lines in [53]. The hierarchical structure of the problem includes reliability and economic efficiency criteria followed by subcriteria of power-off time, operating costs, equipment condition, environmental effects, circuit grade, and consumer losses with respect to each line being considered for maintenance. Thus, power line maintenance is conducted in the order of highest to lowest priority ranking.

The vulnerability of special protection schemes are identified in a power system using AHP in [54]. Hidden failures can cause cascading problems which can affect a large service area of the power system. AHP is implemented in order to detect the locations where hidden failures would have the most damage to the system, using expert opinions.

The modernization of the electric grid is of national and international focus, as seen by the EISA of 2007 in [5], and the Smart Grid European Technology Platform in [55]. This thesis is aligned with the Smart Grid Initiative in perspective of developing tools and methods by which the economic performance of a customer-owned DER installation attracts consumers to embrace the new grid, and make best use of the advantages presented by the Smart Grid. The literature review provided above reflects the optimization and increased performance of DER installations only capable of importing, and in some cases exporting real power. However, this thesis presents a customer-driven energy management system that incorporates load scheduling and the deployment of energy storage, where the system is customized by the consumer. Furthermore, the EMS is capable of real and reactive power exchange with the grid on a dynamic electricity pricing scheme.

1.5 Organization of Thesis

The preceding introduction is followed by chapter 2, where a mathematical and conceptual description of the AHP, as well as a static and dynamic example of AHP is presented. Chapter 3 presents a method for load scheduling implementing the AHP, and a residential set-up.

Chapter 4 presents the heuristic scheduling technique, including its enabling technologies, and several case studies; finally, chapter 5 concludes and discusses possible avenues of future work.

CHAPTER 2
A MATHEMATICAL AND CONCEPTUAL DESCRIPTION OF THE AHP

The following chapter explains the AHP in a mathematical and conceptual framework as described by [42]. AHP is used in order to make complex decisions, incorporating both qualitative and quantitative information and judgments. The problem itself is broken down into a structure that facilitates the examination of each criterion individually with respect to the possible alternatives. The AHP is used later in this thesis to implement a load scheduling algorithm, such that qualitative and quantitative customer preferences can be taken into account. However, the AHP is first defined conceptually and mathematically in the following sections. Additionally, a generic example of the application of AHP is presented, and then the example is extended to a dynamic judgment.

2.1 AHP Definition

AHP is a well established prediction and decision making tool developed by Professor Thomas L. Saaty in the 1970s. A problem is solved by establishing a goal, and then decomposing the original problem into a series of constituent sub-problems in the form of a hierarchy. The hierarchy is built beginning with a clearly defined objective, followed by the criteria that influence the decision. The criteria can be broken down into sub-criteria, and so on, moving from general to more detailed criteria. The final level of the hierarchy consists of the possible decision alternatives to the problem. The following Figure 2.1 shows a basic hierarchical decomposition of a problem.

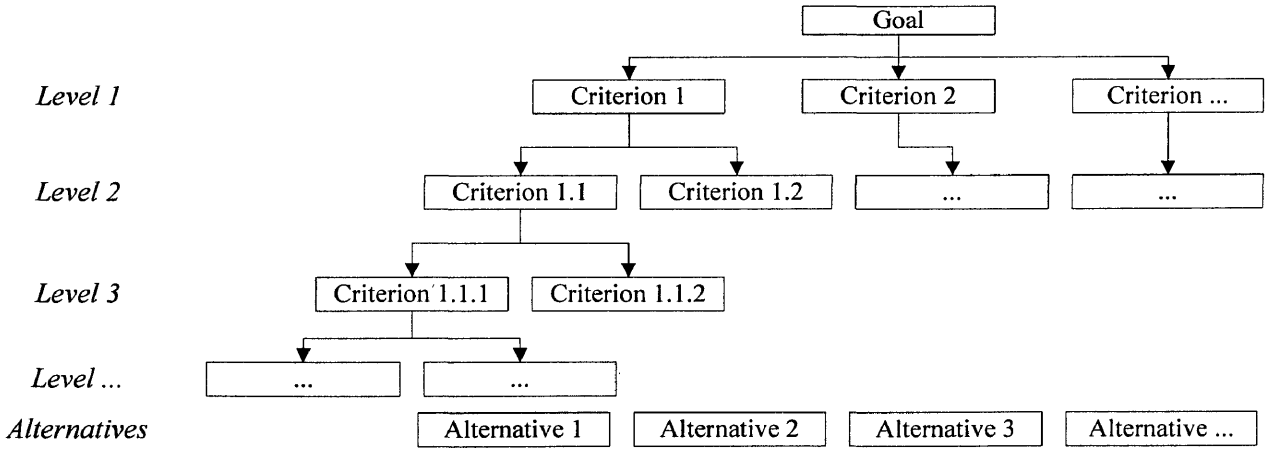

Figure 2.1 Basic AHP hierarchy.

The AHP uses pairwise comparisons of the criteria in order to derive ratio scales of relative magnitudes, with respect to the hierarchy dominance structure. An attractive advantage of AHP is its ability to synthesize both qualitative and quantitative information and judgments. The pairwise comparisons are established based on a fundamental scale of absolute numbers which represent the intensity of the judgment. The fundamental scale is shown in Table 2.1 below. The core of the scale is in intensities 1, 3, 5, 7, and 9, shown in bold, as all qualitative judgments can be represented. The intensities of 2, 4, 6, and 8, are used for a compromise between intensities, and can be further extended for when greater precision in measurement is needed. The scale can be reasonably extended to reciprocity based on the assumption that if activity 'i' can be represented by a nonzero intensity from the fundamental scale with respect to activity 'j', then 'j' must have the reciprocal value when being compared to activity 'i'.

Table 2.1 The fundamental scale of AHP [42].

Intensity of Importance	Definition	Explanation
1	**Equal importance**	**Two activities contribute equally to the objective**
2	Weak	
3	**Moderate importance**	**Experience and judgment slightly favor one activity over another**
4	Moderate plus	
5	**Strong importance**	**Experience and judgment strongly favor one activity over another**
6	Strong plus	
7	**Very strong or demonstrated importance**	**An activity is favored very strongly over another; its dominance demonstrated in practice**
8	Very, very strong	
9	**Extreme importance**	**The evidence favoring one activity over another is of the highest possible order of affirmation**

Once the pairwise comparison matrices of the relevant criteria and the alternatives with respect to those criteria have been formed, the relative weights of each element in the hierarchy are derived by calculating the normalized Eigenvector that corresponds to its maximum Eigenvalue. The local priorities with respect to its overarching criterion are calculated by multiplying the Eigenvector by the weight of the criteria above it in the hierarchy, for all criteria, such that, the local priorities can be

summed for each decision, arriving at the total preference for that alternative. The alternative with the greatest magnitude is the best alternative with respect to the criteria given [42].

2.2 AHP Theory

AHP makes use of the decomposition of a problem into a hierarchy that can then be evaluated through the use of pairwise comparisons. Let us suppose that the pairwise comparison matrix of n activities can be represented by (2.1). The matrix represents the pairwise comparison of n activities compared two at a time with respect to each other. Each element in the matrix then corresponds to the judgment determined using the AHP fundamental scale (i.e.- the influence of activity 'i' with respect to activity 'j', and its reciprocal is used to determine the influence of activity 'j' with respect to activity 'i').

$$A_{(i,j)} = \begin{vmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{vmatrix} \quad \text{for i, j} = 1,2,\dots n \tag{2.1}$$

The Eigenvector corresponding to its maximum Eigenvalue is then calculated using equation (2.2), where w denotes the principal right Eigenvector that corresponds to the maximum Eigenvalue, λ_{max} [56].

$$Aw = \lambda_{max} w \tag{2.2}$$

The maximum Eigenvalue, λ_{max}, is calculated by solving the characteristic equation which corresponds to matrix A, given by equation (2.3), [57], where I_n denotes the n x n identity matrix.

$$det|A - \lambda I_n| = 0 \tag{2.3}$$

The mathematical basis for this approach lies primarily in the *Perron-Frobenius* Theorem, which states for a strictly positive stochastic matrix, λ=1 is the *Perron-Frobenius* Eigenvalue and is also the dominant Eigenvalue, with a corresponding Eigenvector that consists of strictly positive components [58], [59].

2.3 Consistency

The consistency of a pairwise comparison matrix must be quantified. By definition from reference [42], a matrix is consistent if for $A = [a_{ij}]$,

$$a_{ij}a_{jk} = a_{ik} \tag{2.4}$$

Equation (2.4) states that any element in the matrix A can be formed by a chain of other elements in matrix A.

Let us create the matrix W, whereby each element in W is the ratio of the absolute measurement of w_i to every other element in W. The matrix W then takes the form shown in (2.5).

$$W_{(i,j)} = \begin{vmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \dots & \dots & \dots & \dots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{vmatrix} \quad \text{for i, j} = 1,2,\dots n \tag{2.5}$$

Reference [42] states that an nxn matrix is positive and has the ratio form, A= (w_i / w_j), for i,j=1,...n, if, and only if, it is consistent. Moreover, the matrix A "is consistent if and only if λ is its principle Eigenvalue and $Aw=\lambda w$. Further, $w > 0$ is unique to within a multiplicative constant" [42]. By this definition, the matrix A is consistent and has a "rank one because every row is a constant multiple of the first row" [42]. Therefore, the matrix A only has one nonzero Eigenvalue, thus upholding the equality between the sums of the trace of the matrix A, and the sum of the Eigenvalues. For the matrix A that takes the form of (2.1), the sum of the trace of A is equal to n, which is also its maximum Eigenvalue.

2.3.1 Consistency Metric

The metric used to measure the consistency of a matrix is determined using the consistency index (C.I.) and consistency ratio (C.R.). The consistency index is given by the following (2.6), [42]:

$$C.I. = \frac{(\lambda_{max} - n)}{(n-1)} \tag{2.6}$$

The consistency ratio is then calculated using a random consistency index (R.I.) computed in [42], and depicted in Table 2.2.

Table 2.2 Random consistency index, directly taken from [42].

n	1	2	3	4	5	6	7	8
R.I.	0	0	0.52	0.89	1.11	1.25	1.35	1.4

n	9	10	11	12	13	14	15
R.I.	1.45	1.49	1.51	1.54	1.56	1.57	1.58

The R.I. is calculated using reciprocal matrices that were randomly generated using the fundamental AHP scale values, and is the result of the average. Thus, the C.R. is given by the calculated C.I. and corresponding R.I. from Table 2.2, as in equation (2.7).

$$C.R. = \frac{C.I.}{R.I.} \tag{2.7}$$

Given by reference [42] as convention, the acceptable R.I. for $n \geq 5$ is 10%, but if n=3, R.I.=5%, and if n=4, R.I.=8%. The R.I. is chosen such that its value is neither inconsequential nor of such a large magnitude that it rivals the size of the judgment itself. Some inconsistency is permitted because all judgments predicated on experience are not necessarily consistent [42].

2.3.2 Improving Judgment Consistency

The consistency of judgment matrices whose C.R. is less than the acceptable value can be improved through the following method presented in [42]. The method takes the value of the judgment matrix A = $[a_{ij}]$ whose value is the most inconsistent and replaces it with the value (w_i / w_j) corresponding to the Eigenvector of matrix A. The most inconsistent value is calculated using $a_{ij} * (w_i/w_j)$, where the a_{ij} whose magnitude deviates the most from the ratio of corresponding elements of the Eigenvector is replaced with the Eigenvector ratio itself. Thus, the consistency of the matrix is improved because a_{ij} is moving towards the corresponding ratio of the Eigenvector.

For example, let

$$X = \begin{bmatrix} 1 & 2 & 5 \\ 1/2 & 1 & 2 \\ 1/3 & 1/2 & 1 \end{bmatrix},$$

with the Eigenvector corresponding to the maximum Eigenvalue,

$$W_x = \begin{bmatrix} .5827 \\ .2681 \\ .1492 \end{bmatrix}.$$

The C.I. =0.2902, and the C.R. =0.5004, for the matrix X. We will now form the matrix Y, where every element in Y is defined by $X_{ij}*\frac{w_j}{w_i}$. Thus,

$$Y(1,2)=X(1,2)*\frac{W_x(2)}{W_x(1)} = 2 * \frac{0.2681}{0.5827} = 0.92.$$

Evaluating Y for all elements yields:

$$Y = \begin{bmatrix} 1 & .92 & 1.28 \\ 1.087 & 1 & 1.113 \\ 1.302 & .8983 & 1 \end{bmatrix}.$$

The element whose magnitude has the greatest deviation is Y(3,1). This element is selected to replace X(3,1) by the ratio of the corresponding elements of the Eigenvector, namely $\frac{W_x(3)}{W_x(1)} = \frac{0.1492}{0.5827} =$ 0.256. The improved matrix takes the form:

$$X_{new} = \begin{bmatrix} 1 & 2 & 5 \\ 1/2 & 1 & 2 \\ 0.256 & 1/2 & 1 \end{bmatrix},$$

with an improved associated C.I.=0.0450 and C.R.=0.0865.

2.4 Generic AHP Example

In order to illustrate the AHP process, the following example is given. Suppose a young individual, 20 years of age, aspires to choose a new hobby from the following three choices: bridge, football, and billiards. The criteria of his new activity with which he is concerned are physical and mental stimulation, and social interaction. The following Figure 2.2 shows the hierarchical breakdown of the decision.

Physical and mental stimulation correspond to the extent of the activity's physical and mental demand such as running and strategizing, respectively. Social interaction is concerned with the amount of contact and communication with other people of a similar age group, such as teammates or opponents. For a young man at the age of 20, the following assumptions are made in order to build pairwise comparison matrices of criteria and alternatives. A hobby should invoke physical exercise and allow him to be physically active. Mental stimulation is not as important as the social interaction achieved when playing for instance, a team sport. Table 2.3 shows the pairwise comparison matrix which reflects these preferences, and Table 2.4-6 show how each activity compares to each of the criteria, with their respective rankings determined by the corresponding Eigenvector. The

consistency ratio for each pairwise comparison matrix is shown, and all are less than the established maximum 5% consistency threshold, such that the matrices are consistent.

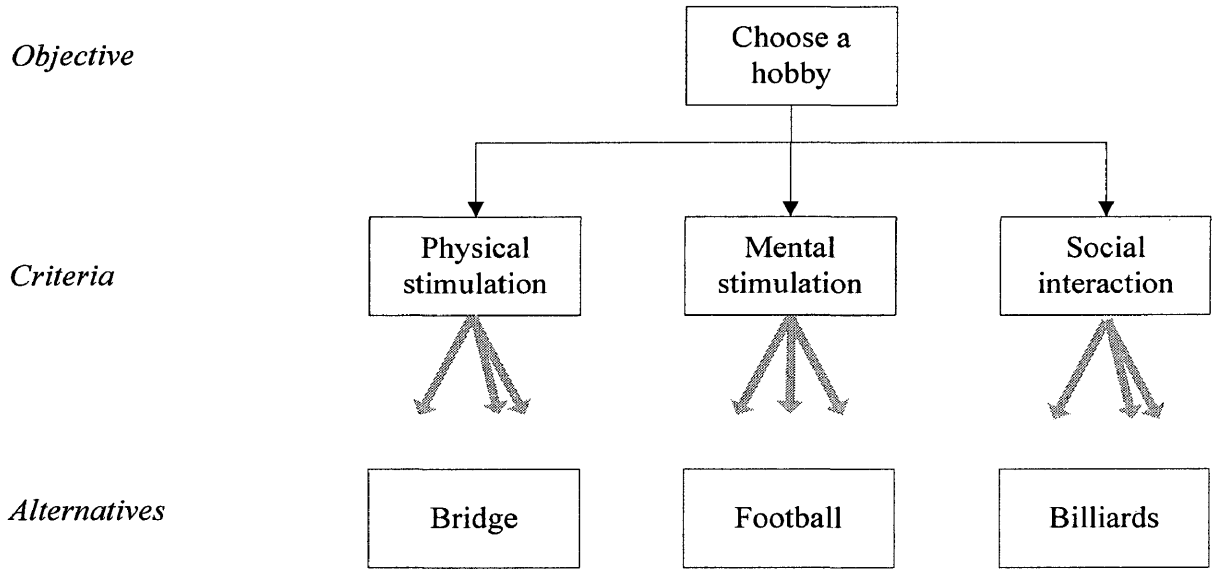

Figure 2.2 Hierarchical breakdown of choosing a new hobby.

Table 2.3 Pairwise comparison matrix representing the relative importance of mental, physical, and social criteria at the age of 20.

Criteria	Mental	Physical	Social	Eigenvector
Mental	1	1/6	1/3	0.1000
Physical	6	1	2	0.6000
Social	3	1/2	1	0.3000
			C.R.=0	

Table 2.4 Pairwise comparison matrix representing the relative comparisons of bridge, football, and billiards with respect to the mental criterion at the age of 20.

Mental	Bridge	Football	Billiards	Eigenvector
Bridge	1	7	1/2	0.3458
Football	1/7	1	1/9	0.0572
Billiards	2	9	1	0.5969
			C.R.=.0209	

Table 2.5 Pairwise comparison matrix representing the relative comparisons of bridge, football, and billiards with respect to the physical criterion at the age of 20.

Physical	Bridge	Football	Billiards	Eigenvector
Bridge	1	1/7	1/2	0.0938
Football	7	1	5	0.7396
Billiards	2	1/5	1	0.1666
			C.R.=.0136	

Table 2.6 Pairwise comparison matrix representing the relative comparisons of bridge, football, and billiards with respect to the social criterion at the age of 20.

Social	Bridge	Football	Billiards	Eigenvector
Bridge	1.00	1/3	3.00	0.2308
Football	3.00	1.00	9.00	0.6923
Billiards	1/3	1/9	1.00	0.0769
			C.R.=0	

When populating the AHP hierarchical structure, as in Figure 2.1, the distinction is made between local and global priorities. Global priorities are seen by the Eigenvector which has not been weighted by the ranking of the criteria directly above it. When weighted through multiplication by the criterion directly above it, the global priority becomes the local priority. Figure 2.3 corresponds to the example case and shows both the global and local priorities.

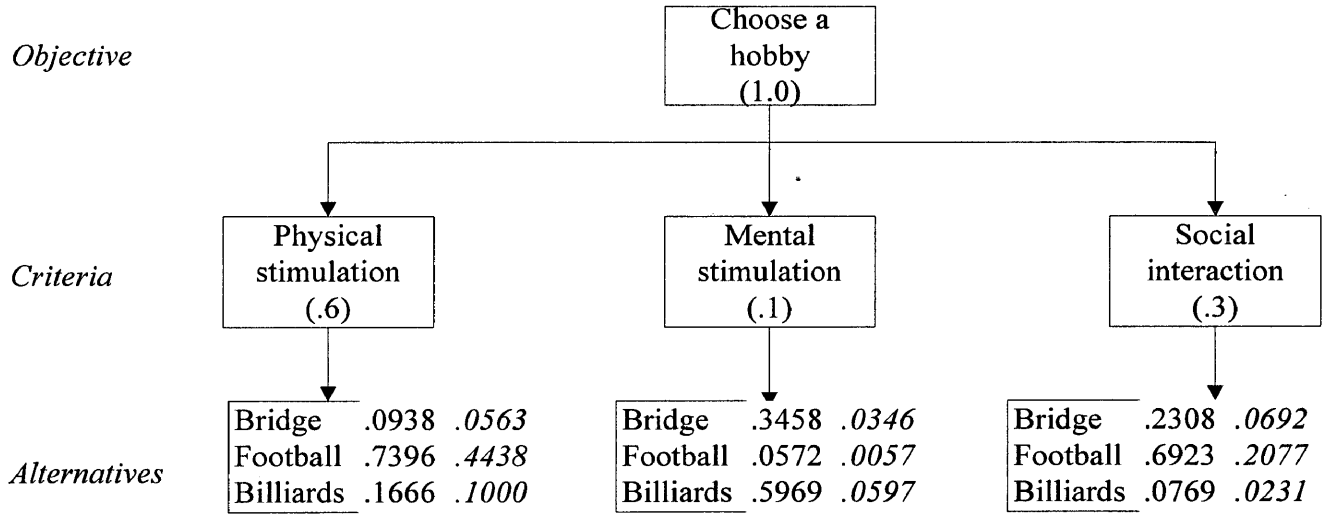

Figure 2.3 AHP hierarchical structure showing global and local priorities for the example case. The local priorities are shown in italics, and the global priorities are not. If no local priority is shown, the local and global priorities are equal.

The final solution to the example case is determined by adding the final level of local priorities for each alternative. In this case, it would be solved as follows:

Bridge: $.0563 + .0346 + .0692 = .1601$

Football: $.4438 + .0057 + .2077 = .6572$

Billiards: $.1000 + .0597 + .0231 = .1828$

The alternative with the greatest magnitude priority, in this case football, is the best decision.

2.5 Dynamic AHP Example

Decisions and judgments are not always static; they often change as a function of time. When this is the case, the AHP becomes a dynamic decision making tool, such that priorities can be calculated over the necessary time period [42]. In order to describe the dynamic AHP process, the previous example will be extended. The Matlab code evaluating this dynamic AHP example can be found in the electronic appendix. The original case represents a young man, at the age of 20 deciding a hobby to pursue. Now, let us suppose that this decision will not only be made at the age of 20, but also when the same individual is 40 and 60 years old. Tables 2.7-10 depict the pairwise comparison matrices that represent the preferences for this individual when he is 40 yrs old.

Table 2.7 Pairwise comparison matrix representing the relative importance of mental, physical, and social criteria at the age of 40.

Criteria	Mental	Physical	Social	Eigenvector
Mental	1	2	3	0.5396
Physical	1/2	1	1/2	0.2970
Social	1/3	2	1	0.1634
			CR=.0088	

Table 2.8 Pairwise comparison matrix representing the relative comparisons of bridge, football, and billiards with respect to the mental criterion at the age of 40.

Mental	Bridge	Football	Billiards	Eigenvector
Bridge	1	3	1/3	0.2426
Football	1/3	1	1/7	0.0879
Billiards	3	7	1	0.6694
			C.R.=.0068	

Table 2.9 Pairwise comparison matrix representing the relative comparison of bridge, football, and billiards with respect to the physical criterion at the age of 40.

Physical	Bridge	Football	Billiards	Eigenvector
Bridge	1	1/9	1/3	0.0704
Football	9	1	5	0.7514
Billiards	3	1/5	1	0.1782
			C.R.=.0279	

Table 2.10 Pairwise comparison matrix representing the relative comparison of bridge, football, and billiards with respect to the social criterion at the age of 40.

Social	Bridge	Football	Billiards	Eigenvector
Bridge	1.00	1/3	3.00	0.2308
Football	3.00	1.00	9.00	0.6923
Billiards	1/3	1/9	1.00	0.0769
			C.R.=0	

Previously, at the age of 20 the physical criterion was considered the most important. However by the age of 40, it is considered that physical activity is simply a way to stay in shape, while mental stimulation is the more appealing aspect. Furthermore, it is considered that at the age of 40, social interaction with one's peer group is less important because one's life and friends are already well established with family and friends. These preferences are reflected in Tables 2.7-10. The consistency ratio of each matrix is displayed below each table, such that all matrices are known to be consistent.

By the age of 60, the priorities of the criteria have again changed as shown in Table 2.11. At 60, the importance of physical activity is almost negligible with respect to the mental and social criteria because physical activity naturally declines with age. However, the social interactions obtained from enjoying the company of peers is more appealing, as is the allure of mental challenges. The comparison matrices of the activities with respect to the mental, physical, and social criteria at the age of 60 are presented in Tables 2.12- 14.

Table 2.11 Pairwise comparison matrix representing the relative importance of mental, physical, and social criteria at the age of 60.

Criteria	Mental	Physical	Social	Eigenvector
Mental	1	7	1/2	0.3458
Physical	1/7	1	1/9	0.0572
Social	2	9	1	0.5969
			C.R.=.0209	

Table 2.12 Pairwise comparison matrix representing the relative comparisons of bridge, football, and billiards with respect to the mental criterion at the age of 60.

Mental	Bridge	Football	Billiards	Eigenvector
Bridge	1	2	1/3	0.2053
Football	1/2	1	1/9	0.0897
Billiards	3	9	1	0.7050
			C.R.=.0176	

Table 2.13 Pairwise comparison matrix representing the relative comparison of bridge, football, and billiards with respect to the physical criterion at the age of 60.

Physical	Bridge	Football	Billiards	Eigenvector
Bridge	1	1/7	1/2	0.0938
Football	7	1	5	0.7396
Billiards	2	1/5	1	0.1666
			C.R.=.0136	

Table 2.14 Pairwise comparison matrix representing the relative comparison of bridge, football, and billiards with respect to the social criterion at the age of 60.

Social	Bridge	Football	Billiards	Eigenvector
Bridge	1.00	9	5.00	0.7514
Football	1/9	1.00	0.33	0.0704
Billiards	1/5	3	1.00	0.1782
			C.R.=.02790	

In order to form a dynamic judgment, each element of the pairwise comparison matrix is extrapolated over the desired time frame. Based on the finite number of pairwise comparison matrices established, one *time dependent* pairwise comparison matrix, A(t), is defined. A(t) defines the pairwise comparison matrix at any instance in time desired. Each element of A is a function of time a_{ij}(t). Each element function, a_{ij}(t), is determined based on a Piecewise Cubic Hermite Interpolation (pchip) of the set of data points that were explicitly defined, for this example, $a_{ij}(20)$, $a_{ij}(40)$, $a_{ij}(60)$. The interpolating polynomial for each element is defined by $P(x_k) = y_k$. The pchip implemented is shape-preserving, where the key to the interpolant is the definition of the slope, d_k, to ascertain the interpolating function has no overshoot [60]. If the first divided difference, δ_k, where $\delta_k = \frac{y_{k+1}-y_k}{x_{k+1}-x_k}$, and δ_{k-1} have opposite signs or either is zero, then x_k is a discrete local minimum or maximum such that $d_k = 0$. This method of choosing d_k, is what prevents any overshoot from occurring and why this specific interpolation method was implemented. The reason there can be no overshoot is because the extrapolated preferences of the pairwise comparison matrices

cannot be negative, nor should they lie outside the fundamental AHP scale. The slope of the interior breakpoints is defined through the weighted harmonic mean in equation (2.8). The weights are based on the length of the intervals h_k and h_{k-1}, where h_k defines the interval length as in equation (2.9). The corresponding weight of the interval is calculated as seen in equation (2.10).

$$\frac{w_1 + w_2}{d_k} = \frac{w_1}{\delta_{k-1}} + \frac{w_2}{\delta_k} \tag{2.8}$$

$$h_k = x_{k+1} + x_k \tag{2.9}$$

$$w_1 = 2h_k + h_{k-1}, w_2 = h_k + 2h_{k-1} \tag{2.10}$$

Implementing the shape preserving pchip for each element of each pairwise comparison matrix, functions were formed for each element of the pairwise comparison matrices and evaluated from age 20 to 60. A time step of one year was used so as to represent the changes in preference on a yearly basis, from the age of 20 until 60. A total of 38 new pairwise comparison matrices were formed; the priority vector or Eigenvector corresponding to each element of the matrix A(t) was calculated using AHP. Therefore, each function was evaluated for every year between 20 and 60 years, such that a complete picture of the preferences and priorities was formed. The following Figures 2.4-5 show the changes in priorities of the criterion themselves, and the changes of each alternative with respect to the criteria, respectively.

Let us examine the example for the individual's age of 58. At 58, the AHP hierarchy takes the form of Figure 2.6. The criteria level shows that social interaction and mental stimulation are almost equally as important, and both are significantly more important than physical stimulation. This follows the pairwise comparison trend which makes physical stimulation less important with increasing age. According to the AHP hierarchy, the best hobby in which to partake at the age of 58 is bridge, followed by billiards, and then football. Overall, the AHP priority rankings according to Figure 2.5 dictate that football is the best hobby from ages 20-35, billiards has the greatest priority from 36-55, and from 55 onwards bridge is the best alternative.

This chapter has presented the mathematical and conceptual framework of AHP, including a generic example for both a static and dynamic decision. The consistency of each pairwise comparison matrix has an associated consistency metric, if a matrix is inconsistent then a method to improve matrix consistency was presented using the appropriate ratio of the Eigenvector. Using AHP, this thesis incorporates customer preferences and input into the operation of the DER

installation, thus making it customer-driven. The customer-driven nature of the DER installation not only reflects the Smart Grid Initiative, but allows for the customer to tailor its operation as desired to meet individual needs.

Figure 2.4 Time dependence of criteria from age 20 to 60 years old.

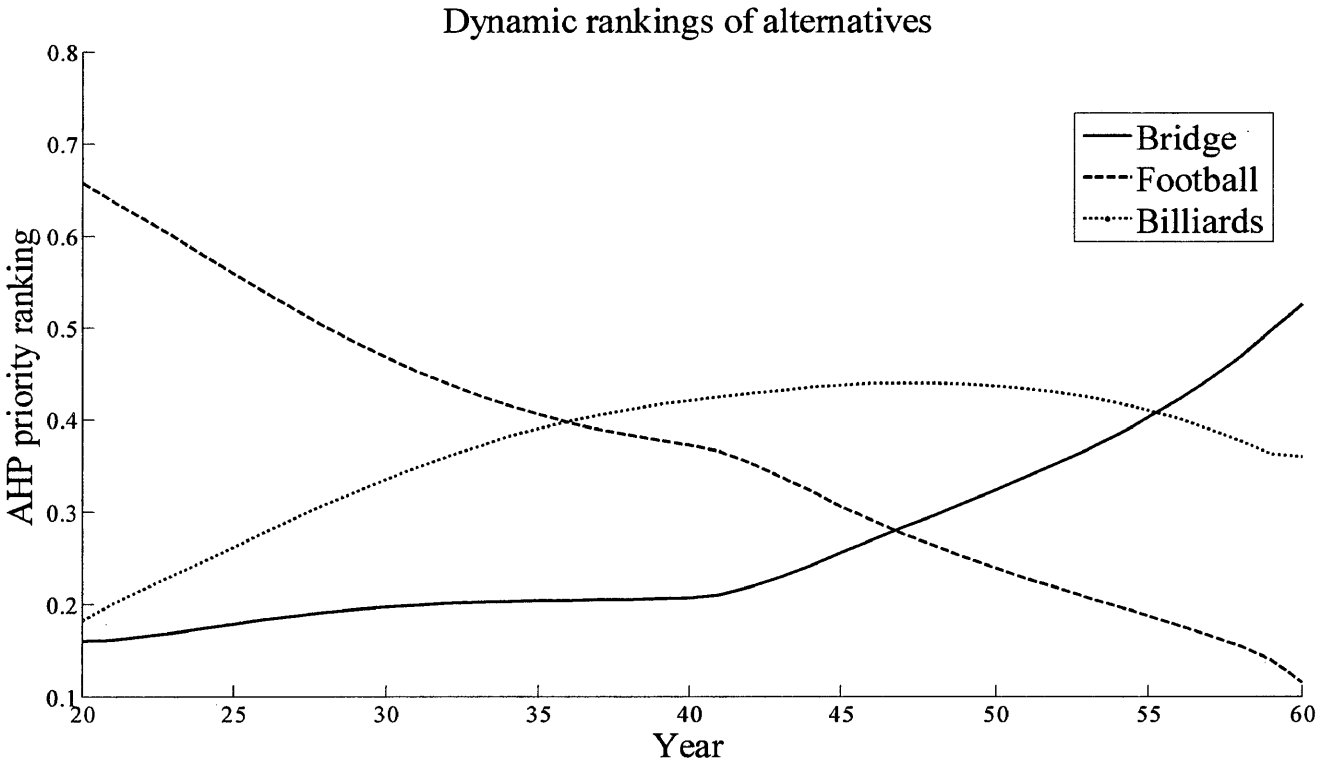

Figure 2.5 Dynamic rankings of alternatives from age 20 to 60 years old.

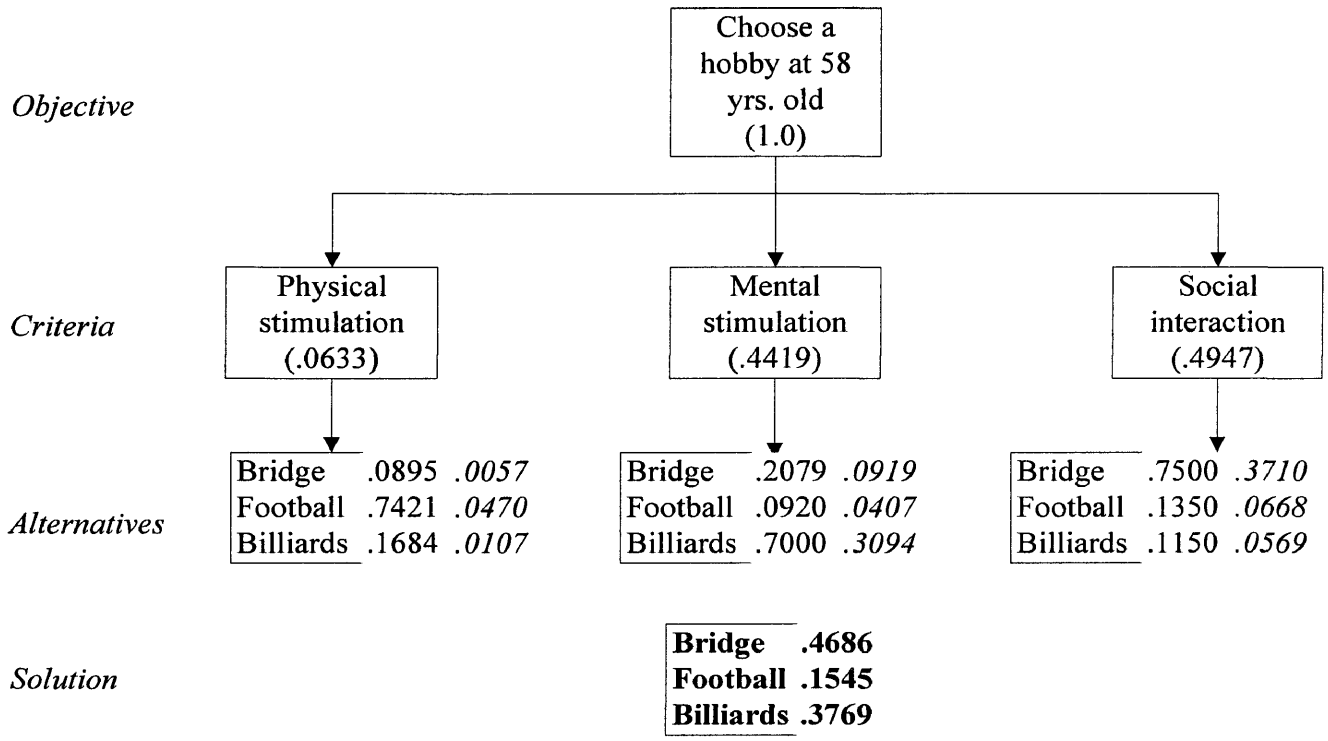

Figure 2.6 AHP hierarchy at the age of 58. The global priorities are shown in regular type-font, and the local priorities are shown in italics.

CHAPTER 3
IMPLEMENTATION OF THE AHP FOR CUSTOMER-DRIVEN LOAD SCHEDULING

This chapter presents a method of load scheduling that allows the customer to incorporate their individual preferences in deciding when local loads will be scheduled. Previously, in Chapter 2 the AHP was presented, using both a static and dynamic example. The dynamic AHP is now implemented for load scheduling. A salient feature of the AHP is its ability to synthesize empirical and subjective criteria in the decision making process, as is beneficial in the case of local load shedding. The incorporation of subjective criteria is the feature which allows the customer control over their own system. This customer-driven nature of the load scheduling method (LSM) is aligned with the policy stated in the Smart Grid Initiative, specifically with respect to the deployment of DER, 'smart' technologies, and demand side management [5].

3.1 General Description of the LSM using AHP

The LSM can be implemented in a variety of applications. For an industrial and/or commercial application the LSM can be used to decide when to schedule specific automated processes. The application of the LSM to an industrial plant with sensitive power quality constraints, high noise and smoke pollution, etc. could take the hierarchical form as shown in Figure 3.1.

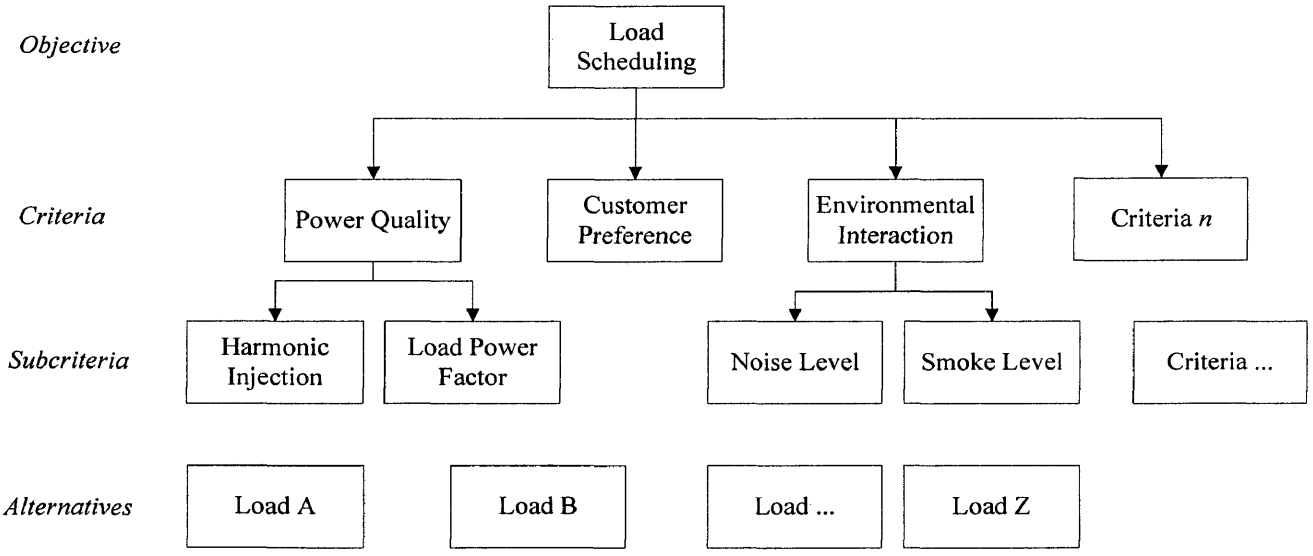

Figure 3.1 Framework for an industrial LSM application.

For residential applications, the LSM can be used to schedule a portion of the local load, like the dishwasher, washing machine, and clothes dryer. However, in a residential setting there is a large

portion of loads that constitute the base residential load, and are not available for load scheduling. In addition, the LSM can be used under a variety of circumstances, such as for specific seasons, weekdays, weekend, working day, holidays, etc., by defining a pairwise comparison matrix for the importance of each scenario with respect to each other. The customer would first complete the LSM for each scenario they wish to define. Then, the scenarios being implemented would be ranked according to the LSM, but the priorities would be weighted using the appropriate weighting factor of that scenario with respect to the other scenarios also in effect that day. For example, on a winter weekday the priorities determined by the LSM would be weighted by the importance assigned to the winter scenario over the weekday scenario by the customer.

The general algorithm of the LSM over a 24-hr period is defined as:

Step 1: Identify the desired loads to be scheduled

Step 2: Structure a hierarchy of criteria and subcriteria with respect to the individual characteristics of the application; this is unique to the customer and application

Step 3a: Define pairwise comparison matrices for the criteria and loads to be scheduled for at least the hours of $t = \{1, 6, 12, 16, 20, 24\}$ using customer preferences

Step 3b: Improve the consistencies of the pairwise comparison matrices, if necessary

Step 4: Calculate the priorities of the loads as defined by the AHP in chapter 2

Step 4b: Improve the consistencies of the generated pairwise comparison matrices, if necessary

Step 5: Define the runtime for each load

Step 6: Calculate the moving average for each load priority with respect to its individual runtime

Step 7a: Schedule each load when the moving average value of the load priority is at its maximum

Step 7b: If so desired by the customer, any load scheduled during the period of peak pricing will be rescheduled to the next moving average maximum that falls outside of the peak pricing range

The LSM is easily customizable to accommodate a few or more loads as needed for the specific application. The following section employs the LSM for a residential application.

3.2 LSM Case Study for a Residential Application

In a residential application, the LSM is straightforward, because criteria such as the power quality of loads is inconsequential with respect to the kinds of loads being scheduled, such as a dishwasher, washing machine, and clothes dryer. For this case study, the example will be restricted to a residential setting where the customer preference is the only criteria of consequence. The example was programmed in Matlab 7.6.0 (r2008a) and is available in the electronic appendix; see the Appendix for more information.

Let us suppose the LSM will schedule three residential loads, namely Loads A, B, and C, where all other residential loads comprise the base load and are not schedulable. The residence is assumed to be in an area with peak and off-peak TOU pricing. The energy consumption for Loads A, B, and C, is 0.4 kWh, 1.8 kWh, and 2 kWh, respectively. The synthetic customer generated pairwise comparison matrices in Tables 3.1-6, which reflect the load preferences of the customer. The C.R. for each pairwise comparison matrix is shown, where the C.R. for all matrices is below the allowable threshold of 5%, except at hour 12. The consistency of the pairwise comparison matrix shown in Table 3.3 was improved using the method described in section 2.3.2. The resulting pairwise comparison matrix shown in Table 3.7, where the C.R. =0.0153, is now less than the 5% tolerance.

Table 3.1 Pairwise comparison matrix of customer load preferences at hour 1.

t=1	Load A	Load B	Load C
Load A	1	1/5	1/3
Load B	5	1	2
Load C	3	½	1

C.R.=.0036

Table 3.2 Pairwise comparison matrix of customer load preferences at hour 6.

t=6	Load A	Load B	Load C
Load A	1	9	5
Load B	1/9	1	1/3
Load C	1/5	3	1

C.R.=.0279

Table 3.3 Pairwise comparison matrix of customer load preferences at hour 12.

t=12	Load A	Load B	Load C
Load A	1	1/7	4
Load B	7	1	9
Load C	¼	1/9	1

C.R.=.1393

Table 3.4 Pairwise comparison matrix of customer load preferences at hour 16.

t=16	Load A	Load B	Load C
Load A	1	2	¼
Load B	½	1	1/7
Load C	4	7	1

C.R.=.0019

Table 3.5 Pairwise comparison matrix of customer load preferences at hour 20.

t=20	Load A	Load B	Load C
Load A	1	½	1/9
Load B	2	1	1/6
Load C	9	6	1

C.R.=.0088

Table 3.6 Pairwise comparison matrix of customer load preferences at hour 24.

t=24	Load A	Load B	Load C
Load A	1	1/3	3
Load B	3	1	9
Load C	1/3	1/9	1

C.R.=0

Table 3.7 Pairwise comparison matrix with improved consistency for customer load preferences at hour 12.

t=12	Load A	Load B	Load C
Load A	1	0.209	2.740
Load B	4.795	1	9
Load C	0.365	1/9	1

C.R.=.0153

Now using these pairwise comparison matrices, pchip was used to define a function for each element of the pairwise comparison matrix. For this case study, the time step is 15 minutes, such that for a 24-hr period, 96 pairwise comparison matrices are evaluated for the day's load scheduling

availability. For example, the first element of A(t) is defined by the 3rd order piecewise segment functions shown below in the coefficient matrix of Table 3.8. Each of the five rows of the coefficient matrix comprises the piecewise function of the time segment specified.

Table 3.8 Piecewise defined coefficient matrix for element $a_{12}(t)$ of the LSM.

$a_{12}(t)=$

t^3	t^2	t^1	t^0	
0.000	-0.015	0.749	0.200	, for $0 < t < 24$
0.001	-0.046	0.000	9.000	, for $24 < t < 48$
-0.001	0.021	0.000	0.209	, for $48 < t < 64$
0.001	-0.016	0.000	2.000	, for $64 < t < 80$
0.000	0.000	-0.019	0.500	, for $80 < t < 96$

To illustrate how to use the coefficient matrix above, we know that t is in multiples of the timestep, (0.25 hrs) such that to convert the unit to hours, $t = 24*0.25 = 6$, so for $a_{12}(t)$, for t between 0001 and 0600, the element is defined by (3.1).

$$a_{12}(t) = (0)\, t^3 + (-0.015)\, t^2 + (0.749)\, t^1 + (0.200)\, t^0, \quad \text{for } 0 < t < 24 \tag{3.1}$$

The following Tables 3.9-10 represent the piecewise defined coefficient matrices of elements $a_{13}(t)$ and $a_{23}(t)$, respectively.

Table 3.9 Piecewise defined coefficient matrix for element $a_{13}(t)$ of the LSM.

$a_{13}(t)=$

t^3	t^2	t^1	t^0	
-0.0001	-0.0038	0.3483	0.3333	, for $0 < t < 24$
0.0001	-0.0068	0	5.0000	, for $24 < t < 48$
0.0007	-0.0132	-0.1193	2.7400	, for $48 < t < 64$
0	0.0004	-0.0164	0.2500	, for $64 < t < 80$
-0.0003	0.0167	0	0.1111	, for $80 < t < 96$

Table 3.10 Piecewise defined coefficient matrix for element $a_{23}(t)$ of the LSM.

$a_{23}(t)=$

t^3	t^2	t^1	t^0	
-0.0001	-0.0095	-0.2174	2.0000	, for $0 < t < 24$
-0.0013	-0.0451	0	0.3333	, for $24 < t < 48$
0.0043	-0.1038	0	9.0000	, for $48 < t < 64$
0	0.0001	0	0.1429	, for $64 < t < 80$
-0.0011	0.0514	0.0030	0.1667	, for $80 < t < 96$

Each element within the matrix, A(t) has its own piecewise defined function using pchip. Symbolically, A(t) takes the form shown in (3.2).

$$A(t)_{(i,j)} = \begin{vmatrix} 1 & a_{12}(t) & \dots & a_{1n}(t) \\ a_{12}^{-1} & 1 & \dots & a_{2n}(t) \\ \dots & \dots & \dots & \dots \\ a_{1n}(t)^{-1} & a_{2n}(t)^{-1} & \dots & 1 \end{vmatrix} \quad \text{for } i, j = 1,2,\dots n \tag{3.2}$$

In line with the dynamic AHP discussed in chapter 2.5, the priority rankings of each of the 96 pairwise comparison matrix are calculated, and plotted in Figure 3.2. As illustrated by Figure 3.2, Load A is generally preferred to be run in the morning, whereas Load B is generally preferred during the early afternoon, followed by Load C during the early to late evening.

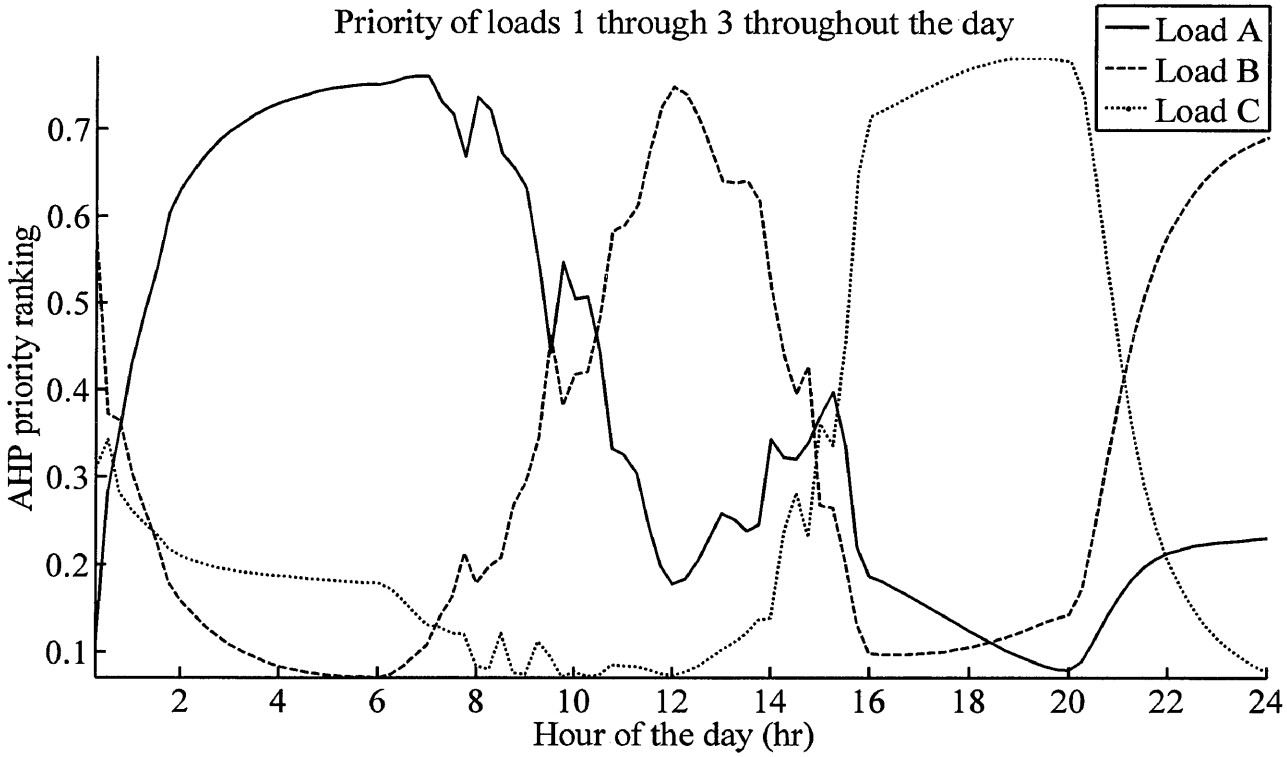

Figure 3.2 Priority of loads A, B, and C throughout the day.

Loads A, B, and C are residential and assumed to have approximate runtimes of 45min, 60min, and 75min, respectively. As such, in order to determine when the load should be scheduled, a moving average is calculated for each load with a window the size of the individual load runtime. The moving average implemented is the sum of the priorities within the window during the load runtime divided by the load runtime, calculated throughout the day. The moving average is calculated because the loads are not being run intermittently, but continuously for their runtime.

Thus, the best time to schedule each load is when the priority is highest over the window of time for which each load will run. Figure 3.3 shows the priorities and moving averages of Loads A, B, and C with respect to their runtimes.

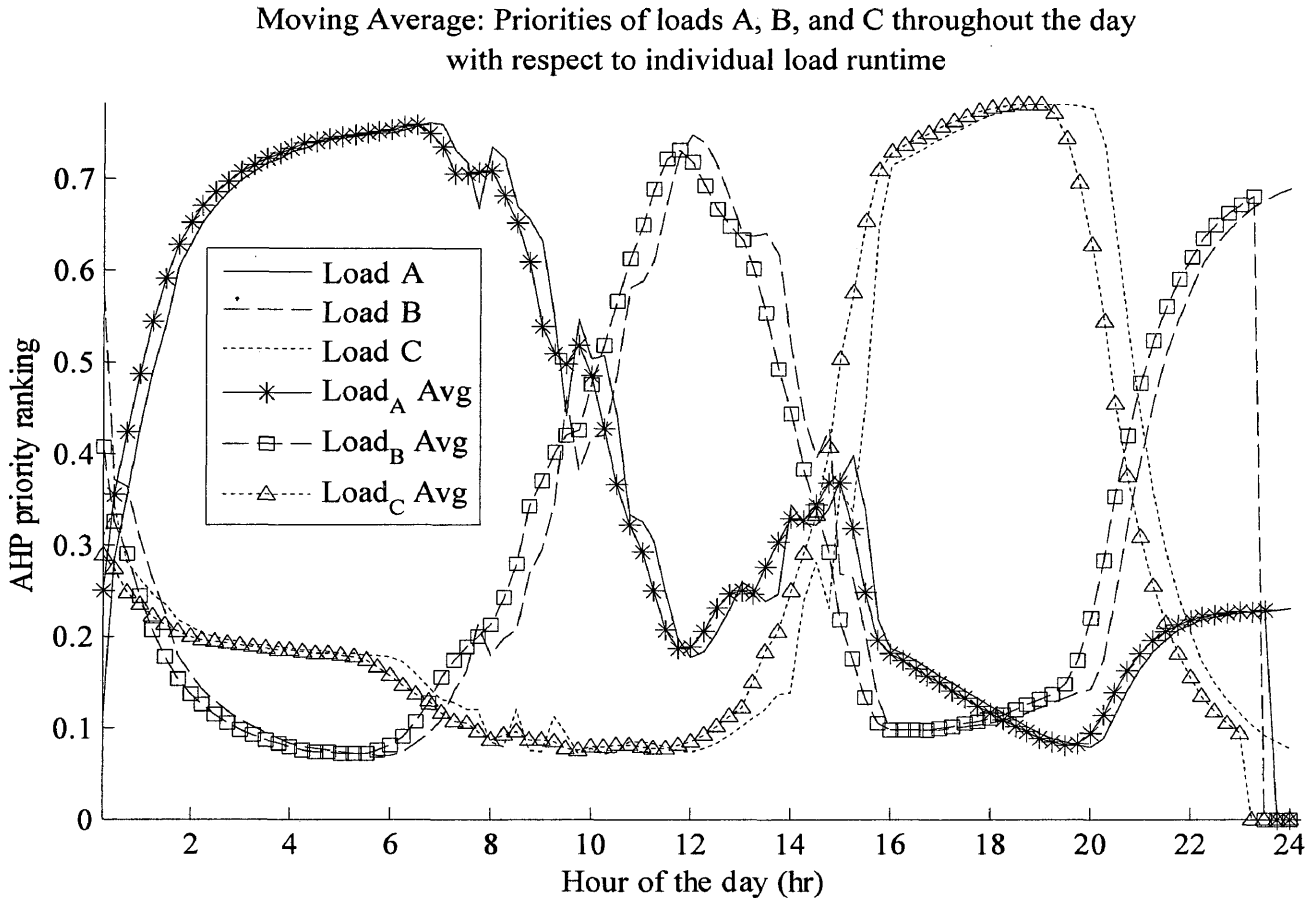

Figure 3.3 The original priorities and moving average of priorities of loads A, B, and C throughout the day with respect to individual load runtime.

Each load will be scheduled according to its maximum moving average priority value. If the maximum occurs during peak pricing hours, the load is scheduled at the next highest maximum outside of the peak pricing range. For this example, it is assumed that peak pricing occurs from 1600-1900 daily. The maximum moving average priority for Loads A, B, and C occur at 0630, 1145, and 1845, respectively. However, Load C cannot be scheduled at 1845 because it coincides with peak pricing, thus Load C should be scheduled at 1915. The day's load profile, consisting of the base and scheduled load appears as in Figure 3.4 and is stated explicitly in Table 3.11.

The LSM is adaptable to customer needs and criteria, as well as having a wide range for residential, commercial, and industrial applications. The most important feature of this LSM is its flexibility with respect to its application and the ability of the preferences of the customer to be

included in load scheduling. The LSM presents a method for DSM, and incorporates customer participation in the Smart Grid, as part of the Smart Grid Initiative [5]. The following chapter 4 presents an energy management system for further including customer preferences and participation in the operation of a customer-owned DER installation.

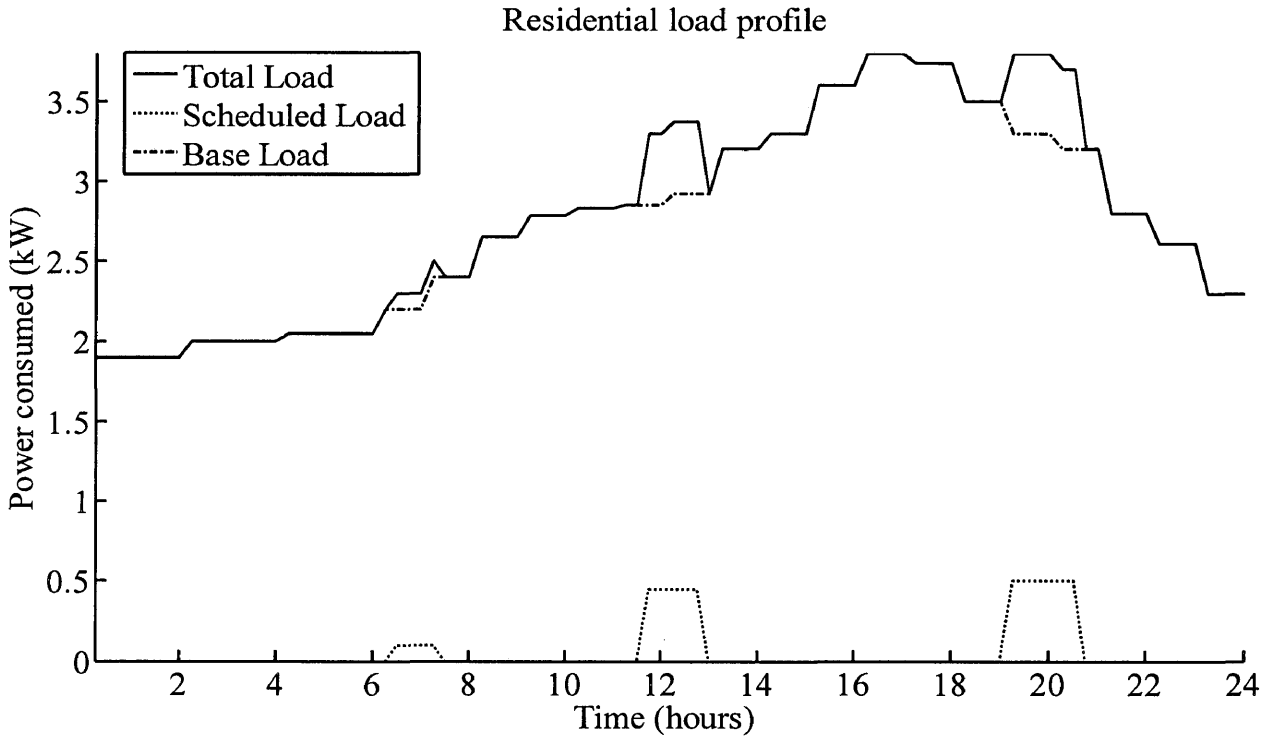

Figure 3.4 Residential load profile.

Table 3.11 Base, scheduled, and total load for the 24 hr period. All loads are represented in kWh.

Hour	Total Load	Scheduled Load	Base Load	Hour	Total Load	Scheduled Load	Base Load
0025	1.90	0.00	1.90	1225	3.37	0.45	2.92
0050	1.90	0.00	1.90	1250	3.37	0.45	2.92
0075	1.90	0.00	1.90	1275	3.37	0.45	2.92
0100	1.90	0.00	1.90	1300	2.92	0.00	2.92
0125	1.90	0.00	1.90	1325	3.20	0.00	3.20
0150	1.90	0.00	1.90	1350	3.20	0.00	3.20
0175	1.90	0.00	1.90	1375	3.20	0.00	3.20
0200	1.90	0.00	1.90	1400	3.20	0.00	3.20
0225	2.00	0.00	2.00	1425	3.30	0.00	3.30
0250	2.00	0.00	2.00	1450	3.30	0.00	3.30
0275	2.00	0.00	2.00	1475	3.30	0.00	3.30
0300	2.00	0.00	2.00	1500	3.30	0.00	3.30
0325	2.00	0.00	2.00	1525	3.60	0.00	3.60
0350	2.00	0.00	2.00	1550	3.60	0.00	3.60
0375	2.00	0.00	2.00	1575	3.60	0.00	3.60
0400	2.00	0.00	2.00	1600	3.60	0.00	3.60
0425	2.05	0.00	2.05	1625	3.80	0.00	3.80
0450	2.05	0.00	2.05	1650	3.80	0.00	3.80
0475	2.05	0.00	2.05	1675	3.80	0.00	3.80
0500	2.05	0.00	2.05	1700	3.80	0.00	3.80
0525	2.05	0.00	2.05	1725	3.74	0.00	3.74
0550	2.05	0.00	2.05	1750	3.74	0.00	3.74
0575	2.05	0.00	2.05	1775	3.74	0.00	3.74
0600	2.05	0.00	2.05	1800	3.74	0.00	3.74
0625	2.20	0.00	2.20	1825	3.50	0.00	3.50
0650	2.30	0.10	2.20	1850	3.50	0.00	3.50
0675	2.30	0.10	2.20	1875	3.50	0.00	3.50
0700	2.30	0.10	2.20	1900	3.50	0.00	3.50
0725	2.50	0.10	2.40	1925	3.80	0.50	3.30
0750	2.40	0.00	2.40	1950	3.80	0.50	3.30
0775	2.40	0.00	2.40	1975	3.80	0.50	3.30
0800	2.40	0.00	2.40	2000	3.80	0.50	3.30
0825	2.65	0.00	2.65	2025	3.70	0.50	3.20
0850	2.65	0.00	2.65	2050	3.70	0.50	3.20
0875	2.65	0.00	2.65	2075	3.20	0.00	3.20
0900	2.65	0.00	2.65	2100	3.20	0.00	3.20
0925	2.78	0.00	2.78	2125	2.80	0.00	2.80
0950	2.78	0.00	2.78	2150	2.80	0.00	2.80
0975	2.78	0.00	2.78	2175	2.80	0.00	2.80
1000	2.78	0.00	2.78	2200	2.80	0.00	2.80
1025	2.83	0.00	2.83	2225	2.61	0.00	2.61
1050	2.83	0.00	2.83	2250	2.61	0.00	2.61
1075	2.83	0.00	2.83	2275	2.61	0.00	2.61
1100	2.83	0.00	2.83	2300	2.61	0.00	2.61
1125	2.85	0.00	2.85	2325	2.30	0.00	2.30
1150	2.85	0.00	2.85	2350	2.30	0.00	2.30
1175	3.30	0.45	2.85	2375	2.30	0.00	2.30
1200	3.30	0.45	2.85	2400	2.30	0.00	2.30

CHAPTER 4
HEURISTIC ENERGY MANAGEMENT TECHNIQUE AND LP VERIFICATION

In light of the Smart Grid Initiative and RPS, it is apparent that customers that install DER would seek to attain optimal operational profits from the installation, while the utilities to which such customers connect may potentially use the DER installations for peak shaving [11]. In another avenue of the Smart Grid Initiative, several computer firms have embarked on developing home energy management software for consumers [61, 62]. Such smart applications are expected to provide timely information and possibly control options to the customer that has installed a smart appliance or a DER in their facility. Smart applications may be fitted with intelligent algorithms for optimal operation of the customer owned DER so as to realize an economic profit by trading services with the utility grid. Other DER application avenues include performing least cost optimizations through Lagrangian optimization [11], and LP [39]. However, developing an operational algorithm for a DER installation that maximizes the profit of the consumers makes the idea of Smart Grid more attractive. It is in this area that the scope for intelligent systems such as agent technology appears attractive. The technique described in this thesis differs from the work in [11] in incorporating a heuristic technique for customer-driven scheduling and considering the trade of reactive power in addition to real power with the grid. In that regard, this thesis will address an economic and customer-driven approach for scheduling the operation of a DER installation – a roof top PV set up interfacing the grid through a 'smart' inverter and associated energy storage [29].

The scope of this thesis does not include the design, topology, and operation of the smart inverter itself, which is described in [28]. This chapter focuses on a heuristic technique for scheduling the operation of the smart inverter, realizing an economic profit from the customer-owned DER installation. It is pertinent to note that the work described in the following sections relates to the following points of the Smart Grid Initiative: deployment and integration of DER including renewable sources, DSM, deployment of smart technologies, the incorporation of energy storage and peak-shaving technologies, and the ability of consumers to access usage data and have subsequent control options. It is envisioned that the heuristic scheduling technique – or its evolved version – will function as the intelligence of the control systems used in home energy management.

4.1 Enabling Technologies

In order for the developed technique to function at the highest level, several enabling technologies must be present, and concomitantly, some necessary assumptions have been made for the purposes of the work described in this thesis. Prior to listing the enabling technologies, it is imperative to define the term 'customer-driven' as it pertains to DER. Reference [63] describes 'customer-driven' as an electric power distribution system in which the

> customers install utility compatible generation sources in their homes or facilities; each such distributed resource is an autonomous agent with characteristics that include economic, technical and social responses to system generated signals. Economic responses involve a willingness to generate more (or consume less) in response to a signal, to be willing to supply reactive power, or to participate in frequency regulation. Technical responses of this agent include safe startup and shutdown, while social response involves proper operation under islanded conditions.

The developed heuristic scheduling technique relies specifically on the customer's response to economic signals. However, in order to fully realize customer-driven DER, some enabling technologies must first evolve into practice.

The enabling technologies for the customer-driven DER include: a) necessary enhancements to the existing distribution system, including higher voltage level interconnects, transitioning from a primarily radial distribution topology to meshed topology, and an accompanying adaptive protective system that can handle bidirectional power flows; b) the existence of a market structure that recognizes the DER installation as a fully participating entity; c) the progression toward standards for operation of DER that do not preclude the DER from providing voltage support at the point of common coupling (PCC) (the safety consideration of existing standards such as the IEEE Standard 1547 in disallowing such an operation in current times is acknowledged [64]); d) the proliferation of 'smart' power electronic devices and agent-like control technology for incorporating local control and intelligence to DER; e) the availability of prognostic information on weather conditions, dynamic pricing of electricity, load management; and f) the ubiquitous installations of smart meters interacting with the grid via HAN [65]. The customer-owned DER installation interfacing the grid through a 'smart' inverter [29] – which is considered as an ideal candidate for implementing the heuristic scheduling technique described in this thesis – adheres to the above definition of a customer-driven DER. For completeness, a brief description of the residential DER installation that uses the 'smart' inverter from [29] is provided.

4.2 Customer-Driven DER Test System

The customer-driven DER installation test system developed in [29] serves to interface a PV array to the grid through a 'smart' inverter and local energy storage. The test system is also comprised of a residential load (which is partitioned into high priority and non-critical loads), a smart meter, and appropriate interconnections with the utility grid. The non-critical loads are available for the AHP-based LSM, while the high priority loads constitute the portion of the load that must be served at all times. A block diagram of the test system is shown in Figure 4.1 [29].

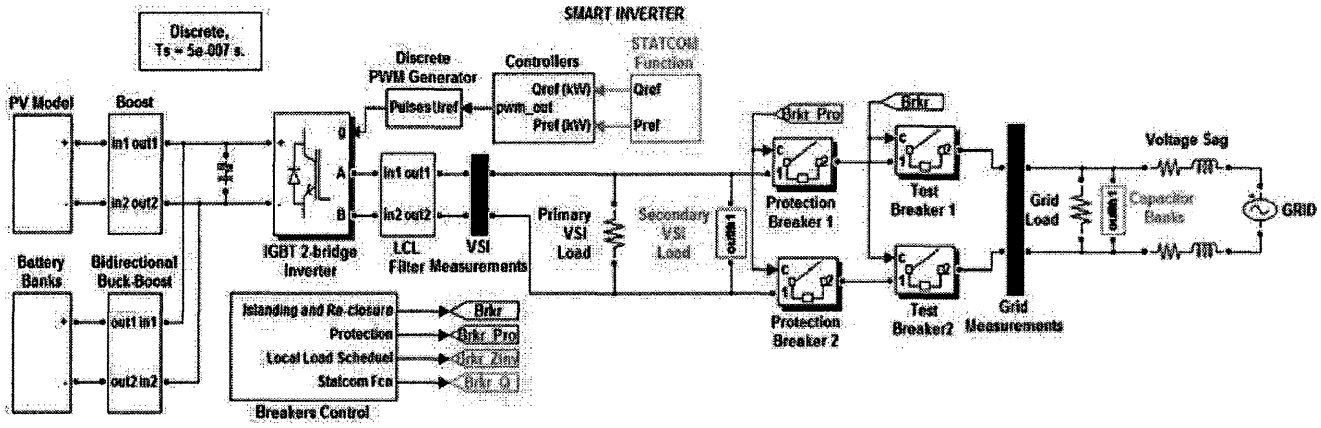

Figure 4.1 Block diagram of customer-driven DER test system using 'smart' inverter [29].

The PV array, modeled in [29] is assumed to connect to the 'smart' inverter through a DC-DC converter which outputs a constant DC voltage of 350 V. The PV array is assumed to have a surface array of $40m^2$, with a constant efficiency of 12%. The PV array size was chosen such that the array could fit on a residential rooftop, with a typical efficiency. The solar irradiance is assumed to be constant over the entire PV array. The voltage source inverter in [29] is rated at 5 kVA, 120 V, single phase 60 Hz AC and is characterized as 'smart' because it has the ability to regulate the voltage at the PCC, supply local load as well as utility loads, and incorporate customer preferences in control [29].

For the study described in this thesis, a lead-acid battery energy storage system rated at 260 Ah is assumed to be associated with this customer-driven DER test system. The battery bank was sized using [66], with a modification for autonomy measured in hours as opposed to days. The maximum power demand on the battery at any given time is 5 kW, and the battery bank must be of sufficient size that it can supply the load at maximum demand for at least 4 hrs according to [67]. The depth of discharge has been assumed to be 40%. The connecting voltage of the battery bank is 192 V according to the model in [29], so that the appropriate battery size was determined using (4.1):

$$\frac{5kW * 4hrs}{.4 * 192V} = 260Ah \tag{4.1}$$

A lead acid battery bank containing 32 batteries connected in a string (in series) each having a 6 V terminal voltage, and a capacity of 260 Ah is appropriate, such that the battery bank voltage is 192 V.

For applications where the battery is exposed to low ambient temperatures, the battery capacity must be appropriately derated. According to (4.1) the proper capacity is 260 Ah when assuming the lowest temperature the battery will be exposed to is 80° F, such that the battery has been derated by a factor of 1.0 [66]. However, if the battery will be exposed to lower temperatures, for instance 40-50° F, the battery would have to be derated by a factor between 1.19-1.30 [66]. Assuming a derating factor of 1.20, the minimum battery capacity would be $260Ah \times 1.20 = 325Ah$. An example of a 325 Ah battery suitable for this renewable application is the Trojan L16RE-A flooded deep cycle battery [68]. This model battery has a terminal voltage of 6 V, such that 32 batteries would be connected in series, each battery having the dimensions 295 cm x 178 cm x 450 cm, a battery bank that could easily fit in a residential and/or commercial application. The total size of the battery bank if configured as a stack two batteries high, with two rows of eight batteries in each level would be approximately 2.36 m x .356 m x .9 m.

The test system in [29] features a controller that can switch the mode of operation between grid connected and isolated – by employing current control and voltage control, respectively – and specifies real and reactive power outputs based on reference points of operation. For running the scheduling technique the test system is assumed to possess an intelligent LEMS [35], which performs the task of setting the necessary operating points and communicating with it on an hourly basis to the controller of the test system. The input data to the LEMS may include up-to-date information on parameters such as battery state of charge, residential loading forecast, weather information (specifically the solar irradiance for this test system), net energy flow measurements, and the hourly energy prices for real and reactive power as communicated by the utility. A conceptual block diagram of the paths for energy flow and communication flow assumed in the customer-driven DER test system is shown in Figure 4.2.

In alignment with the evolving home energy management schemes, it is contended that this information flow within the customer-driven DER installation may be available for customer access via a dedicated account on a communication network (i.e., HAN). The information may pertain to inverter settings, and the inputs (forecasting, real time pricing from utility, smart meter readings), and an hourly breakdown of the operational profit made in a 24 hour period.

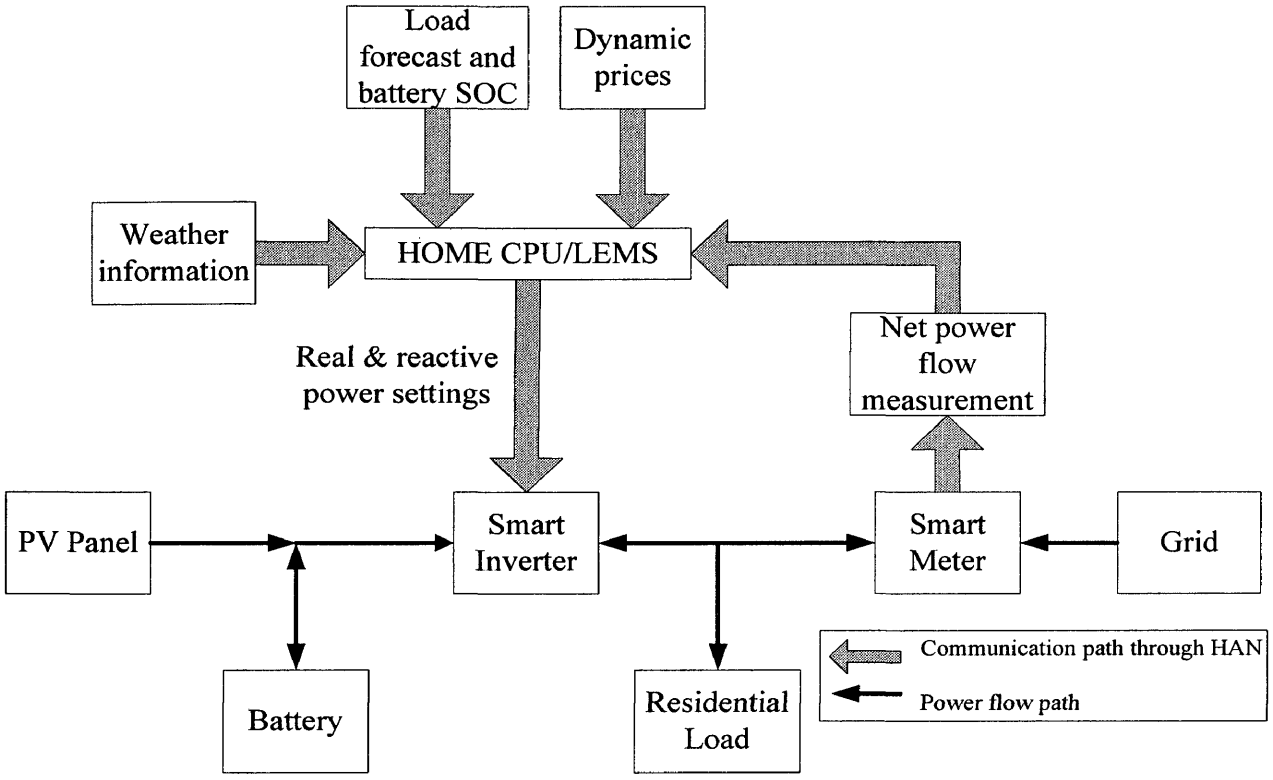

Figure 4.2 Assumed DER installation communication and power flow paths [35].

4.3 Heuristic Energy Management Scheduling Technique

The heuristic scheduling technique is designed to run once every 24 hours using the forecasted information for the following day. The objective of this heuristic scheduling technique is to drive the operation of the residential DER toward a region of operational profit through user inputs – thus contributing to the customer-driven nature of the DER installation. The heuristic scheduling technique is viewed as a framework for incorporating further intelligence to the LEMS for managing the customer-driven DER.

Operating set points are established on an hourly basis and communicated to the 'smart' inverter. The set points include the quantity of real and reactive power to export to the grid, and/or to purchase from the grid. The technique also outputs the quantity of real power that is bought from the grid for storage, as it is assumed that all PV input is stored to the battery. Furthermore, the technique establishes the quantity and type of power (real or reactive) that is used directly from storage to supply power to the local load, and/or the utility.

It is assumed that information such as daily set points, expected profits, and overall system information can be accessed by the consumer through the LEMS which may be run on a personal

computer [61]. At this point, the consumer has the option of changing future system set points based on individual preferences. Assumptions have been made that include full accuracy and availability of 24-hr forecasts of solar irradiance, TOU pricing for real and reactive power, and residential loading information. It is assumed that the price to buy either real or reactive power is the same as the price to sell. The utility grid is further assumed to have an infinite demand such that the supply from the local DER is always bought by the grid and the system investment recovery corresponding to the capital cost is not considered. The focus of this heuristic technique is placed on maximizing the daily operational profit of the customer-driven DER installation.

4.3.1 Description of Zones

The technique divides a 24 hr block into four zones. PV scheduling has previously been based on solar insolation levels, the availability of energy storage, and system loading, [11], [37]. However, in this thesis the delineation of the zones is made by a customer-established minimum and maximum price threshold for electricity that is bought and sold. The customer established minimum (P_{min}) is the maximum price the customer is willing to pay to the utility to supply their own storage. P_{max} is the maximum price the customer is willing to pay for electricity supplied from the utility. All rates that fall below the minimum threshold pertain to Zone 1; Zone 2 is defined by hours where the rates fall above P_{min} and below P_{max}. Zone 3 occurs for all hours where the rate is above P_{max}. Zone 4 is different in that it occurs after Zone 3, where the pricing signal is declining by the hour.

A pricing signal is used as the driving function of the heuristic scheduling technique. The pricing signal is generated by comparing the price of real and reactive power for each hour, where the greater value forms the pricing signal. The price of real and reactive power for the example shown in this thesis is synthetic data that mirrors a residential demand profile. Figure 4.3 illustrates the price signal formed by P_{min} = \$0.20 and P_{max} = \$0.37, while Figure 4.4 shows how the price signal forms the zones used in the heuristic scheduling technique.

4.3.2 Zonal Operation

For the following description of the heuristic technique based on zones of operation, it is assumed that the customer has chosen a maximum depth of discharge (MDD) in line with the battery manufacturer's specifications, in order to protect the life of the battery [40]. To further protect the life of the battery the charging rate of the lead acid battery was limited based on the SOC, such that the battery charges more slowly as the SOC approaches 100%.

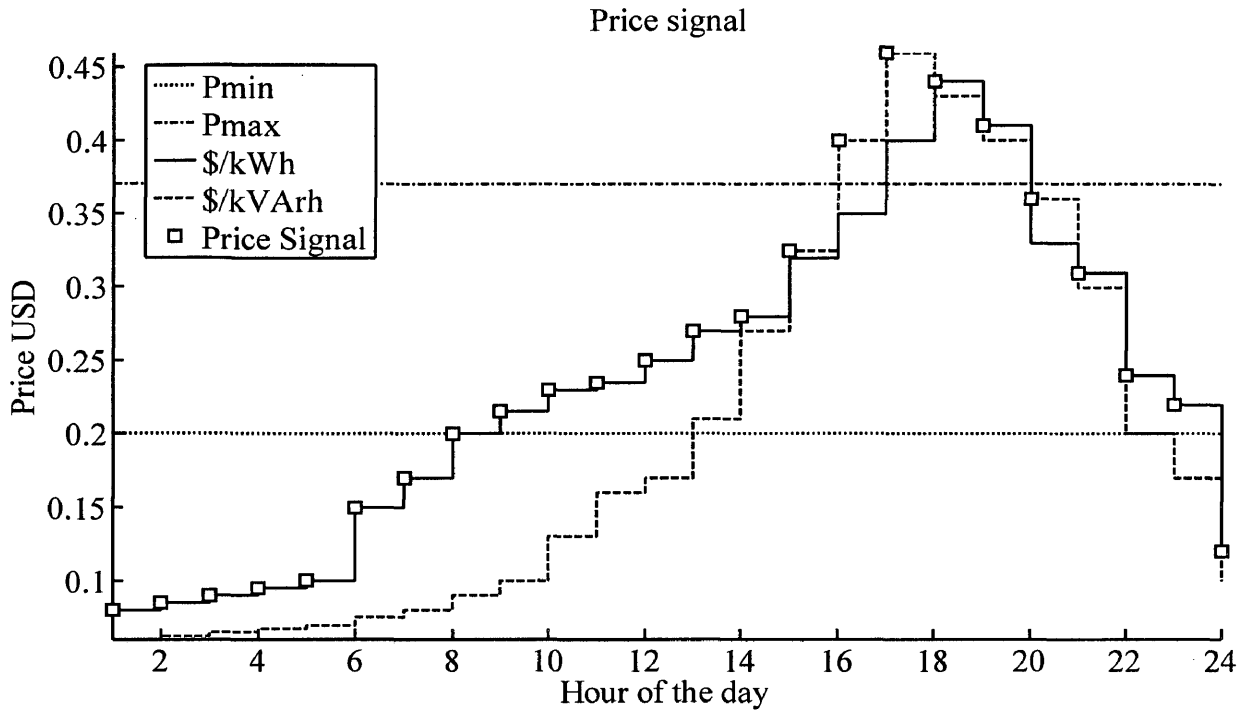

Figure 4.3 Price of real and reactive power over a one day period, with price signal.

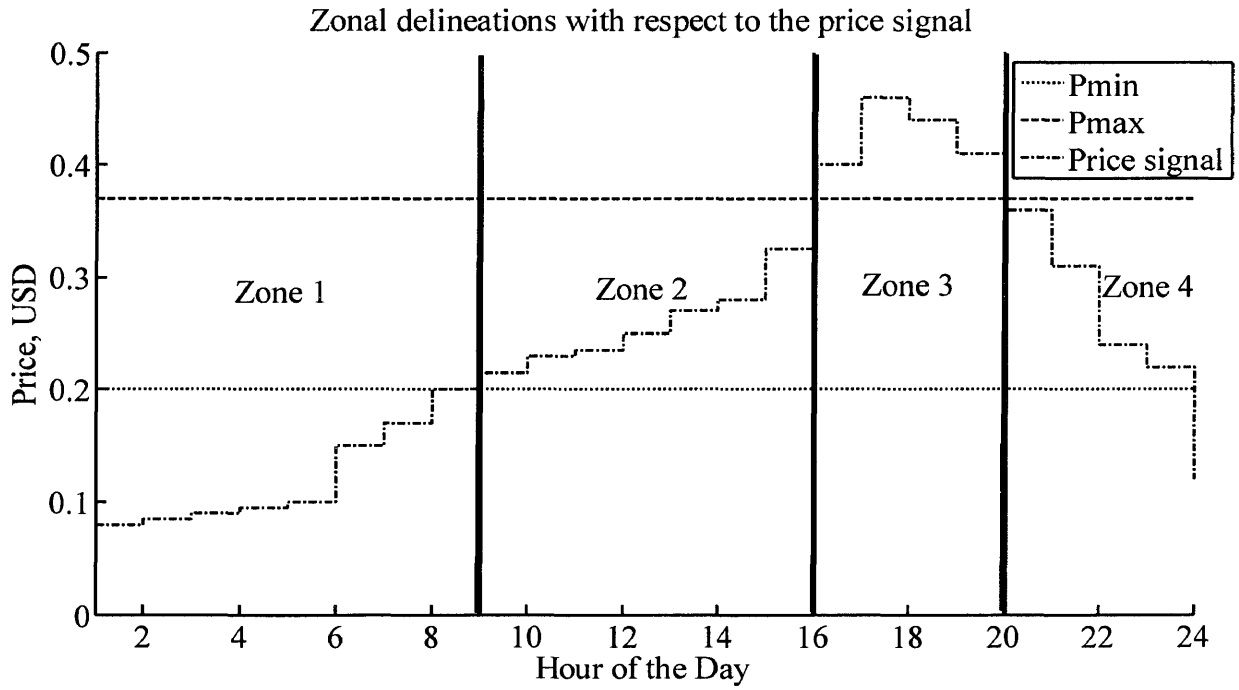

Figure 4.4 Pricing signal delineating zones of heuristic technique.

In *Zone 1*, the operation of the test system is defined by using the available PV input, if any, and scheduling electricity purchase from the grid in order to supply the local load. Moreover,

electricity is purchased from the grid in order to charge the battery to 100% during this zone. Nothing is scheduled to be sold from the customer installation to the grid during this zone.

Zone 2 typically occurs from late morning to early afternoon, such that greater solar irradiance levels are experienced during Zone 2 than in Zone 1. The goal during this zone is to maintain 100% SOC, therefore using the immediately available PV input to supply the local load. If there is not enough immediate PV input to supply the local load fully, then the difference is scheduled to be purchased from the grid. The battery is forced to remain at 100% SOC during this zone, so that it can be utilized in the most expensive zone, Zone 3.

In *Zone 3*, when the electricity prices are high (according to rate based on time of use model), the first priority of the technique is to supply the local load completely using the PV input (if available) and through the use of the battery. Once the local loads have been supplied, the remaining energy available from the battery is scheduled to be sold at the most expensive hour to a maximum of 5 kVAh, using the method shown below. This continues at descending prices until the SOC has reached its MDD. At this point no further sale of electric energy from the customer-driven DER is scheduled. In the case that the SOC reaches the customer pre-established MDD before the local load for each hour is supplied, then the heuristic method will require the battery to serve the local load in line with the decision of the customer to not purchase electricity at a price greater than P_{max}. The greatest priority will be given to the hour with the greatest cost for supplying the local load, and so forth in decreasing priority until the SOC reaches MDD. After the battery has been depleted to its minimum MDD, then the local load for the remaining hours will be served from the grid, and there is no more local energy available to sell during this day's operation.

Zone 4 typically follows Zone 3, when the pricing signal hits the P_{max} threshold on the descent. It is fair to assume that the SOC at the start of Zone 4 is most likely depleted to the MDD. However, if there is any more energy available for supply in this zone, it is scheduled to be used during the most expensive hour in Zone 4; this is progressively performed until the SOC reaches its MDD. Afterwards, the local load is fully supported by electricity purchased from the grid, and nothing is scheduled for sale during the remainder of Zone 4. As the pricing signal crosses the P_{min} threshold on the descent, the heuristic technique resets to a new cycle beginning at Zone 1.

In order to determine how much real and reactive power to sell during any given hour with maximum profit, the corresponding amount of reactive power with respect to each possible real power setting is determined using (4.2). Equation 4.3 is used to determine the possible real power

settings according to the amount of real power necessary to supply the local load, given a load power factor of 1.0.

$$S = \sqrt{P^2 + Q^2} \tag{4.2}$$

$$S = \sqrt{(P + Z_{inv})^2 + Q^2} \tag{4.3}$$

The profit for each P-Q combination is calculated, and the real and reactive power set points corresponding to the maximum profit are used. As an example, suppose that the local load demand is 3.5 kW. The maximum value available to supply is 5 kVA, as limited by the maximum flow through the inverter. In order for (4.4) to be satisfied, the real power available to sell is constrained between 0 and 1.5 kW. Knowing the possible values for P, the limits on reactive power are placed between 0 and 3.49 kVAr. The profit for each possible P and Q set point is determined with respect to the individual P and Q prices, and the set points corresponding to the maximum profit are used. In this example, the maximum profit is attained when the set points for P and Q are 0.08 kW and 3.49 kVAr, respectively.

$$5 = \sqrt{(P + 3.5)^2 + Q^2} \tag{4.4}$$

4.4 Illustrative Case Studies

The following case studies represent the operation of the heuristic scheduling technique when the DER installation has the following characteristics:

1. Only real power exchanged with the grid
2. No available PV input, real and reactive power exchanged with the grid
3. PV input, real and reactive power exchanged with the grid

All case studies are carried out on the test system described in section 4.2, with the same TOU pricing and loading profile such that comparisons can be made across all three case studies. Case studies 1-3 were programmed in Matlab 7.6.0 (r2008a) and are available in the electronic appendix; see the Appendix for more information.

4.4.1 Case Study 1: Only Real Power Exchanged with the Grid

This case study illustrates the performance of the DER installation when the system can only buy and sell real power. The available power from the DER and the synthetic loading profile is seen in Figure 4.5. The solar irradiance data presented is for Golden, CO on July 4th, 2005 [69], and is explicitly given in Table 4.1. In this case, there is no reactive power pricing, such that the pricing signal and delineations of the zones are determined by the price of real power and the customer-preferences for P_{min} and P_{max}, illustrated by Figure 4.6. Furthermore, the maximum possible charging capacity for the battery bank in the system is not limited as the SOC approaches 100%, and the MDD for the battery has been established at 60%.

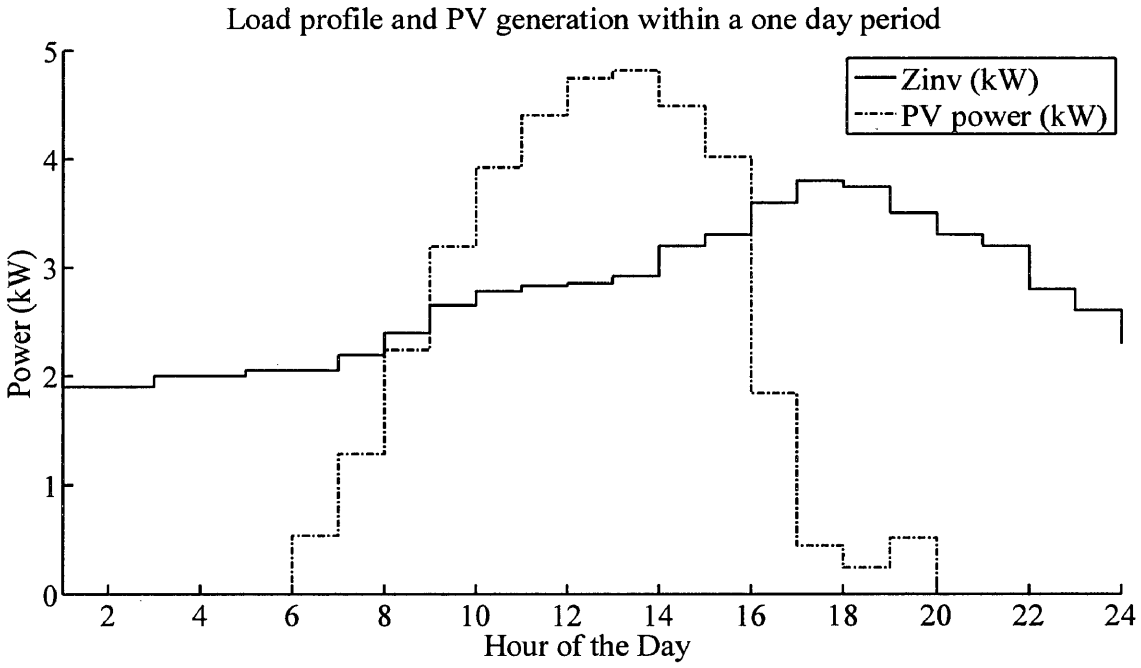

Figure 4.5 Load profile and PV power availability for case study 1.

Table 4.1 Solar irradiance data for July 4th, 2005 in Golden, CO according to [69].

Hour of Day	1	2	3	4	5	6	7	8	9	10	11	12
Wh/m^2	0	0	0	0	0	112	268	466	665	817	918	989
Hour of Day	13	14	15	16	17	18	19	20	21	22	23	24
Wh/m^2	1004	935	838	384	93	51	108	0	0	0	0	0

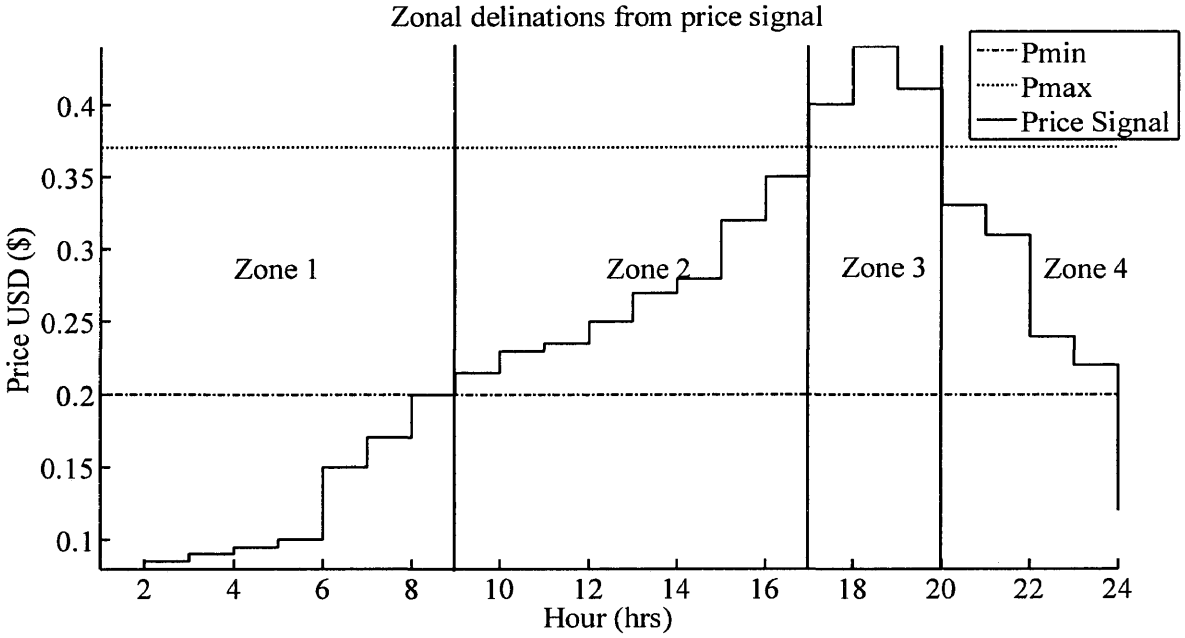

Figure 4.6 Pricing signal over a one day period when only buying/selling real power for case study 1.

The performance of the energy management technique when only buying and selling real power is as shown in Figure 4.7-8. From Figure 4.7 the battery is charged from the grid only within Zone 1, from 00:01 to 08:00. In the beginning of Zone 1, when the price of electricity is the least expensive, the battery is charged as quickly as possible, to a maximum of 5kVA during a one hour period, until reaching the SOC where the PV available during Zone 1 will finish charging the battery to 100%. At all times during Zone 1, the load is being supplied by the grid.

Figure 4.8 shows the amount of power purchased during Zone 1 in order to charge the battery, but in Zone 2 when the power input from the PV is greater than the load for the hour as illustrated by Figure 4.5, the excess is sold to the grid. During the last hour of Zone 2, the PV input is less than the load, such that the load must also be powered by the grid. In Zone 3, during the region of peak pricing, the heuristic energy management technique dictates that the local load be supplied first, and the remainder be sold to the grid when most profitable. Zone 4 begins at 20:00, and lasts until 24:00, such that the load is supplied fully by the grid, because the local storage SOC is at its MDD limit of 60%. The energy exchange and profit generated is shown in Table 4.2.

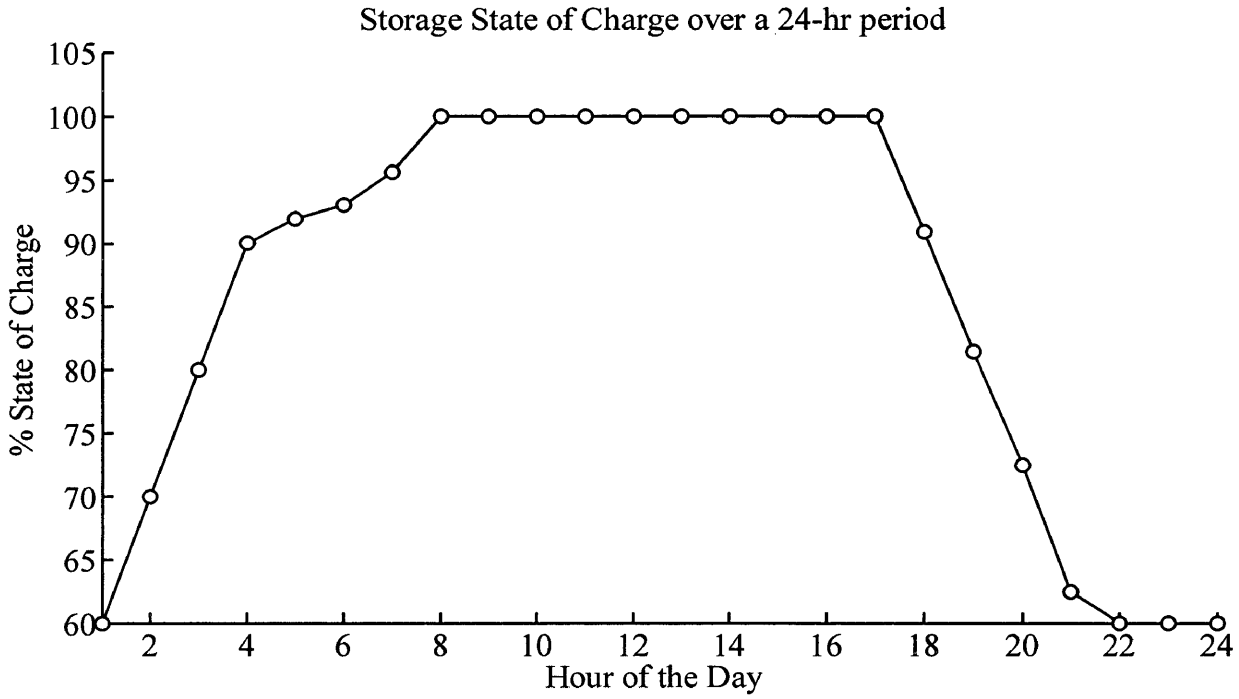

Figure 4.7 Storage SOC over a 24 hr period when only buying/selling real power for case study 1.

Table 4.2 shows a cost of $3.41 during Zone 1 that is incurred due to supplying the load from the grid, as well as charging the battery to 100% SOC. In Zone 2, there is a profit observed due to selling the excess PV generation available after supplying the load. Another profit is observed in Zone 3, because the battery is now being discharged to supply the local load, and any extra power available from the battery is then sold for the maximum profit until the battery reached the MDD. Within Zone 4, the price of electricity is falling, and the MDD was not reached in the previous Zone 3, such that 1.70 kWh was sold to the grid. The cost is incurred after the battery reaches MDD, where afterwards the load is supplied by the grid. For the 24 hr operation, when only being able to buy and sell real power, the total cost of operation is $1.63. For comparison, the cost for the 24 hr operation of this system without any energy management, storage, or PV array is $16.84.

4.4.2 Case Study 2: No Available PV Input, Real and Reactive Power Exchanged with the Grid

This case study represents the operation of the DER installation on a cloudy day, without any PV based generation. However, the DER installation is capable of purchasing and selling both real and reactive power. The price of real and reactive power is shown in Figure 4.9 below, with the subsequent price signal. The price signal and the customer established P_{min} and P_{max} define the zones

of operation. Zone 1 occurs from 00:00 to 08:59, Zone 2 begins at 09:00 until 15:59, Zone 3 from 16:00 to 19:59, and Zone 4 is from 20:00 until 23:59, as shown in Figure 4.10.

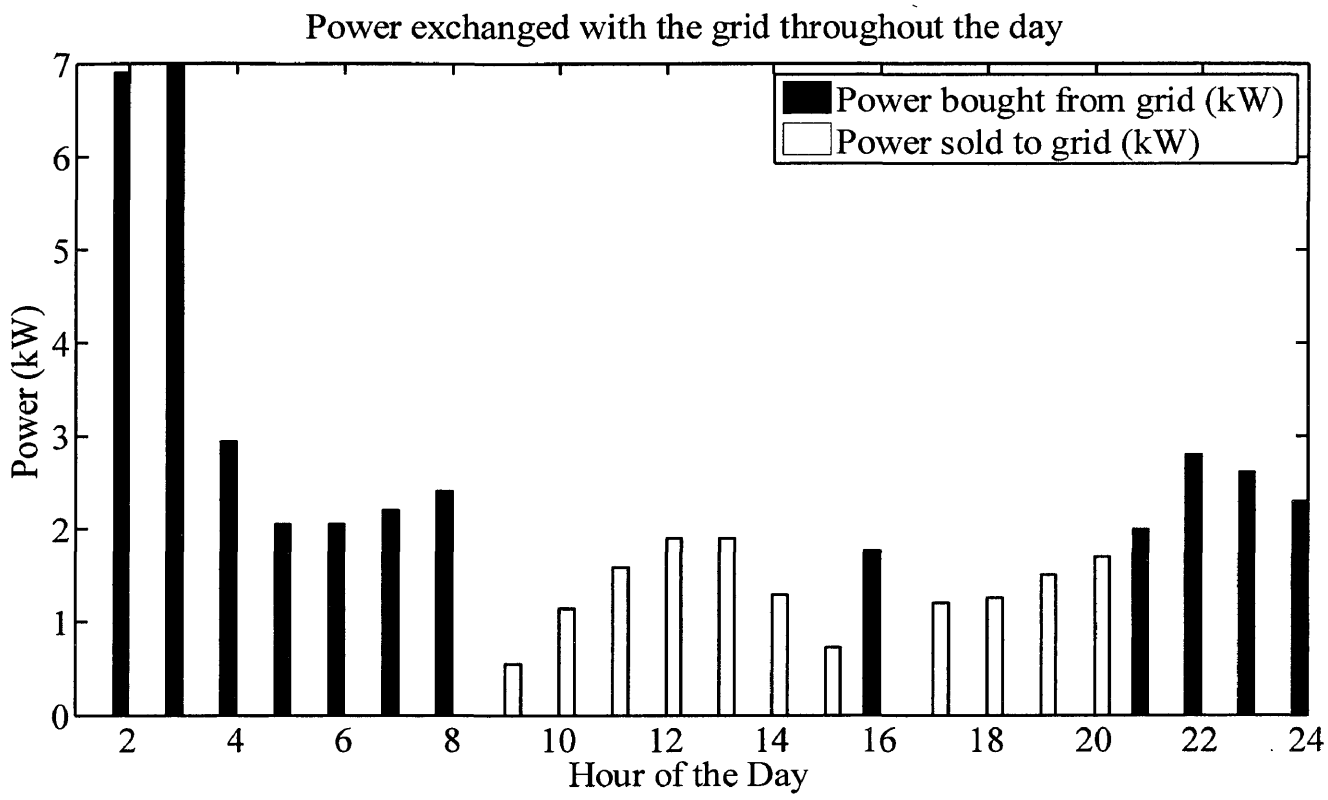

Figure 4.8 Real power exchanged with the grid for case study 1.

Table 4.2 Operation of DER installation for case study 1, where only real power is exchanged with the grid. A negative profit indicates a cost for that zone.

	PV input (kWh)	Energy bought from grid (kWh)	Energy sold to the grid (kWh)	Profit generated ($)
Zone 1	4.06	32.44	0.00	-3.41
Zone 2	31.44	1.76	9.07	1.71
Zone 3	1.21	0.00	3.96	1.65
Zone 4	0.00	9.70	1.70	-1.58
Total	36.71	43.90	14.73	-1.63

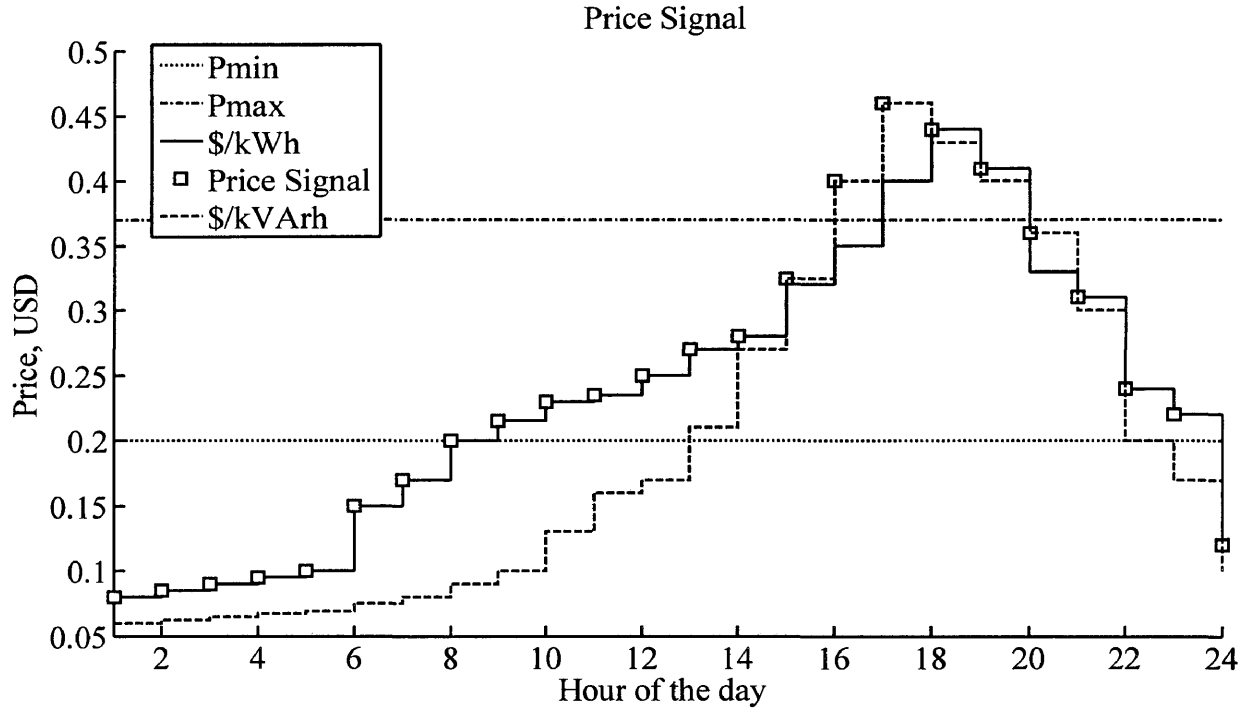

Figure 4.9 Price of real and reactive power, and price signal for 24 hr period for case study 2.

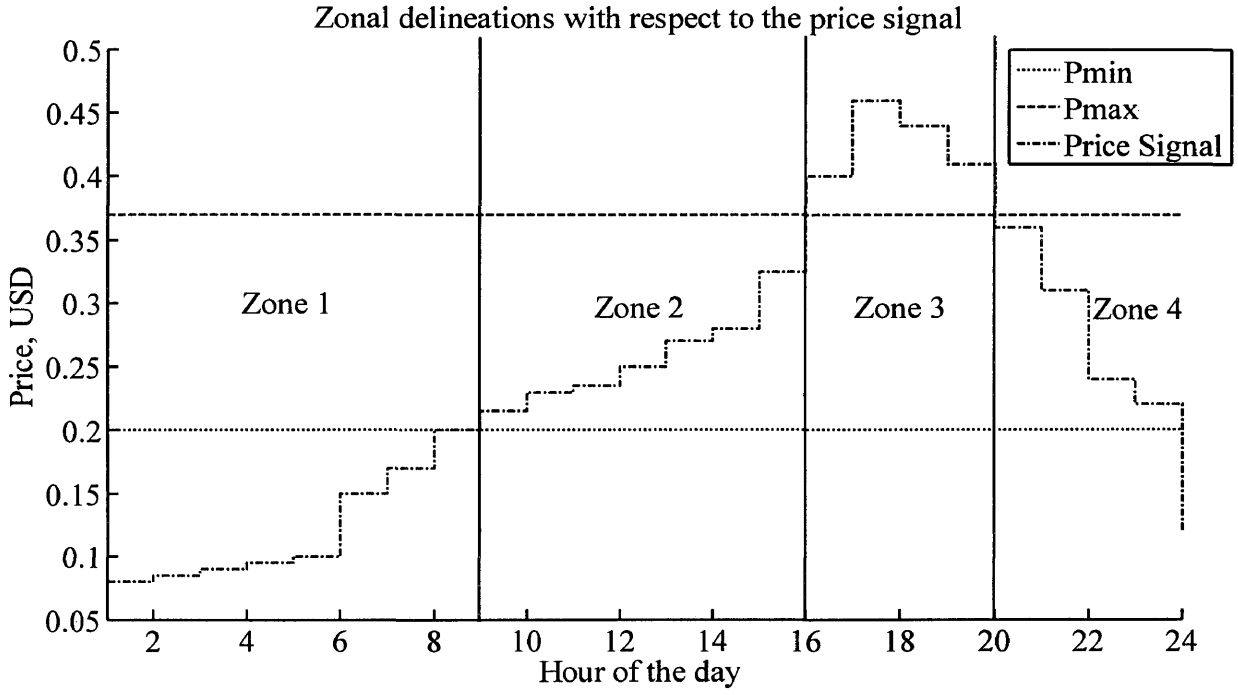

Figure 4.10 Price signal with zonal delineations for case study 2.

In order to protect the life of the battery, the maximum possible charging capacity for the battery bank in the system is limited, such that the battery is charged more slowly as its SOC

approaches 100%. Figure 4.11 is a synthetic representation of the limited charging capacity, as the specifications of the manufacturer are unique to the battery model. The MDD for the battery remains at 60% for this case study. The load profile for this case study remains unchanged from the previous case study 1, as seen by Figure 4.12, though there is no longer any power generated from the PV.

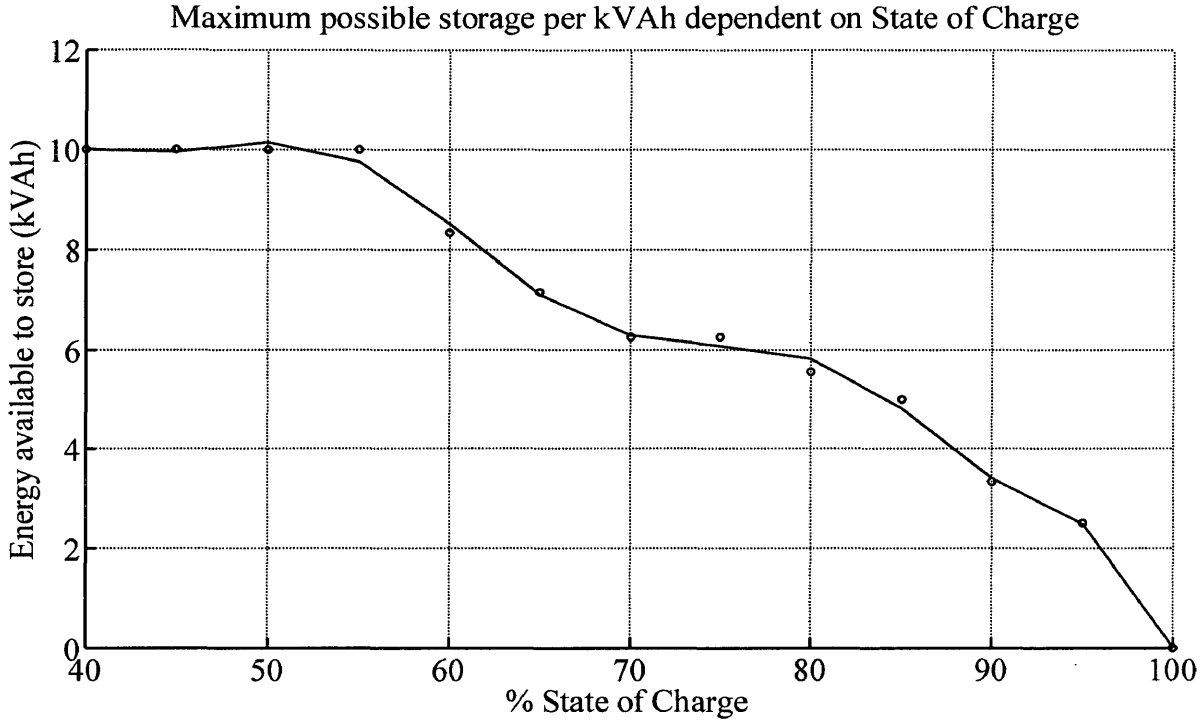

Figure 4.11 Limited storage charging capacity for case study 2.

The operation of the DER installation according to the heuristic scheduling technique is as follows when there is no PV generation. The battery SOC in Figure 4.13, and the power exchanged with the grid is shown in Figure 4.14. It is seen that the battery begins at its MDD of 60% at the beginning of the first hour of Zone 1, and is subsequently charged. Upon reaching full SOC, the battery is not discharged again until Zone 3, in order to supply the local load and sell anything extra to the grid. In Zone 2, there is no PV generation available, such that power is purchased from the grid in order to supply the load. Once the battery reaches the MDD at 60% at the end of Zone 3, the load is fully supplied from the grid until the end of the 24 hr period.

As illustrated in Figure 4.15, the amount of reactive power sold to the grid is significantly greater than the real power sold. This occurs because the local load is fixed and resistive. Thus, a greater amount of reactive power than real power is available without violating the maximum 5 kVA constraint.

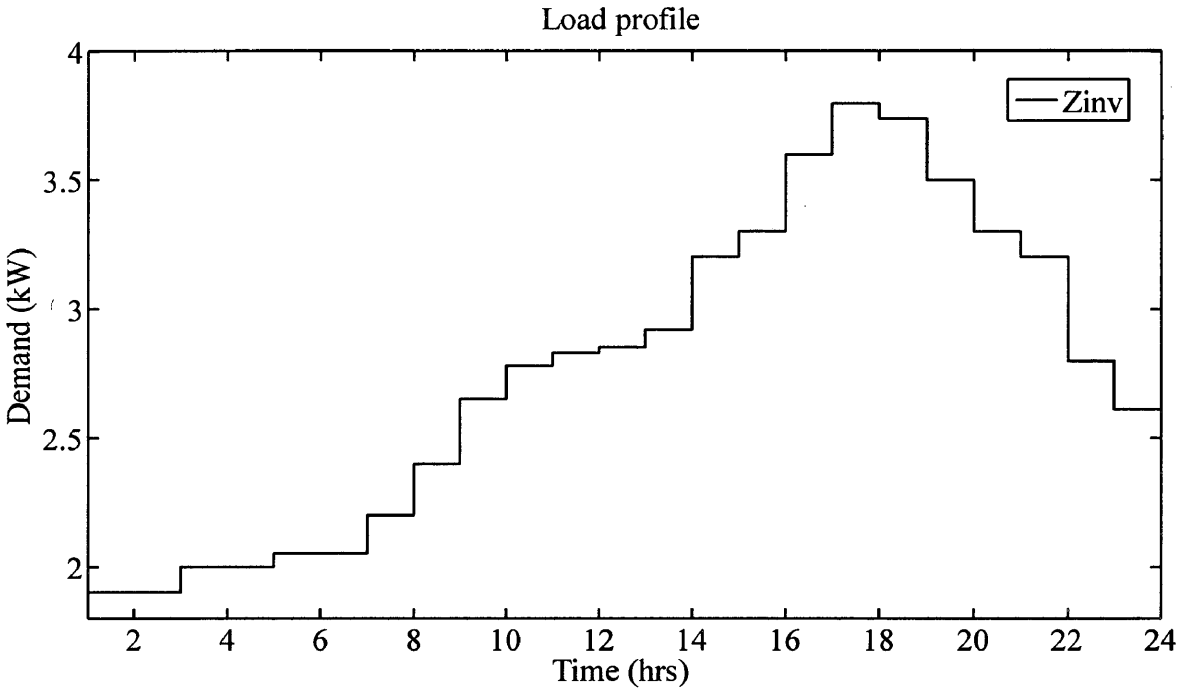

Figure 4.12 Load profile for case study 2.

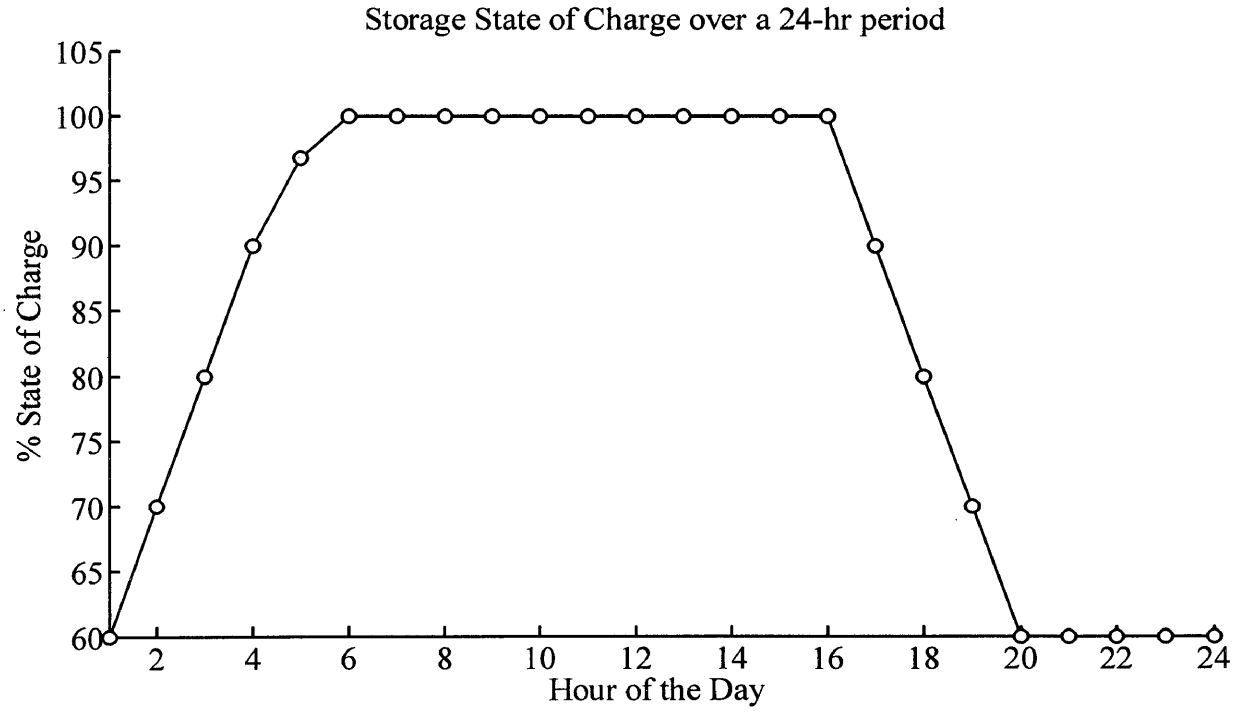

Figure 4.13 Battery SOC for a 24 hr period in case study.

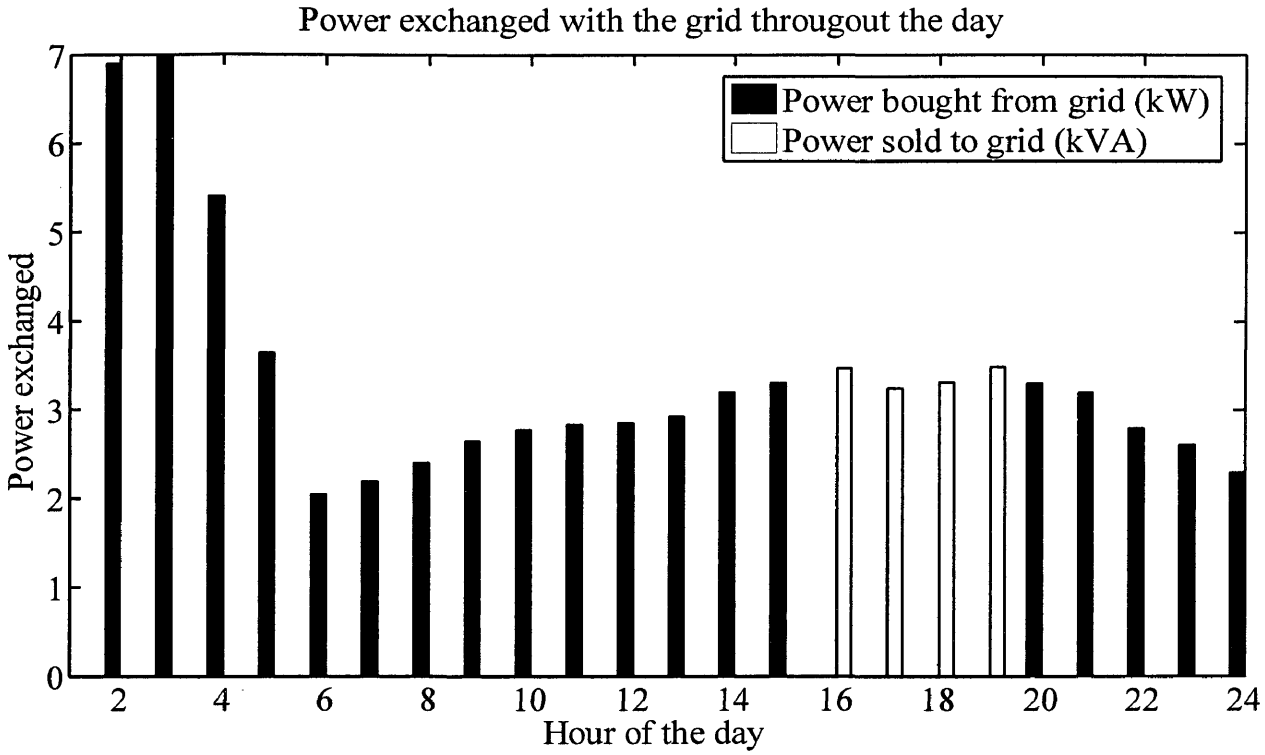

Figure 4.14 Comparison of power bought from and sold to the grid for case study 2.

Table 4.3 represents the operation of the DER installation according to the heuristic scheduling technique. The daily operating cost is $7.00. In Zone 1, the load is fully supplied by the grid, and the battery is being charged to 100%, according to the limited charging capacity curve. However, Zone 2 incurs a cost because there is no PV generation to supply the load or excess left to sell. Zone 3 is relatively unaffected by the lack of PV power input because there is normally very little to no solar irradiance by that time of day. In Zone 4 the load is completely supplied by the grid.

4.4.3 Case Study 3: PV Input, Real and Reactive Power Exchanged with the Grid

The following case study is for the DER installation on a sunny day, where the DER installation has the capability to import and export both real and reactive power. The solar irradiation levels are for Golden, CO, on July 4th, 2005, [69], and repeated from case study 1 for convenience in Figure 4.16 in addition to the load profile. The price of real and reactive power for the 24 hr period, and the pricing signal with zone delineations are shown in Figure 4.17-18, respectively.

The operation of the heuristic technique on the DER installation on a sunny day, when able to buy and sell, real and reactive power is shown by this case study. Figure 4.19 demonstrate that the battery SOC increases to full capacity within Zone 1, this was accomplished through a combination of

energy purchases early during Zone 1, followed by PV generation input towards the end of Zone 1. The battery SOC remains at 100% until the beginning of Zone 3, where it is steadily depleted to its MDD.

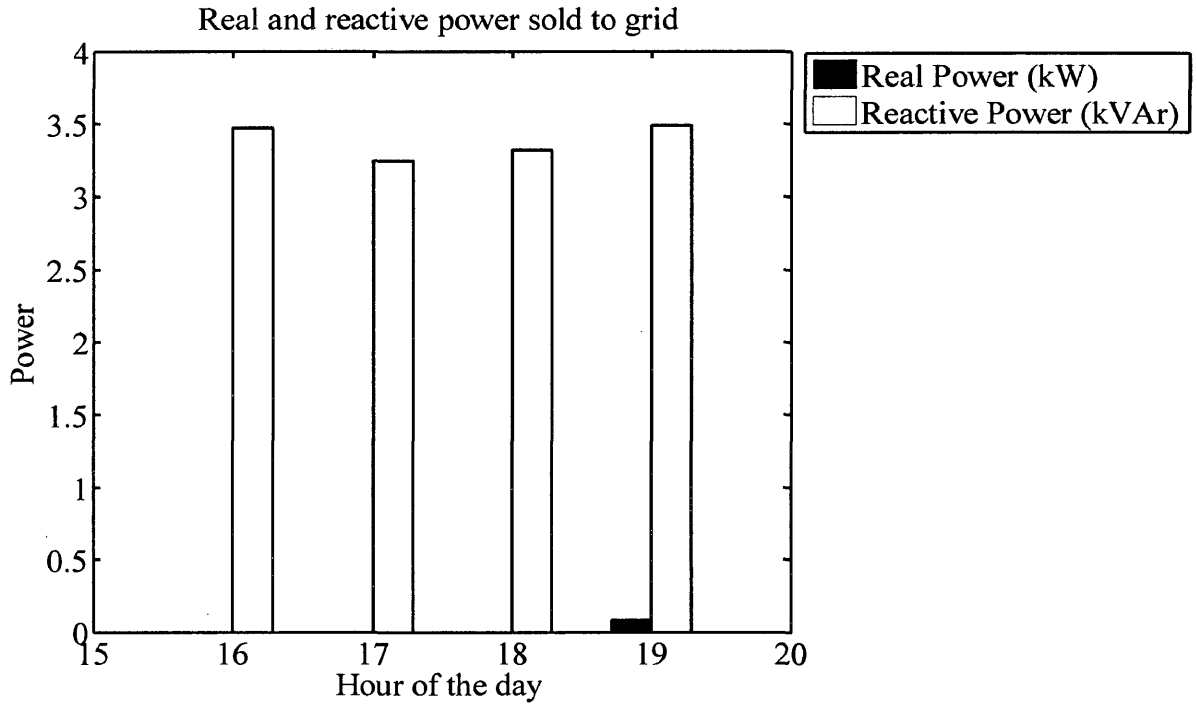

Figure 4.15 Breakdown of real and reactive power sold to the grid for case study 2.

Table 4.3 Operation of DER installation for case study 2, where there is no PV generation. A negative profit indicates a cost for that zone.

	PV input (kWh)	Energy bought from grid (kWh)	Energy sold to the grid (kVAh)	Energy sold to the grid (kWh)	Energy sold to the grid (kVArh)	Profit generated ($)
Zone 1	0.00	36.50	0.00	0.00	0.00	-3.81
Zone 2	0.00	20.53	0.00	0.00	0.00	-5.33
Zone 3	0.00	0.00	13.53	0.08	13.53	5.74
Zone 4	0.00	14.21	0.00	0.00	0.00	-3.60
Total	0.00	71.24	13.53	0.08	13.53	-7.00

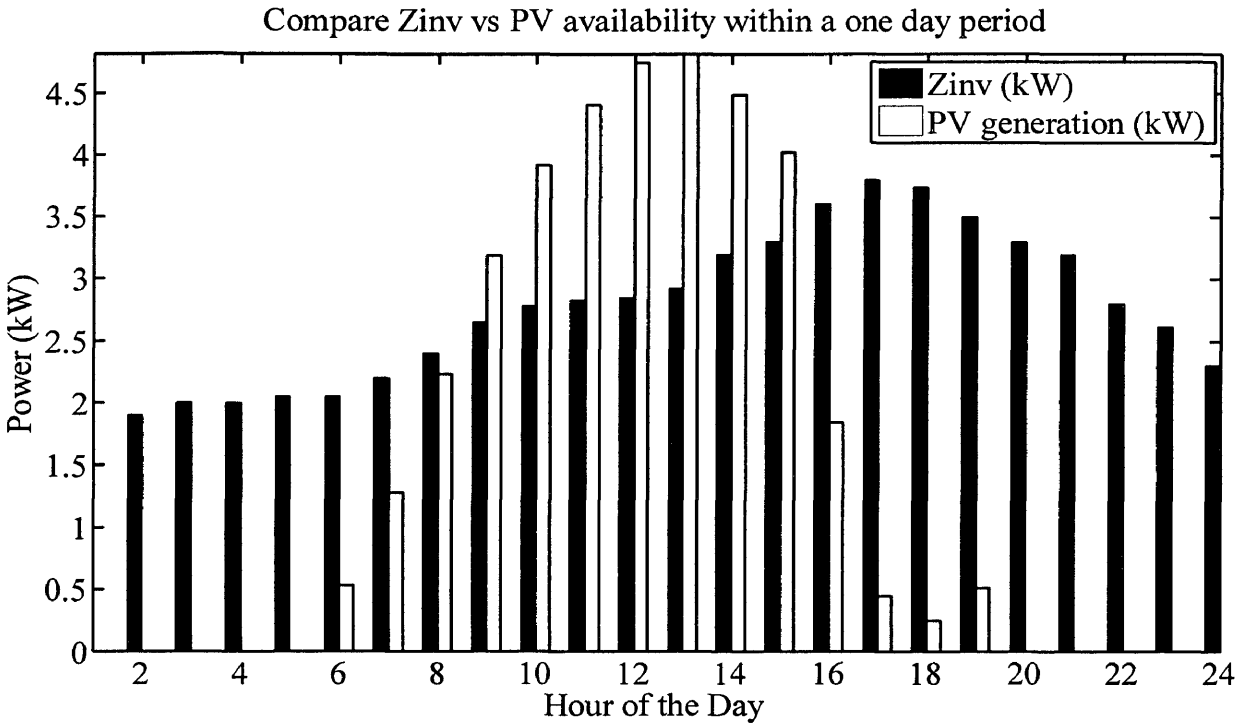

Figure 4.16 Load and PV generation profiles for case study 3.

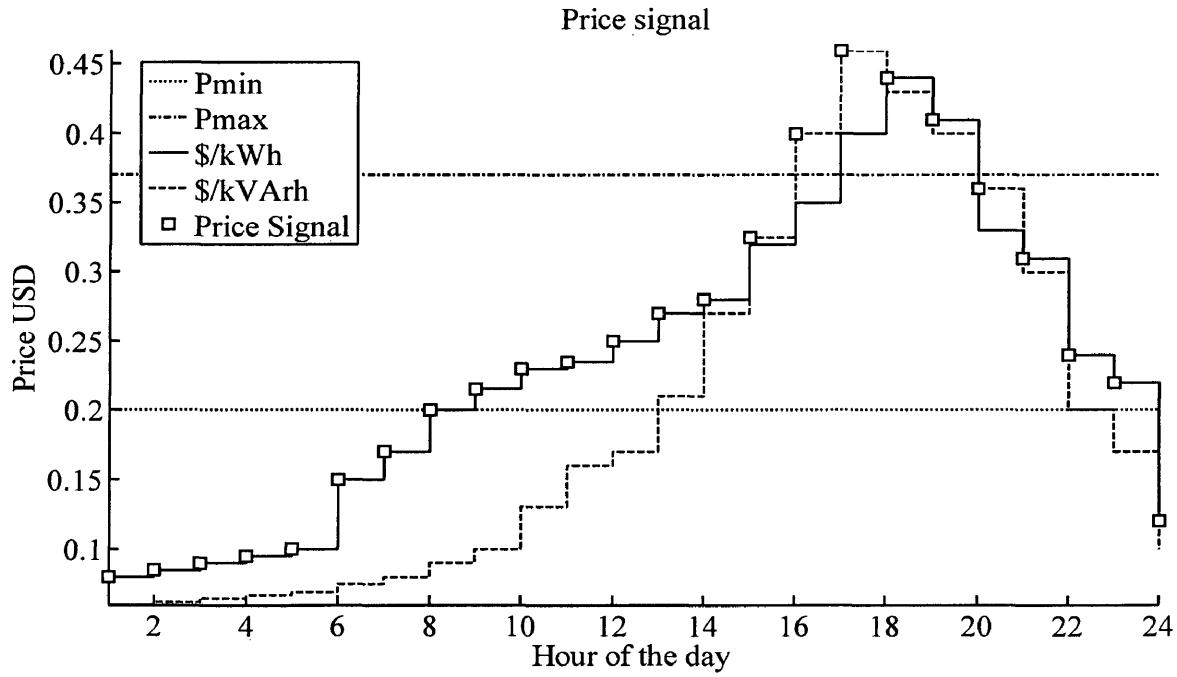

Figure 4.17 Real and reactive power prices, and the price signal for case study 3.

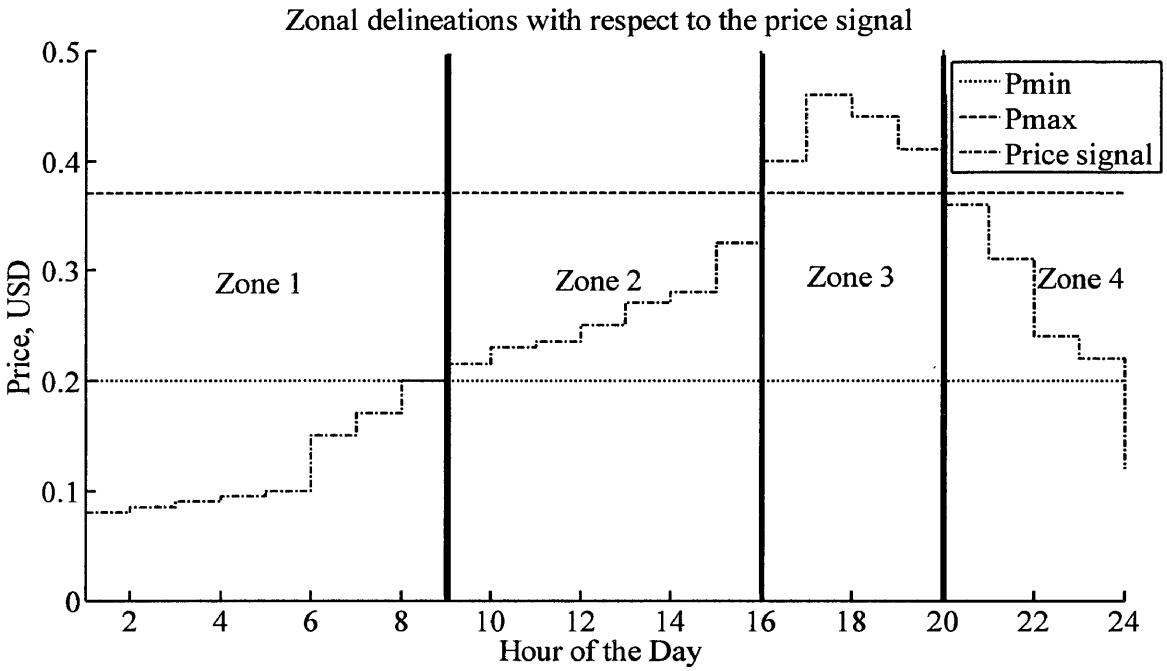

Figure 4.18 Price signal, P_{min} and P_{max} for case study 3.

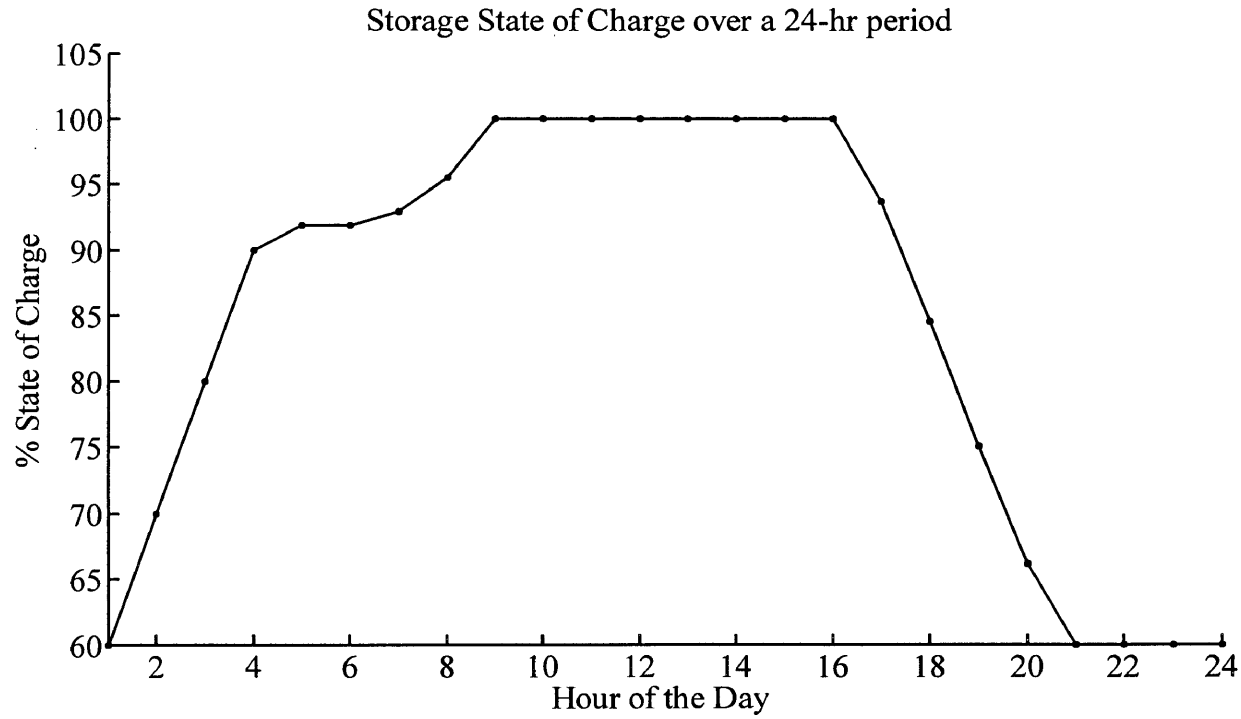

Figure 4.19 Battery SOC in case study 3.

Figure 4.20 displays the increase in electricity purchases during Zone 1 that is used to charge the battery and supply the load. However, in Zones 2 and 3, the energy sold to the grid reflects the excess PV generation after supplying the load. In Zone 4, the battery has been depleted to the MDD

and the load is again supplied by the grid. Figure 4.21 breaks down the real and reactive power sold to the grid. According to the heuristic scheduling technique, the reactive power is what is predominantly sold to the grid.

The trends of selling and purchasing are reflected in Table 4.4, where the only zonal net costs associated with the 24 hr operation occurred in Zone 1, when charging the battery and supplying the load, and in Zone 4, when the battery is discharged to MDD and the load is supplied from the grid for the rest of the 24 hr period. The largest zonal profit occurs during Zone 2, when the excess PV generation is sold to the grid, though a profit is also made during the peak hours of Zone 3, such that the overall cost of operation is a profit of $3.18 for the day.

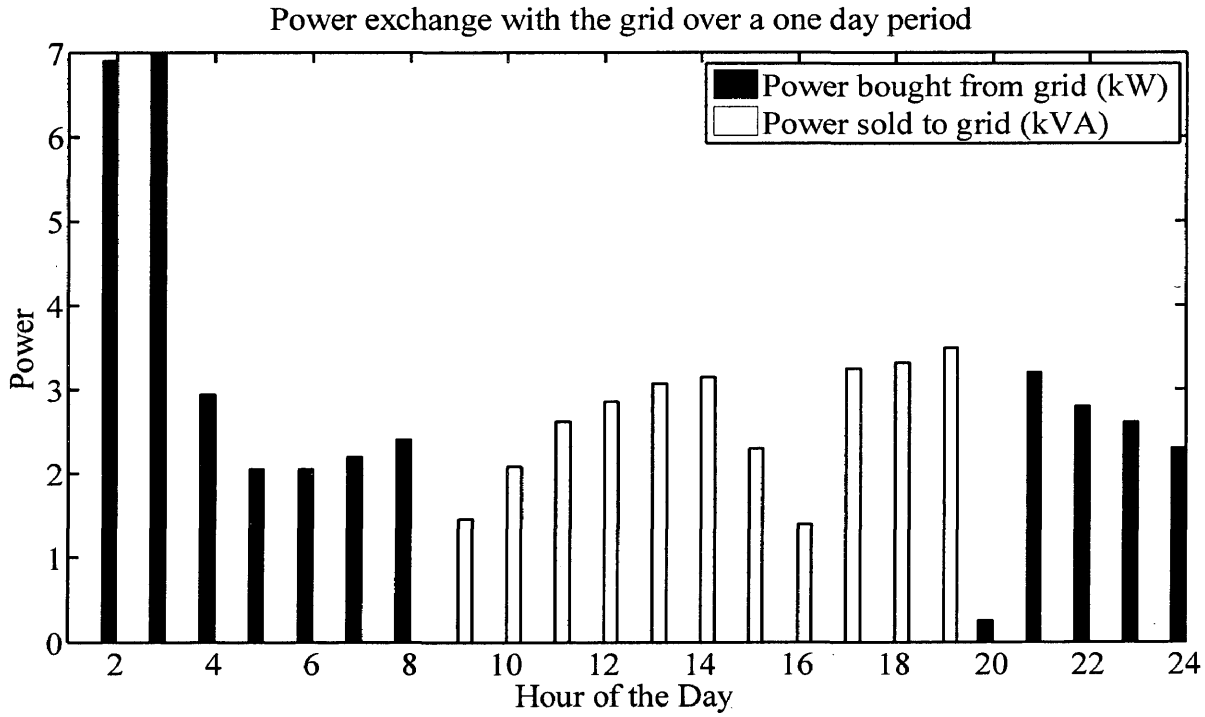

Figure 4.20 Power exchanged with the grid for a 24 hr period in case study 3.

4.5 Verification of Heuristic Technique using Linear Programming

LP is utilized in this section to provide verification for the operation of the heuristic technique when exchanging real power with the grid. The following section briefly describes LP, and the solution method implemented. The case and constraints are presented, as well as the solution and comparison to the operation of the heuristic technique.

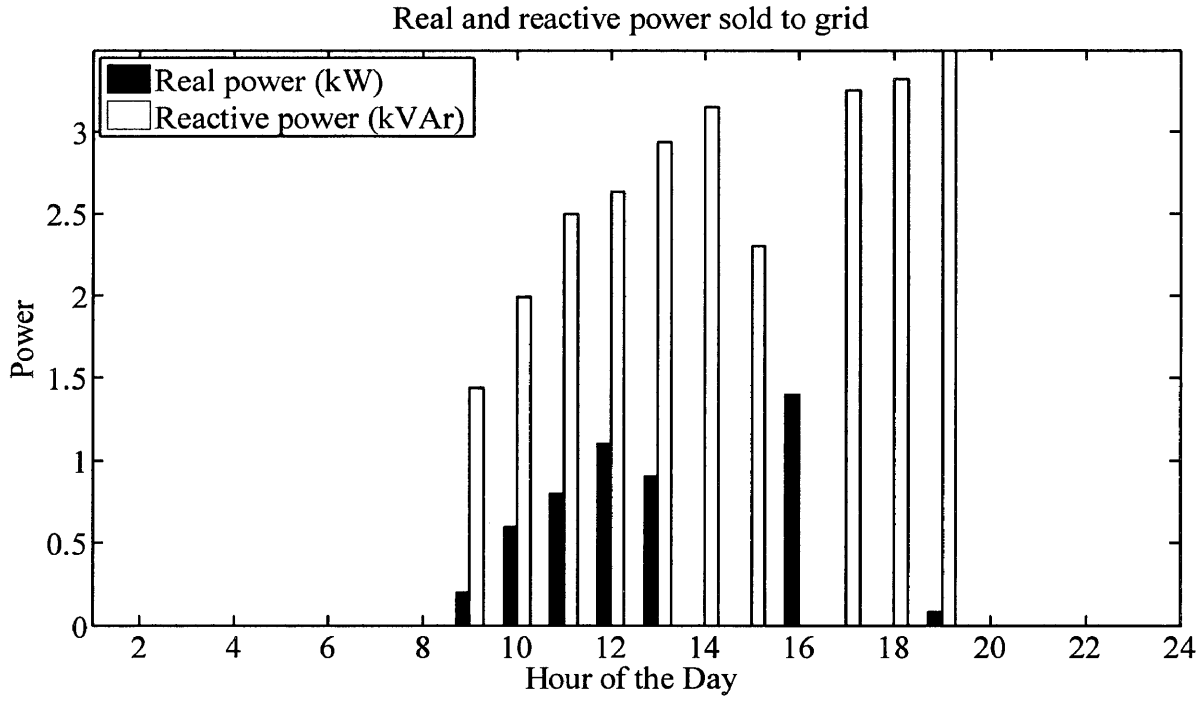

Figure 4.21 Real and reactive power exchange with grid for a 24 hr period in case study 3.

Table 4.4 Operation of the DER installation in case study 3.

	PV input (kWh)	Energy bought from grid (kWh)	Energy sold to the grid (kVAh)	Energy sold to the grid (kWh)	Energy sold to the grid (kVArh)	Profit generated ($)
Zone 1	4.06	32.44	0.00	0.00	0.00	-3.41
Zone 2	29.60	0.00	17.52	3.60	16.94	4.35
Zone 3	3.05	0.00	11.46	1.48	10.06	4.84
Zone 4	0.00	11.16	0.00	0.00	0.00	-2.60
Total	36.71	43.60	28.98	5.08	27.00	3.18

4.5.1 Linear Programming

An LP can be defined as a problem consisting of a linear objective function subject to linear constraints that are subsequently minimized or maximized [70]. The Simplex Method, developed by George Dantzig in 1947 [71], tests the objective function value at adjacent extreme points, i.e., basic feasible solutions. As all linear functions are convex, the LP consisting of only linear functions is also convex. Thus, when moving between adjacent basic feasible solutions, the Simplex Method will continue until the algorithm has established that its current objective function value is at least as good as the adjacent basic feasible solutions [72]. The Simplex Method is a well established solution method, and the interested reader is referred to Reference [73] for a more in-depth description. AMPL

version 9.1 is the mathematical computing environment used to implement the LP case study shown below, [70].

4.5.2 Case Study 4: LP Based Scheduling of DER

The following case study was specifically modeled after Case Study 1 in section 4.4.1, such that the load profile, MDD, and PV generation remain unchanged from case study 1. Furthermore, there is no limit on the charging rate of the storage. The price signal and zonal delineations are also equivalent to that of Case Study 1, but are repeated in Figure 4.22 below, for convenience. This example was coded in AMPL version 9.1, and is available in the attached electronic Appendix. See the Appendix for more information. The DER installation utilized in the LP model is as follows in Figure 4.23, where the power flows are designated by the arrows.

The objective of the LP is to maximize the operational profit, described by (4.5). The profit is defined by the difference between the revenue generated from selling real power to the grid and the cost of purchasing real power from the grid in this case study. The power flows used to define the LP case study are illustrated in Figure 4.23, and represent the power flow at time, t, between the system elements. The battery SOC at time, t, is defined by the SOC(t). The zonal delineations of the LP case study are set to match the first and second zones in Case Study 1. Zone 1 begins at time, t_1, and ends at t_1', while Zone 2 begins at time, t_2, and ends at t_2'.

$$\max c(t)\sum_{t=1}^{24} p_{34}(t) - p_4(t) \tag{4.5}$$

The operation of the DER installation is limited by the following constraints:

$$SOC(t+1) = SOC(t) + (p_{12}(t) + p_{32}(t)) - p_{23}(t) \tag{4.6}$$

$$p_3(t) = p_{34}(t) + p_{35}(t) \tag{4.7}$$

$$p_4(t) = p_{43}(t) + p_{45}(t) \tag{4.8}$$

$$p_{23}(t) + p_{43}(t) = p_{32}(t) + p_3(t) \tag{4.9}$$

$$p_{35}(t) + p_{45}(t) = d(t) \tag{4.10}$$

$$p_3(t) + p_{32}(t) \leq 5 \tag{4.11}$$

$$p_{43}(t) + p_{23}(t) \leq 5 \tag{4.12}$$

$$p_{35}(t) = 0, \text{for } t_1 \leq t \leq t_1' \tag{4.13}$$

$$30 \leq SOC(t) \leq 50 \tag{4.14}$$

$$SOC(t) = 50, \text{ for } t = t_2 \tag{4.15}$$

$$SOC(t+1) = SOC(t), \text{for } t_2 \leq t \leq t_2' \tag{4.16}$$

Constraint 4.6 maintains the proper battery SOC, with respect to the power flow going through the battery. Constraints 4.7 and 4.8 are used to account for the total power flow through the inverter from the battery, supplying both the grid and the load, and from the grid, supplying both the inverter and the load, respectively. The total power flow through the inverter is verified through (4.9). Constraint 4.10 assures that the load is always fully served through a combination of the grid and inverter. Constraints 4.11 and 4.12 make certain that the power flow through the inverter must always be less than 5 kVAh in both directions. The DER installation is forced to not supply the load from the battery during Zone 1 through (4.13). The battery SOC must remain within 60-100%, which is equivalent to 30-50 kVAh at all times, as seen by (4.14). The operation is committed to 100% SOC by the beginning of Zone 2, and not using any energy from the battery to supply the load through Zone 2, as established by (4.15) and (4.16) respectively. Finally, all power flows and the SOC for all hours must be nonnegative.

With respect to the previously described constraints, the operation of the DER installation according to the described LP formulation is as follows. The SOC increases by 10% for every hour in Zone 1 until reaching 100%, as seen in Figure 4.24. Once reaching 100% SOC, the battery is not depleted until reaching Zone 3, where it is steadily depleted into the beginning of Zone 4.

The power exchanged with the grid during the 24 hr operation is presented in Figure 4.25. At the end of Zone 1, the DER installation is exporting and importing power from the grid. The power bought from the grid for the hours where power is also being sold, corresponds to the local load level for that hour. According to the LP solution, the DER installation purchases power to supply the load at every hour, and sells the maximum, such that it is the necessary to examine the net power

exchange. The power being sold is the excess PV generation input that is present after the battery reaches 100% SOC. In Zone 2, the PV generation is used to supply the load, and the excess is sold, until the final hour of Zone 2, where the PV input is less than the load. Within Zone 3, the battery is depleted close to the MDD to supply the load and sell the available power to the grid for a profit. By the beginning of Zone 3 in hour 21, the load is served primarily by the grid, but also by the remainder of the battery that was left slightly above the MDD.

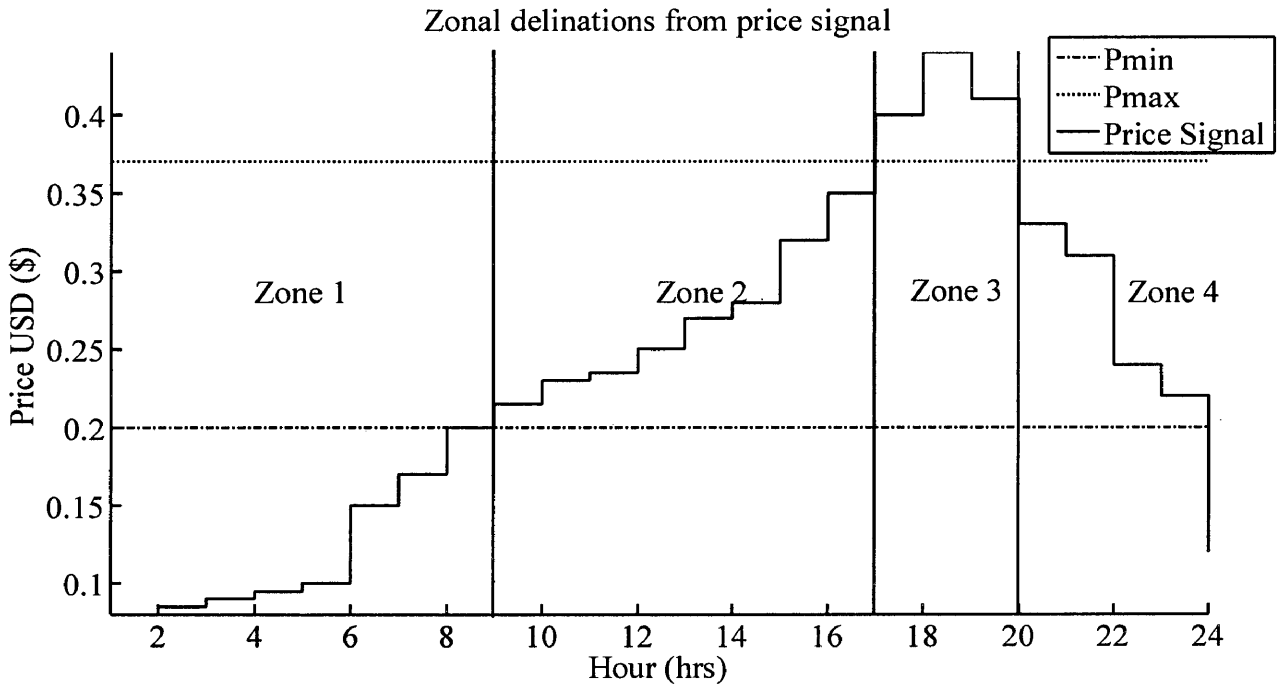

Figure 4.22 Zonal delineations from price signal for case study 4.

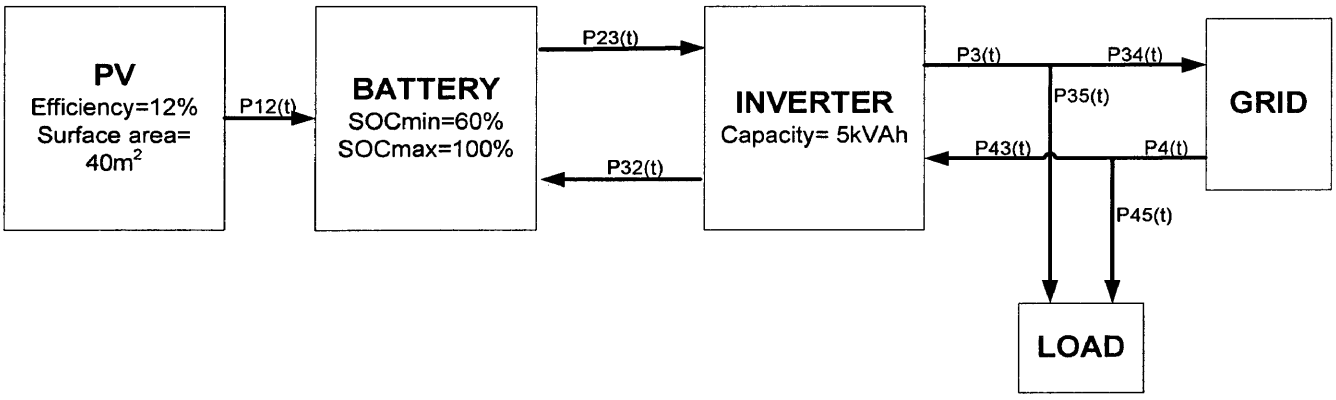

Figure 4.23 Component and power flow model for case study 4.

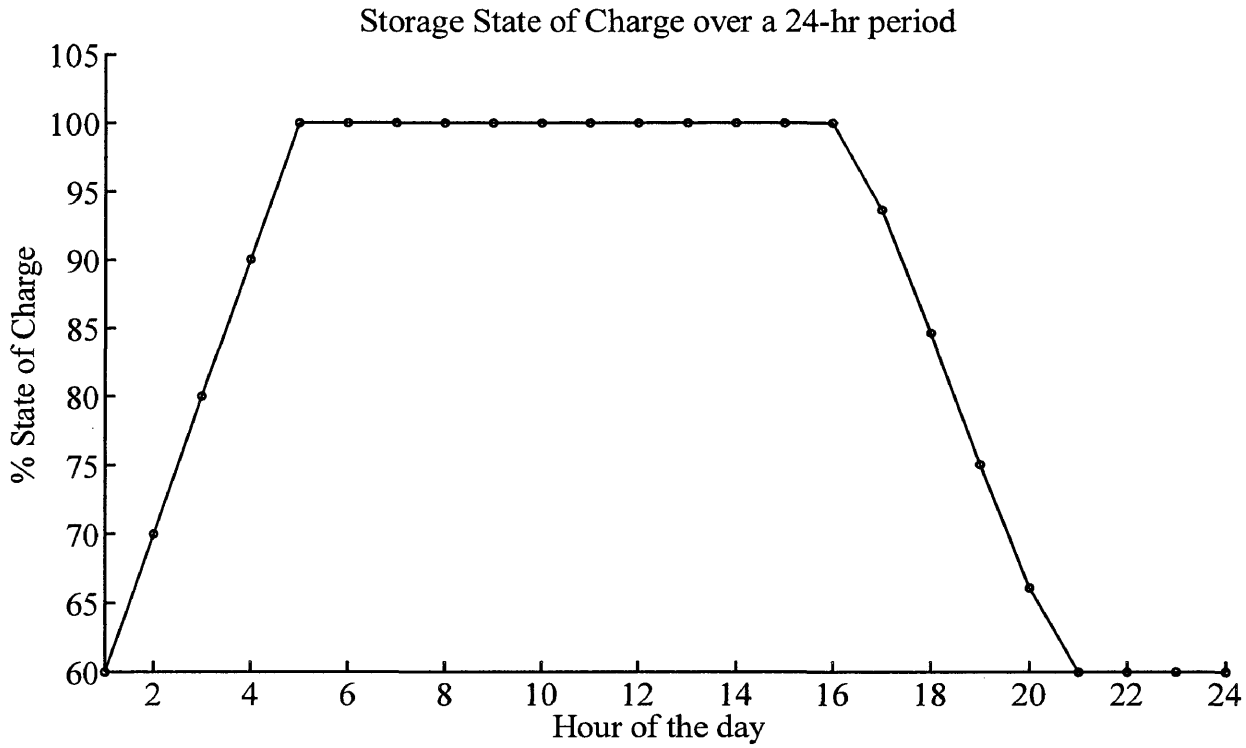

Figure 4.24 Storage SOC over 24-hr period for case study 4.

Table 4.5 presents the operation of the DER installation for this case study 4, where the cost for the 24 hr operation is $1.27. The comparison of the profits generated in case study 1 compared to case study 4 are presented in Table 4.6. The profits generated for Zones 2-4 are identical. However, the profit in Zone 1 differs for each case study because the LP in case study 4 charges the battery as soon as possible within Zone 1 and sells the excess PV input generated at the end of Zone 1 for a profit. The heuristic technique in case study 1 does not sell any power during Zone 1, and instead uses the PV generation to finish charging the battery to 100% SOC.

4.6 Conclusion

The heuristic technique presented appears to be a viable energy management system for a customer-owned DER installation. The technique may be applied to systems in which there is no PV generation, and where power exchanged with the grid is constrained to real power only. However, Table 4.7 summarizes the performance of the heuristic technique with respect to each case study; the best performance is comparatively observed by the DER installation capable of exchanging real and reactive power with the grid when PV generation is available. Given the same price of real power and load profile, the cost of operation for a 24 hr period with no energy management would be

$16.84. The interested reader is directed to reference [35] for an additional case study where the option to sell either real or reactive power was presented.

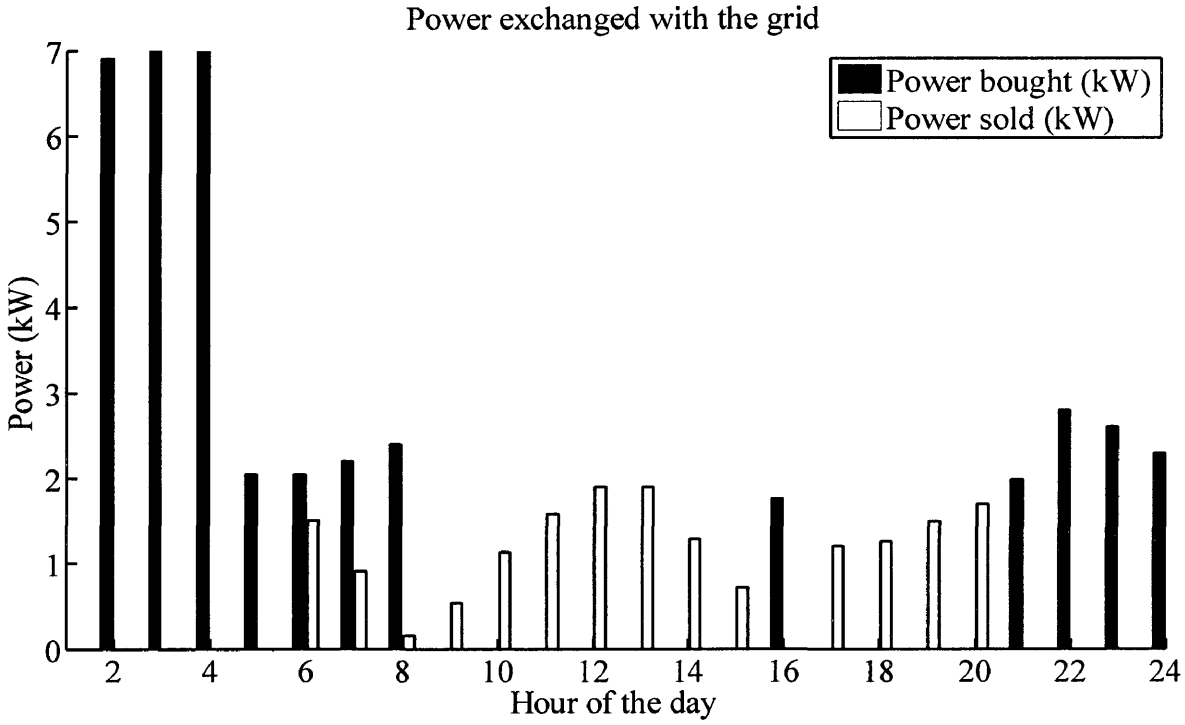

Figure 4.25 Power exchanged with the grid in case study 4.

Table 4.5 Operation of the DER installation according to the LP during case study 4.

	PV input (kWh)	Energy bought from grid (kWh)	Energy sold to the grid (kWh)	Profit generated ($)
Zone 1	4.06	36.50	4.06	-3.05
Zone 2	31.44	24.13	31.44	1.71
Zone 3	1.21	11.04	15.00	1.65
Zone 4	0.00	14.21	6.21	-1.58
Total	36.71	85.88	56.71	-1.27

Table 4.6 Operation of DER installation comparison between case study 1 and 4.

Case Study	Profit for case study 1 ($)	Profit for case study 4 ($)	Difference between case study 1 and 4 ($)
Zone 1	-3.41	-3.05	-0.36
Zone 2	1.71	1.71	0.00
Zone 3	1.65	1.65	0.00
Zone 4	-1.58	-1.58	0.00
Total	-1.63	-1.27	-0.36

Table 4.7 Summary of operational profit according to case study.

Case Study	Real power exchange available	Reactive power exchange available	PV generation available	Profit ($)
1	yes	no	yes	-1.63
2	yes	yes	no	-7.00
3	yes	yes	yes	3.18
4	yes	no	yes	-1.27
Base	no	no	no	-16.84

CHAPTER 5
CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

The prominent feature of the developed EMS presented in this thesis is to support the Smart Grid Initiative [5]. This thesis uniquely contributes an economically driven methodology for the operation of a customer-owned DER installation, including load scheduling. Explicitly, the energy management system supports the utilization of renewable DER, energy storage, and schedulable loads into the distribution system. This includes providing a platform on which the customer can participate in DSM and demand side response when enabling technologies and access to information such as dynamic electricity pricing is present. The proposed economic benefit to customers with schedulable loads promotes the integration of 'smart' appliances for mainstream use. Moreover, the system provides the customer with up-to-date information and control options, both through the EMS platform and through the increased deployment of AMI.

The LSM affords the customer a load scheduling technique that is customizable, unique to both the customer and application in an intuitive manner. For example, the LSM can be tailored to suit needs according to the season, or day of the week. The case study presented in chapter 3 illustrates how the dynamic AHP can be utilized to quantify changing load preferences with respect to the time of day, and provides the customer with an option for rescheduling during off-peak pricing. This peak-shaving can potentially decrease the stress placed on the overburdened electrical grid, which is worsened during peak hours of operation.

The heuristic scheduling technique takes full economic advantage of exchanging real and reactive power with the utility grid, while also protecting the battery life. According to the case studies presented in this thesis, the most profitable DER installation setup consists of the installation having the ability to sell both real and reactive power, when the customer is given access to dynamic electricity pricing and is able to sell both real and reactive power to the grid on a day with available PV generation. However, when compared to the operating cost of the base case study, without PV generation, storage, or any EMS, the heuristic scheduling technique improves the economic operation of the system.

5.2 Future Work

There are several avenues for future work available from this thesis. Specifically, making the heuristic scheduling technique more robust by including stochastic modeling for weather and load forecasting, more detailed modeling of energy storage characteristics, incorporating more component efficiencies, and expanding the technique to other DER sources and storage technologies would contribute to making the technique stronger. Furthermore, the heuristic scheduling technique could be verified with respect to traditional nonlinear optimization methods with respect to selling both real and reactive power. Computer simulations could be evaluated to determine the feasibility of applying the technique to a small physical test system, and any modifications that might be needed to be made therein.

The LSM can be extended by incorporating more load and customer parameters. The LSM could also be advanced by including costs like employee wages, productivity, etc. for the LSM operation, especially in industrial and large commercial settings with a variety of loads that can be scheduled around a 24 hr clock.

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APPENDIX

This appendix contains the programming information for all presented case studies, including the AHP example, LSM example, and the heuristic scheduling technique case studies. The programs in their entirety are found in the electronic appendix. The following is a readme file that can also be found on the CD outlining the functions for use with specific examples, and their respective programming environment. Each example and/or case study is separated in a folder with all associated files needed to run them.

A.1 Dynamic AHP

Description:

This program was developed in Matlab 7.6.0 (r2008a), and is used to evaluate a dynamic example of the AHP.

Running:

Dynamic_AHP_ex.m is the master function;

i. consistency.m,
ii. ahp_powers.m, and
iii. matrix_max.m

are the subfunctions necessary for evaluation.

Functions:

Dynamic_AHP_ex.m:

Description: Master function evaluating the dynamic AHP example

Inputs: Pairwise comparison matrices are as given in chapter 2 dynamic example

Outputs: Time dependence of criteria from age 20 to 60 yrs old, AHP priority ranking from age 20 to 60 yrs old, and time dependence of alternatives with respect to each criterion are output as graphs.

consistency.m:

Description: Improves the consistency of an inconsistent pairwise comparison matrix

Input: The inconsistent matrix

Outputs: The improved matrix, and its new C.I. and C.R.

ahp_powers.m:

Description: Determines the Eigenvector of the matrix A by raising it to successive powers

Inputs: Matrix A

Output: Final Eigenvector solution and the output of each iteration as it converges to the final solution

matrix_max.m:

Description: Find the maximum value and its location in the matrix x

Input: matrix x

Output: location of the maximum value in matrix x, and its location

A.2 LSM

Description:

This program was developed in Matlab 7.6.0 (r2008a), and is used to evaluate the LSM.

Running:

LSM.m is the master function;

i. consistency.m,
ii. average.m,
iii. ahp_powers.m, and
iv. matrix_max.m

are the subfunctions necessary for evaluation.

Functions:

LSM.m

Inputs: All inputs are automatic, corresponding to the example case.

Outputs: Command window displays the hour at which each load should be scheduled, and its respective load runtime. The priorities of loads, the upper triangular elements of the pairwise comparison matrix as a function of time, the moving average of load priorities, and the load profile are output as graphs.

consistency.m:

Description: Improves the consistency of an inconsistent pairwise comparison matrix

Input: The inconsistent matrix

Outputs: The improved matrix, and its new C.I. and C.R.

average.m:

Description: Calculates the weighted average over the appropriate window of time corresponding to the load runtime

Inputs: Vector over which moving vector is calculated, load runtime in multiples of the timestep, and the timestep

Output: Vector containing all evaluated moving averages

ahp_powers.m:

Description: Determines the Eigenvector of the matrix A by raising it to successive powers

Inputs: Matrix A

Output: Final Eigenvector solution and the output of each iteration as it converges to the final solution

matrix_max.m:

Description: Find the maximum value and its location in the matrix x

Input: matrix x

Output: location of the maximum value in matrix x, and its location

A.3 Case Study 1

Description:

This program was developed in Matlab 7.6.0 (r2008a), and is used to evaluate the operation of the heuristic scheduling technique when the DER installation consists of a $40m^2$ PV array, with local energy storage. The maximum storage depth of discharge is 60%, and the DER installation is capable of exchanging only real power with the grid. The solar irradiance data utilized is for July 4th, 2005 in Golden, CO.

Running:

Case_Study_1.m is the master function; Zones.m is the only subfunction necessary for evaluation.

Functions:

Case_Study_1.m:

Inputs: All necessary inputs, including solar irradiance data, load profile, electricity pricing, customer price thresholds, etc. are already established.

Outputs: Command window displays zonal breakdown of PV generation, energy purchased from the grid, energy sold to the grid (real and reactive power), operational profit, revenue generated from real and reactive power, and the cost of operation if no energy management system was present. The

storage state of charge over the 24 hr period, local load profile, PV generation, power exchanged with the grid, and price thresholds with price signal are output as graphs.

Zones.m:

Description: used to determine the proper zonal delineations with respect to the price signal.

Inputs: Price Signal, minimum and maximum price thresholds

Outputs: Delineations of hour for the beginning and end of each Zone, 1-4.

A.4 Case Study 2

Description:

This program was developed in Matlab 7.6.0 (r2008a), and is used to evaluate the operation of the heuristic scheduling technique when the DER installation consists of a PV array with local energy storage. However, during this case study there is no available PV generation. The maximum storage depth of discharge is 60%, and the DER installation is capable of exchanging real and reactive power with the grid.

Running:

Case_Study_2.m is the master function;

i. Zones.m,
ii. Case_Study_2_Zone_2.m,
iii. Case_Study_2_Zone_3.m,
iv. Case_Study_2_Zone_3_avail2sell.m,
v. Case_Study_2_Zone_3_constrained.m, and
vi. Case_Study_2_Zone_4.m

are necessary for evaluation.

Functions:

Case_Study_2.m:

Inputs: All necessary inputs, including load profile, real and reactive electricity pricing, customer price thresholds, etc. are already established.

Outputs: Command window displays zonal breakdown of PV generation, energy purchased from the grid, energy sold to the grid (real and reactive power), operational profit, revenue generated from real and reactive power, and the cost of operation if no energy management system was present. The maximum possible storage charging capacity with respect to storage state of

charge, storage state of charge over 24 hr period, real and reactive electricity pricing, price signal with price thresholds, local load profile, and power exchanged with the grid are output as graphs.

Zones.m:

Description: Used to determine the proper zonal delineations with respect to the price signal.

Inputs: Price Signal, minimum and maximum price thresholds

Outputs: Delineations of hour for the beginning and end of each Zone, 1-4.

Case_Study_2_Zone_2.m:

Description: Calculate the most profitable P and Q setpoint values, if the PV generation is insufficient to supply the load for that hour nothing is sold.

Inputs: PV generation per hour, real power price in Zone 2, reactive power price in Zone 2, first hour of Zone 2, last hour of Zone 2, and the local load per hour

Outputs: P and Q setpoints

Case_Study_2_Zone_3.m:

Description: Calculate the most profitable P and Q setpoint values.

Inputs: Local load, cost of real and reactive power, and the first and last hours of Zone 3

Outputs: Established P and Q setpoints, and their associated profit

Case_Study_2_Zone_3_avail2sell.m:

Description: Calculate the most profitable P and Q setpoint values with respect to the amount of power available to sell for that hour of operation.

Inputs: Amount of power available to sell, local load, PV generation, and the cost of real and reactive power

Outputs: Established P and Q setpoints, and their associated profit

Case_Study_2_Zone_3_constrained.m:

Description: Recalculate P and Q setpoint values when the total capacity for the hour is less than the maximum inverter capacity of 5kVA.

Inputs: How much the maximum inverter capacity (5kVA) must be decreased, the amount of power available to sell, local load, PV generation, and cost of real and reactive power

Outputs: Established P and Q setpoints, with their associated profit

Case_Study_2_Zone_4.m:

Description: Calculate the most profitable P and Q setpoint values with respect to the cost for supplying the load for that hour

Inputs: Local load, price of real and reactive power, and the first and last hour of Zone 4

Outputs: Net profit with respect to P and Q setpoints, and the cost to supply the load, P and Q setpoints, and the profit from P and Q setpoints

A.5 Case Study 3

Description:

This program was developed in Matlab 7.6.0 (r2008a), and is used to evaluate the operation of the heuristic scheduling technique when the DER installation consists of a PV array (40m^2 with 12% efficiency) and local energy storage. The maximum storage depth of discharge is 60%, and the DER installation is capable of selling real and reactive power with the grid.

Running:

Case_Study_3.m is the master function;

i. Case_Study_3_Zone_2.m,
ii. Case_Study_3_Zone_3.m,
iii. Case_Study_3_Zone_3_avail2sell.m,
iv. Case_Study_3_Zone_3_constrained.m, and
v. Case_Study_3_Zone_4.m

are necessary for evaluation.

Functions:

Case_Study_3.m:

Inputs: All necessary inputs, including load profile, real and reactive electricity pricing, customer price thresholds, etc. are already established.

Outputs: Command window displays zonal breakdown of PV generation, energy purchased from the grid, energy sold to the grid (real and reactive power), operational profit, revenue generated from real and reactive power, and the cost of operation if no energy management system was present. The maximum possible storage charging capacity with respect to storage state of charge, storage state of charge over 24 hr period, real and reactive electricity pricing, price signal with price thresholds, local load profile and PV generation, and the power exchanged with the grid are output as graphs.

Case_Study_3_Zone_2.m:

Description: Determine the most profitable P and Q setpoints, when PV generation is available

Inputs: PV generation, real and reactive power pricing, first and last hour of Zone 2, and local load

Outputs: P and Q setpoint values

Case_Study_3_Zone_3.m:

Description: Calculate the most profitable P and Q setpoint values for every hour within Zone 3.

Inputs: Local load, cost of real and reactive power, and the first and last hours of Zone 3

Outputs: Established P and Q setpoints, and their associated profit

Case_Study_3_Zone_3_avail2sell.m:

Description: Calculate the most profitable P and Q setpoint values with respect to the amount of power available to sell for that hour of operation.

Inputs: Amount of power available to sell, local load, PV generation, and the cost of real and reactive power

Outputs: Established P and Q setpoints, and their associated profit

Case_Study_3_Zone_3_constrained.m:

Description: Recalculate P and Q setpoint values when the total capacity for the hour is less than the maximum inverter capacity of 5kVA.

Inputs: How much the maximum inverter capacity (5kVA) must be decreased, the amount of power available to sell, local load, PV generation, and cost of real and reactive power

Outputs: Established P and Q setpoints, with their associated profit

Case_Study_3_Zone_4.m:

Description: Calculate the most profitable P and Q setpoint values with respect to the cost for supplying the load for that hour

Inputs: Local load, price of real and reactive power, and the first and last hour of Zone 4

Outputs: Net profit with respect to P and Q setpoints, and the cost to supply the load, P and Q setpoints, and the profit from P and Q setpoints

A.6 Case Study 4

Description:

This program was developed in AMPL version 9.1, and is used to verify the operation of the DER installation with respect to Case Study 1.

Files:

Model: CaseStudy4.mod

Description:

This file contains the model of the DER installation, as well as all necessary constraints for use in AMPL version 9.1.

Data: CaseStudy4.dat

Description:

This file contains the input information, including the index, PV generation, load profile, zonal delineations, and the cost of electricity

Running:

Both CaseStudy4.mod and CaseStudy4.dat must be loaded into AMPL version 9.1 to solve.