An Intelligent Decision Support System for Efficient Scheduling of Smart Home Appliances in a Smart Grid

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Abstract

Many new Demand-Side Integration (DSI) load scheduling strategies are emerging for energy management in smart grids. The focus of this thesis is upon smart homes and end-user DSI participation using Intelligent Decision Support Systems (IDSSs). The use of IDSSs can assist consumers to respond effectively to Real-Time Pricing (RTP) tariffs and other DSI pricing signals relayed to customers by utilities.

For many DSI load management strategies, mathematical optimization and metaheuristic strategies have previously been suggested. For an end-consumer IDSS, these may not be acceptable from a computational complexity perspective, due to the non-deterministic polynomial hardness (NP-hardness) of the scheduling problem encountered by the IDSS. In this thesis, an efficient polynomial-time heuristic algorithm for scheduling residential smart home appliances across a receding time horizon is proposed. The heuristic algorithm is extensively evaluated using a generic cost model for electricity prices and a variety of representative smart home configurations. Results indicate that, when compared to an exact optimal algorithm, the proposed heuristic algorithm consistently produces results which are very close to optimal at a fraction of the computing cost.

A prototype of the heuristic algorithm is implemented on a resource-constrained embedded processor, and testing and validation confirm its suitability for co-location on a smart meter. The final sections of the thesis are therefore concerned with the performance of multiple implementations of the heuristic from the perspective of a utility company. This thesis concludes that the proposed heuristic algorithm is a good candidate for the large-scale deployment of residential consumer oriented DSI and could be deployed as a useful and low-cost extension of an Advanced Metering Infrastructure (AMI) in smart grids.

Keywords *– Smart grid; Demand-side integration; Demand-side management; Demand response; Load scheduling; Heuristic algorithm; embedded processor.*

Dedication

This thesis is dedicated to God Almighty and the whole heaven. God’s love, goodness, and mercies endureth forever.

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God bless you all.

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Nomenclature

I	appliance(s)
N	number of appliances
ni	number of stages of appliance
$P_{i,j}$	power assigned to every stage of an appliance
T	length of timeslot
H	hourly timeslot
x_h	unit of energy consumed
$C_h(x_h)$	cost function of energy consumed during a particular hour
J	objective cost function
s_i	schedule start time
s_i^{Min}	minimum start time for appliance scheduling
s_i^{Max}	maximum execution time of appliance scheduling
X_h^{Max}	maximum power threshold
µs	microseconds
C_B	best feasible cost
Bps	bytes per second
Kbps	kilobytes per second
Mbps	megabytes per second
Gbps	gigabytes per second
Wh	watt hour
kWh	kilowatt hour
MHz	Megahertz
O(H)	big launder notation

Abbreviations

Terms	**Description**
ACO	Ant colony optimization
AutoDR	Automated demand response
AMI	Advanced metering infrastructure
AMR	Automated meter reading
ANSI	American national standard institute
ARM	Advanced reduced instruction set computing machine
AS	Ancillary service
BACnet	Building automation and control network
BPSO	Binary particle swarm optimization
CNC	Cellular network communication
CPLEX	C-complex
CPP	Critical peak pricing
CPU	Central processing unit
DA	Distribution automation
DER	Distributed energy resources
DG	Distributed generation
DNO	Distribution network operator
DR	Demand response
DSB	Demand-side bidding
DSI	Demand-side integration
DSM	Demand-side management
DSP	Demand-side participation
EII	European industrial initiative
EISA	Energy independent and security act
EMS	Energy management system
ERP	Electric resource plan
ESS	Energy storage system
EU	European Union
EV	Electric vehicle
FACTS	Flexible AC transmission system
2G	Second generation
GA	Genetic algorithm

GPRS	General packet radio service
GSM	Global system for mobile communication
GUI	Graphical user interface
GVT	Generic variable tariff
HAN	Home area network
HEMS	Home energy management system
HVDC	High voltage direct current
ICT	Information and communication technology
I-DSI	Incentive-based demand side integration
IDSS	Intelligent decision support system
IEC	International electro-technical commission
IEEE	Institute of electrical and electronic engineers
ILP	Integer linear programming
IRP	Integrated resource plan
ISA	International society of automation
ISO	International standard organization
ITU	International telecommunication union
LAN	Local area network
LP	Linear programming
LTE	Long term evolution
LTPP	Long term procurement plan
MATLAB	Matrix laboratory
MIP	Mixed Integer programming
MILP	Mixed Integer linear programming
MINLP	Mixed Integer nonlinear programming
NAN	Neighborhood area network
NIST	National institute of standards and technology
OpenADR	Open automated demand response
PAN	Personal area network
P-DSI	Priced-based demand side integration
PHEV	Plug-in hybrid electric vehicle
PLC	Power line communication
PLL	Phase locked loop
PON	Passive optical network
PRIME	PoweRine intelligent metering evolution

PSO	Particle swarm optimization
PV	Photovoltaic system
PWN	Pulse width modulation
QoS	Quality of service
QP	Quadratic programming
RAM	Random access memory
R&D	Research and development
RES	Renewable energy system
RFID	Radio-frequency identification
ROI	Return on investment
RTP	Real time pricing
SA	Simulated annealing
SCADA	Supervisory control and data acquisition
SDH	Synchronous digital hierarchy
SEP	Smart energy profile
SONET	Synchronous optical network
SRAM	Static random-access memory
TOUP	Time of use pricing
2TP	2-tier pricing
USB	Universal serial bus
V2G	Vehicle-to-grid
WAN	Wide area network
WCN	Wireless communication network
WDN	Wireless data network
WiMAX	Worldwide interoperability for microwave access
WLAN	Wireless local area network

Chapter 1

1 Introduction

A smart grid is an electricity power network that utilizes digital technology to improve reliability, security, and efficiency of the electricity system from large generation, via the delivery systems to electricity consumers and an increasing number of distributed generation and storage systems [1]. Energy and business-related data flows and information management are central to the smart grid and help to facilitate advanced functionality which would otherwise not be available or not as effective without them. Such advanced functionality includes (but is not limited to) real-time electronic power conditioning, renewables integration, advanced metering, energy trading and Demand-side Integration (DSI). The scope of this thesis falls into the latter area, that of DSI. Specifically, the thesis is concerned with management of end-use domestic electricity loads through intelligent reactive scheduling of smart appliances.

1.1 Motivation

The recent advancement in smart grid technology offers interesting opportunities for residential customers who wish to actively participate in managing their energy consumption effectively. Modern information & communication technology (ICT) components (e.g., Advanced Metering Infrastructures) help to facilitate Demand-side Integration (DSI) by allowing duplex communication between utility service providers and consumers. In this thesis, the effective use of electricity in support of activities, which focuses on end-use efficiency, demand response and energy efficiency, are discussed under DSI. The implementation of DSI is aimed at encouraging shifts in residential load in response to specific contingencies affecting the wider power network by using, amongst other mechanisms, pricing signals and dynamic tariff mechanisms [2]. Such signals are mostly offered in real-time (or near real-time) by the utilities. In such schemes, active interaction between automatic energy management of smart homes and utility companies interconnected by smart grid is enabled [3]. As such, residential smart buildings help to create a modernized environment, supporting the more efficient and reliable distribution of electricity. Energy consumption in the built environment (households and services sector) forms a major portion (40.3 %) of the total energy consumption in EU member states [4]. Household energy consumption accounts for the largest portion of electricity usage in this built environment sector. This is driven by a continuous increase in population as well as growth in energy demands of home appliances etc. [5]. Thus, the built environment sector (including residential and commercial customers and other blocks of buildings) has a potential of making a significant contribution to achieving the EU's 2020 targets for combating climate change [6]. This can be done through the incorporation of Distributed energy resources (DERs) to the grid network, usually on small-scale production located closer to the load, which helps to reduce the transmission loss, while enhancing voltage profiles [7].

Over the past years, several energy management solutions have been proposed in the literature to achieve DSI in building stock, and five distinct use-cases (generic variable tariff, direct load control, DER program, capacity bidding program and Ancillary services program) are emerging [6]. Of these use-cases, generic variable tariff (GVT) DSI programs offer promise for residential applications; although the business model (from and end-user perspective) is not yet clear due to the complex energy billing and taxation mechanisms in use across Europe [6],[8]. Although much research (from a technological perspective) has been carried out on efficient DSI load scheduling strategies (e.g., investigations of energy cost optimization and load scheduling algorithms [9],[10],[11], specialized software architectures for optimization [12],[13] and residential energy management system design and testing [14],[15],[16], at present the specific value of DSI in residential applications and general building blocks is not yet thoroughly proven [2],[6]. Despite the advances in smart grid applications, most research on energy management of residential homes are relatively immature for practical purposes. Therefore, to effectively leverage the potential features and benefits of DSI in these applications, efficient, low-cost, and highly autonomous implementations (which maximize the use of any existing infrastructure) would be very beneficial [6]

In this research work, the focus is on heuristic load scheduling, which can be considered as potentially a very efficient DSI load management strategy for the implementation of a consumer Intelligent Decision Support System (IDSS) for energy. The IDSS aims to enable the autonomous management of smart home devices and their overall energy consumption profile to improve energy efficiency. This thesis proposes that a classical heuristic scheduling algorithm – based upon the list-processing algorithm for multiprocessor task scheduling – is a good candidate for solving the load-scheduling problem. The main crux of the discussion is that it can handle very well the trade-off between optimality and complexity inherent in the implementation of IDSS by sacrificing optimality at the expense of near optimality, features a comparatively very low computational overhead, and is well suited to analysis. The low computational overhead is necessary to ensure that regular re-optimization with updated state information can take place in the IDSS as environmental conditions evolve.

1.2 Aims and objectives of the research

The main aims of the thesis are summarized below:

- To develop a low-resource and effective scheduling scheme (IDSS) to be deployed as part of domestic smart metering configuration for DSI participation.

- To explore how utilities can moderate the aggregate electricity demand while ensuring consumer benefits in terms of cost savings and otherwise.

To achieve the aims of the research, the following objectives are set:

- To understand the smart grid concept, enabling technologies and DSI load management strategies for optimal scheduling of residential loads.
- To propose an effective heuristic scheduling algorithm and evaluate/benchmark its performance against an optimal exact algorithm in representative simulation studies.
- To present a generic cost model for dynamic and mixed electricity pricing.
- To demonstrate a prototype implementation of IDSS on a constrained embedded processor.
- To further evaluate the proposed heuristic algorithm from the wider perspective of a utility company, considering multiple households and smart meters with multiple instances of the heuristic algorithm deployed as a part of a distribution network responding to utility DSI event pricing signals.

1.3 Research questions

Since the aim of the research is to develop an IDSS, with considerations to the control performance, real-time schedulability and for practical implementation on a resource-constrained embedded processor, this study has considered answering the following main research questions:

Question 1: What is the impact of an IDSS as a major component of DSI in encouraging consumer participation in peak demand reduction, and to what extent are the DSI load management strategies able to influence a typical power consumption profile and what potential energy cost savings could be made?

Question 2: To what extent is the influence of a chosen DSI load management strategy (heuristic or exact/optimal) and its cost model capable of being configured for generic use, in the presence of dynamic energy pricing, mixed pricing, and for multi-household appliances/configuration scheduling?

Question 3: What are the overheads of a practical implementation of an IDSS, and are they suitable for use on a resource-constrained embedded processor (e.g., ARM), and to what extent do overheads compare with an equivalent PC-based IDSS implementation on a high performing PC in a MATLAB© simulated experiment, in terms of cost savings and computational time evaluation?

Question 4: To what extent does an area equipped with multiple IDSSs respond in an aggregated fashion to external signals (e.g., DSI event signaled by the utility) and what is the extent to which an IDSS can help shift aggregated demand in response to normal and stringent DSI prices?

1.4 Appraisal of previous work

As will be discussed in depth in Chapter 3, the main optimization strategies available in the literature for the load scheduling problem include mathematical programming / optimization, heuristic optimization, and metaheuristic search strategies. Each of these strategies has an array of appliance models and assumptions, a problem formulation, and power and timing requirements/constraints. The diversity in appliance modeling and assumptions made by researchers for the residential appliance modeling makes it difficult to compare the effectiveness of the load scheduling strategies. However, as the thesis aims to implement a simplified IDSS, which can be easily integrated into an AMI, the following three requirements are essential: (1) the IDSS should not require specialized software (e.g., integer programming libraries) and have a straightforward code implementation; (2) It should be implementable on a small computing device such as will be found within a smart meter; (3) It should be configurable for a wide variety of cost models and functions.

Researchers in [17],[18] investigated the load scheduling problem using mathematical optimization methods by formulating the cost functions as a Mixed Integer Linear programming (MILP) and Mixed Integer non-linear programming (MINLP) respectively.

The results of the formulated cost models prove to be effective in reduction of electricity bill, while ensuring user comfort. It is also a common knowledge from the literature that the use of mathematical optimization strategy, in particular Linear Programming (LP) and integer LP variants guarantee an optimal solution, as opposed to heuristic and metaheuristic approaches which do not give such guarantees. However, mathematical formulation of the optimization problem with integer constraints is computationally expensive (due to NP-hardness) and requires specialized solvers/software (e.g., MATLAB interfaced with MILP solvers such as CPLEX [19], Gurobi [20], etc.). As such, heuristic and metaheuristic algorithms provide lower complexity alternative options for complex load scheduling.

Heuristic approach to load scheduling requires knowledge (or experience) of the scheduling problem and its requirements (e.g., energy profile and time requirement of the scheduling devices) as well as other parameters to achieve good 'feasible' solutions based on a set of prescribed rules [21]. The heuristic approach can also be developed and configured to significantly reduce the computational burden of a specific optimization problem while achieving an acceptable or 'good enough' solution. On the other hand, metaheuristic approaches based on complex and iterative-search (e.g., Particle Swarm Optimization, Genetic Algorithms, Ant Colony Optimization etc.) provide high-level problem–independent frameworks that can be applied in solving general classes of problems. Metaheuristics may not be sufficient to achieve the desired performance for consumer IDSS due to the complexity of the load scheduling problem encountered by the IDSS, or a rigorous performance bound (experimental and/or analytical).

Additionally, further research on mathematical programming, (discrete optimization in particular) has led to the interoperation of metaheuristic and mathematical programming optimization technique and is known as matheuristics [22]. This relatively new approach requires the exploitation of some features derived from the mathematical model of the problem (e.g., MIP model) in a metaheuristic framework. Many successful matheuristic schemes use 'black boxes' to generate high-quality heuristic solutions for solving complex optimization problems [23]. The resultant effect of this approach is a possibility of incomplete MIP model (optimization problem formulation) and an external solver that iteratively solves the available sub-MIPs by introducing invalid constraints (e.g., variable fixing) that defines neighborhoods of certain solutions. In such cases, it requires the use of a general MIP refining approach (e.g., proximity search [24], evolutionary polishing method [25], etc.), to iteratively obtain a sequence of better solutions and refine the best solution within a feasible computational time. The drawback is that the MIP refinement approach does not generally guarantee feasible solution in some complex cases and might not have any good solution to refine. Further research is clearly needed in this area.

In choosing the appropriate strategy for IDSS implementation on a resource constrained embedded processor, finding better solutions within a reasonable computational time is not only the deciding factor, but also the ability to find acceptable solution for large instances of the load scheduling problem autonomously in real world. In this thesis, an efficient heuristic scheduling algorithm is proposed for use in the consumer IDSS for minimizing smart appliances energy costs. The proposed heuristic algorithm is simple and has low computational overhead. Unlike previously heuristic algorithms presented by other authors, with cost functions that utilizes specialized pricing signals, for example Customer Incentive pricing (CIP) signals [26], a generic and flexible cost function for hourly energy pricing is presented in this thesis. The generic cost model can be configured for traditional on/off peak pricing, RTP, Time of Use Pricing (TOUP), Two-Tier Pricing (2TP) and various combinations thereof. The generic cost model presented in this thesis is used to test the effectiveness of the proposed algorithms across multiple households with variety of representative smart home configurations. Particularly, cost-based scheduling of smart home appliances in response to RTP, TOUP and 2TP. To the best of my knowledge, no results related to the performance of a heuristic scheduling algorithm in the presence of such cost models have previously been published in the literature.

In practice, the implementation of automated IDSS for residential load scheduling on a low-cost, resource-constrained embedded processor for potential co-location on a smart meter does not seem to have been widely addressed in the literature and warrants further research study. This thesis investigates the implementation of a prototype of heuristic algorithm on a low-cost resource constrained embedded processor to respond to utility signals, provide scheduling advice and recommendations to end-users, which in turns, would enable active consumer DSI participation. A significant research focus has been on the demand side Integration and there have been interesting results reported in [27],[28]. However, it is comparatively rare to find research studies, which aim to evaluate the performance of heuristic scheduling algorithms from both consumer DSI viewpoint and the perspectives of utility planning, with the primary objective of minimizing end-user economic costs. In this thesis, the effectiveness of the heuristic algorithm for residential appliance scheduling in terms of achieved cost solutions, computational overheads, suitability for multi-household appliance scheduling is experimentally is investigated. The extent to which a heuristic algorithm for household load scheduling can help shift aggregated demand in response to normal and stringent DSI prices advertised by the utility are also explored.

1.5 Original contributions and publications

To achieve the objectives of the thesis and to obtain the answers to the research questions in Research questions Research questions, different DSI load management strategies have been reviewed, followed by the development of load scheduling algorithms (exact and heuristic algorithms). Exact algorithm is proposed for comparative purposes of benchmarking the performance of the heuristic algorithm, in terms of minimum cost schedule achieved, while the heuristic algorithm is utilized in the embedded implementation of the consumer IDSS.

These algorithms have been proposed to support the research described in this thesis, and as such, considered as part of the original contributions.

The outcomes of the overall thesis are categorized into technical and research contributions to knowledge.

Technical contributions and the associated published paper(s) include:

- The notion of heuristic scheduling algorithm as an effective DSI load management strategy to express the desired behaviour of a consumer IDSS and for real-time implementation.

  C. Ogwumike, M. Short, M. Denai, Near-optimal scheduling of residential smart home appliances using heuristic approach. *In IEEE International conference on Industrial Technology (ICIT),* Seville, Spain, pp. 3128-3133, 2015.

- A Prototype implementation of IDSS on a resource constrained embedded processor (ARM7-TDMI 32-bit microcontroller).

  C. Ogwumike, M. Short, F. Abugchem, An embedded prototype of a residential smart appliance scheduling system, *In IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA),* Berlin, Germany, pp. 1-5, 2016.

Research contributions includes the performance evaluation and benchmarking of the proposed heuristic algorithm against an optimal exact algorithm; the designed experiments / simulation studies and result analysis, which are as follows:

- A generic cost model employed with the heuristic scheduling algorithm.

  C. Ogwumike, M. Short, F. Abugchem, Heuristic optimization of consumer electricity costs using a generic cost model. *Energies* 2016, 9(1), 6; doi: 10.3390/en9010006.

- The impact of heuristic algorithm on both consumer DSI and utility planning perspectives respectively.

  C. Ogwumike, M. Short, Evaluation of a heuristic approach for efficient scheduling of residential smart home appliances, *In IEEE 15th International Conference on Environmental and Electrical Engineering (EEEIC)*, Rome, Italy, pp. 2017-2022, 2015.

  C. Ogwumike, M. Short, F. Abugchem, Heuristic scheduling of multiple smart home appliances: Utility planning perspective., *In IEEE International Conference for Students on Applied Engineering (ICSAE*), Newcastle, United Kingdom, 2016.

1.6 Thesis structure

An outline of the thesis are as follows:

Chapter 2: Smart grid concept and enabling technology

An introduction to smart grid concepts and the enabling technologies are discussed, followed by the requirements for smart grid communications and the most acceptable standards relevant for smart grid implementations at the consumption level.

Chapter 3: Review of Demand-side Integration and load management strategies

The concept of DSI and various load management strategies are reviewed. Residential load scheduling objectives, modeling considerations and the most effective DSI load management strategy for IDSS implementation on embedded processor are also discussed.

Chapter 4: A heuristic scheduling algorithm for smart appliances

A low-overhead heuristic algorithm for smart home appliance scheduling is proposed. Exact scheduling algorithm and a generic cost model for dynamic electricity pricing are also presented in this chapter.

Chapter 5: Evaluation of the proposed heuristic algorithm (Part 1 - Consumer viewpoint)

Various computational experiments to demonstrate the effectiveness of the proposed heuristic algorithm against exact search algorithm in achieving DSI participation at the consumption level are presented in this chapter.

Chapter 6: Prototype embedded implementation of the heuristic

In this chapter, a prototype-embedded implementation of the proposed heuristic algorithm for scheduling smart appliances is presented. Its performance is validated against MATLAB© based IDSS implementation on a high-performance computer.

Chapter 7: Evaluation of the proposed heuristic algorithm (Part 2 - Utility viewpoint)

In this chapter, the effects of multiple households using an effective heuristic algorithm for scheduling smart appliances is tested from the perspective of utility company planning. The chapter explores the behaviour of multiple instances of the heuristic algorithm in response to unexpected events affecting the wider grid.

Chapter 8: Conclusions and future work

This chapter concludes the thesis and presents the suggestions for future research.

Chapter 2

2 Smart Grid Concepts and Enabling Technology

2.1 Introduction

Reuters [29] estimated that the global demand for energy would gradually rise to 44% by 2030. This is sequel to the report by the U.S. Department of Energy that electricity demand and consumption in the US have an annual increase of 2.5% every year over the last 20 years [30]. As such, there is a significant increase in the annual energy consumption (domestic consumption in particular) due to the varying needs of the residential customers with respect to comfort, convenience and flexibility. However, while the components of the conventional grid - which has been progressively developing for over a century - is ageing, the demand for energy is increasing with insufficient improvements [31]. The existing power grid is mostly characterized by a lack of intelligent and automated control systems, self-healing features, poor visibility, mechanical switches causing low response times, and other factors which have all contributed to the electricity supply failure or black outs [32]. Therefore, there is need for a smarter grid to address these deficiencies to suit the needs of the 21st century. Although smart grid does not have a single clear definition, the concept integrates many technologies, generator/consumer solutions and addresses several policy and regulatory drivers [33],[34]. The European Technology platform [35] defines Smart grid as a modern electricity infrastructure network that can intelligently integrate the actions of all connected users such as generators, consumers and those that do both to efficiently deliver sustainable, economic, and secure electricity supplies. This requires innovative technologies: recent advances in information & communication technology (ICT), automation & control, sensing & metering technologies, high-power converters and so on to provide the main technological enablers. Higher-level energy management techniques based on energy supply and demand prediction, dispatch optimization, network availability and unit commitment are also required to addresses the challenges proactively [36],[37].

In this emerging smart grid, residential energy users will be given the opportunity to participate in the decision-making aimed at using the energy infrastructure more efficiently. By the freedom of interaction with grid through the Advanced Metering Infrastructure (AMI), and available electricity pricing signals, a customer's satisfaction with the electricity consumption and its economic cost could potentially be improved. From a researcher's perspective, this notion can serve as a motivation to addressing the Demand-side integration (DSI) in the emerging smart grid. This chapter describes the smart grid concept and the expected ICT evolutions that will enable the transition to a modern electricity power grid, which in turn, will transform society in the future. The chapter is focused on the state of art in the smart grid enabling technologies, requirements, standards, and the challenges that have provoked research interests in this field.

2.2 Background and state of the art

The concept of applying intelligent techniques in the interaction of distributed assets emerged in the 1980s as a call for a modern power grid that would allow the utilization of alternative and renewable energy resources, while performing self-healing, awareness, and coordination [38]. Vu and Begovic [39] seemingly first mentioned the term smart grid in 1997. Amin and Wollenberg [40] in 2005 referred to the term *smart grid* in their attempt to present some useful features of modern electricity network for future power delivery. In 2007, the Energy Independence and Security Act (EISA) started an official use of the term *smart grid* to define a future electricity grid [41]. The existing electricity grid was built to meet requirements set up in the last century. The grid is primarily radial, designed for centralized power generation, and relies mostly on manual restoration following tripping incidents. Increasingly, the reliability of the conventional electric grid is mainly ensured by having excessive power capacity in the whole system, with unidirectional power flow from power plants to consumers [42],[43]. **Table 2.1** below describes the essence of smart grid transformation in addressing the drawback features associated with the existing grids, such as the lack of bidirectional communications, limited control options, inefficient use of electricity with no user participation, and so on, While the smart grid concept (before and after smart grid) is shown in **Figure 2.1**

Table 2.1. Comparison of smart grid with existing grid [42]

Features	**Smart grid**	**Existing grid**
Electricity generation	Distributed/Centralized	Mostly centralized generation
Information flow	Bidirectional	Mostly unidirectional
Testing	Remote check	Partial remote/Manual Check
Sensors	Digital	Mostly electromechanical
Recovery/monitoring	Autonomous self-healing	Semi-autonomous /manual monitoring
Control type/ability	Active/pervasive control	Passive/limited control
Reliability	High	Low
Environmental pollution	Low	High

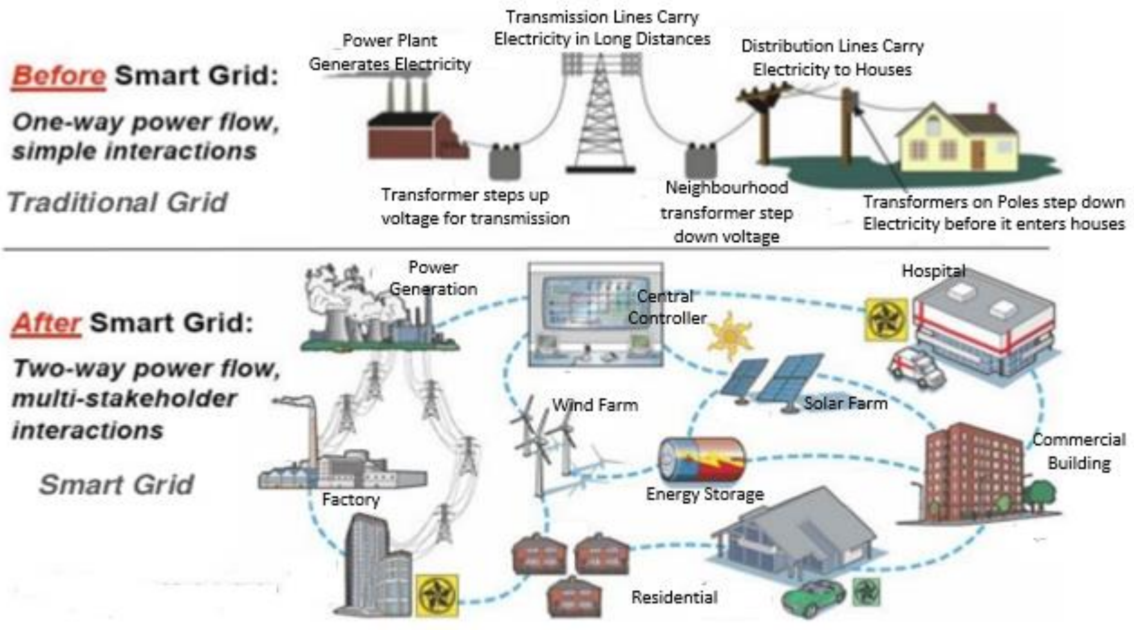


Figure 2.1. Smart grid concept [43]

Consequently, the U.S, EU countries, China, Canada, Australia, South Korea started major research and investment in the smart grid transition and applications aimed at sustaining the society and industry needs. In particular, U.S. and EU have developed different strategies to making their respective power grids smarter. EU has been impacted by concerns derived from the advancement and quality of power grids across European countries, while the U.S. aims to increase stability of the power grid and respond to the forecasted growth in demand for a long-term vision. It is anticipated that such technologies will have far-reaching development subject to economies of scale. For example, the U. S. National Institute of Standards and Technology (NIST) [44] have provided a conceptual model that pinpoints seven domains in the implementation of a smart grid. The domains include generation, transmission, distribution, operations, customers, service providers, and markets. The U.S government also announced a massive $3.4 billion in grant awards to fund a wide range of smart grid technologies [30]. Whereas the European strategy is spurred by ideas of advancement with respect to environmental and social reforms, which depends on security of supply, sustainability, and market efficiency [45]. Importantly, six objectives have been set for the EU strategy in [38], which includes:

- To accomplish the highest levels of safety and security.
- To achieve an energy-efficient Europe by enhancing building structures, transportation, and distribution grids.
- To augment Europe's leadership in energy technology and innovation.
- To empower consumers.
- To build a European integrated energy market.
- To strengthen the external dimension of the EU energy market.

Additionally, the European Strategic Energy Technology Plan includes eight European Industrial Initiatives (EIIs) in the field of energy. The EIIs on electrical grids is known as the European Electricity Grid Initiative and has a budget estimated to € 2 billion over a period of ten years with guidelines and activities for research and development (R&D) and a program with 20 massive demonstration projects [46]. Distribution Network Operators (DNOs) are incorporating AMI and Supervisory Control and Data Acquisition (SCADA) systems along with automation technologies to their distribution systems [47]. In addition to research and development projects, numerous electric utilities are also taking significant steps to smart grid transformation. Most of these projects are consenting to arrangements with smart meter vendors to collaborate in smart grid projects. The arrangements characterize the required features of AMI to provide 2-way communication between the users and the utility [48].

Smart grid is an interesting and complex topic that can be addressed from different perspectives due to its wide applications. Academia and industry have been undertaking considerable research and development of smart grid applications for residential, commercial, industrial as well as business customers. Reference [49] presents the different areas for smart grid technologies by identifying the benefits for reliable and efficient grid networks. The authors concluded that proper utilization of the technologies could improve the operation of future smart grids while eliminating the existing grid challenges. A comprehensive state-of-the-art review on smart grid issues, communications, opportunities, and challenges were presented in [42], [50]. The current state of the ICT for smart grid was reviewed with the objective of predicting future trends on the relationships between various ICT technologies. The resulting taxonomy provides guidelines for further studies of ICT architectures and highlights how the standards in the last mile of the smart grid are converging to common solutions to enhance ICT infrastructure interoperability [51].

However, one of the most significant applications of smart grid will take place at the residential homes/buildings level, which would provide consumers the opportunity to participate in realising the potential benefits of the transition to smart grid. Hence, in this thesis, the focus of the smart grid application is on residential buildings for residential customers. The residential area of Stockholm Royal Seaport project [52] is currently one of the research bases for the practical implementation of smart grid utilising residential buildings. This chapter addresses primarily the enabling technologies and communication requirements for the realisation of smart grid, particularly at the consumption level where households are encouraged to ensure efficient use of energy infrastructure. **Figure 2.2** shows the Return on Investment (ROI) in the transition from the Automated Meter Reading (AMR) and Advanced Metering Infrastructure (AMI) to smart grid with various investments on technologies and capacities.

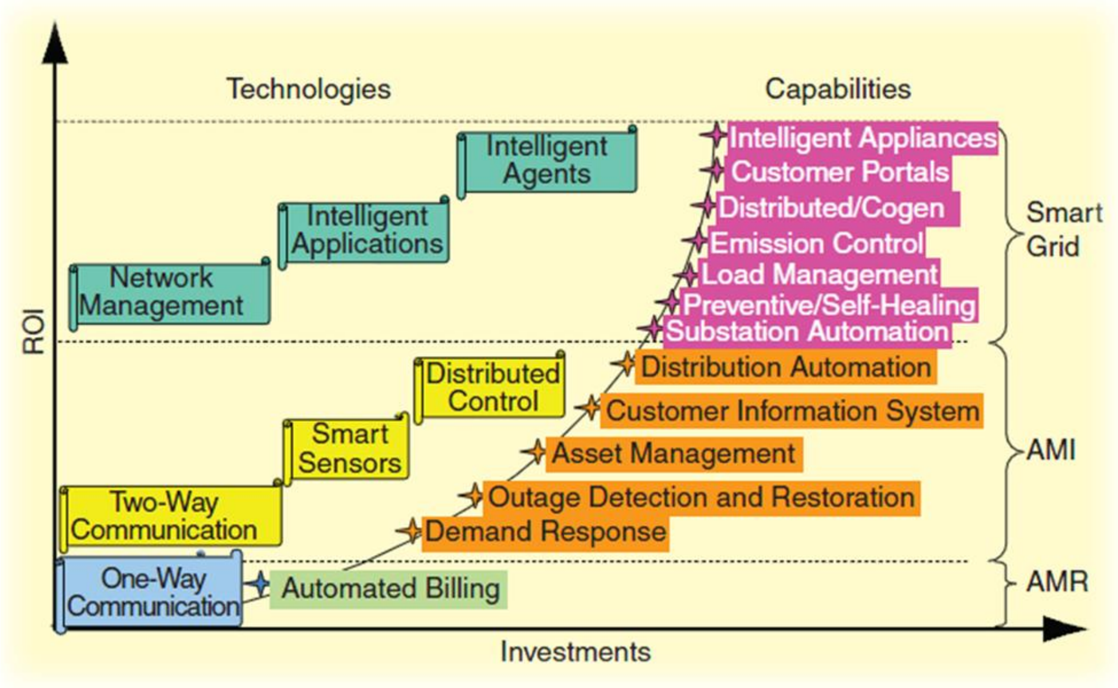


Figure 2.2. Transition to smart grid technology [53]

In the next section, the enabling technologies that form the bases for smart grid implementation are discussed.

2.3 Smart grid enabling technology

This section presents the enabling technologies that enable the smooth transition to smart grid. The technologies come in the form of hardware, control & communication infrastructure as well as network operations and real-time analytic systems to address the challenges facing smart grid. These challenges include the intermittent nature of renewable energy generation that affects electricity power output and quality, high complexities of small-distributed generation like plug-in hybrid electric vehicles (PHEV), batteries etc. The challenges also include the application of information and communication technologies (ICT), advanced power electronics etc., to improve and optimize the energy use efficiency.

2.3.1 Distributed Generation

Effective distributed generation (DG) based upon renewable resources is a major enabling technology of the emerging smart grid. DG sometimes referred to as dispersed generation or embedded generation is located close to the point of consumption. The proximity to the consumption point is key to reducing energy wastage. Indeed, they could help to reduce the distance between energy production and consumption to about 8% [53], since the existing power grid is designed to deliver power to consumers from centralized generation units over transmission networks, which takes up to 14% [54] of the input energy generated. Such distributed generation can provide clean and sustainable energy and (potentially) enhance power system capacity and security. However, distributed energy sources such as solar panels and wind turbines, which are the main sources for smart grid, are intermittent in nature and the output characteristics of generator and converter sets (i.e., their voltage, frequency, and power) depends on the weather condition. This intermittency results to high complexity as it affects the large-scale production and potential integration to the grid. Therefore, there is a need for energy storage alongside a power electronic converter to store the excess generated energy during good weather condition, which may be beneficial during the pitfall of energy generation or integrated to the grid.

2.3.2 Energy storage

The challenges in conserving energy and reducing greenhouse effect requires the integration of increasing penetration of renewable energy sources, improving efficiency and reliability issues in power system. Energy storage systems (ESSs) are expected to play important role in giving flexibility to balance the smart grid by providing back up and buffering/slack capacity to renewable energy resources [55]. ESS can also assist users to participate in energy management in a distribution network and reduce the electricity cost through opportunistic DSI, in particular residential buildings where individual households are equipped with an ESS [56]. The use of ESS can help to significantly leverage the efficient flows of energy within the household, generate revenues for the stakeholders, while helping to decarbonize the electricity grid. However, some ESS such as electric vehicles (EVs) that require high-capacity charger may not be installed within the residential building but in different commercial charging station. These ESSs for EVs can be used to provide ancillary services to both local energy providers and residential households [57]. There is also a category of vehicle to-grid (V2G) operation modes, where the charging and discharging cycles of the batteries of plug-in hybrid electric vehicles (PHEV) and electric vehicles (EV) are connected to network operation [58]

In addition, some of the ESS developed for different purposes include but not limited to supercapacitor energy storage [59], flywheels [60] and Lithium-ion battery [61], etc. The utilization of these storage technologies depends on a specific application as they have individual characteristics and performances such as (power, energy, and cost) for different applications. Energy storage system interfaced with a suitable power electronics unit can help to create virtual synchronous generators (with rotational inertia) to reduce large frequency variations that can result in an unstable grid [62].

2.3.3 Power electronics

With power electronics, the high penetration of renewable energy sources (e.g., solar, wind, tidal) with stochastic energy production, using power active converter systems can be achieved in the smart grid. Power electronics converters serve as interface circuits between different smart grid components such as renewable energy sources, energy storage systems, power grid and customers to control power flow, helping with grid stability [54]. For each agent, the front end to the smart grid is required to possess an intelligent energy conversion system interacting with the other front ends. The interconnections of these agents through transmission systems such as High Voltage DC (HVDC) or flexible AC transmission system (FACTS) enable larger and more efficient energy transfers [63]. It is also possible for transmission systems to manage a 2-way controlled power flow, which relies on the use of bi-directional energy conversion structure by adopting pulsewidth modulation (PWM) technology and control algorithms [63]. In a smart grid application, the objective function and operation of these agents can be continuously changed to meet the specific demands while ensuring safety and power processing efficiency.

2.3.4 Smart metering

Smart metering is a major enabling technology for realizing the vision of smart grid. Smart meter refers to an advanced/intelligent energy meter that obtains information from the end user's load devices, measures the energy consumption of the consumer supply, and then provides added information to the utility service company [64]. Under the metering process, there are numerous types of data measurements such as consumption data, event data, energy generation information and power factor/power quality. Before the advancement of smart metering, Automated Meter Reading (AMR) initially was in place to reduce the manual effort of end-user cost calculation. AMRs are one-way communication electromechanical device installed inside the premises of the customers to provide the utilities with an on-demand collection of meter records of subscribers [65]. Consumption data, which are regular and predictable, are only available at the substation level.

With the transformation to smart grid technology, there is need for bilateral real-time interactions between the consumers and the utility service companies. Subsequently, Advanced Metering Infrastructure (AMI) has been developed to replace the AMR. AMI is a two-way communications technology and is the integration of advanced sensors; smart meters, monitoring systems, computer hardware, software and data management systems that enable the collection and distribution of information between meters and utilities [66]. AMI can remotely control the supply and cut-off when necessary such that consumption data could be provided at time-interval with aggregated data for billing and other purposes [66], [67]. This provides consumers the opportunity to analyse the consumption data and potential cost of electricity for different time of the day. Utilities can also manage and ensure a better performance of the infrastructure across their service areas through the user modification of the energy demand and control system. **Figure 2.3** shows the energy and secure communication flow between the utility and the smart meter interconnected to home appliances. The data aggregator/concentrator as shown in the figure provides the technology to measure and collect the aggregated energy usage data from the various appliances across the households, which is also passed to the utility [53]. It serves as the data and energy manager in the AMI.

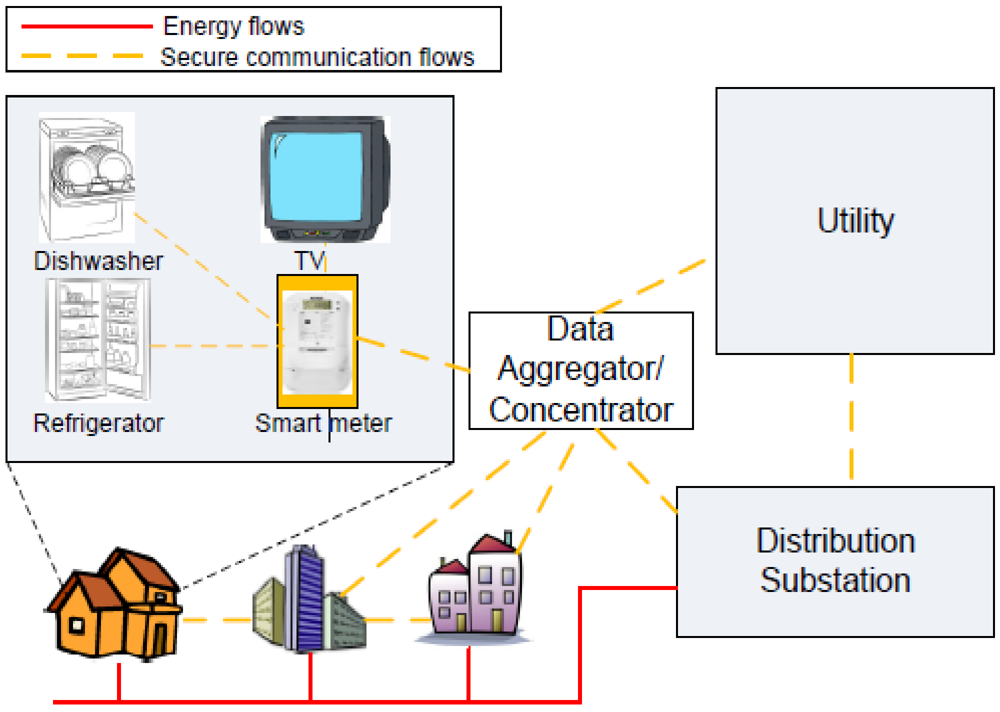


Figure 2.3. Smart metering communication system [53]

For a wider application, optimization of energy consumption cost for various smart appliances and diagnosis of component wearing issues are some of the additional services that can be provided to end consumers with the help of smart meters. The development of the required infrastructure (e.g., IDSS) for these services would complement the smart meter for potential user benefit. However, this natural extension in features of smart metering would form the bases for my research.

2.3.5 Information & Communication Technology

Adoption of Information and communications technology (ICT) is major step in the transition to smart energy grids. EU commission [68] noted that ICT based innovations provides the most cost-effective means of achieving 20% increase in energy efficiency by 2020, while reducing carbon emission. ICT has the capability to transform the existing grid infrastructures by:

- Supporting bidirectional energy and information flow
- Facilitating the control and integration of renewable energy into the grid and
- Extending to consumer control over their energy consumption by responding to pricing signals through the energy management systems.

ICT is at centre of smart grid implementation; bringing together transmission system operators, power generators and energy consumers into a real time interactive network. Sustaining the existing electric grid requires the use of ICT as information channels to enhance energy efficient behaviour across sectors such as blocks of buildings, transport, and industries.

2.4 Communication technologies available for smart grid applications

The effectiveness of modern grid control depends on the quality of communication and information obtainable by the control system. Significant advanced technologies and applications are recently developed to provide communication services aimed at achieving a smarter grid electricity infrastructure. Communication technologies carry information generated by other systems (e.g., utilities and consumers) and process the information to effectively manage power and protect the grid. This involves the generation of large data from different applications for real-time control and analysis. Therefore, it is imperative for electric utilities to establish communication requirements for their communication infrastructure to process reliable and secure data output throughout the overall system. The communication infrastructure as seen in **Figure 2.4** is at the center of smart grid architecture interfacing with other smart grid stakeholders and enabling technologies. The importance of the communication infrastructure spreads from electric utilities to the DSI where the energy management system and smart home devices must be able to communicate effectively via control and external information signals (e.g., spot prices) to optimize energy consumption cost and production schedule.

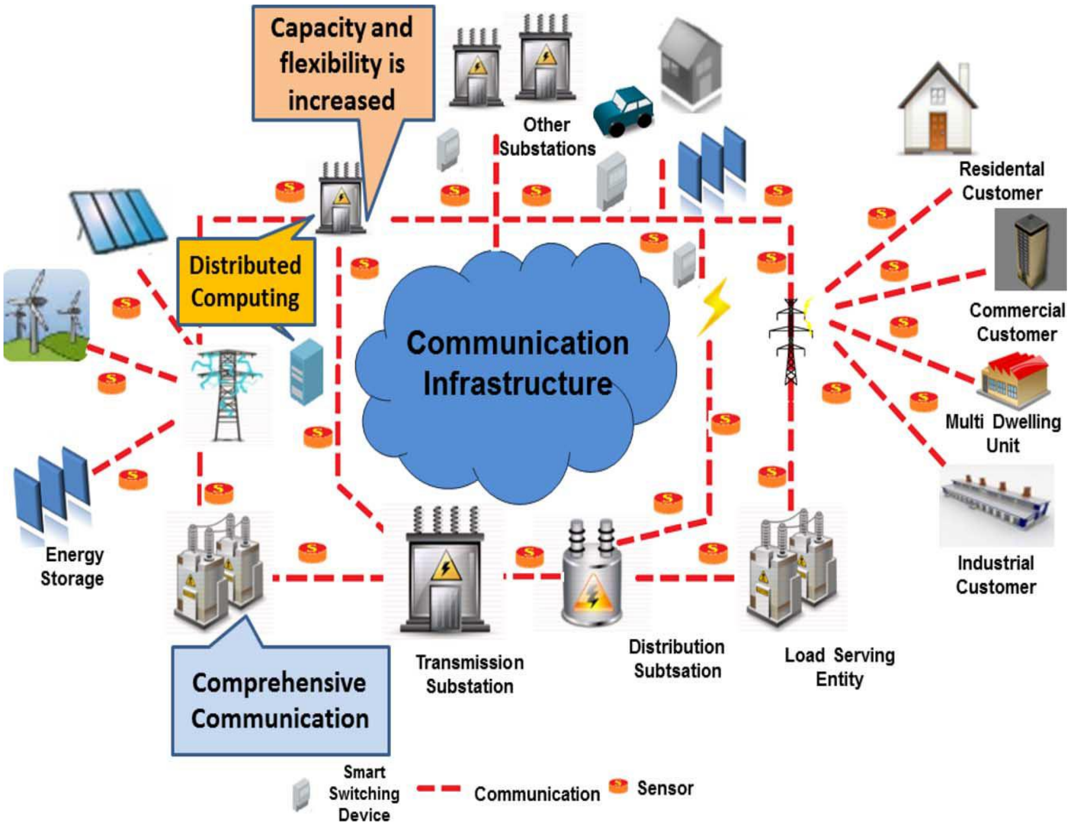


Figure 2.4. Smart grid architecture with modern communication infrastructure [48]

The United States (U.S NIST) [69] defined a hierarchical information networks for smart grid system. These networks are classified into three categories namely: Home Area

Network (HAN), Neighborhood Area Network (NAN), and Wide Area Network (WAN) [70]. HAN is focused on small-scale data communications between devices in a typical residential setting; while NAN provides a backbone for transmitted data from multiple HANs that are deployed in residential/commercial buildings. WAN on the hand connects HANs and NANs, providing high-end capacities across vast area of smart grid network [71]. However, in a smart building setting, there is need to support message exchange among smart meters, smart appliances, IDSS and utilities. Two types of information infrastructure are required for information flow [48]:

- The flow from sensor and electric appliances to smart meters
- The flow between smart meters and the utility's data centers

These information flows can be accomplished through wired and wireless communication technologies as described in the sections below:

2.4.1 Wired technologies

Dedicated cables are used for communications separately from the electrical power lines due to its increase in capacity and low latency [72]. Fiber optic and copper are typical examples of wired technologies for safe and reliable data transfer. Fiber optic cables are immune to electromagnetic interference and are used for relatively long-distance communication without the need for intermediate relays. However, the cost associated with the wired technologies and its maintenance is a major shortcoming in terms of long-distance cable deployments, for example when integrating DERs in remote areas to the grid and various connections in the populated cities. The major wired technologies are as follows:

2.4.1.1 Powerline communication

Powerline communication (PLC) is one of the most promising communication technologies for the implementation of smart grid. PLC is a low-cost technique mainly used to transmit broad data signals from one device to another. Although commercially viable at the current time, it is not in widespread use (although usage is currently on the increase). With the existing powerline infrastructure (electric wires), there is no need for new cable installation. Though, electric utilities prefer to have their own networks, they use this technology for remote metering and load control using narrowband solutions in the low frequency range (CENELEC band [73] from 3 kHz) with data rates up to 9.6 kbps [74]. However, the availability and reliability of communication system offered by the PLC transmission channel is very difficult to guarantee under extremely adverse channel conditions. Therefore, a crucial stage in designing an efficient PLC system is gathering sufficient knowledge on channel characteristics such as access impedance, attenuation, multiple interferences, and synchronization [74]. One major application of PLC is on Home Area Network (HAN) interconnecting a number of smart appliances and might not be suitable for widespread application due to several shortcomings such as limited data, signal distortion when crossing transformers and others.

Additionally, PLC depends on signal quality and is sensitive to disturbances (e.g., noise/interference in power lines). Therefore, there is need to combine PLC technology with other technologies such as General Packet Radio Service (GPRS), Global system for mobile communication (GSM) etc., to provide better connectivity. Hence, in a typical PLC network, electrical device such as powerline transceiver-based meter can be connected to the powerline and used to transmit metering data to a central location [75]. While PLC technology is required for data communication between the smart meters and the data concentrator, GPRS technology is used for transferring data from data concentrator to the utility’s data center.

2.4.1.2 Ethernet

Ethernets is a wired communication technology popularly used for small-scale deployments to provide connections to HANs and Distribution Automation (DA) equipment. Ethernet has been extensively implemented in the existing power systems for localized protection functions to provide real-time monitoring and control through LAN [72]. Network hub and cables such as fiber optic, coaxial are required for Ethernet implementation, which can provide data ranging from 10 Mbs to 100 Gbs. Since it a wired network, it is sensitive to noise and distortion. Moreover, connecting power devices in large, distributed areas require scalable network that can quickly adapt to topology changes [76].

2.4.1.3 Serial communication

Serial communication is a process of sending/receiving the bits of a byte in a timed sequence on a single communication channel (wire) [77]. It has become a standard for inter-device communication and is different from parallel communications where several bits are sent on a link with several parallel channels. TIA-232 is the most popular serial interface designed to allow one transmitter and one receiver on each line. It can support data rates ranging from $\approx$ 300 bps up to 115.2kbps and even 1 Mbps. Most computer networks use serial communication for a long-distance communication where parallel communication cannot be implemented due to cable cost and synchronization shortcomings. Moreover, only a few interconnecting cables are required for serial connection, as such, occupies less space which allows reasonable isolation of the channels from its surroundings. TIA-485 extends the basic point-to-point nature of TIA-232 connections to point-to-multipoint, with the restriction that communication is half-duplex.

2.4.2 Wireless technologies

Wireless technologies are considered a genuine alternative to bolstering smart grid functions within the power distribution network and enabling consistent communication any place at low cost. Smart grid applications (e.g., load scheduling, etc.) make use of data collected from sensors and smart meters in understanding the current state of the system before deciding the best control action to improve the efficiency and for other purposes [78]. Therefore, to implement these applications effectively, wireless communication network (WCN) is needed to deliver data from sensors and smart meter to control center and to convey the signals in opposite direction to the actuators and smart meters. Wireless communication technologies have more advantages over the wired technologies because they have low cost of deployment, more scalability, flexibility, and portability. However, they are constrained to bandwidth and security options. Wi-Fi is the most popular wireless technology used to connect electronic devices to a Wireless Local Area Network (WLAN). Other wireless technologies include Radio Frequency Identification (RFID), Bluetooth, and Wave2M etc. [78]. In particular, RFID is used in HAN applications such as lighting control. Key relevant wireless technologies available for smart communications are discussed below:

2.4.2.1 ZigBee

With the advancement of wireless technologies, it has become necessary to implement applications based on wireless protocol. ZigBee is an industrial standard of wireless Personal Area Network (PAN) that is targeted to wireless communications with low power usage, low-data rate and low-cost of deployment [79]. It is based on IEEE 802.14.4 standard [80], and is an ideal technology for home automation, energy management, energy monitoring, smart lightning etc. In relation to home automation application, AMI vendors such as Elster, Landis Gyr, etc., prefer smart meters that allow the integration of ZigBee protocols [75]. ZigBee Smart Energy profile (SEP) offers these vendors an open standard for implementing

HAN communication [81]. This enables the communication and control of smart devices while benefiting household energy customers by allowing them to manage their consumption wisely based on the real-time consumption information provided by the utility. However, the constraints in the practical implementation of ZigBee are low processing capabilities, and small memory size as result of license-free Industrial, Scientific, and Medical (ISM) frequency band ranging from IEEE 802.11 wireless local area networks (WLANs), microwave and Wi-Fi [82].

2.4.2.2 Wireless mesh

Wireless mess networks (WMN) are deployed in smart grid to provide high-speed and easy-to-deploy wireless backbone for NANs [83]. WMN can also provide wireless transmission methods in different applications such as AMI, HEMS, and internet services etc. Through a mesh network, a remote-control station can collect updated operation information from many devices located in a large area while also responding to any emergency. For example, in Pacific gas and electric (PG&E's) smart meter system, every smart device is equipped with a radio module, which routes the metering data through a nearby meter. Each meter acts as a signal repeater until the connected data reaches the electric network access point. The collected data is then transferred to the utility via a communication network [48]. Two-tier architecture consisting of mesh routers and mesh clients are used by a mesh network to manage many electrical devices at a distributive location [84]. These architectures can be installed across power domains since the mesh network is independent from the power system operation. The major challenges encountered by mesh network is that its metering information passes through every access point managed by a third-party company, as such requires some level of data encryption for security purposes.

2.4.3 Cellular network communication

Cellular network communication (CNC) is an existing option for communication between smart meters and the utility and between far nodes. The communications rely on a widely adopted communication infrastructure that allows deployment of smart metering that spans across wide area environments and remote endpoints to be connected into the same management network [81]. Hence, CNC can be rolled out quickly using an existing cellular infrastructure to enable wide-range communications among grid entities residing in different geographical locations. Some of the cellular CNC technologies available to utilities for smart metering deployments are 2G, 3G, LTE, 4G, WiMAX, etc. In a pilot deployment of virtual power plant [85], medium voltage remote applications were implemented over 2G and 3G mobile radio networks as such can also be used in NAN metering and control applications to facilitate communication. However, long term evolution (LTE) standards offer energy utilities some satisfactory requirements (e.g., low end-to-end latency, peak data rates etc.) for advanced smart grid application such as DSI and restoration applications. Both GSM and GPRS support applications in DSI, AMI and HAN. WiMAX has been chosen for communication function of a smart meter in a dedicated communication network built by an Australian energy delivery company (SP AusNet) [48]. They embedded WiMAX chip sets into smart meters and wireless communications are dedicated between smart meters and their central system. With CNC, there may be network congestion or shortfall of network performance in emergency events due to many customers in the cellular network.

The range of coverage, data range requirements and communication technologies for the different hierarchy of networks are shown in **Table 2.2**

Table 2.2. Communication technologies for different hierarchy of networks and communication mediums [70],[71],[76]

Communication technologies between smart meter and home appliances					
Technology	**Standard**	**Data rate**	**Coverage**	**Application**	**Limitation**
Z-wave	Z-wave	40kbps	Up to 30m	HAN	Low data range
Bluetooth	802.15.1	721 kbps	Up to 100m	HAN	Low data range, costly to install
ZigBee	802.14.4	250 kbps	Up to 175m	HAN	Low data range
Wi-Fi	802.11x	2-600 Mbps	<100m	HAN, NAN	Costly to install, noisy channel
PLC	HomePlug	14 - 200mbps	Up to 200m	HAN	Noisy channel

Communication technologies between Utility and smart meter					
Technology	**Standard**	**Data rate**	**Coverage**	**Application**	**Limitation**
Fiber optic	PON	155Mbps to 2.5Gbps	Up to 60 km	WAN	Costly to install, Low scalability
	WDN	40Gbps	Up to 100km		
	SONET/SDH	10Gbps	Up to 100km		
Cellular	2G-4G	Up to 100Mbps	Up to 50km	NAN, WAN	Costly spectrum fee
WiMAX	802.16	57Mbps	Up to 50km	NAN, WAN	Not widely spread
PLC	Narrowband	10 - 500kbps	Up to 3km	NAN	Harsh and noisy channel
Ethernet	802.3x	10 Mbps - 10Gbps	Up to 100m	HAN, NAN	Short range

2.5 Requirements for smart grid communication

Implementing smart grid demands a better understanding and identification of key features and requirements. While this includes different interdisciplinary areas, this section will focus on the communication features that will form the basis for a smarter power system that can meet the future electricity needs. Key features for smart grid communication are discussed below:

2.5.1 System security, robustness, availability and reliability

The operation of smart grid system requires a dedicated, secure, robust, and reliable communication network. It has been long acknowledged that the critical infrastructure network should be resilient and protected against failures and attack. Secure information storage is very important for the utilities, especially for grid control, billing, and other purposes [86]. In the case where public internet is used to connect customer devices with the utility infrastructure, solid encryption and authentication measures must be taken to ensure the security of data in transit. Existing power grid is faced with unreliability issues arising from the ageing infrastructure, which results to power failure in some cases. Harnessing the modern ICT, control, and intelligent devices from energy generation level to customer level will significantly strengthen the system availability, reliability, and robustness [87].

2.5.2 System design and data aggregation

Given that smart grid is expected to integrate the actions and behaviors of all the connected users, the architecture for the communication system must be systematically designed. In particular, the development of energy distribution system and data aggregation method will be critical to making the system respond to localized changes. Hence, there has to be careful decisions on the design choices and potential trade-off analysis between the available system design objectives. Example, in the case of energy management system, a trade-off exists for design models with multi-objective optimization functions such as the minimization of electricity consumption cost on one hand and the maximization of customer's comfort (well-being) on the other hand.

2.5.3 System efficiency and scalabilty

The deployable infrastructure on the smart grid network must be simple and scalable enough to facilitate an efficient operation of the power grid. The efficiency of the system must be viewed in its entirety and not in isolation. Advanced functionalities such as self-configuration, self-healing etc., are needed to provide scalability to different components such as communication devices and DER integrated to the power grid.

2.5.4 Quality of service

Mechanisms for delivering Quality of service (QoS) must be provided by the communication network to satisfy communication requirements, while ensuring effective communication in conveying data and control signals from the utility company (supplier) to consumers. For example, in sending DSI pricing (e.g., RTP, CPP) to customers, a transmission error or excessive delay in the communication network will impose limits on the update intervals of energy prices. The packet delay for a DSI application can range from 500ms to several minutes at the same reliability [88], which when exceeded may lead to system instability, affecting the QoS. Different forms and levels of QoS are needed for various smart grid applications [78]. In supporting the QoS requirements for DSI application, an important question that comes up is how to define QoS requirements and ensure requirements from smart home appliances are available in the communication network. The answer to the question would require investigation into the energy prices and consumption details based on load profile. This would likely result to the development of an energy support unit (e.g., IDSS) to schedule and optimize energy consumption cost based on pricing information (signals) and knowledge of the appliance specifications, which will in turn, improve the communication and QoS.

2.6 Smart grid standards

Significant number of standards for smart grid have been developed in parallel or are still in development phase by different research institutes and organizations. Most of the standards are not widely accepted for smart grid implementation. It is therefore very important to select standards that meet the smart grid requirements, to enable the integration of advanced applications such as smart meters, renewable energy sources etc., while ensuring the interoperability between them. National and regional Institutes/organization have played a major role in presenting key standards to realize an integrated and interoperable smart grid.

Example of such institutes and organizations includes American National Standard Institute (ANSI), NIST, International Standard organization (ISO), Institute of Electrical and Electronics Engineers (IEEE), International Electro technical commission (IEC) etc. In particular, IEC Smart grid standardization road map, NIST framework and Roadmap for smart grid interoperability standards release 2.0 and so on. For reader's description, the details of the smart grid standards, which are most relevant to smart grid application at household level, are explained below:

2.6.1 Building automation

- BACnet is a communication protocol designed by American Society of Heating, Refrigeration and Air-conditioning Engineers (ASHRAE) for building automation and control network. BACnet protocol provides the mechanism for smart building devices performing different services to exchange information.

2.6.2 Powerline networking

- **HomePNA** is an industry standard for interconnecting computers within a home using existing coaxial cables and telephone wires or lines [77]. It serves a similar purpose with HomePlug and Ethernet and is considered as an enabling technology for an in-house broadband.

- **HomePlug** is a family name designated for numerous powerline communications specification. HomePlug specifications are targeted at broadband applications (in-home distribution low data rate), as well as in-home communication with smart meters to connect smart appliances to HAN.
- **PRIME** (PoweRline Intelligent Metering Evolution) is an open international powerline standard for applications such as advanced metering and grid control. It

provides interoperability among several devices and systems from different manufacturers.

2.6.3 Application level energy management systems

- **OpenADR** is an internationally recognized standard for Automated Demand Response. The adoption of OpenADR to smart grid implementation has become necessary to deploy demand response and dynamic pricing effectively, while ensuring grid stability.

- **IEC 61970 and IEC 61968** are standards for the integration of advanced smart grid application. IEC 61970 is defined to improve communication interoperability for energy management systems while IEC 61968 standardize interface for meter reading & control, network operations etc.

2.6.4 Interoperability center communications

- **IEEE P2030** is a guideline for smart grid interoperability of the electric power system with end-use application. The guide provides a basic understanding and knowledge required for grid architectural designs and operation, while also providing alternative approaches to good practices for smart grid.

- **ITU-T** is a standard for wired communication and networking developed by International Telecommunication Union's Telecommunication. ITU-T standards support communication over low and medium voltage powerlines in both urban and rural communications.

- **ISA 100.11a** is a standard for wireless network systems, developed by the International Society of Automation (ISA). ISA 100.11a standard defines the procedures for implementing wireless systems in the automation and control open field level.

- **ANSI C12.22** is a standard protocol for interface to data communication networks. The standard enables secure communications including confidentiality and data integrity by using AES encryption.

2.7 Summary

The information provided in this chapter is a scene setter to understanding the features of smart grid and puts the research ideology into context. Although smart grid technology and its application is progressing very quickly, the focus was on the enabling technologies that are relevant to the work subsequently presented in this thesis. State of art of current smart grid communication technologies and their impacts, requirements and standards have also been presented. It is assumed for the remainder of the thesis that some of the highlighted enabling technologies will be in place to support smart grid applications. For example, smart meters through AMI will be in place to provide 2-way communication on energy prices, consumption data and other related information to both consumers and utility companies respectively. Although smart grid enables the transition to intelligent power grid with advanced capabilities, it also opens many new challenges that surround the uncertainty in future energy generation, preventing network planners and consumers from making informed decision. The major drawback to achieving the potential benefits of smart grid at the consumption level has been the lack of automated IDSS to provide an informed decision-making on energy schedule, optimization and control of various interconnected devices and activities. Consequently, various smart home appliances, smart meters, electric vehicles (EVs), and IDSS are expected to communicate properly with each other, while also ensuring communication with consumers and utility service companies. Additionally, it is expected that this chapter will benefit researchers who are interested in smart grid and related fields by providing an insight into the enabling technologies and standards.

In the next chapter, DSI and load management strategies available for smart grid implementation in residential buildings will be described, which forms the core area of the research in the later chapters of the thesis.

Chapter 3

3 Review of Demand-side Integration and load management strategies

3.1 Introduction

Load management is the most significant strategy for addressing the Demand-side Integration (DSI) problems [89]. Efficient load management strategies are critical to achieving DSI at the consumption level of smart grid and have recently gained increasing research interest [90]. Consequently, Demand-Side Management (DSM), Demand Response (DR) and Demand-Side Bidding (DSB) have been systematically used to describe load management and a range of different demand side initiatives (as will be defined in Intelligent Decision Support System). To avoid confusion and inconsistent use of the concepts and terminologies, Demand-side Integration (DSI) is used in this chapter to refer to the underlying aspects of the relationships between the electric power systems, the energy supply and end-user energy consumption. Hence, the DSI encompasses all activities focused on end-use efficiency and effective electricity utilization including demand response and energy efficiency. Towards the effective implementation of DSI load management strategy, an Intelligent Decision Support System (IDSS) will play an important role for efficient and coordinated load scheduling and optimization using pricing signals [91]. An IDSS aims to enable the autonomous management of smart home devices and their energy consumption profile to improve energy efficiency. In this chapter, the concept of DSI load management strategies is reviewed. Load scheduling objectives, appliance-modelling considerations, and the required algorithm for an effective IDSS implementation are also discussed.

3.2 Demand-side Integration

Demand-side integration (DSI) is a set of measures designed to utilize loads and local generation to support network management and improve the quality of power supply [33].

DSI aims at addressing the problem of electric power systems such as financial risks of infrastructure investment and load management using pricing programs that encourage peak demand reduction. This requires the interaction between the consumers and utility service companies to deal with the increasing electricity demand; while providing the technological platform to implement demand sensitive pricing notions aimed at using energy more efficiently and effectively. Hence, utilizing price signals that reflect the known (or forecasted) value of energy during a particular hour—and its uncertainty—may help to enable improved coordination between electricity supply and demand. This, in turn, can help to integrate renewables with intermittent output into the grid. In addition to reducing consumer energy costs, DSI approaches should be able to help manage the integration of renewable resources, since a large proportion of energy generation in smart grid is expected to come from non-dispatchable renewable resources such as wind, solar and wave energy [92]. These renewables are intermittent in nature and it remains an important challenging factor to manage their output generation with demand fluctuations. Furthermore, the required generation capacity for peak demand can be reduced by DSI approaches [93]. Achieving the potential benefits of DSI depends on the following:

- The availability and timing of the information provided to the customers, e.g., the spot prices of electricity relayed to the customers by the utilities via the AMI.
- The duration and timing of the consumer DSI participation.
- The efficiency of the ICT infrastructure e.g., the smart metering.
- The automation of end-use energy management system e.g., the IDSS.

DSI is a generic term for the various terminologies used in demand side, whose meanings are closely related to each but with slightly different focuses. These terms are defined as follows:

3.1.1 Demand-Side Management

Demand-Side Management (DSM) is an enhancing concept for the activities of utility that influences customer use of electricity. DSM can be defined as the planning, implementation and monitoring of activities designed to encourage consumers to change their electricity consumption pattern [33],[94]. The initiative of the concepts of DSM was first introduced in 1985 by Gellings [95]. The principally objectives of DSM include influencing energy demand, reducing peak demand and reducing greenhouse gas emissions. Effective techniques for DSM can also help to stabilize and sustain the grid. Therefore, the development of different new methods/approaches for the implementation of DSM are considered in the various on-going research by the academia and industry. DSM approaches are meant to achieve demand response at the consumption level and for large-scale customers. In the residential area, DSM refers to the activities designed by the utility companies to reduce peak demand at the consumption level [96]. However, the success of DSM will mostly depend on the active participation of the end-users.

3.1.2 Demand Response

While DSM refers to long-term and short-term measures designed by the utility to influence the consumption pattern, Demand Response (DR) is the actions or mechanisms taken to directly adjust demand curve of consumers in response to specific supply conditions [97]. Examples of DR includes the user modification of consumption pattern by shifting loads between times of the day; reducing the level of instantaneous peak demands, particularly when power utilization approaches supply limits. Traditionally, DR is focused on load curtailment during peak period to enable grid stability. On the other hand, DR is a more cost effective alternative than adding generation capabilities to meet the occasional demand at peak times. Incorporating DR within the constraints of the electricity network could have a significant reduction in the electricity prices in the market and in turn, reduces the exercise of market power by the generation company [98].

3.1.3 Demand-Side Participation

Demand-Side Participation (DSP) is a set of techniques/strategies used in a competitive electricity market by end-use customers to contribute to economic, system security and environmental benefits [33]. DSP seeks to improve energy efficiency and control the effects of load on the supply chain. The major issue with DSP is how to make efficient energy consumption schedules with increasing number of loads. Consequently, customers are more willing to voluntarily participate in DSI by adapting to pricing programs advertised by the utilities and making effort to shifting some high-load consumption devices to off-peak periods to reduce electricity cost. This can be done through automatic response to pricing signals based on direct communication between the energy consumer, the system operator and the utility as shown in **Figure 3.1**[86]

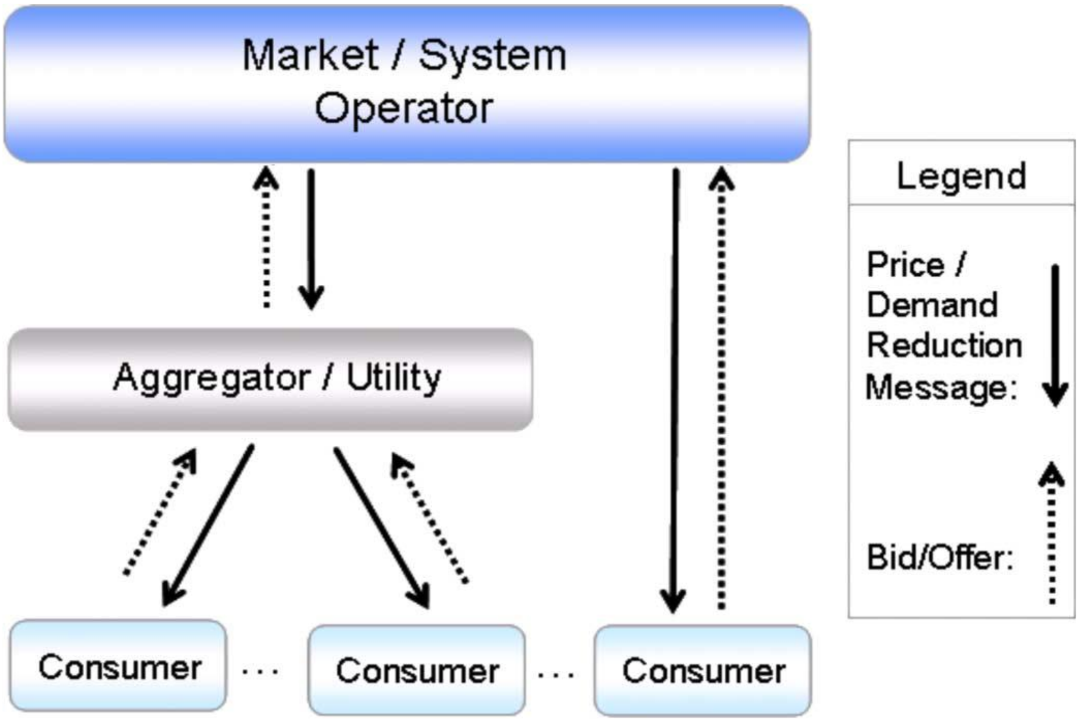


Figure 3.1. Demand-side Integration communications

3.1.4 Implementations of Demand-side Integration

As shown in **Table 3.1** below, the implementation of DSI can be done through DSI pricing programs, which provide the opportunity for consumers to control their energy consumption. They are of two types: 1) Pricing-based DSI (P-DSI); and 2) Incentive-based DSI (I-DSI) programs [33],[99]. P-DSI programs also known as time-varying prices that motivate consumers to change the consumption patterns, while I-DSI programs reward the participating customers for reducing their electricity consumption in response to utility signals. I-DSI programs (e.g., direct load control [100]) can be customized to a particular operational objective such as localised load reduction during transmission congestion to diversify the contribution of DSI load scheduling strategy to efficient grid operations [99]. However, I-DSI poses a serious threat to customer privacy as the time intervals of meter measurement varies from hours to seconds based on several trigger conditions [101],[102]. This privacy issue is a major challenge of I-DSI, as it involves third party company (or utility company) collecting metering measurements to calculate the aggregate demand side resources of customers and reward customers based on their participation on demand curtailment during DSI events.

Table 3.1. Demand-side integration pricing scheme [103]

Priced-based DSI programs	Incentive-based DSI programs
Real Time Pricing (RTP) Time of Use Pricing (TOUP) Critical Peak Pricing (CPP)	Direct load control (DLC) Emergency load shedding Demand bidding/Buybacks Interruptible/curtailable load

P-DSI or time-varying pricing mechanisms enable consumers to instantly identify the likely duration of a period of high price levels during which they can reduce their energy consumption. Hence, this could lead to cost-reflective consumption, driven by aspects of the entire supply chain involved in delivering electricity during a certain period in a given quantity at a specific location [2]. Each of the time-varying pricing rate which includes real time pricing, time of use pricing and critical peak pricing is described below [2],[103],[104]:

Real time pricing (RTP): Customers that participate in RTP are provided with electricity prices within a certain period on hour ahead basis. It is also possible to forecast the spot prices a day ahead depending on category of customers (residential, business customers etc.) RTP reflects the wholesale cost of energy production during a certain hour and represents the best and flexible pricing signals advertised to customers to reduce consumptions at the periods of high tariff.

Time of use pricing (TOUP): A typical model of TOUP is where a day is divided into several periods (times) and schedule of rate is provided for each period. For example, a period of 2pm to 10pm on a weekend (Saturdays & Sundays) might be defined as peak period during which prices of electricity are higher, while the remaining hours are the off-peak period. TOU rates in some cases might include a shoulder (mid-peak) period, as there is a certainty on the rates at any given period. TOU rate is very simple for customers to understand and participate in. However, they are not dispatched based on the changes in actual wholesale prices, and as such are not dynamic.

Critical peak pricing (CPP): Participating customers under a CPP model pay higher tariff during a few days of an unexpected event (CPP event day) affecting the grid. At these periods, the wholesale prices may be the highest. Typically, this must not be more than 15 days per season in a year according to regulations, and customers may decline not to participate. Customers are notified of any upcoming CPP event one day in advance and the participants receive incentives (e.g., discounted tariff during the remainder of the season) to balance the utility's total annual revenue.

However, the use of P-DSI to achieve demand response is most effective with the use of smart home devices, which can be scheduled or shifted to adapt to the pricing signals advertised by the utility companies. To manage electricity consumption in response to time-varying prices, there is a need for an automated system. For example, the use of Home energy management system (HEMS) or Intelligent Decision Support System (IDSS) to control the smart appliance scheduling in the residential building. For business and industrial customers, automated demand response (Auto-DR) would enable customers to automate reductions of electricity consumption in a range of processes through integration with the facility's DSI support [104].

3.2 Intelligent Decision Support System

The emerging smart grid has presented new opportunities for DSI support to incorporate the concept of smart homes and smart grid. Intelligent Decision Support System (IDSS) is a DSI load scheduling tool that enables an informed decision-making aimed at shifting and curtailing demand to improve energy consumption and production profile in response to pricing signals and user comfort [105]. IDSS enables optimal and near-optimal consumption and production schedules with different objective functions such as economic benefits (e.g., energy cost optimization, load profiles), environmental benefits (CO_2 emission reduction) and consumer well-being (comfort) etc. IDSS is seen as a major driver for automated DSI participation, as it is unrealistic for consumers to spend time manually analyzing load profiles and consumption costs of the household devices to save money. As such, IDSS is expected to plan for appropriate responses such as price, demand uncertainties and so on, without human intervention. Hence, the implementation of IDSS increases the responsiveness of residential electricity consumers to dynamic pricing signals advertised by the utilities [105], [106]. For example, reductions in peak consumption are larger by 10-27% in critical peak pricing and 22% in time-of-use pricing when the pricing program is tested with a specialized system such as an IDSS [106].

In a wider context, IDSS often incorporates forecasts of renewable uncertainties as well as energy consumption patterns/behaviors in household appliance scheduling. Forecasting tools such as fuzzy logic [107], Neural networks [108], support vector machines [109], etc., can be used to determine the accuracy of load forecasting, which also depends on the forecasting methods being employed. However, it can also be assumed that the forecasts are made available for IDSS through external sources (e.g., spot prices from the utilities) or can be addressed by a different component of DSI support tool. To utilize the IDSS effectively, complementary communication devices (e.g., smart meter/AMI) are needed to provide access to certain required information (e.g., electricity prices), and to the appliances themselves.

Many terms have been broadly used in the literature to describe the IDSS and DSI support that manages home devices to improve energy consumption pattern and production profile. Home energy management systems (HEMS) [110]-[112]; Energy Management System (EMS) [113],[114]; Demand side management system (DSMS) [115],[116]; Residential energy management system (REMS) [117] are the most common terms used in the literature for DSI support unit. In this thesis, the use of the term IDSS is preferred to maintain consistency of discussion.

3.2.1 Multi-objective functions of IDSS

While the purpose of the terms used to describe the residential energy management units found in the literature are consistent, their objective functions can vary significantly. In general, the types of quantities comprising the components of an objective function employed in an IDSS have included the following:

Economic Cost: these components constitute any financial savings from effective utilization of the energy infrastructure. Cost minimization is the predominant objective of IDSS, as energy cost saving is the major driver for consumers, and electricity prices (spot prices) are readily available for consumption cost optimization and other purposes. Consumer costs might include per-unit taxation and distribution charges, which form a large proportion of the final price. The objective is aimed at finding the least expensive set of power profiles subject to necessary constraints. Cost objective function can also include the device start-up cost as well as cost of carbon or other emissions taxes [105].

Customer Well-being: are the objective function components that consider the satisfaction of consumer's lifestyle, patterns, and behavior in managing the energy consumption. This ensures the minimization of consumers' inconveniences, while maximizing the quality of services rendered by the energy delivery. Hence, the objective is such that customers do not lose any degree of comfort.

Load profile: This objective component considers the modification of the set of appliance stages (phases) along with their energy consumption to minimize peak demand through load shedding, shifting etc. Peak reduction is desirable to improve the usage of available grid capacity [118]

Environmental impact (CO_2 Emissions): This objective component refers to the minimization of greenhouse gas emissions relating to electricity consumption. Emissions may be based on grid intensity, measured in grams of CO_2 equivalent per kWh of electricity consumed [105]. If an estimate of the economic cost of emissions (taxation levels) are known, then actual emissions are often eliminated and replaced by equivalent economic costs.

While economic cost [17],[118],[119] is the dominant objective function component considered in the literature, several multi-objective function components are often combined, such as costs and well-being [10],[120], cost and emission [121], cost, well-being, and emission [122] and different combinations thereof. A multi-objective optimization considers a trade-off analysis between two functions using two approaches. The first is a *priori approach*, which is considered when it is possible to analyze the decision-maker's trade-off between various objectives before solving the optimization problem. The second is referred to as *posterior approach* (e.g., Pareto frontier) when the prior approach is not possible. The most commonly used methods for addressing multi-objective optimization problems are bounded objectives [123], which uses constraints with acceptable range; and weighted sum [124], which adds scalar weights to combine components into a new objective function.

3.2.2 IDSS for smart home with smart devices (appliances)

Smart homes are technological augmented residential buildings that have several intelligent interconnected devices, which provide services and automation to support the running of the household and its internal/external environment [125]. The services provided by a smart home application include appliance scheduling & optimization, lighting control services, heating and cooling services, ambient media services, security services, etc. Electronic sensors and actuators, automation devices and communication channels are used to control and coordinate the activities of various devices in the smart home. However, there is large diversity in the energy consumption patterns of devices because of certain dwelling characteristics such as occupancy, affluence, and lifestyle [105]. Therefore, it is imperative for an IDSS to be effective enough to coordinate the scheduling of multiple devices with different configurations (such as operation stages and power constraints) along with a variety of user preference constraints (such as start and stop times or usage windows).

3.2.3 Household appliance scheduling considerations for IDSS modeling

For a coordinated scheduling and optimization using IDSS, there is need to address the modeling issues and considerations for the control of various appliances with unique characteristics in residential buildings. Many existing research on load scheduling in the literature categorized the devices into different classes in attempt to simply the modeling complexity. The different classes based on appliance behavior and controllability include controllable loads, uncontrollable loads, regulation loads [105], etc. Controllable appliances such as washing machines, dishwasher, tumble dryers, water heaters, are selected candidates for demand response modeling. They are called controllable because they can be scheduled or shifted to operate at any hour of the day (within given user constraints), hence helping to reduce peak consumption and saving cost. Also, from the literature, certain appliances such as refrigerator are considered as uncontrollable [126] at hourly time resolution because of the short cycling characteristics (20-45 minutes), while most research consider it as regulating loads [10],[100] at the minute resolution, depending on the optimization or control technique being applied. Controllable appliances can be either interruptible or uninterruptible loads; and may have one or many operation cycles (stages) and constraints. For example, tumble dryer is modelled as uninterruptible load as it has only one stage (drying) which can start and finish without any in-stage interruption. In addition, renewable energy generations (PV panels and wind turbines), energy storage devices and Plug-in hybrid electric vehicles (PHEV) are also controllable /schedulable for environmentally friendly smart homes.

3.3 Load scheduling Strategies

Load scheduling is a significant service provided by DSI through demand side resources (e.g., flexible loads, distributed generation, and storage) to the power system by modifying the load consumption patterns [33]. The major objective of load scheduling is to determine starting times for controllable appliances to balance the residential electricity profile and to minimize the economic cost of energy consumption. This involves scheduling multiple appliances (which may be interruptible or non-interruptible) within various time and user comfort constraints. Since most scheduling problems are known to be NP-Complete, it is unlikely that an optimal solution to an appliance load-scheduling problem can be found in polynomial time [21]. To simplify the solutions to such scheduling problems, there is often a need to approximate the optimal scheduling of household devices; there is a trade-off between optimality and low computational overheads. Three key techniques are most commonly used to schedule residential smart devices: those based upon mathematical optimization formulations, heuristic methods, and meta-heuristic searches [105]. These techniques are summarized below:

3.3.1 Mathematical optimization (Mathematical programming)

Mathematical optimization minimizes or maximizes an objective function by systematically choosing input values from a given set such that 'best' feasible solution satisfying any given constraints is achieved (this solution is known as the optimal solution). In a case where no feasible solution to an instance exists, the problem is termed 'infeasible'. Both the objective functions and the constraints are formulated mathematically. The types of mathematical constructions appearing in an objective function and the types of constraints on the variables define the class of problem. Typical generalizations of problem classes are as follows [105]:

Linear programming (LP): This is a special case of mathematical optimization for determining the best outcome in a given mathematical model for some list of requirements represented as linear relationships [127]. Hence, linear programming techniques are used for the optimization of linear objective functions subject to linear equality and inequality constraints. The objective function is a real-valued affine summation of the optimized variables. The solution procedure aims to find a point in the polyhedron where the function has the minimum or maximum value (if such a point exists). For real-valued decision variables, the best solution can be found in polynomial time using interior point methods [128], but specialized software is required for its implementation.

Integer linear programming (ILP): When additional constraints are added to linear program to enforce that all of the variables take on integer values, the resulting optimization program is known as an integer linear program (ILP). This increases the complexity of the problem considerably over a standard linear program, and the problem becomes NP-hard to solve [129]. Algorithms such as branch and bound and cutting planes are required to make progress on such problems. In the worst case, all such approaches will default to exhaustive search [130]. Specialized software is needed to solve ILPs.

Mixed Integer linear programming (MILP): This is a generalization of an ILP, which requires only a subset of the decision variables to be integer. MILP problems are also NP-hard and have similar requirements to ILPs.

Quadratic programming (QP): This is a type of mathematical programming problem with a quadratic objective function in several variables that are subject to linear constraints. QP problems are simple to solve in polynomial time if the objective function is positive definite and only equality constraints are present. The problem becomes NP-hard when the objective function is indefinite, and one or more variables are required to be integer.

Non-linear programming (NLP): This is a type of optimization problem where the objective function is nonlinear, and the best feasible solution is determined by linear nonlinear constraints.

Mixed integer non-linear programming (MINLP): defines the optimization problems where the objective function and constraints have general nonlinear components (e.g., sigmoid functions). This type of scheduling problem formulation can be difficult to solve computationally and may not guarantee any global solution. In many cases, an NLP can be well approximated by a LP or MILP to obtain approximate solutions at appropriate computational cost, and if possible, to do so, it is mostly recommended to avoid ad-hoc solution techniques.

Convex/Non-convex programming: Convex optimization problem is where all of the constraints have convex functions, such that the objective is a convex function if minimizing, subject to linear inequality constraints or a concave function if maximizing subject to concave inequality constraints [131]. Hence, a concave optimization problem is a problem where the objective function or any of the constraints are concave or non-convex. The non-convex may have many feasible regions and local point within its region, which can take exponential time to determine the optimal solution across all regions. An illustration of convex/non-convex optimization is shown in **Figure 3.2** below.

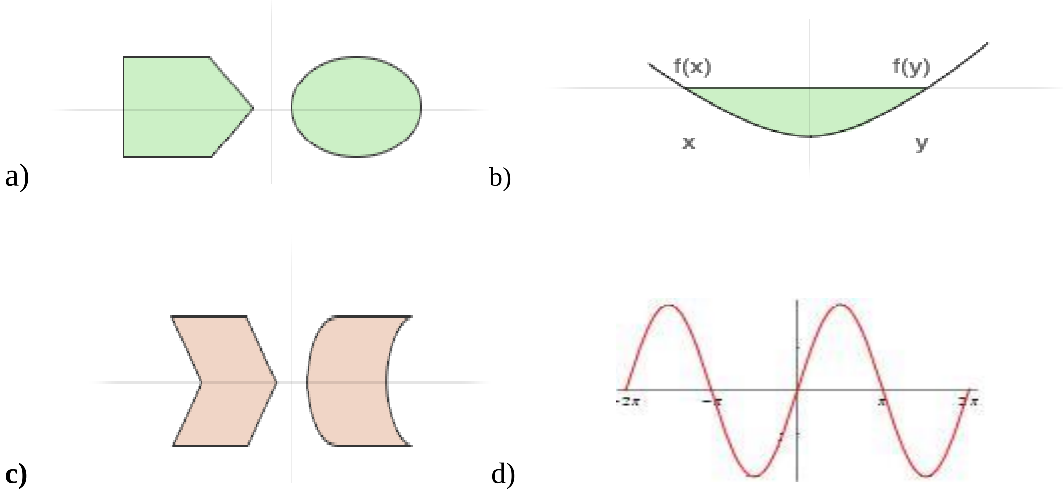


Figure 3.2. Illustration of convex/non-convex optimization: (a, b) Convex region and convex function respectively, (c, d) non-convex region and non-convex function (e.g., sine function) respectively [131].

Convex problems (e.g., linear programming) have only one local optimum point, which is also the global optimum point. Well-behaved iterative algorithms such as the interior point methods can be used to either find the feasible or global solution if such exists [48].

Dynamic programming: This is a method of solving complex optimization problems by breaking them down into smaller sub-problems, solving and storing the solutions of each one the sub-problems. For residential DSI support, variables are confined to be discrete values only.

3.3.2 Heuristic algorithm

Algorithms are generally defined as step-by-step procedures for solving problems. They can simply be referred to as computer programs written in a precise computer language to solve and produce solutions to instances of optimization problems [129]. In the case of the Travelling Salesman optimization problem [132], an algorithm does not solve the problem unless it is designed in such a way that it gives the minimum length tour. Hence, an efficient algorithm could mean the fastest in obtaining the solution. In practice, time requirements are often a dominant factor in determining whether an algorithm is efficient enough or not. The time requirement for any algorithm is expressed by time complexity function to give the largest amount of time required to solve a problem instance of that size for each given length.

Computer scientists recognise that algorithms have different time complexity functions because of distinctions between polynomial time algorithms and exponential time algorithms. A polynomial-time algorithm is one in which the computing time required to produce a correct solution for an input of input size x (in bits) is always less than some polynomial function $p(x)$. On the other hand, an exponential time algorithm is any algorithm whose time complexity function cannot be bounded by a simple polynomial in this way [129]. This definition includes non-polynomial exponential time functions e.g., $t^{log\ t}$. The distinction in time complexity between polynomial time algorithms and exponential time algorithms has a great significant when considering the solution for a large problem instance; polynomial time algorithms scale reasonably well in the input, whereas exponential time algorithms do not.

In computational complexity theory, Non-deterministic Polynomial (NP) is a class of decision problems where candidate solutions can be verified as solutions in polynomial time by a deterministic Turing machine [129]. Polynomial (P) problems represents a class of decision problems which are both solvable and verifiable in polynomial time and is a sub-class of NP. Another sub-class of NP are NP-Complete problems which are thought to be ‘hard’ to solve and are related to each other through polynomial transformations. NP-hard problems are search (c.f. decision) problems which although they are not in NP, are at least as hard to solve as NP-complete problems. The relationship between the classes: NP, NP-hard, NPC is shown in **Figure 3.3** below.

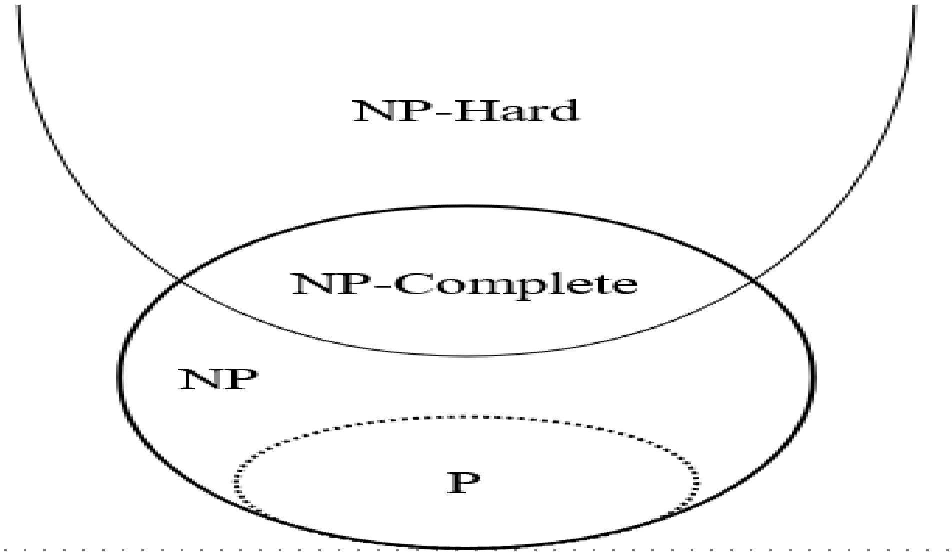


Figure 3.3. Relationship between complexity classes [21]

If it is possible to solve any instance of an NP-Complete problem in a polynomial time, then all NP-Complete and NP problems can be solved in a polynomial time due to the polynomial transformability between NP-Complete problems [21]. However, for many NP-Complete problems such as subgraph isomorphism [133], Travelling Salesman and others, no polynomial time solution algorithms have been found at the time of writing this thesis, and it remains an open question as whether P = NP. Heuristic algorithms have been considered in the literature to solve the NPC problems.

A heuristic algorithm applies a set of prescribed rules based on the knowledge of modeling processes realized for individual steps in a problem solution [21]. Heuristic approaches can be efficient in achieving faster solutions to an NPC optimization problem in many practical scenarios. Heuristic algorithm does not guarantee optimal solution; however, an efficient heuristic will provide approximate solution which is ‘good enough’ most times.

A significant focus of recent research has been on heuristic scheduling algorithms applicable to residential and industrial scheduling problems. Keqin [134] proposed three types of heuristic power allocation and scheduling algorithms for sequential tasks with energy and time constraints namely: pre-power determination, post-power determination and hybrid algorithms. The author analysed the performance of the algorithms, compared the solutions with analytical optimal schedule and concluded that the algorithms are applicable in real-time energy efficient task scheduling. Barbato and Carpentieri [135] proposed a set of heuristics and an optimization model for the online demand side management. They combined online and offline approaches to control home appliances and energy storage systems for efficient management of the energy resources. In [9], an intelligent Home Energy Management (HEM) algorithm is presented for managing high power consumption household loads according to a pre-set priority. Authors in [136] proposed a heuristic algorithm to determine price update interval and step size required for limiting deviation of power load from a desired load. An aggregator-based residential DR approach for scheduling residential assets was proposed in [26]. They further designed a heuristic framework to perform optimization on the profit of the aggregator.

Since load scheduling is faced with some inherent problems in terms of computational time complexity of the algorithm and the quality of the obtained solution, the best-fit heuristic algorithm could be used to potentially reduce the complexity of the scheduling framework. Several studies on heuristic algorithm for DSI support follow a simple greedy algorithm approach [137],[138], which makes use of locally optimal solution at each stage with limited backtracking. In greedy algorithm approach, decisions are made from the given solution horizon by choosing the nearest solution to optimality. In reality, greedy algorithm does not provide globally optimized solution because they do not search exhaustively on the set of decision horizon (e.g., time horizon). However, they achieve fast solution within a reasonable computational time.

Additionally, heuristic approach based on list-processing scheduling is widely used for applications requiring the scheduling of tasks with prescribed execution times upon interconnected microprocessors to obtain near-optimal solutions to the task scheduling problems [139]. List-processing scheduling evaluates and determines the degree of priority for different tasks, and finally assign the nodes to the processors that are ready to be executed based on a particular heuristic in order of scheduling priority. Commonly, the list of tasks is first permuted such that the priorities of tasks are indexed in non-increasing order of execution time; assignment of the next task to a processor is then done such that the lowest-loaded processor (in terms of already-assigned task execution times) is chosen next. If more than one task has the same priority (or more than one processor has the same load), it randomly or deterministically breaks ties. List-processing heuristic scheduling is constrained (in an on-line situation) such that only ready tasks are considered for mapping. However, this constraint can be overcome by using 'chaining' method proposed in [140]; which allows mapping for the non-ready tasks. Chaining is a single pass deterministic algorithm based on list scheduling techniques that enables tasks to be selected for mapping in any order, irrespective of the task dependencies or priority. Consequently, chaining method based on list processing scheduling only tries to partition the task graph among the processors but does not allow for duplication of tasks [139],[140]. For multi-processor scheduling, list-processing scheduling is known to perform better in both average and known cases compared to other types of heuristics (e.g., clustering algorithm [141]) in minimizing the execution tasks due to its feasibility, good performance and low complexity [71]. At the current time, it does not seem to have been applied in the smart grid/smart appliance context. Clustering algorithm is mostly applied in scheduling a network of unlimited number of processors and therefore cannot be used for real-time implementation because of high computational burden. This method also seems complicated when utilized in scheduling limited number of processors, as it requires two stages to finding solutions [139].

3.3.3 Metaheuristic algorithm

Metaheuristic search algorithms have been proposed in the literature over the last two decades for more efficient solving of hard optimization problems, including residential and commercial load scheduling. The fact remains that most mathematical optimization methods are not readily applicable for scheduling large numbers of appliances and for real-time implementation in households due to high complexity. Metaheuristic makes few assumptions about the optimization problem and can often find feasible solutions within less computational time when compared to mathematical optimization. Most of the existing metaheuristic methods are inspired by natural phenomenon, the studies explore alternative means of scheduling, and optimizing power profile at any hour of the day since an optimal deterministic technique is unrealistic to most customers. Many metaheuristic algorithms exist in the literature such as Tabu search [142], Harmony search [143], etc. The most widely used metaheuristics for residential scheduling applications are described below:

Particle Swarm Optimization (PSO): is a population-based optimization technique proposed by Kennedy and Eberhart in 1995 [144]. It is inspired by flocks of birds or school of fishes that fly/swim synchronously, such that the animal (particles) behaviors are used to search for solutions in the optimization problem. Hence, each particle represents a candidate solution to the problem and is pulled by the best position it has achieved. All particles have their own velocities and fitness level and will eventually settle around the optimum, assuming a convex objective function, to determine the best performing particle. PSO increases the stochastic nature of particles and achieves global best minima with reasonably good solution to the optimization problem. A discrete binary extension of PSO called BPSO has also been proposed in [145], to solve optimization problems that requires discrete values as decision variables.

Ant Colony Optimization (ACO): is a combinatorial optimization technique based on behavior of insects (ants) [146]. The technique is inspired by the ability of ants to find the shortest distance from their nests to food, despite any impending obstacles (constraints). In searching the shortest distance to locate food, the ants communicate with each other by depositing chemical substance called *pherome* as they randomly move around. The ant that locates the food more quickly (within shortest distance) returns to the nest sooner, while depositing more *pherome* on the way back, which serves as a promising path for other ants to recognize and follow. ACO can be run continuously to adapt to changes and has been used for load balancing problems to produce near-optimal solutions. However, it is very difficult to estimate the theoretical speed of convergence like most metaheuristics.

Genetic Algorithm (GA): is an evolutionary algorithm based on genetic properties. GA is used to generate solutions for optimization problems by evaluating genetic operators (e.g., mutation, crossover, selection, etc.) as objective functions [147]. GA can be used for load scheduling problem by formulating the optimization problem as a template and defining the fitness (value of the objective function) and chromosomes (variables) which represents the solution. In [148], chromosomes are considered as an array of bits which represents the appliance' ON/OFF state. Hence, the length of chromosomes would depend on the number of appliances. An initial population of solutions is generated by evaluating the fitness of each chromosome, followed by improving it through repetitive application of GA set operators. Fitness function ensures the evaluation and removal of poor performing individual. The algorithm is terminated when the global minimum is found. GA might not be fast enough for the IDSS due to the complexity in evaluating the cost function for the large number of populations involved.

Simulated Annealing (SA): is a variant of local search used to find better solutions to unconstrained and bound constrained optimization problems by randomly varying the current solutions. SA is inspired by annealing metallurgy, to solve hard combinatorial optimization problem by simulating the temperature falling procedure of a particular systems in thermodynamic [149]. A new point is newly generated at each iteration of SA, which is accepted with a certain probability (i.e., points that either lower or increases the objective function). During early iteration, SA is able to search globally for better solutions by accepting points that increases the objective function, to avoid being trapped in local minima.

3.4 Discussion and comparison

This chapter has presented several existing load-scheduling strategies in the literature such as:

- Mathematical programming optimization
- Heuristic optimization
- Metaheuristic methods

Each of these strategies has an array of appliance models in terms of assumptions, problem formulations, power, and timing requirements. The diversity in appliance modeling and assumptions made by developers for the residential appliance modelling makes it difficult to compare the effectiveness of the load scheduling techniques. The advantage of finding better solutions within a reasonable computational time is not only the deciding factor in choosing the appropriate technique for IDSS, but also the ability to find acceptable solution for large instances of the appliance scheduling problem autonomously in real-world. Therefore, this chapter has provided a descriptive analysis of the load scheduling methods with emphasis on the need for optimal/near-optimal schedule solutions, computational limitations, and suitability for consumer IDSS implementation in a constrained embedded processor. The main advantage of using mathematical optimization technique, in particular Linear programming (LP) and integer variants is that it guarantees an optimal solution, as opposed to heuristic, and metaheuristic which do not. However, mathematical formulation of the optimization problem with ILP, MIP or MILP adds additional constraints and variables to the objective function, which are not only difficult to solve (due to NP-hardness) but are also computationally expensive due to the need for specialized solvers/software (e.g., MATLAB interfaced with MILP solvers such as CPLEX [19]. As such, heuristic and metaheuristic algorithms provide the alternative options for complex load scheduling.

Heuristic approach to load scheduling requires knowledge (or experience) of the scheduling problem and its requirements (e.g., energy profile and time requirement of the scheduling devices) as well as other parameters to achieve good ‘feasible’ solutions based on a set of prescribed rules. The heuristic approach can also be developed and configured to significantly reduce the computational burden of a specific optimization problem while achieving an acceptable ‘good enough’ schedule solution. On the other hand, metaheuristic approaches based on complex and iterative-search is a high-level problem–independent framework that can be applied in solving general classes of problems. Metaheuristic is likely to outperform (not always) the heuristic approach in terms of the achieved solution, but their computational complexity makes them less scalable and might not be feasible for real-word problem instances such as the scheduling problems encountered by the IDSS.

Further research on mathematical programming, (discrete optimization in particular) has led to the interoperation of metaheuristic and mathematical programming optimization technique and is known as matheuristics [22]. This requires the exploitation of some features derived from the mathematical model (e.g., MIP model) of a problem instance in a metaheuristic framework. However, many successful matheuristic schemes use ‘black boxes’ (e.g., MIP Solver) to generate high-quality heuristic solutions for solving complex optimization problems [23]. The resultant effect of this approach is a possibility of incomplete MIP model (optimization problem formulation) and an external solver that iteratively solves the available sub-MIPs by introducing invalid constraints (e.g., variable fixing) that defines neighborhoods of certain solutions. As such, it might not guarantee feasible solution within required computational time for complex cases like that of IDSS.

3.6 Summary

In this chapter, DSI components and load scheduling strategies have been reviewed to select a suitable strategy to implement consumer IDSS, and some useful definitions were given. While the heuristic algorithm quickly finds feasible solution, metaheuristic sometimes exploits the interoperation of MIP model to improve the feasible solution by reaching a degree that is computationally difficult to attain. Therefore, for practical purposes, a standalone heuristic scheduling approach, without the need for any specialized solver is a more realistic strategy to actualizing the aim of the research. Essentially, a good trade-off will likely be based upon a list-processing heuristic, in line with greedy principles; such that appliance scheduling would follow a typical list scheduling process, scheduled in order of preference and sequentially (one-by one) without backtracking. This will likely produce fast, feasible solutions and allow for ease of implementation in real-time applications leading to a practical solution approach. In such an approach, the potential gap in optimality will require explicit evaluation in comparison to optimal exact algorithms, and the potential reduction in computational overheads requires similar treatment. This will better allow the effectiveness of the approach to be quantified with respect to a practical, large-scale roll out on smart meters. As such, in the next chapter the heuristic algorithm will be proposed and evaluated from consumer viewpoint in Chapter 5. An embedded implementation of the heuristic algorithm is described in Chapter 6 and thoroughly tested from utility planning perspective in Chapter 7.

Chapter 4

4 Heuristic Scheduling Algorithm for Smart Appliances

4.1 Introduction

In the previous chapter, DSI load management strategies were reviewed, and it was highlighted that the use of scheduling algorithm is a key functional requirement in the realization of a consumer IDSS. The use of load scheduling in IDSSs has become necessary in order to enable consumers to automatically respond to the changing economic value of energy across different hours of the day. Moreover, an IDSS is ideally also required to be responsive to unexpected or emergency events, such as specific DSI requests relayed through the AMI following unexpected events affecting the wider grid. Even disregarding the technical challenges and complexities of connecting an IDSS to both an AMI and controllable home appliances, smart home load scheduling using variable price signals remains a difficult problem to solve computationally. In most cases the problem is NP-hard [21],[129], and is affected by uncertainties such as variations in appliance power profiles. This warrants the search for good heuristics with efficient computational performance and ease of implementation. Since smart home appliance scheduling, like other forms of real-world scheduling problems, can be affected by uncertainties; in such circumstances regular re-optimization using a ‘rolling-horizon’ approach can be beneficial. For example, small changes in the electrical grid frequency - within statutory limits - can affect power consumption profiles by a small but not negligible margin because of imbalance between supply and demand; wear-and-tear of physical components such as motor brushes can also cause deviations from nominal appliance behaviour. To be of practical use, the optimization carried out by the IDSS must be able to deliver results of reasonable quality in a short space of time. A simplified representation of the optimization algorithm for load scheduling with various sources of energy supply to the residential building is shown in **Figure 4.1**.

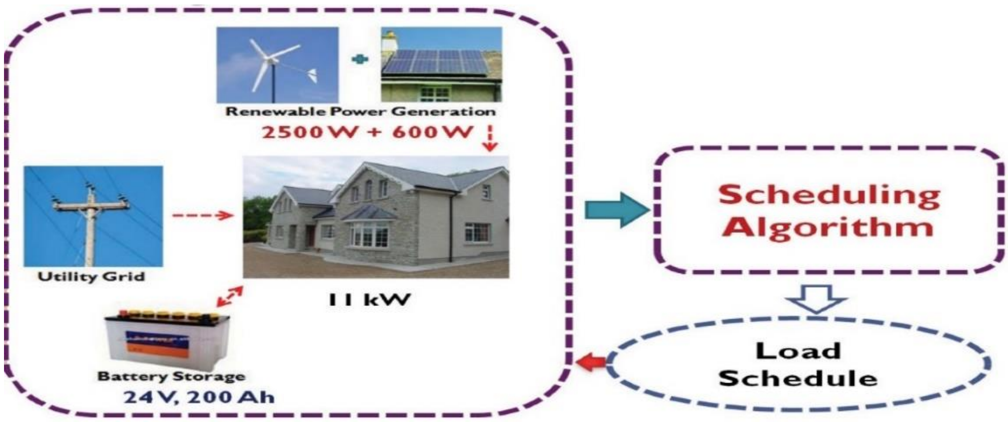


Figure 4.1. Residential load scheduling showing different forms of energy supply

In this chapter, a low-overhead heuristic scheduling algorithm for use in a consumer IDSS for minimizing smart appliance energy costs will be presented. Heuristic approaches can be efficient in achieving faster solutions, which – as will be demonstrated in a later chapter – enable easier implementation on an embedded computing system for the purposes of a consumer decision support system. On the other hand, a “good”, but not necessarily optimal solution to the optimization problem is only likely to be found; but it will be found in a reasonable time. Therefore, exact optimality with possibly excessive computation time is sacrificed for near optimality with much lower computational time, such that regular re-optimization with updated state information can take place in real-time. Although some loss of optimality is unavoidable with heuristics, this loss may well be compensated for in the longer-term by having a system that is efficient enough to react to changing circumstances. Hence, a heuristic solution, which is simple enough to be embedded in a microcontroller or computer for the purposes of a consumer decision support system, is desirable. As stated in Introduction, the aim of the research is to implement a simplified IDSS, which can be easily integrated into an AMI. Hence, the following three requirements are essential:

- The IDSS should not require specialized software (e.g., integer programming libraries) and have a straightforward code implementation.
- It should be implementable on a small computing device such as will be found within a smart meter.

- It should be configurable for a wide variety of cost models and functions.

This chapter first presents the formulation of an optimization model for home appliance scheduling alongside a generic cost model for dynamic pricing. The NP-completeness of this mathematical minimization problem is then proven. This is followed by a detailed description of a heuristic algorithm for solution of the optimization problem, which is proposed to meet the above list of key requirements. A broader discussion regarding the configuration of the optimization cost model in combination with Two-tier pricing (2TP) for generic applications in smart homes with different types of pricing mechanisms then follows. Additionally, an exact algorithm is also proposed as a benchmark to obtain optimal solutions; due to its high computational overheads, it is principally employed for comparative purposes with the heuristic algorithm in a series of detailed performance evaluations, which follow in subsequent chapters.

4.2 Optimization overview

Electricity supplied to the residential home is assumed to be hybrid generation comprising the conventional forms of generation (coal, gas, etc.) along with distributed energy renewables (solar, wind etc.), with an hourly price that reflects the value of the energy during that hour. The hourly price of electricity (or its forecast) is assumed advertised to the resident 24 hours in advance via the smart meter and will be used by the optimization algorithm to determine the cost-effective scheduling of the appliances. **Figure 4.2** shows the block diagram of a DSI support unit, which comprises the data and power flow between an IDSS equipped in a smart meter, and the smart home appliances. The smart meter receives external signals (e.g., spot prices of electricity) from the utility service providers. This information is used by the optimizer (IDSS) to determine the cost-effective scheduling of controllable smart appliances. Residential users can visualize the optimized cost schedule and recommendations provided by the IDSS to enable informed decisions on their energy consumption pattern/usage.

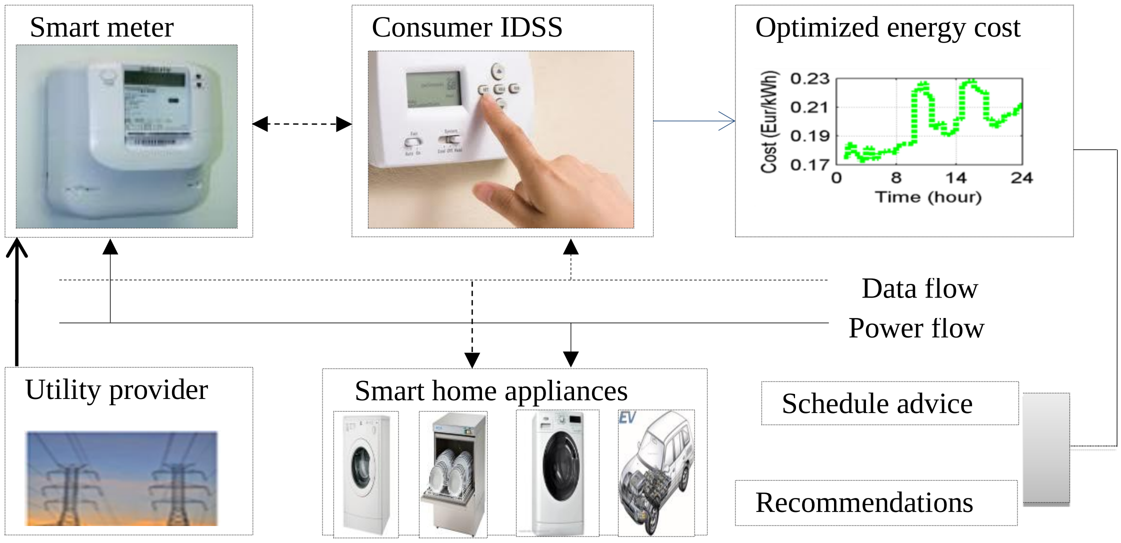


Figure 4.2. Block diagram of DSI support unit comprising consumer IDSS for Residential smart appliance scheduling.

4.3 Optimization Model

This section provides the mathematical formulation of the residential load scheduling problems. The focus is to optimize the power (and hence energy) profile at any given timeslot to minimize costs subject to the given constraints. It is assumed that the scheduling/planning horizon is divided into $H > 0$ uniform time slots; each time slot is of length $T > 0$ h. Typically, each slot will be of length $T = 1$ h, as obtainable in the Scandinavian electricity market, although this does not necessarily have to be so in the general case. Let the number of appliances be denoted as N, and the number of stages of appliance i be denoted as $n_i > 0$. The power consumption during stage j of appliance i is denoted by $P_{i,j}$, $i \in [1, N]$, $j \in [1, n_i]$. Let the starting time of appliance i be denoted by the integer variable $s_i \in [1, H]$. The power consumed by appliance i is determined from start time s_i during timeslot h such that the decision of whether or not to schedule appliances is given by the decision rule.

$$x_i(h) = \begin{cases} P_{i,h-s_i+1} & : \text{If } 0 < (h - s_i + 1) \le n_i \\ 0 & : \text{Otherwise} \end{cases} \tag{1}$$

Let the cost of consuming $x_h \geq 0$ units of energy during a particular hour h be represented by the cost function $C_h(x_h) \geq 0$. The optimization problem objective function J can then be formulated as the sum of the energy costs across each slot in the horizon as follows:

$$J = \sum_{h=1}^{H} C_h \left(T \cdot \sum_{i=1}^{N} x_i(h) \right) \tag{2}$$

The basic form of the optimization problem can then be formulated as follows:

$$\begin{aligned} & \min(J) \\ & \text{with respect to:} \\ & s_j : 1 \leq j \leq N; \\ & \text{subject to:} \\ & s_i^{Min} \leq s_i \leq s_i^{Max},\ s_i \in I : 1 \leq i \leq N; \end{aligned} \tag{3}$$

$$\sum_{i=1}^{N} x_i(h) \leq X_h^{Max} : 1 \leq h \leq H; \tag{4}$$

Constraints (3) are the user start time preferences, which ensure that each appliance does not operate outside of the set time preference interval given by s_i^{Min} and s_i^{Max}. Constraints (4) ensure the maximum power consumption for all the appliances at any time slot h does not exceed the power threshold, where X_h^{Max} is the threshold at slot h. Typically, this will be set by the household to suit its own specific constraints, such as the maximum power rating of the incoming supply or consumer unit. In addition, appliance specific constraints can be applied to ensure certain appliances start or finish before each other. An example is the case of washing machine and dryer where the latter must not start until the former has completed all of its operation stages. For certain types of interruptible appliances, it may also be possible to schedule a bounded amount of time-delay between two consecutive operation stages (e.g., a delay between a rinse cycle and the next wash cycle in a washing machine). In such cases, appropriate splitting of the main appliance into a number of sub-appliances, each with a separately considered start-time; appropriate constraints relating the start times of each sub-appliance will then model the required behavior, may extend the model.

By appropriate choice of T and H, the model may be configured to a given level of temporal fidelity and future planning horizon length. In the remainder of the chapter, we assume that $T = 1$ and $H = 24$, *i.e.*, hourly slots are considered over a planning horizon of one day. In the next section, the proof of the NP-Completeness of the decision version of the problem described above is shown and is hence intractable for large problem sizes unless P = NP. The optimization version of the problem is therefore NP-hard [129].

4.4 Proof of NP–Completeness of IDSS scheduling problem

Consider the decision version of the optimization model presented in [Section 4.3]:

IDSS problem instance: An integer $H > 0$ representing the number of considered time slots, an integer $T > 0$ representing the length of each slot, an integer $N > 0$ representing the number of appliances, integers $n_i > 0$ representing the number of appliance stages, and real-valued power consumption values for each stage denoted by $P_{i,j} > 0$, $i \in [1, N]$, $j \in [1, n_i]$, cost function $C_h(x_h) \geq 0$ and maximum power consumption thresholds $X_h^{Max} > 0$ for each hour of the day, plus user start time preferences $0 \leq s_i^{Min} \leq s_i^{Max} \leq H$ for each appliance, and a real-valued cost budget $B \geq 0$.

Question: Is there a set of appliances start times s_i such that Constraints (3) and (4) are satisfied, and the cost calculated using Equations (1) and (2) satisfies $J \leq B$?

In order to consider the computational complexity of the above problem, a well-known ‘hard’ problem from the field of computational task scheduling is now introduced. This problem is known as the MULTIPROCESSOR SCHEDULING PROBLEM.

Multiprocessor scheduling problem instance: Set Γ of tasks with cardinality L, number $M > 1$ of uniform processors, real-valued length $l_i > 0$ for each task, real-values deadline $D > 0$.

Question: Does a non-preemptive M-processor schedule for Γ exist, *i.e.*, a function $f(j) \in [1, \ldots, M]$ mapping all L tasks $j \in \Gamma$ to a processor (without overlap), such that the finish time for the schedule F:

$$F = \max_{1 \le i \le M} \sum_{\substack{f(j)=i \\ j \in \Gamma}} l_j$$

Satisfies the constraint that it is less than the deadline, *i.e.*, $F \le D$?

The multiprocessor scheduling problem above is known to be NP-Complete [120] and is in fact NP-Complete in the strong sense when $M \ge 2$. NP-Completeness of the IDSS problem is now shown by transformation from MULTIPROCESSOR SCHEDULING.

Theorem: IDSS is NP-Complete.

Proof: Transformation from the MULTIPROCESSOR SCHEDULING PROBLEM. Given an instance of the multiprocessor scheduling problem, we configure the following instance of an IDSS problem:

$$\begin{aligned}
&H = M; \\
&T = 1; \\
&N = L; \\
&s_i^{MIN} = 1; 1 \le i \le N; \\
&s_i^{Max} = M; 1 \le i \le N; \\
&n_i = 1; 1 \le i \le N; \\
&P_{i,1} = l_i, 1 \le i \le N; \\
&X_i^{Max} = D; 1 \le i \le H; \\
&C_i(x) = x, 1 \le i \le H; \\
&B = \sum_{i=1}^{L} l_i;
\end{aligned}$$

Observe that M timeslots have been created in IDSS, each with unit length, and that L appliances have been constructed each with a single stage having power requirement l_i. By the choice of s_i^{Min} and s_i^{Max}, each appliance is free to be started in any of the M available timeslots and incurs an economic cost l_i regardless of which slot it is assigned to. Given the choice of the budget B, any assignment of start times satisfies the budget constraint eliminating it from the IDSS problem. It is clear from this construction, however, that assigning an appliance start time $s_i = j$ incurs a power cost of l_i units in timeslot j. The claim is that a feasible schedule to this instance of the IDSS problem exists if and only if a feasible schedule exists for this instance of the MULTIPROCESSOR SCHEDULING problem. This is proven by taking the assignment of $s_i = j$ as equivalent to the assignment of task i on processor j, and equivalently it must hold that:

$$\forall h, 1 \leq h \leq H :$$
$$\sum_{i=1}^{N} x_i(h) = \sum_{\substack{f(i)=h \\ i \in \Gamma}} l_i$$

From which it is easy to see that the finish time of the schedule F is equivalent to the maximum power assigned to any of the $H = M$ timeslots, and since the maximum power constraints are constructed as $X_i^{Max} = D$ for each timeslot a feasible schedule to MULTIPROCESSOR SCHEDULING exists if and only if there is a feasible solution to IDSS, proving the claim.

This result established the complexity of the problem at hand, even when the costs are restricted to be simple linear functions of the power consumption. In the next section, a generic cost model to be employed for more complex classes of cost functions that may occur in the context of a smart home is presented.

4.5 Generic cost model

As stated in the optimization model, it is assumed that the cost of energy during a particular time slot h is a generic function $C_h(x_h)$ of the amount of energy consumed, which is x_h units. Typically, the form of C_h will depend heavily upon pricing of electricity in a day-ahead (spot) market and any specific DSI initiatives advertised to the subscribed residents by the supply/distribution company via the smart meter/AMI. The source of the energy supply is assumed a hybrid generation comprising the conventional forms of generation (gas, coal *etc.*) and distributed renewables (solar, wind, biomass *etc.*); hence, the nature and form of C_h can also depend upon the availability of these latter renewables, and have components linked to balancing (real-time) energy market prices. Two particular cases seem to be of most interest at the present time for representing costs in the presence of fluctuating costs and DSI pricing signals; in these cases, costs are represented by a concave/convex combination of two piecewise affine functions:

$$C_h(x_h) = \max\{a_1 + b_1 x_h, a_2 + b_2 x_h\}, b_1 \leq b_2 \quad (5)$$

$$C_h(x_h) = \min\{a_1 + b_1 x_h, a_2 + b_2 x_h\}, b_2 \leq b_1 \quad (6)$$

In particular, Equation (5) represents a case in which a cover charge (a_1 €) plus a base price (b_1 €/kWh) is incurred for energy used up to a certain limit (($a_1 - a_2$) / ($b_2 - b_1$) kWh), beyond which a higher price (b_2 €/kWh) is incurred for each extra unit consumed. This represents a pricing model in which increased production costs are reflected as increased consumer costs for increased consumption, and with the prices and low consumption limit linked to external market conditions. Equation (6) represents a similar situation except a reduction in cost is incurred for consumption above the limit, reflecting an economy of scale. Models (5) and (6) can be used to reflect specific cost incentives encouraging consumers to shift their consumption from peak to off-peak times, with both base and high consumption prices that can be linked to an underlying pricing plan. The cost functions Equations (5) and (6) are shown graphically in **Figure 4.3** below.

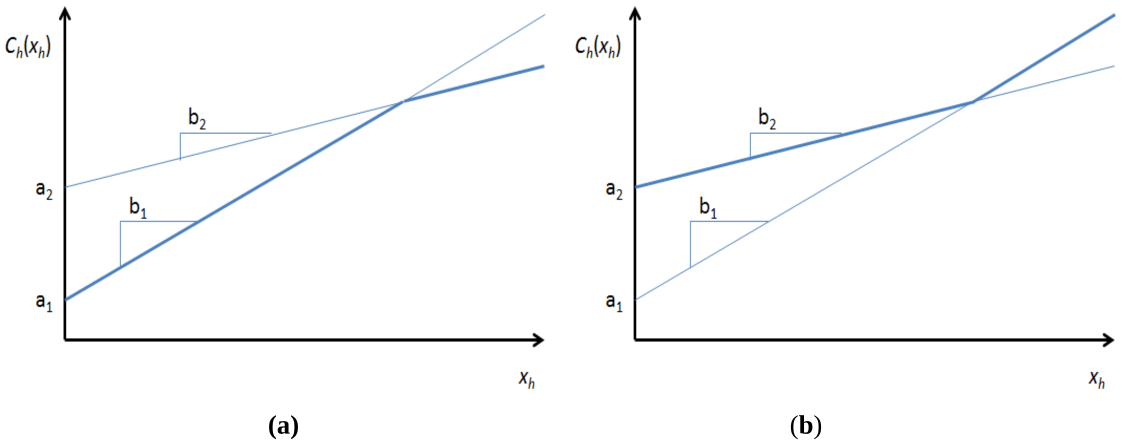


Figure 4.3. Illustration of the piecewise affine price model. (a) Concave (min) configuration, (b) Convex (max) configuration. Note: In most cases, either the parameter a1 or a2 will be equal to zero

By appropriate choice of the parameters a_1, a_2, b_1 and b_2 for each hour, such a cost model is flexible enough to capture the salient features of RTP, TOUP, 2TP and various combinations in addition to specific DSI incentives. Unlike RTP, TOUPs are more customer friendly due to the predictable nature of the pricing signals. Adopting TOUP scheme has an effect on load shifting, which in turns helps to achieve demand response [150]. TOUP mainly consist of two or more-tier rates namely peak, off-peak and in some cases, mid-peak prices depending on customers need and load profile pattern, which varies across different countries and locations. However, the more the tiers, the more difficult the model would be for customers to participate. Hence, 2TP will be considered in this thesis to reduce complexity, since mid-peak rates only examines the average costs between the peak and off-peak periods. 2TP is organized such that the rate of tariff paid below a certain power threshold is lower than the rate paid above it; this to penalize high consumption in any one hour and encourage even load distribution. However, the effect on demand response of combining 2TP with RTP—in which a customer may pay a basic unit rate until the threshold is exceeded, at which time a price linked to the spot price is incurred—has not been investigated fully in the presence of load scheduling. The simple functions proposed in equations (5) and (6) allow such an investigation to be carried out in the subsequent chapter.

Under the assumption that the cost functions $C_h(x_h)$ are linear, or piecewise linear and convex, the optimization problem above can be solved using mixed integer linear programming (MILP) software such as the IBM ILOG CPLEX and the YALMIP interface to MATLAB [140]. Nevertheless, solving such MILPs efficiently can only be done for relatively small instances of appliances [121]. Algorithms such as cutting plane methods and the branch and bound method [151] can also be used to reduce the average execution time complexity. In the case that the costs may be arbitrary non-linear functions—or combinations of even simple convex and concave functions at different hours over the horizon—then a large number of additional binary variables may need to be introduced to solve the problem. This may result in unacceptable overhead, even for relatively small numbers of appliances; in addition, the use of specialized solvers will be impractical and should be avoided on small devices such as smart meters and an IDSS computer. Therefore, instead this work seeks to find *good*—not necessarily optimal—solutions to the load-scheduling problem, in a reasonable time without undue computational overheads. The proposed heuristic algorithm is described in the next Section.

4.6 Proposed scheduling algorithms

In this section, the proposed scheduling algorithms (exact and heuristic) to solve the stated residential appliance scheduling problem are presented. The algorithms use appliance start times s_i as the decision variables and search over the future time horizon (window) H for the start times, which minimize the expected electricity cost J subject to the given constraints. Parameters such as the number of appliances N, length of timeslot T, hourly timeslot cost functions ($C_h(x_h)$), constraints, etc., are assumed given and define the problem instance.

4.6.1 Exact method

In principle, exact methods can guarantee an optimal solution to this NP-hard optimization problem. This can be achieved by searching the timeslots within the set time window exhaustively. In the proposed exact method—shown in pseudocode below—the algorithm exhaustively searches appliance start times for the best possible combination of starting times to obtain the minimum costs, which also satisfy the given constraints. The exact algorithm iterates through each possible combination of start times in the specified user intervals in turn. In the worst case, each of these intervals will be of length H timeslots, giving an exponential run-time complexity of $O(H^N)$ for the algorithm. During the search iteration, the exact algorithm updates the best solution whenever a feasible cheaper cost solution is found at each stage. The proposed exact algorithm could clearly be improved by adding features such as backtracking of partial solutions that cannot improve upon the best solution found so far; however, its use in this chapter is to principally obtain optimal solutions for comparative purposes.

Algorithm 1: Exact method

Initialization: Set and initialize the N appliances, constraints, and cost functions;
for $i = 1$ **to** N **do**
    $s_i := s_i^{Min}$;
end for;
$C_B :=$ INF;
$S := []$;
Done:= FALSE;
while Done == FALSE **do**
if Constraints Satisfied **do**
    $J :=$ Evaluate Full Schedule Cost;
    if $J < C_B$ **do**
        $C_B := J$;
        $S := [s_1, s_2, \ldots s_N]$;
    end if;
end if;
for $i = 1$ **to** N **do**
$s_i := s_i + 1$;
    if $s_i > s_i^{Max}$ **do**
        $s_i = s_i^{Min}$;
        if $i == N$ **do**
            Done=TRUE;
        end if;
    else
        break;
    end if;
end for;
end while;
return $[C_B, S]$;

4.6.2 Heuristic method

In the proposed heuristic algorithm, appliances are scheduled sequentially based on a greedy strategy without backtracking. This is such that the worst-case computation time is reduced compared to an exact search, at the expense of a potential loss of optimality in the obtained solution. Appliances start times are scheduled one-by-one, cost is evaluated for each feasible start time and considers only the current appliance and those, which have already been scheduled, and their start times fixed. Once the minimum cost for the current appliance is determined, its start time is fixed and is not subsequently changed once scheduling continues to the next un-scheduled appliance. All appliances are scheduled in this way.

Algorithm 2: Heuristic method

Initialization: Set and initialize the N appliances, constraints, and cost functions;

$C_B := 0$;

$S := []$;

for $i = 1$ **to** N **do**

    $C_B := \mathrm{INF}$;

    for $s_i = s_i^{Min}$ **to** s_i^{Max} **do**

        $J :=$ Evaluate Partial Schedule Cost;

            if Constraints Satisfied

                if $J < C_B$

                    $C_B := J$;

                end if;

            end if;

    end for;

$s_i := s_B$;

end for;

$S := [s_1, s_2, \ldots s_N]$;

return $[C_B, S]$;

A single loop over N appliances, considering the start times of each appliance within its specified user interval is performed. In the worst case, each of these intervals will be of length H timeslots, giving a polynomial run-time complexity of $O(HN)$ for the heuristic algorithm. Given the similarity of the heuristic algorithm to the "List-processing" algorithm for multiprocessor scheduling [152] and the similarity of the considered appliance scheduling to multiprocessor scheduling as demonstrated in Section 4.4, it follows that the proposed heuristic may inherit some of the known good performance bounds of the "List-processing" algorithm. Indeed, if appliances are all single-stage and are sorted in non-increasing order of power requirements, then for identical (linear) cost functions across each hour of the optimization horizon of length $H = 24$, the heuristic would achieve a cost not greater than 32% more than the optimal cost, which represents the best possible bound for a simple special case of a more general result in multi-processor scheduling [150]. In the case of more complicated cost functions, this worst-case gap could be either amplified or attenuated. Determination of the exact bound would require inspection of each cost function on a case-by-case basis due to the non-linearity involved. Nevertheless, the power allocation (c.f. costs) would still satisfy the 32% bound, regardless of cost functions.

4.7 Summary

In this chapter, a heuristic scheduling algorithm for the implementation of a consumer IDSS and an exact algorithm for benchmarking the performance of the propose heuristic in a realistic configuration have been proposed. Clearly, there are differences between the exact and the heuristic approaches; the largest one being in the number of iterations required by the two methods. The exact algorithm iterates through N nested loops, considering each of the H timeslots in turn, giving a complexity $O(H^N)$. The heuristic algorithm iterates through one loop N times, in each case considering each of the H timeslots in turn; giving a complexity $O(NH)$. Clearly, this reduces the worst-case running complexity from exponential time to polynomial-time. The price paid for this efficiency is that the heuristic is not guaranteed to obtain the optimal solution. A generic and flexible cost model for hourly pricing has been presented to be utilized by the heuristic algorithm, to capture the salient characteristics of traditional on/off peak pricing, RTP, Time of Use Pricing (TOUP), Two-Tier Pricing (2TP) and combinations thereof. In the next chapter, testing the performance of the proposed heuristic algorithm will begin with an extensive array of simulation and computational experiments.

Chapter 5

5 Evaluation of the Proposed Heuristic Algorithm Part 1) Consumer Viewpoint

5.1 Introduction

In Chapter 4 of this thesis, a heuristic scheduling algorithm was proposed as a solution to the load-scheduling problem. The heuristic provides a link between a utility company signals and individual household demands but is principally aimed at residential energy consumers. Consequently, there is a need to evaluate its performance under realistic conditions. An exhaustive search algorithm was also proposed for comparison and benchmarking purposes. In this chapter, a variety of different computational experiments is documented with the purpose of exploring the effectiveness of the proposed scheduling algorithm. The following aspects have been explored:

- The effectiveness of the proposed heuristic algorithm against the exact algorithm in terms of energy cost savings achieved for a single household with controllable appliances in the presence of dynamic energy prices is evaluated.

- The performance of the proposed heuristic within the framework of pricing models such as (RTP, 2TP, TOUP, etc.) and different combinations thereof (e.g., RTP/2TP, TOUP/2TP etc.), are investigated.

- The behavior of the heuristic algorithm for multiple household scenarios with various differing appliance constraints and configurations are explored.

- The disparity in power distribution between the heuristic and exact algorithms is quantified.

- The computational scalability of the heuristic and exact algorithms following an increase in the number of appliances and other configuration aspects such as length of timeslot, power assignments etc. is considered.

This chapter focuses on benchmarking the performance of the proposed heuristic algorithm against optimal exact search algorithm in a realistic simulation study. Possible wider aspects of the use of the proposed heuristic algorithm for potential cost savings due to DSI and power shifts from peak to off-peak period during DSI event days will be subjected to further attention in Chapter 7.

5.2 Experimental setup and technical data specification of appliances

Experiments were conducted on the two proposed algorithms using various instances of dynamic pricing and combinations including Two-tier pricing (2TP), with different appliance configuration scenarios. MATLAB [153] was the computational platform on which the algorithms were developed. All experiments are performed on a HP© PC with an Intel Core i5 CPU, 3.40GHz speed and 6GB of memory. Data specification for Electric vehicle (EV) in **Table 5.1** is a simple representation which may not fully represent the modern situation of an EV. Ideally, the oldest standard power rating of EV chargers should be 3kW for household analysis [154]. Under this circumstance, the charging time window would be at least 8 hours.

Table 5.1. Data specification of the appliance scheduling for a single household [17]

Devices	Power consumption (Watts)	User time preference
Washing machine	2100	10:00–20:00
Tumble dryer	1200	10:00–22:00
Dish washer	1900	17:00–23:00
Electric vehicle	1000	1:00–5:00

5.3 Cost evaluation for a single household

This experiment is aimed at determining the differences in the cost of scheduling appliances with the exact and heuristic algorithms respectively. First, to evaluate and compare the minimum cost of appliance schedule based on RTP; second to evaluate the test result based on TOUP, combined with 2TP (TOUP/2TP), and to compare the results (exact and heuristic) with the RTP/2TP test results. The scheduling consists of four controllable appliances namely washing machine, dishwasher, tumble dryer and Electric Vehicle (EV) as indicated in **Table 5.1** above. The scheduling is within the given constraints (e.g., appliance operation constraints which ensures that a certain appliance must finish before the start of the other as in the case of washing machine finishing its stages before tumble dryer phase starts).

5.3.1 Cost evaluation based on Real-Time Pricing (RTP)

RTP was used for optimization, which was carried out once every 24 h for one simulated year duration, considering the period from 1 December 2013 to 30 November 2014. The hourly pricing data for the RTP was taken from the Scandinavian electricity market Nordpoolspot [155] and samples of these prices are shown in **Figure 5.1**. Note that the raw (wholesale) costs for electricity were employed; in reality, consumer costs would also include per-unit taxation and distribution charges which actually form a large proportion of the final price and are typically over 50% in the EU. Nevertheless, price variations with the inclusion of these extra charges are still primarily as a result of wholesale price fluctuations, and the experiments still give a realistic indication of algorithm behavior.

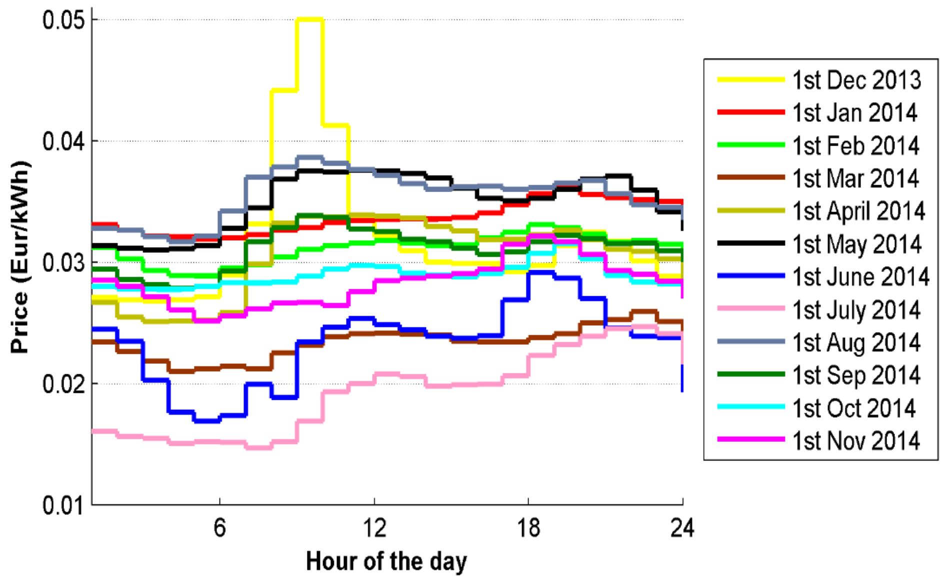
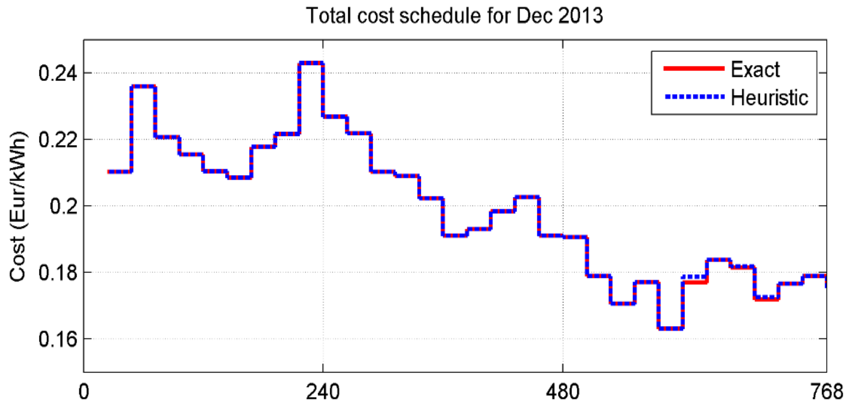
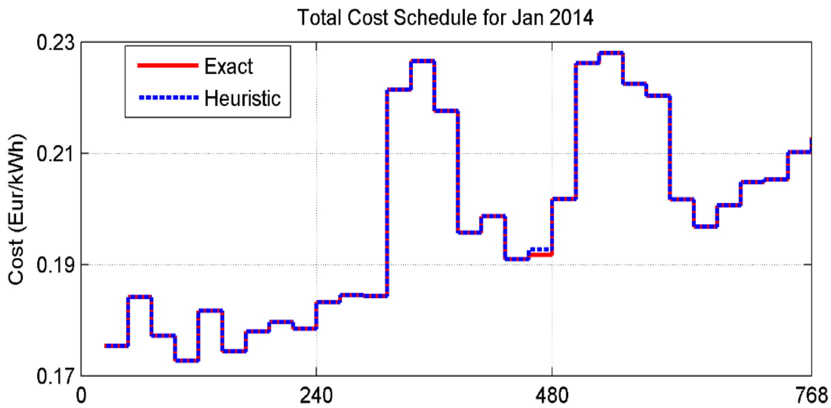


Figure 5.1. Example of the hourly pricing of electricity used in the simulation, showing the plot for 1st day of every month from December 2013 to November 2014. [155]

The simulation results of the total consumption costs for the exact and heuristic algorithms across the different months of the year used are plotted in **Figure 5.2**. The performance result illustrates that the cost scheduling for heuristics and exact algorithms for December 2013 and January are almost the same, although an insignificant difference can be seen on two days in December 2013 [i.e., 624th hour (26^{th} December 2013) and 696^{th} hour (29^{th} December 2013)], and only one day in January 2014 [i.e., 480^{th} hour (20^{th} January 2014). In February 2014, there seems to be eight days in which there are little disparity in the economic cost between the exact and heuristic algorithm. However, some difference in cost scheduling for heuristic and exact algorithm across a number of days are quite visible between March and September 2014. In October and November 2015, the differences in cost scheduling are only visible across 8 days and 5 days respectively. Nevertheless, it can be seen visually from the overall results that the heuristic achieves a near optimal solution across the course of the whole year. Average monthly consumption costs of €2.1674 were incurred as compared to €2.1582 obtained by the exact algorithm. Percentage cost difference in these figures confirms that the proposed heuristic achieves up to $(2.1674 - 2.1582)/2.1674 = 0.0042\%$ of the optimal solution obtained by the exact algorithm. However, both algorithms schedule the same amount of energy in the household, but the heuristic takes significantly smaller computation time (0.000704 s) for four controllable appliances when compared to the proposed exact algorithm (0.00246 s) which is approximately 71% difference in the solving time (see [95] for a detailed comparison of CPU execution times for typical configurations).





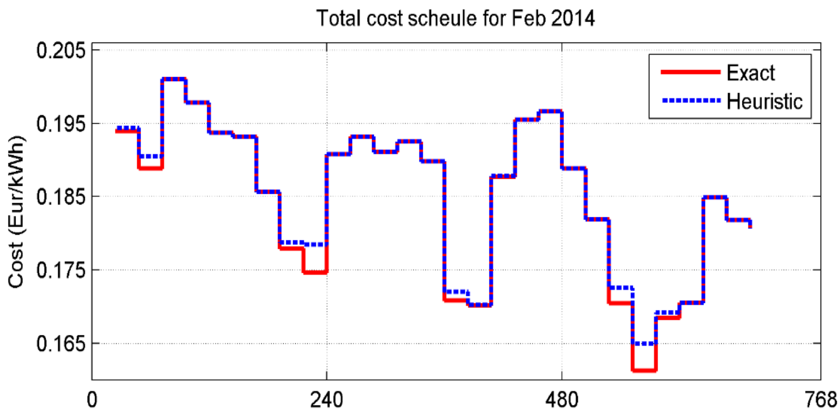
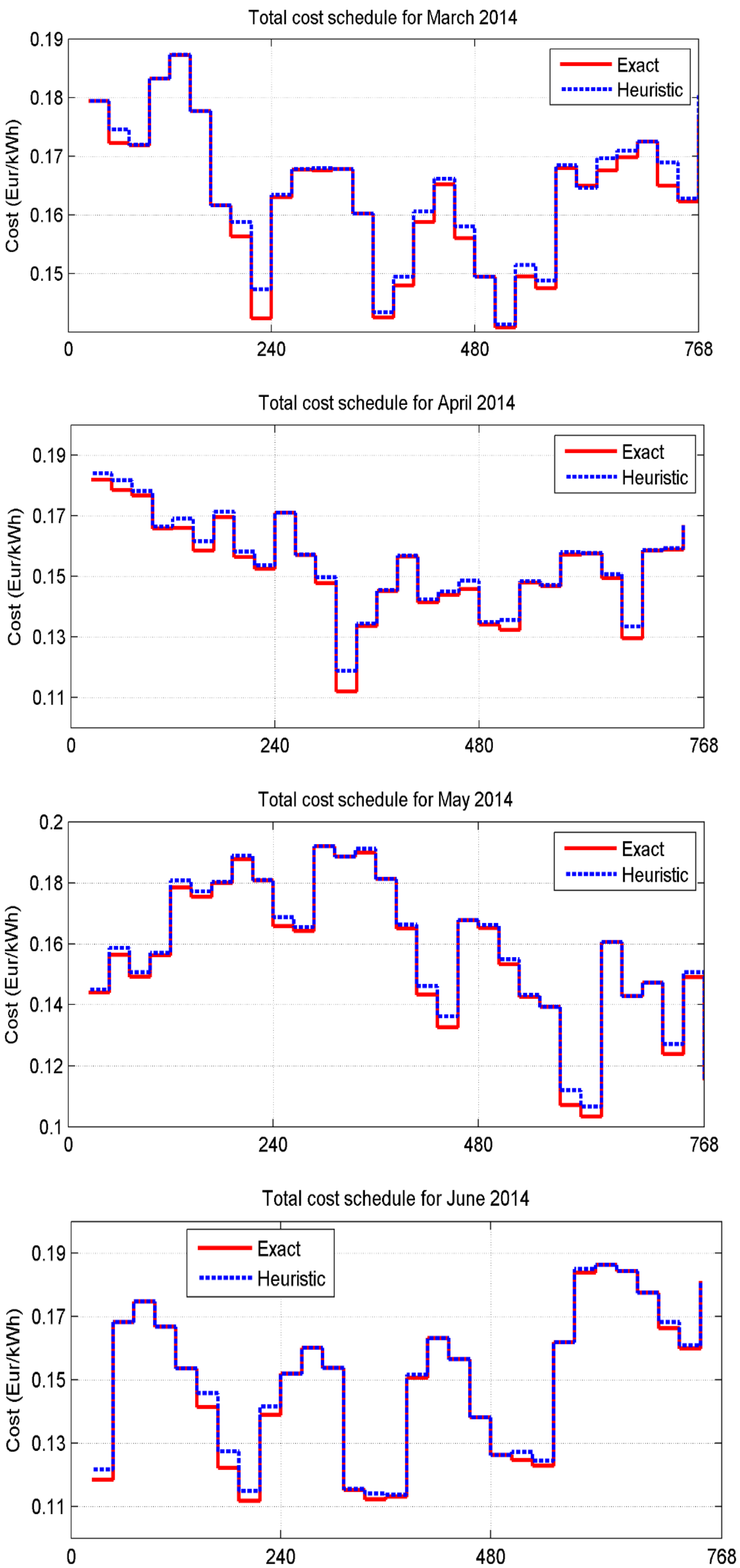


Figure 5.2 Cont.



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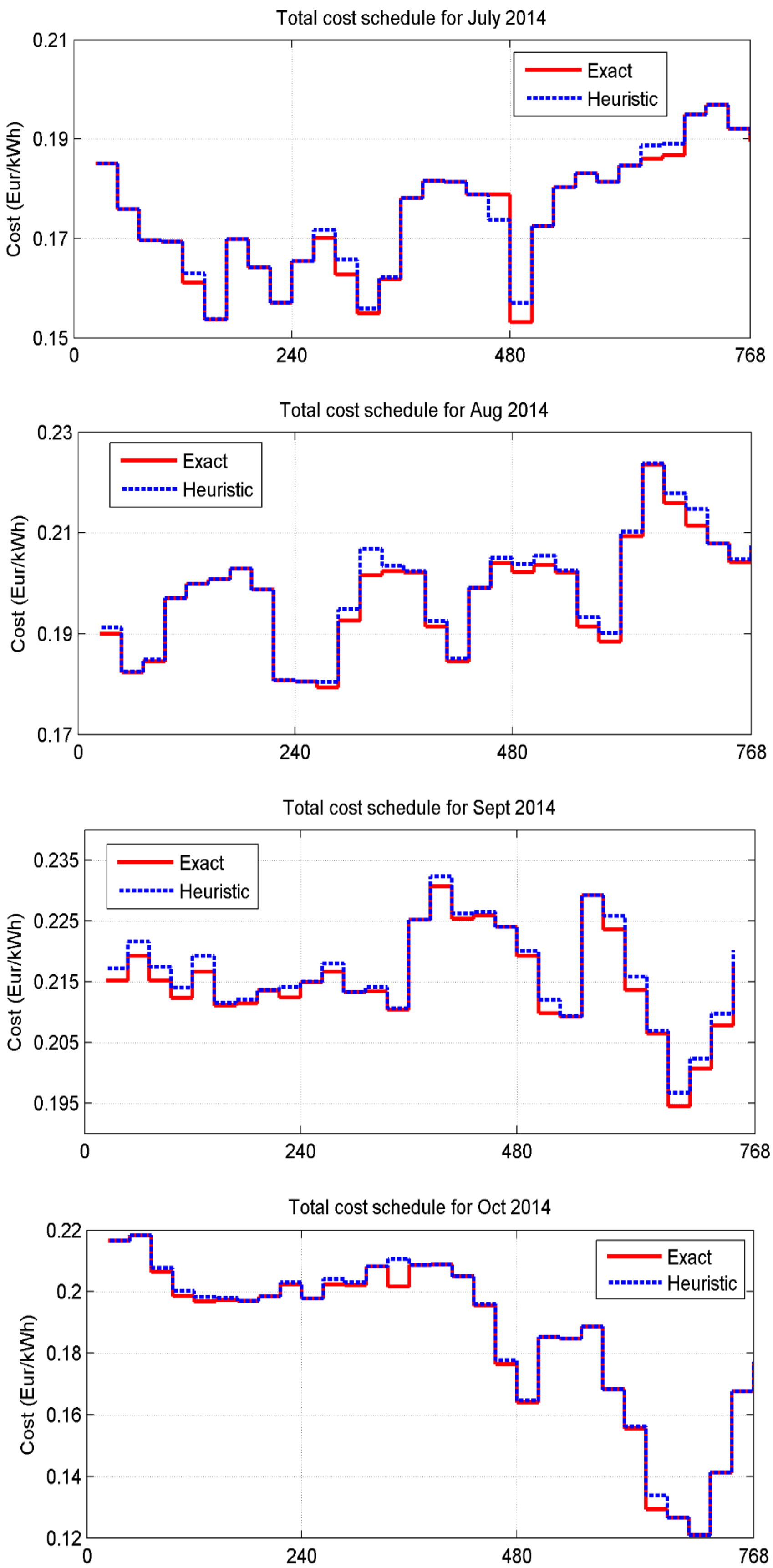


Figure 5.2 Cont.

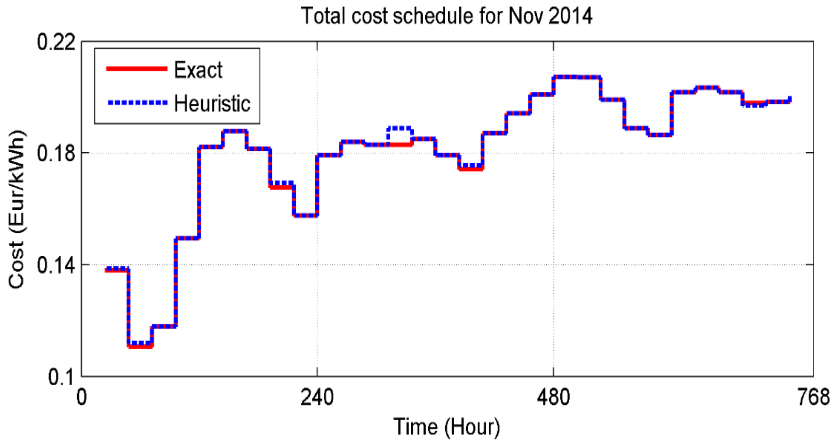


Figure 5.2. Total consumption cost solutions obtained with exact and heuristic algorithms across 12 months for the simulation period from December 2013 to November 2014.

5.3.2 Cost evaluation based on Two-Tier Pricing (2TP)

This experiment studies the impact of using a 2TP model in conjunction with a RTP model on both the residential electricity consumption cost and energy consumption profile. In a basic 2TP, the amount of energy consumed above a given power threshold is set as the tier-two price, and a tier-one is charged for consumption below this threshold. This allows more even balancing of the electricity used during the overall billing period [156]. Both the tier-one and tier-two prices could be fixed, follow typical on/off peak periods, or even change hourly.

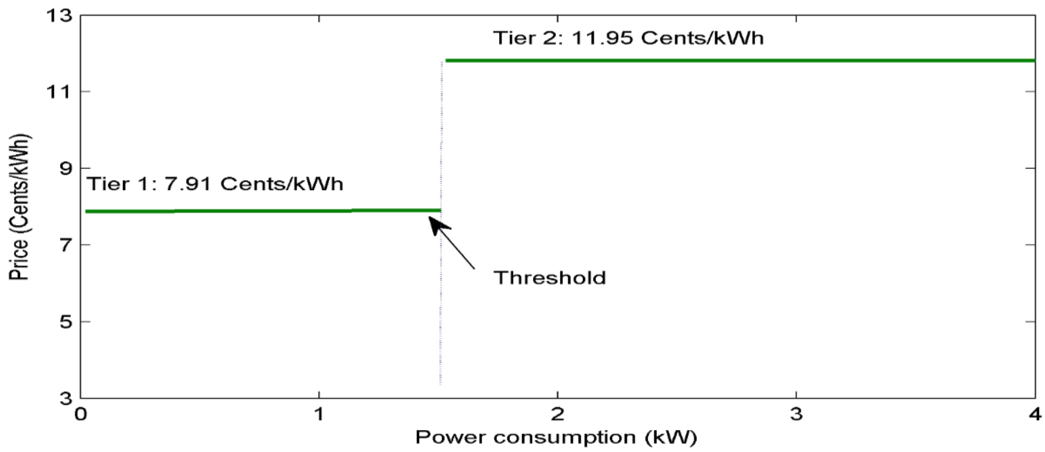


Figure 5.3. Example of 2TP model used by the British Columbia Hydro Residential usage charge updated on 1 April 2015 [156]

In this study, the 2TP is modeled such that the basic rate charged follows the hourly RTP (wholesale price as in Introduction), and the high rate—charged for consumption over a fixed threshold—is a multiple (>1) of this base price. In this simulation, the higher price was set to be 150% of the base price for consumption exceeding 1500 Wh. This configuration was drawn from a realistic example and was motivated by the British Columbia hydro two-tier pricing system as shown in **Figure 5.3**. The experiment investigates whether the heuristic algorithm was as effective at enabling residential energy consumers to respond to the 2TP/RTP charges by shifting peak consumption to off-peak period as with the response to the RTP-only charges reported above.

In this experiment, the simulation was carried out across four months in 2014—January, April, July, and October, representing samples of the four seasons of the year (winter, spring, summer, and autumn) respectively. Again, the heuristic achieves almost the same result—with respect to costs—compared with the exact algorithm as seen in **Table 5.2** below. Comparing these results with those obtained for RTP alone in the previous section, the relative cost between the RTP and RTP/2TP is approximately a 20% increase for the latter under both the heuristic and exact algorithm solutions. RTP/2TP being the more expensive of the two schemes is to be expected, however, given the nature of the cost models.

Table 5.2. Simulation result for 2TP/RTP model across representative seasons of the year

Months of the year (2014)	Heuristic algorithm average total cost (Eur/kWh)	Exact algorithm average total cost (Eur/kWh)	Relative difference in average total Cost (%)
January	0.46451	0.46221	0.00495
April	0.36140	0.35502	0.01765
July	0.40928	0.40461	0.00467
October	0.43770	0.43247	0.01195

In the next section, additional experiments were carried out in which the RTP and 2TP/RTP were evaluated against a basic TOUP cost model and a 2TP/TOUP with the same appliance characteristics.

5.3.3 Cost evaluation based on Time of Use Pricing (TOUP)

The TOUP model used in this experiment was derived as follows: the highest and lowest daily rates of the hourly RTP (wholesale price as in previous 77) were taken as the fixed prices charged for peak and off-peak periods across the simulation period. The peak period was defined as the hours between 06:00–08:00 and 17:00–21:00, and the off-peak the remaining hours of the day. The resulting solutions obtained with both the heuristic and exact algorithms for TOUP is shown in **Table 5.3**.

Table 5.3. Simulation result for TOUP model across representative seasons of the year

Months of the year (2014)	Heuristic algorithm average total cost (Eur/kWh)	Exact algorithm average total cost (Eur/kWh)	Relative difference in average total cost (%)
January	0.18635	0.18635	0.00000
April	0.16816	0.16814	0.00011
July	0.16049	0.16049	0.00000
October	0.16028	0.16028	0.00000

In the 2TP/TOUP cost model, the same procedure was used to set the 2TP base price during the on-peak and off-peak times, with the higher price again set to be 150% of the base price for consumption exceeding 1500 Wh.

Table 5.4. Simulation result for 2TP/TOUP model across representative seasons of the year

Months of the year (2014)	Heuristic algorithm average total cost (Eur/kWh)	Exact algorithm average total cost (Eur/kWh)	Relative Difference in average total cost (%)	Difference with 2TP/RTP (%)
January	0.43131	0.43130	0.0000023	0.004948
April	0.38822	0.38807	0.0000390	0.17611
July	0.37157	0.37157	0.0000000	0.00467
October	0.37098	0.37098	0.0000000	0.01195

The corresponding result for 2TP/TOUP is shown in **Table 5.4**, while the average total cost consumptions for RTP and RTP/2TP *vs.* TOUP and 2TP/TOUP are plotted in **Figure 5.4** and **Figure 5.5** below:

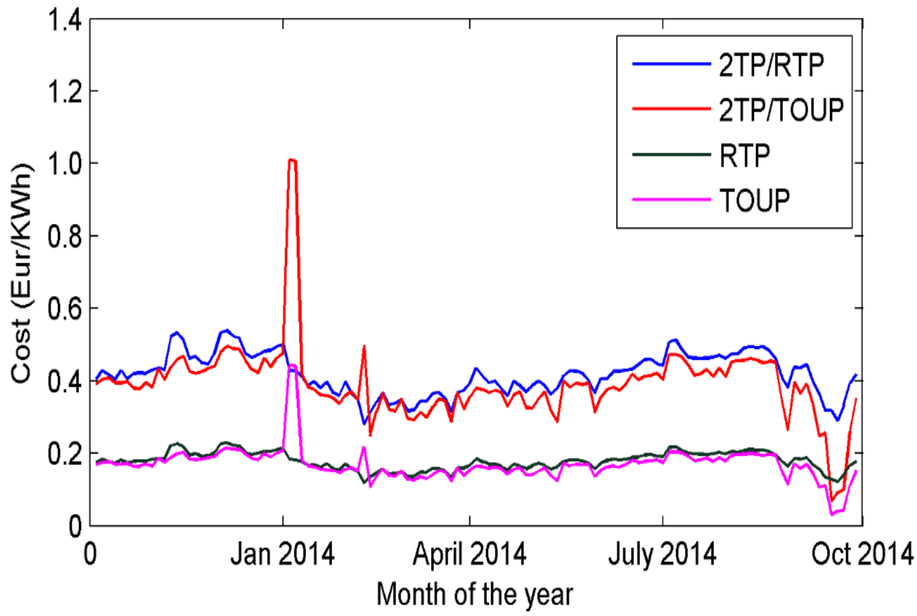


Figure 5.4. RTP and RTP/2TP vs. TOUP and 2TP/TOUP cost scheduling solution for heuristic algorithm.

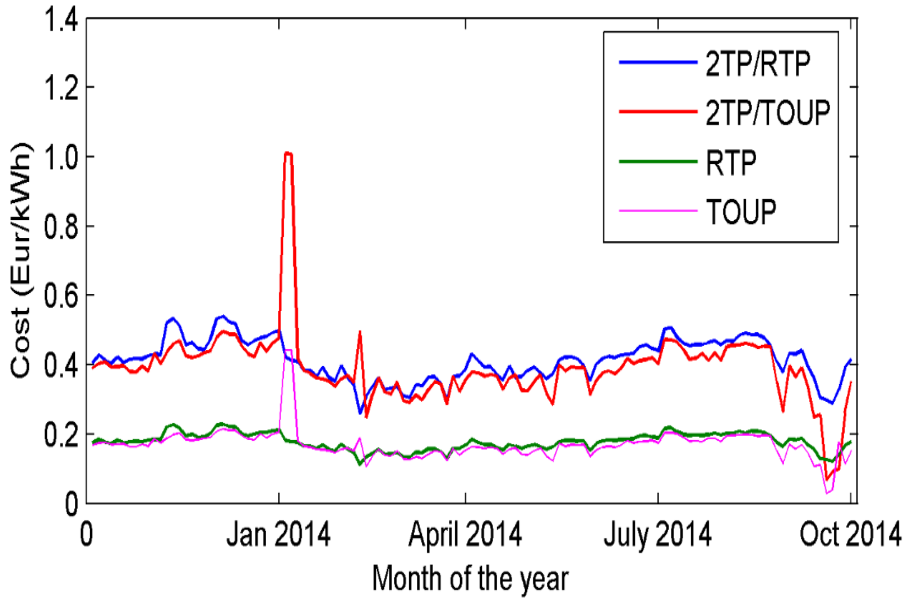


Figure 5.5. RTP and RTP/2TP vs. TOUP and 2TP/TOUP cost scheduling solution for exact algorithm.

Considering Figures 5.4 and 5.5, one may observe that the heuristic algorithm achieves almost identical costs when compared to the exact algorithm over the course of the simulated months. In terms of consumer costs, better results (in terms of slightly lower billing) are achieved with 2TP/TOUP when compared to the 2TP/RTP model.

In summary, the results that have been presented in these sections suggest that the proposed heuristic algorithm was found to be very effective across different types of pricing model when compared to the exact algorithm, in terms of the end consumer costs. In the next section, results related to the achieved power consumption profile are reported.

5.4 Power distribution experiment

The proposed algorithms were further tested to determine the differences in power distribution of appliance scheduling. In each simulation within the range of data considered for this experiment, there was a power distribution in terms of the aggregated household power demand allocated across the timeslots that was dependent upon the algorithm employed (exact or heuristic). In this experiment, two power distribution tests were conducted for exact and heuristic algorithms using RTP only and a combination of RTP & 2TP.

5.4.1 Power consumption using RTP with Heuristic and Exact algorithms

The power distribution solution within the first week of December 2013, March 2014, June 2014, and September 2014, representing the 4 different seasons of the year are analysed to determine if any seasonal power deviations of the exact and heuristic algorithm are present. The absolute difference of the power distribution for both algorithms is plotted in **Figure 5.6**, **Figure 5.7**, **Figure 5.8**, and **Figure 5.9** respectively.

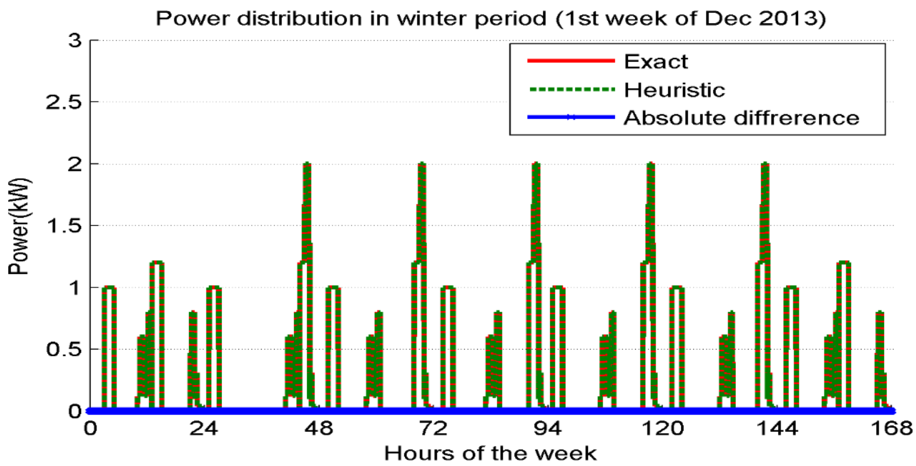


Figure 5.6. Power distribution for exact and heuristic algorithm in winter period.

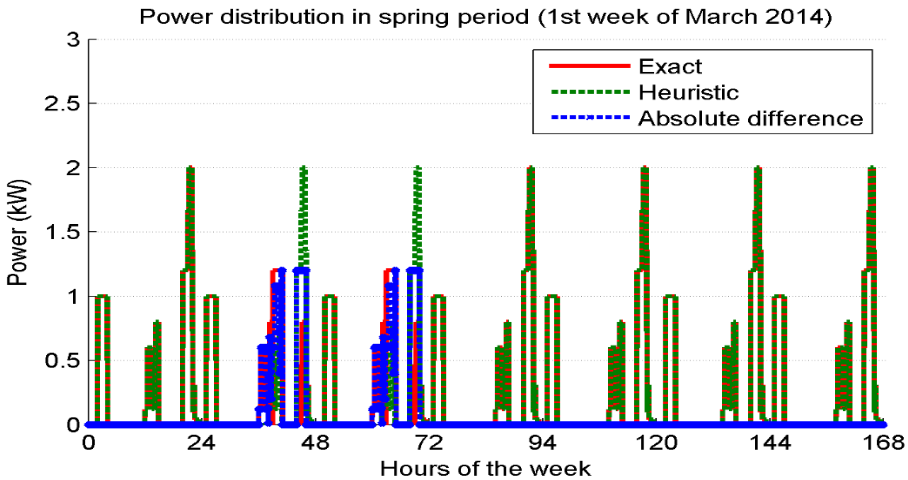


Figure 5.7. Power distribution for exact and heuristic algorithm in spring period.

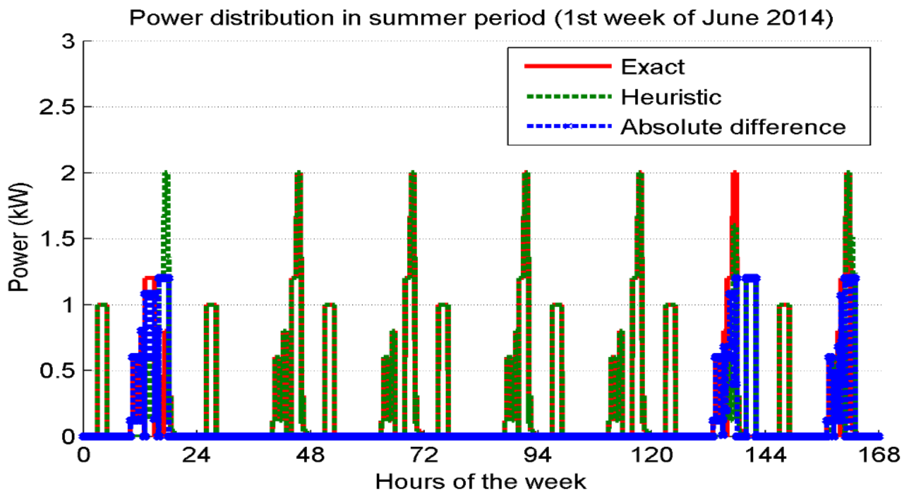


Figure 5.8. Power distribution for exact and heuristic algorithm in summer period.

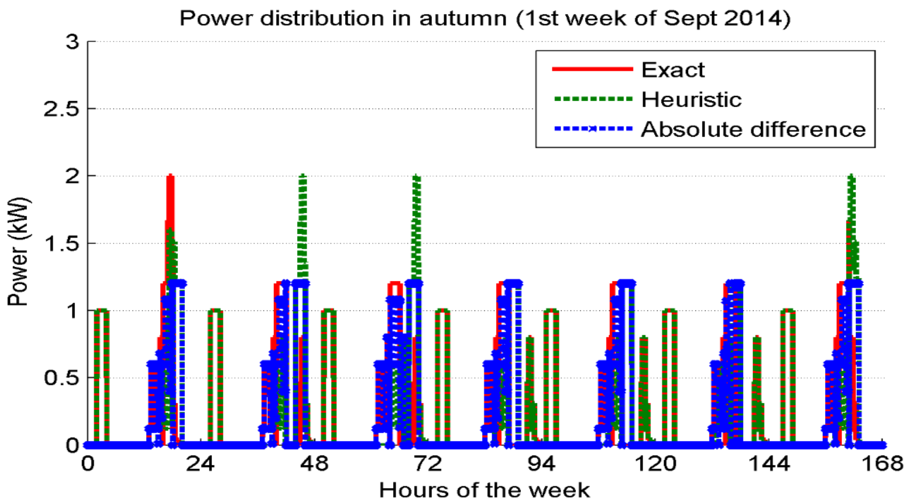


Figure 5.9. Power distribution for exact and heuristic algorithm in autumn period.

These performance investigations illustrate that there is no significant deviation of the power consumption profile in the winter period, and some differences can be observed during 2 days in the spring period and 3 days in the summer period respectively. In the autumn period, however, there is evidence that the solution schedules differ considerably; appliances are scheduled in differing timeslots on a daily basis during the selected week. Nevertheless, the obtained schedules are all feasible (with respect to the household maximum power constraint) and from Figure 5.6 – 5.9, there was little difference in the final obtained cost. This presents an interesting observation in that although the heuristic and exact algorithms differ very little in terms of the obtained economic costs, differences in the obtained power consumption profiles and appliance schedules can be found.

5.4.2 Power Consumption using RTP and 2TP with Heuristic and Exact Algorithms

The obtained power consumption for the two pricing models was tested with both the exact and heuristic algorithms to verify the energy distribution across different hours, days, months, and respective seasons of the year. This is displayed in **Figure 5.10**, **Figure 5.11**, **Figure 5.12**, and **Figure 5.13** below. As can be seen in these figures, under the RTP-only model there are several hourly timeslots in which the power consumption is significantly different between the heuristic and exact algorithm. In particular, there are 13 situations in which the heuristic consumes over 1.5 kW while the exact algorithm remains below this level. Whilst this has an almost negligible impact upon cost—as detailed in the previous section—it indicates that problem solution is quite sensitive near the optimal cost. Examining the results obtained for the RTP/2TP pricing model, it can be observed that, although some differences exist, they are less pronounced under the 2TP extension. In particular, there are now no situations in which the heuristic consumes over the 1.5 kW thresholds while the exact algorithm remains below it.

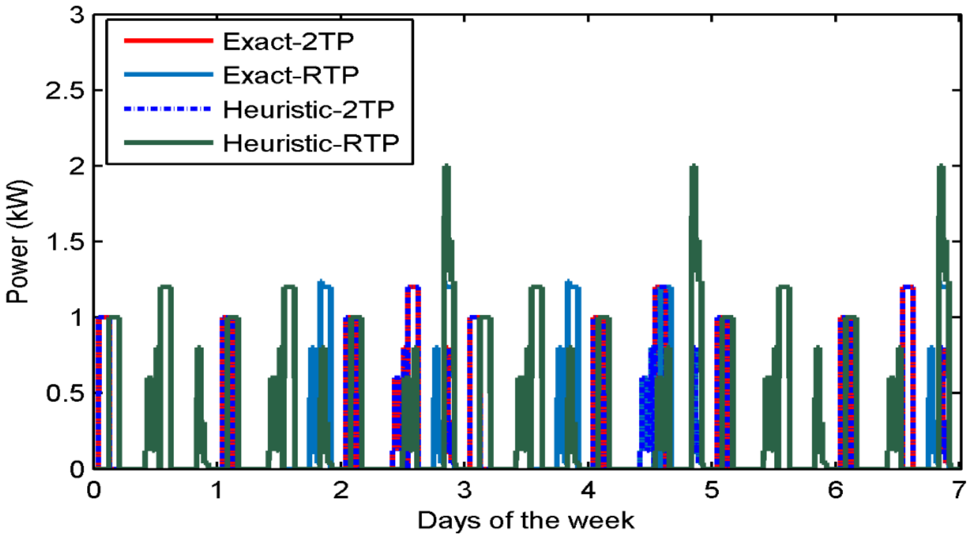


Figure 5.10. Power distribution across the first week of January 2014, representing winter period.

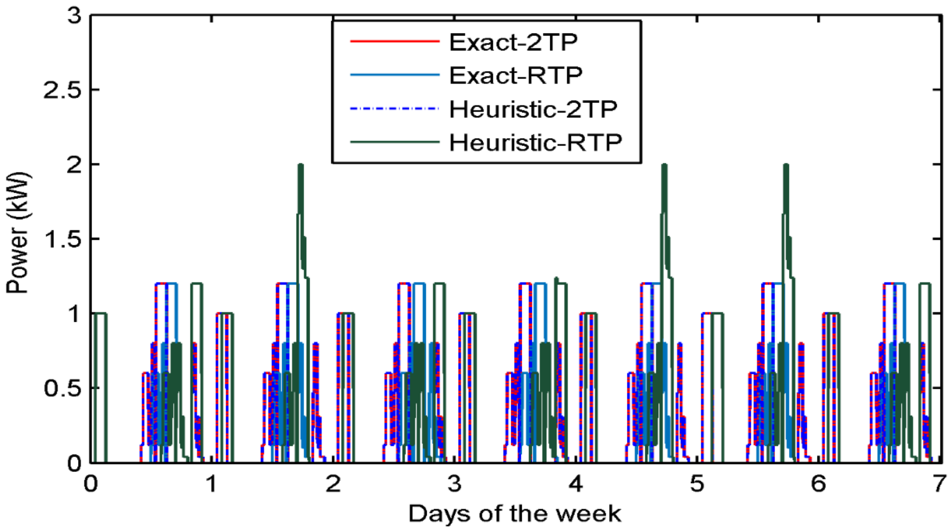


Figure 5.11. Power distribution across the first week of April 2014, representing spring period.

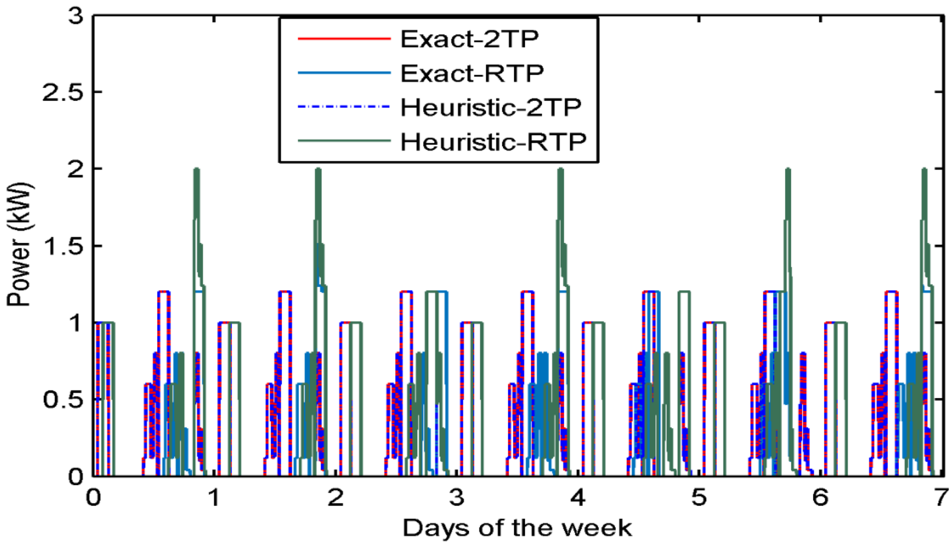


Figure 5.12. Power distribution across the first week of July 2014, representing summer period.

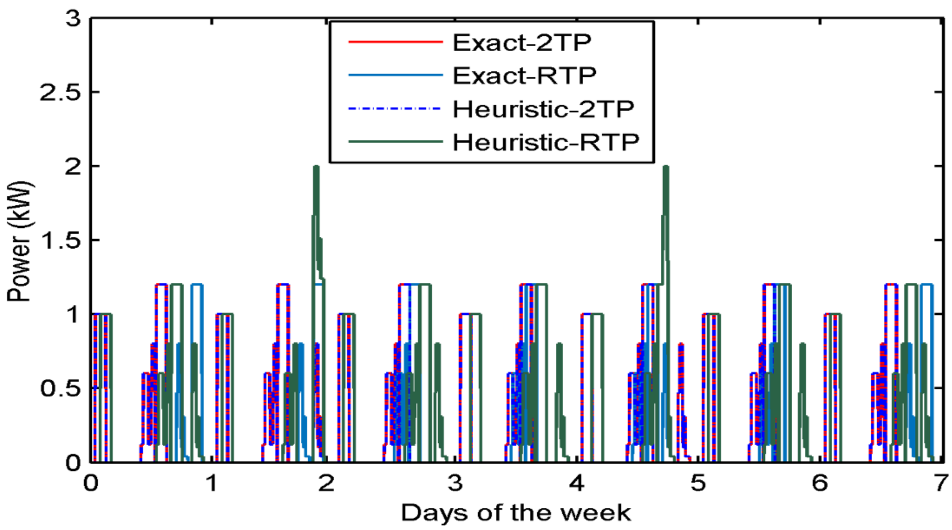


Figure 5.13. Power distribution across the first week of October 2014, representing autumn period.

This was indicative that the 2TP extension may be more effective at peak power reduction and load balancing than the basic RTP approach when households employ approximate, near-optimal scheduling of appliances. The aspects of different households with various appliances and configuration will be investigated in the next section.

5.5 Cost evaluation for different households' configurations

In this experiment, different households with various appliance configurations and pricing mechanisms were considered. Parameters such as Time preference range (*H*), Length of timeslot (*T*) and Total power range ($P_{i,j}$) are the varying inputs that can be set by different household users based on the consumption pattern, desired comfort level and appliance manufacturer's constraints. Each household is assumed to have one of eight possible configurations (C1~C8). Please see Appendix A: Details of household configurations for different appliance scheduling in section 5.5: Tables A1 and A2 for the specific details of these household configurations. Configuration parameters (e.g., different appliance start times, timeslot length operation as well as appliance power rating and assignment) were selected randomly and employed with a particular pricing model (e.g., RTP, RTP/2TP, TOUP, and TOUP/2TP). These inputs were selected randomly in uniform comparison to the recorded data of household appliance technical specification used in [17]. The pricing data used in this experiment is the same with the previous set of experiments reported in this chapter.

For comparison purposes with the exact algorithm, given that the problem is NP-hard it was very difficult to obtain extensive exact results for large problem instances, so the experiments were conducted with five and six appliances, each with four different configurations and price model. The average yearly simulation results for the eight different configurations were as found in **Table 5.5** and **Table 5.6**.

Table 5.5. Simulation result for multiple households with five appliances, different configurations, and pricing models

Average yearly total Cost (Eur/kWh)	Five appliances with configurations (C1~C4)			
	C1 RTP	**C2 RTP/2TP**	**C3 TOUP**	**C4 TOUP/2TP**
Heuristic algorithm	0.2071	0.4763	0.3043	0.5123
Exact algorithm	0.2068	0.4722	0.3037	0.5111
% Difference	0.0014	0.0086	0.0019	0.0023

Table 5.6. Simulation result for multiple households with six appliances, different configurations, and pricing models

Average yearly total Cost (Eur/kWh)	Six appliances with configurations (C6~C8)			
	C5 RTP	**C6 RTP/2TP**	**C7 TOUP**	**C8 TOUP/2TP**
Heuristic algorithm	0.2276	0.4829	0.2117	0.4781
Exact algorithm	0.2068	0.4790	0.2087	0.4758
%Difference	0.0013	0.0080	0.0142	0.0048

The simulation results indicate that the proposed heuristic algorithm with the generic cost model seems to be effective with different appliance and user preference configurations and has managed to bring the final consumption cost close to the optimal results (within 0.15%) across all pricing models and configurations. In the next experiment, the appliance cost schedule using spot prices for different geographical locations will be explored.

5.6 Cost evaluation using spot prices for different geographical electricity market

To test the performance of the heuristic algorithm across different geographical electricity markets, spot prices of electricity for New York City (NYC) [157] and Denmark (DNK) [155] on the 5th November 2014 were used to determine the energy cost difference for a typical day in the fall (autumn) period. See **Figure 5.14** and **Figure 5.15** for the respective NYC and DNK spot prices.

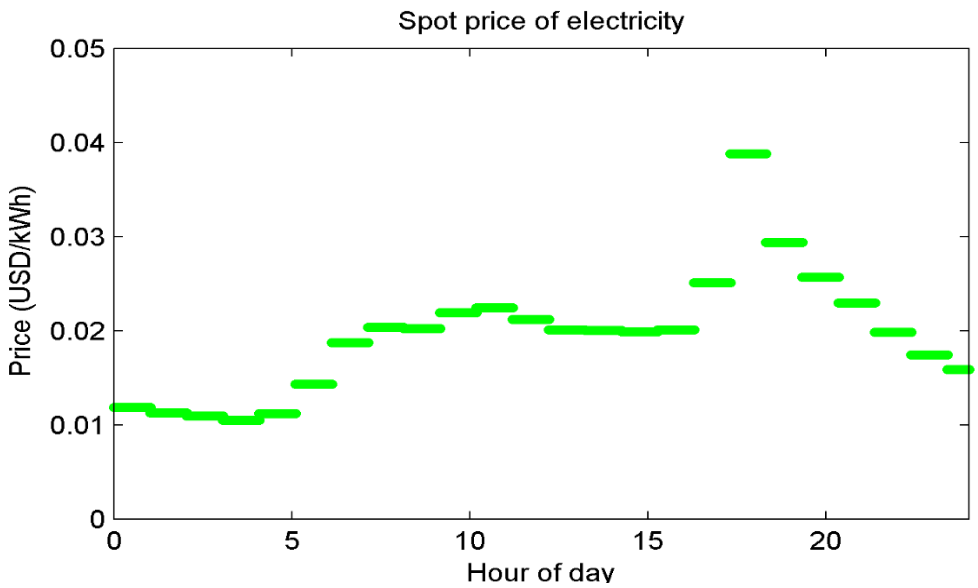


Figure 5.14. Spot price of electricity for New York City on 13th November 2014 [157]

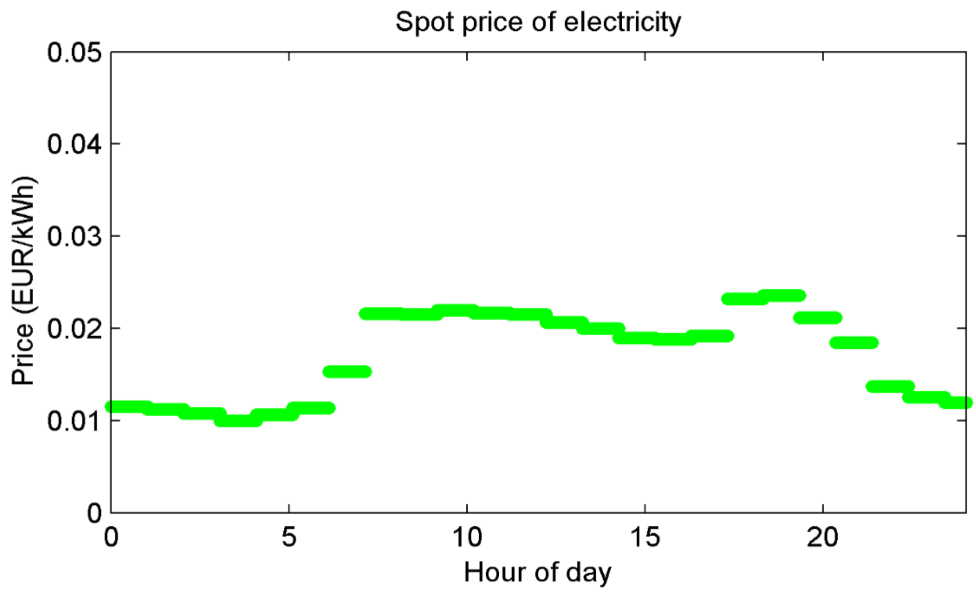


Figure 5.15. Spot price of electricity for Denmark on 13th November 2014 [155]

Using the same number of appliances, values of the technical specification in the **Table 5.1**, the algorithms were tested with two instances of spot prices for NYC and DNK. After solving with heuristic algorithm, the spot price of electricity and the sum of power assigned to all appliances at each timeslot within the simulation horizon are plotted in **Figure 5.16** and **Figure 5.17** below.

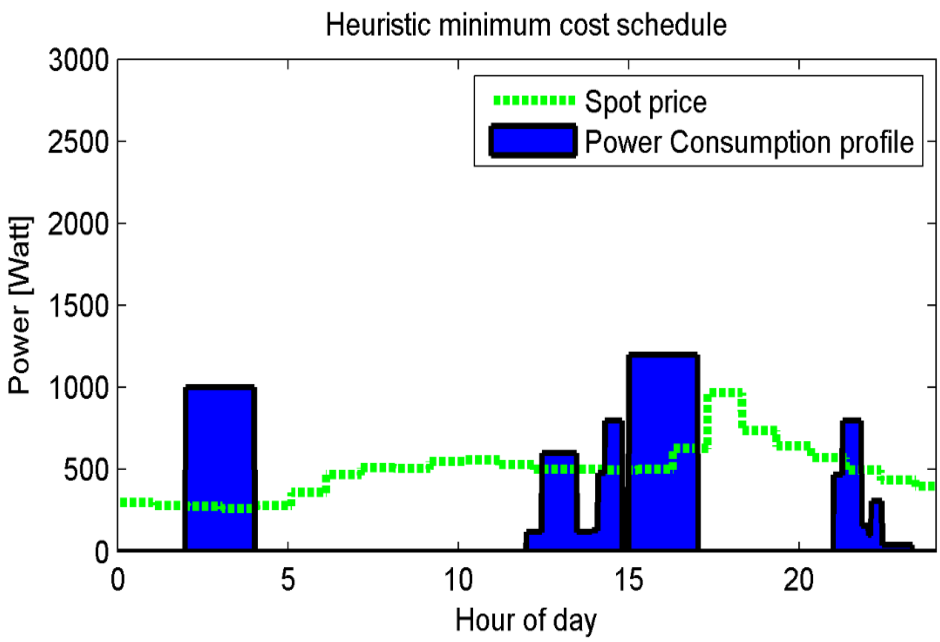


Figure 5.16. Heuristic solution for power consumption profile and the electricity tariff, in the New York City scenario

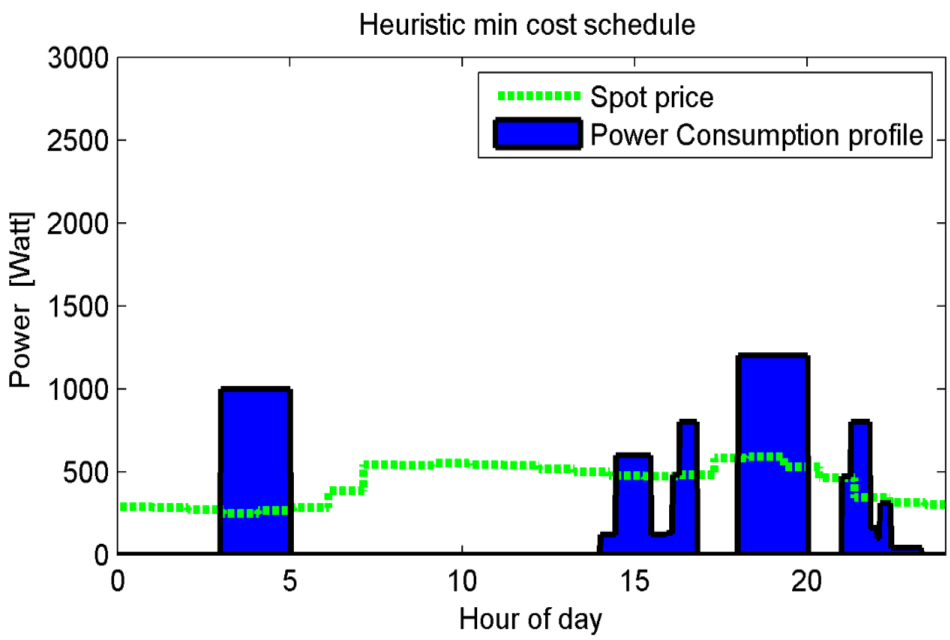


Figure 5.17. Heuristic solution for power consumption profile and the electricity tariff, in the Denmark scenario.

The corresponding results of the total cost obtained for both instances of spot prices using both heuristic and exact algorithms are shown in **Table 5.7**.

Table 5.7. Results of total energy consumption cost for heuristic and exact algorithm with spot prices for New York city (NYC) and Denmark (DNK)

Algorithm with spot prices	(Cost USD)
Heuristic: with NYC	0.2841 [8.523 per month]
Exact: with NYC	0.2751 [8.253 per month]
Heuristic: with DNK	0.2670 [8.01 per month]
Exact: with DNK	0.2565 [7.695 per month]

In the next experiment, the solving time for heuristic and exact algorithm with increasing number of appliance scheduling will be evaluated.

5.7 Computational time scalability test

In testing the solving time for this scheduling problem, the length of timeslots over the horizon and number of controllable appliances are the major variables dictating problem size and hence algorithm execution time. **Table 5.8** shows the one-week periodic re-optimized average solving time for the heuristic and exact algorithms against increases in the number of controllable appliances. The controllable appliances are increased from 4 to 10 with random (but representative) energy and operating time requirements, specified in a uniform distribution (6 energy phases for each appliance). From the results, there was a significant difference in the average solving times for both algorithms; clearly, the heuristic solving time grows linearly with the increasing appliance number, where the exact algorithm grows exponentially. For 10 controllable appliances, the exact algorithm in 30 minutes computation time allowance returned no result. Extrapolating the growth rate from the data obtained, approximately 12,700 seconds would predictably be required. For 12 controllable appliances, this would rise to over 611 hours. However, at this stage, it must be cautioned that the exact algorithm employed did not utilize pruning techniques (such as branch-and-bound) which may help to reduce the average-case run-time. The extent to which such techniques would influence the computational time is an area of future investigation.

Table 5.8. Solving time for exact and heuristic algorithm with increase in the number of appliances

Number of appliances	Average CPU Solving (in seconds)	
	Heuristic algorithm	**Exact algorithm**
4	0.000704	0.00246
6	0.00123	0.427
8	0.00157	73.56
10	0.00201	No result

Hence, the exact algorithm as presented is not scalable, and should be restricted to the case of a few smart home appliances (e.g., less than 9 appliances) and in situations in which re-solving multiple times during a day is not required. However, the experiment demonstrates that the heuristic algorithm proposed in this research seems to be scalable, comparatively very efficient in terms of computational time complexity and could be applied as a core element in a decision support process for real-time residential appliance scheduling.

5.8 Summary

In this chapter, the evaluation of the proposed heuristic algorithm under consumer viewpoint has been explored and simulation results documented. The obtained results indicate that, for a single household with controllable appliances, the proposed heuristic is highly competitive against exact algorithm in terms of energy cost savings. The proposed heuristic algorithm is also capable of being configured to achieve reasonable performance with mixed pricing. For different household with various appliance configurations, the performance of the heuristic seems very good in the simulation-based experiments. Although the worst-case performance of the algorithm could (in Theory) be closer to the 32% optimality gap, in representative simulations the gaps between the heuristic cost solutions and the optimal achievable costs have been found to be much lower and almost negligible. However, some differences were observed in the power consumption profile between the algorithms, especially in the presence of the RTP policy; this indicates that underlying the appliance-scheduling problem is potentially sensitive to small changes in the decision variables around the optimal achievable costs. In the pricing signal comparison, a combination of RTP and RTP/2TP was found to be less sensitive than RTP alone and gave a better distribution of the power consumption. Possible wider aspects of the use of the proposed heuristic algorithm such as cost savings due to DSI and power shifts from peak to off-peak period during DSI event days will be subjected to further attention in Chapter 7.

Finally, for solving time scalability the heuristic algorithm offers low computational overheads and seems an ideal candidate for the implementation of a consumer energy management IDSS. In the next chapter, the implementation of the heuristic algorithm on a small, resource constrained embedded processor will be demonstrated.

Chapter 6

6 Prototype Embedded Implementation of the Heuristic

6.1 Introduction

In Chapter 5 of this thesis, a series of detailed experiments carried out to evaluate the performance of the proposed heuristic were reported. In this chapter, an embedded implementation of the heuristic algorithm for scheduling smart appliances is presented. This is sequel to the good performance evaluation of the proposed heuristic algorithm as found and reported in Chapter 5. The focus of the current chapter is on the implementation and evaluation of the computational overheads incurred by the algorithm when executed on a small, resource constrained embedded processor (ARM7-TDMI 32-bit microcontroller). The performance of the prototype implementation is validated against previously reported MATLAB©-based simulated experiments on a high-performance personal computer. This was deemed important, as should the heuristic be deployed as a part of an intelligent Decision Support System (IDSS) for Demand-Side Integration (DSI), the overheads should be acceptably low. Before going on to describe this implementation, the overall motivation for this chapter of the work is described.

6.2 Motivation

The motivation for the work described in this chapter was as follows. As mentioned in Chapter 1, energy consumption in the built environment (households and services sector) forms a major portion (40.3 %) of the total energy consumption in EU member states [4]. Household energy consumption accounts for the largest portion of electricity usage in this built environment sector. This is driven by a continuous increase in population as well as growth in energy demands of home appliances etc.[5]. Smart meter devices and automated meter reading have been in increasing use over the past decade, and many EU member states have made good progress on (or commitments to) the installation of Advanced Metering

Infrastructures (AMIs). In the UK, for example, it is planned for every household to have a smart meter by the year 2020 [158]. By leveraging the existing or planned ICT components of an AMI (e.g., 4G connection, utility backhaul network, and smart meter with TCP/IP communication stack) and co-locating an appliance-scheduling algorithm on a residential smart meter, a lower-cost pathway to allow end users and utilities to achieve the potential benefits of DSI could be achieved. In the ideal case (quoting directly from the ENA [159]):

"A completely Smart Grid of the future will enable appliances in the home to communicate with the smart meter and enable the networks to ensure efficient use of infrastructure, demand response and energy management. These are all critical to making the most of intermittent renewables and keeping the lights in an affordable low-carbon energy future."

For practical consumer DSI participation, the scheduling algorithm would need to have acceptably low computational and memory overheads and would likely need to be implementable without high-level operating system support and/or specialized software libraries. It is highly unlikely that techniques such as Mixed-Integer Linear Programming (MILP) could be employed for appliance scheduling in this context. As such, this study will investigate the feasibility of co-locating the heuristic algorithm on a smart meter by examining its overheads on a representative embedded computing platform (ARM-7 platform). Although recognizing that a home energy management system consists of several other key components in addition to an appliance scheduler, these additional aspects are disregarded in this chapter; but it is important to note that a Wireless LAN (WLAN) connection may provide a simple means to provide connectivity to a user interface and the smart appliances themselves.

6.3 Embedded platform

Real time embedded systems are rapidly advancing and are widely used in industrial, medical equipment, house automation applications and communication devices such as smart phones etc. Embedded systems are information processing computer systems embedded into larger mechanical or electrical products [160]. The purpose of the embedded system is to control and provide relevant information required for a specific function. More so, embedded systems are described by particular extra-functional properties such as constrained resources and real-time computing [161]. Majority of the repetitive work done by people can presently be implemented on an embedded system to round the clock, sparing time, and reducing energy wastage. It is vital to decide a suitable platform for the implementation of embedded software running on a programmable component in a specific hardware. Hence, the success of the automated IDSS depends on the careful selection of the platform to support the implementation requirements. The overall features of the embedded system environment consist of hardware and software platforms respectively.

6.3.1 Hardware platform

The hardware unit contains the 32-bit microcontroller with oscillator speed / clock speed of 12 MHz and 60 MHz respectively, a Phase locked loop (PLL) used to up-step the crystal oscillator, 512 kb of FLASH ROM and 32 kb of SRAM, located on a development board containing I/O interfaces and an interface to allow programing and debugging. Recent development in computing and automation has found microcontroller in the heart of every device with a control system. This is a low–cost embedded system particularly used by applications that require computing power delivered within mobile devices, machinery and most importantly consumer appliances etc. [162]. Microcontrollers consist of a microprocessor integrated with memory and general-purpose interfaces in a single chip and are typically shaped as a single board computer hosting control software and executed within real-time environment. An LPC2378 microcontroller with ARM7TDMI-S CPU, running at 72 MHz was selected as the embedded processing target, as shown in **Figure 6.1**.

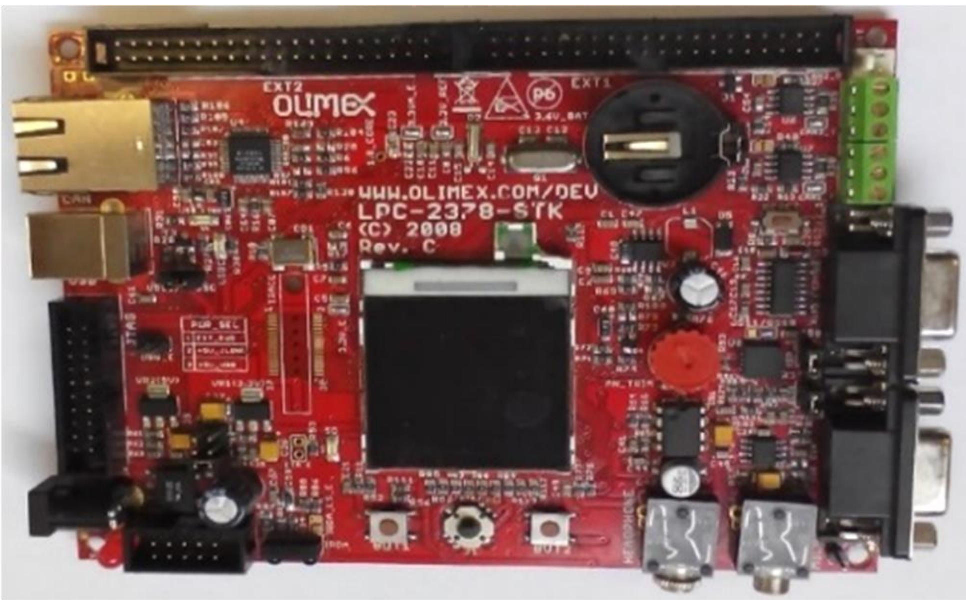


Figure 6.1. Embedded Hardware with the LPC2378 Microprocessor

ARM7TDMI-S [163] is a widely used 32-bit microprocessor in the family of ARM 7, which offers high performance with low power consumption. The ARM7TDMI-S uses a thumb architectural strategy (yielding a super reduced instruction set) which is suited to high volume applications with memory restrictions. This device is produced by NXP semiconductors [164]. The features include a low power Real-time clock and numerous general-purpose I/O interfaces such as multiple UARTs, an Ethernet controller, SD card and USB controllers, etc. The ARM processor is a family of CPU based on reduced instruction set computing (RISC) architecture. The microprocessor found on ARM technology is made up of 75 % market share of the 32-bit RISC processors; and is the architecture choice to meet diverse needs of home applications with more than 55% of consumers [165]. ARM processors include common processor series such as ARM7, ARM9, ARM9E, ARM10E and others such as Intel's Xscale, SecureCore, and Intel's StrongARM [165]. The block diagram of ARM7TDMI-S is shown in **Figure 6.2** below.

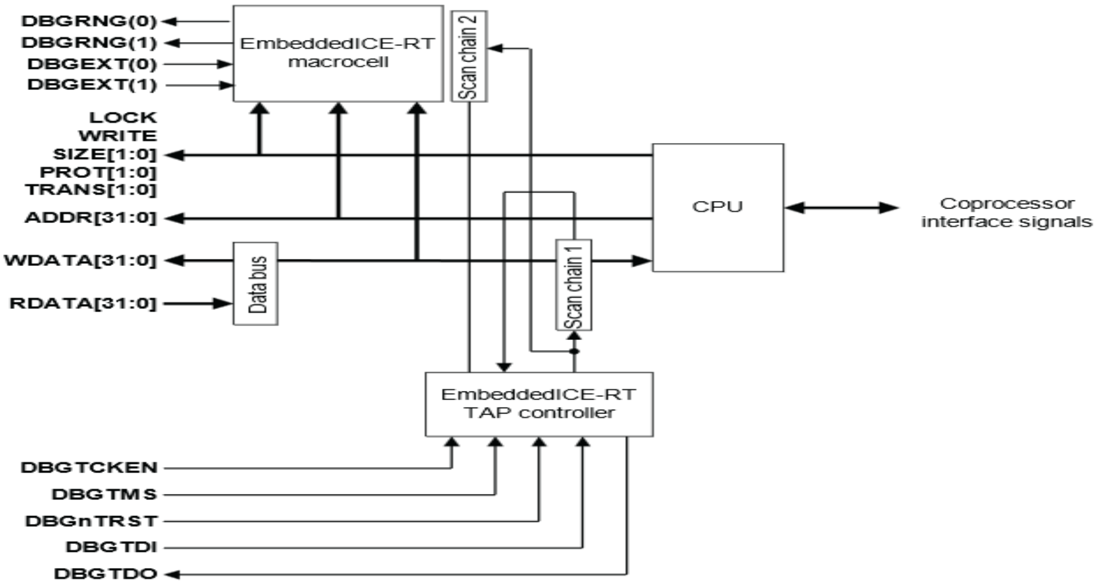


Figure 6.2. Block diagram of ARM7TDMI-S [163]

ARM7 processor core as shown in **Figure 6.3** is used in low power embedded devices like tablets, smart phones, laptops, and many different industrial applications, including automotive control; it therefore provides a representative platform with the necessary features and I/O for a low-cost smart meter.

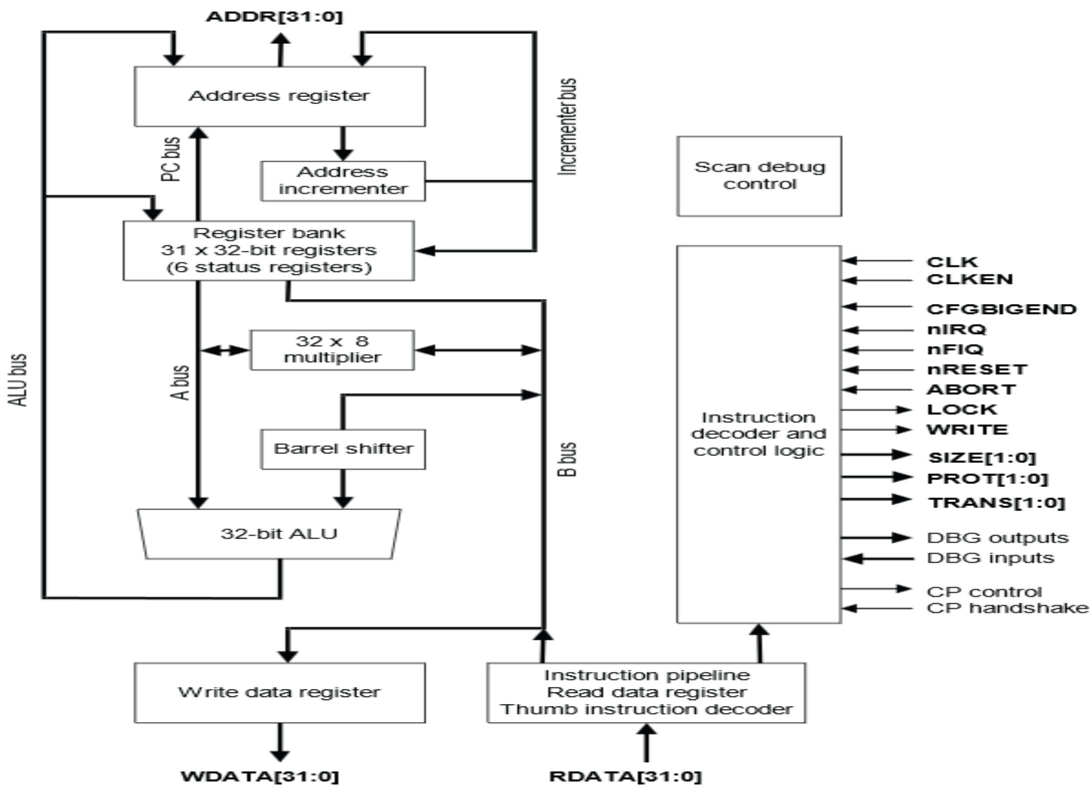


Figure 6.3. ARM7TDMI-S core [163]

6.3.2 Software platform

Embedded software is integrated with physical processes, to manage problems associated with time and concurrency in computational systems [166]. In this platform, the software development and testing facility was partitioned into two parts namely – a C programming language compiler/linker from Keil© with flash tools/JTAG interface for downloading and debugging the binary code into the microcontroller, and MATLAB software. MATLAB is a high-level technical computing language developed by MathWorks, for algorithm development and analysis. The heuristic algorithm was originally developed and tested in the MATLAB© environment. The task and scheduler libraries were re-written using the embedded C language. The communication between the target peripherals and the mentioned libraries are through functions implemented in peripherals and initialization libraries. Therefore, Programs written in C are very portable and can easily work on any CPU type without modification even when the target hardware is changed.

6.4 Embedded Heuristic algorithm

This section explains the data structure that represents the appliance scheduling. The number of bytes in each phase of the appliances as well as the main heuristic algorithm procedures are also presented.

6.4.1 Data structure

Given n is the number of appliances, the data structure can be expressed as follows:

app_st[n] = [app 1, app 2,…, app n]

app_time_limit [n] = [app 1, app 2,…, app n]

nofp[n+1] = [0, app 1 nofp, app 1 nofp + app 2 nofp, + …., app n-1 nofp + app n nofp]

POPT[nofp[n+1]] = [POPT[nofp[1], POPT[nofp[2]], …, POPT nofp[n+1]]

Power[nofp[n+1]] = [Power[nofp[1], Power[nofp[2]], …, Power nofp[n+1]

Where:

- The period of operations of all appliances are set by two arrays of unsigned 8-bit integer number namely:

  Appliance operations start time, denoted by *app_st[number of appliances]*, and

  Appliance operations stop time, denoted by *app_time_limit[number of appliances]*

- The number of phases (stages) of the appliances are set by an array of unsigned 8-bit integer numbers denoted by *nofp[number of appliances + 1]*, where nofp[0]=0 and:

  The number of phases of first appliance is evaluated by nofp[1] – nofp[0]

  The number of phases of second appliance is evaluated by nofp[2] – nofp[1]

  …, and so on.

  Generally, the number of phases of x appliance = nofp[appliance x] – nofp[appliance x-1]

- The duration of operations of the phases of appliances in minutes are stored in array of unsigned 16-bit integer numbers, denoted by *POPT[number of appliances +1].*

- The power consumptions of the phases of appliances in watts are stored in array of float numbers, denoted by *Power[nofp[number of appliances + 1]]*.

- The hourly cost of electricity for each day is stored in array of 24 float numbers *cost [24]*. This is such that the cost of electricity between 1 and 2 o'clock is stored in *cost[1]*, between 2 and 3 o'clock is stored in *cost[2]*, … and so on.

- Adjustable constraint which enforces a certain appliance to start and finish its operation phases before the other starts (e.g., the case of washing machines and tumble dryer) is stored in array of 8-bit unsigned numbers, denoted by *c[number of appliances * number of appliances]*.

6.4.2 Memory (RAM) requirement for appliance scheduling

For an appliance with a single phase (e.g., Tumble dryer with the drying phase only), the appliance start time (app_st), stop time (app_time_limit), and the adjustable constraint *(c)* with 8-bit unsigned integer each, have 1 byte respectively. Number of phases (nofp) and operation time duration of phases (POPT) with 16-bit unsigned integer have 2 bytes each, while power with 32-bit float numbers has 4 bytes. Hourly costs of electricity over a 24-hour horizon are stored as 4-byte floating point numbers requiring 96 bytes of storage. A total of 107 bytes is required for single phase of tumble dryer schedule. For 10 appliances, each with 6 phases (i.e., 60 phases), a total of 6.26KB would be required to run the appliance scheduling. The device in question has 16 KB of on-chip memory, which is enough to store the configuration of 25 devices with 10 phases each; further off-chip RAM may be used to provide extensions. Note that there are several places in which memory consumption could be made more efficient, for example using fixed-point real numbers instead of floating point to reduce storage by approximately one half for these quantities.

6.4.3 Main heuristic algorithm procedures

The embedded heuristic algorithm is shown below. In line 3 to 7, the variable is declared to enable the compiler to decide the storage space to be allocated to the identifier values. The algorithm considers only three variable types, namely **int, float** and **bool.** The execution time measurement of the hardware timer in the microcontroller for the algorithm starts in line 8. From line 9, the algorithm starts iterating across time horizon (app_time_limit) for each appliance one by one to determine the time and cost-effective scheduling of the appliances. This is subject to appliance constraint *(c)* in line 20, which ensures that a certain appliance must finish its operation phases/stages before the start of another appliance. Line 24 calls the objective function to evaluate the best start time for a particular appliance, which is subject to power constraint in line 27. The power constraint is checked to ensure that power assigned to every phase of an appliance does not exceed the maximum power limit. Line 31 and 32 calculate and store the total cost and the best start time respectively for a particular scheduled appliance; while line 42 updates the power distribution for each appliance phases/stage. From line 45 to 47, best time and the total cost for each appliance is sent to the serial board, connected to the serial board of the computer using RS232 serial cable via U1THR port. Line 48 stops the execution time of the algorithm. The corresponding total cost for all appliances are then sent to the serial board of the computer from lines 49 to 54. While lines 50 and 51 send the integer cost, lines 53 and 54 send the float cost. Finally, lines 56 and 57 send the total execution time for the embedded heuristic algorithm to the computer, which can be visualized alongside the total cost via the RealTerm: Serial Capture program 2.0.0.70.

```
/------------------------------------------------------------------------------------------------------------------------
```

Embedded Heuristic main code

```
//-----------------------------------------------------------------------------------------------------------------------
1: void Heuristic(void)
2: {

// variables declaration
3: uint8_t app_no=0,start=0,best_time[4]={0},i,x,valid;
4: float total_cost=0,totalcost[4]={0},app_power[1440]={0},all_cost=0,total_POPT=0;
5:  uint16_t data=0,start_s=0,start_e=0,j;
6:   _Bool ps=1;
7:   uint32_t start_t,stop_t;

// start execution time measurements
8:  start_t = timer;

// start the algorithm
9: for (app_no=0;app_no<appl;app_no++)
10:     {
11:         totalcost[app_no]=100000.0;
12:         total_POPT = 0;

13:         for (i=nofp[app_no];i<nofp[app_no+1];i++)
14:                 total_POPT=total_POPT+POPT[i];
15:         Time_limit[app_no] = Time_limit[app_no] - total_POPT;

16:         for (start=app_st[app_no];start<=Time_limit[app_no];start++)
17:           {
18:              valid = 1;
19:              for (x=0;x<appl;x++)
20:                   if ((c[app_no*appl+x]==1)&&(best_time[x]+total_POPT >= start))
```

```
                valid = 0;
            if (valid == 1)
             {
                total_cost = cost_func_obj(app_no, start, nofp, POPT, Power, cost);
             if (total_cost < totalcost[app_no])
                {
                        ps = power_dist_fun(app_no, start, nofp, POPT, Power, app_power,
                        Max_Power);
                      if (ps == 1)
                        {
                          totalcost[app_no] = total_cost;
                          best_time[app_no] = start;
                        }
                    }
              }
        }
 start_s = best_time[app_no]*60;

 for (i=nofp[app_no];i<nofp[app_no+1];i++ )
    {
      start_e = start_s+POPT[i]*60;

       for (j=start_s;j<start_e;j++)
           app_power[j] = app_power[j] + Power[i];
      start_s = start_s+POPT[i]*60;
    }

  // send the best time for each appliance using RS232
   U1THR = best_time[app_no];
   U1THR = 00;
    all_cost = all_cost + totalcost[app_no];

 // stop execution time measurements
stop_t = timer; // stop timer
 }

 // send the total cost using RS232
data = all_cost;
U1THR = (data & 0xFF);
U1THR = ((data >> 8)&0xFF);
data = ((all_cost-data)*1000);
U1THR = (data & 0xFF);
U1THR = ((data >> 8)&0xFF);

// send the execution time
data = stop_t-start_t;
U1THR = (data & 0xFF);
U1THR = ((data >> 8)&0xFF);
}
```

6.4.4 Embedded configuration

The LPC2378 hosts the embedded heuristic scheduling algorithm code and is ideal for applications based on multi-purpose serial communication. Typically, numerous software tools including but not limited to compilers, linkers, debuggers can be used as a standalone program in the development platform. However, a solitary bundle consisting of full set of the aforementioned software tools is readily available. Keil© embedded development toolchain for ARM, μVision IDE and development/debug tools version 3.62c [167], was selected to compile, assemble, and link the embedded C code into a target binary. The binary codes (strings of 0 and 1) were downloaded to the microcontroller via the USB-JTAG connector which connects the USB port of a PC to a standard 6 pin JTAG programming header. A serial connection to a PC running a simple command line terminal application was used to implement a simple but function GUI. This allowed configuration of the scheduled appliance characteristics, execution of profiling tests and retrieval of results for visualization and analysis. An on-chip timer with 1 μs accuracy was employed to obtain execution timings for the instrumented code. The only notable difference between the PC-based implementation and the embedded implementation was the use of single-precision real (floating-point) number representations in the latter compared to double precision in the former.

6.5 Experimental case study

A set of numerical studies were carried out to verify the functionality of the embedded processor implementation of the scheduling algorithm, and to investigate the processing time overheads. Experiments were performed on the embedded platform and benchmarked against the MATLAB© implementation running on a desktop HP© PC with an Intel Core i5 CPU running at 3.40GHz clock speed with 6GB of physical memory. The embedded processor implementation experimental setup is shown in **Figure 6.4** below.

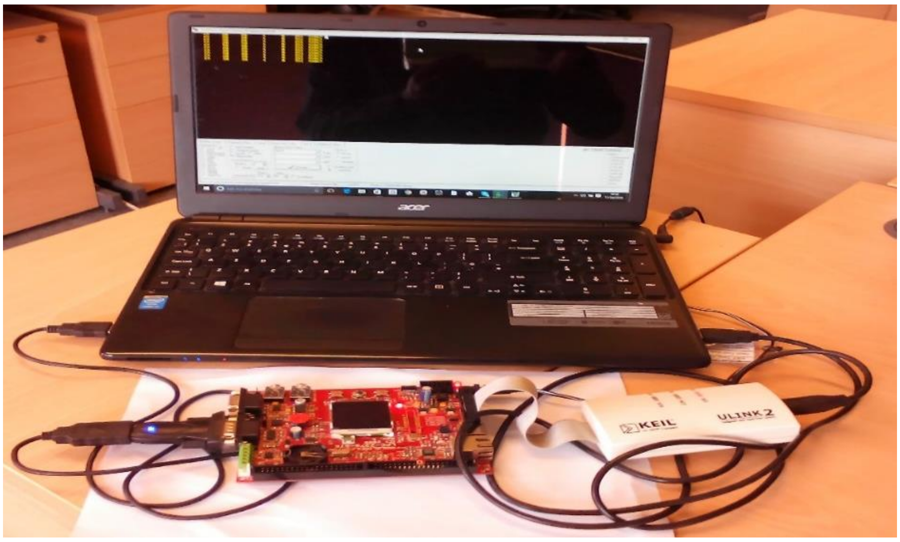


Figure 6.4. Embedded processor implementation experimental setup

6.5.1 Verification of the embedded processor implementation

In this experiment, a single household consisting of four controllable smart home appliances: washing machine, tumble dryer, dishwasher & electric vehicle was considered. The technical specifications for these appliances, such as number of operation stages, time, and energy requirements, are presented in **Table 6.1**

Table 6.1. Appliance priorities and preference settings based on decreasing order of power consumption [17]

Appliances	No of stages	Total Power (watts)	Priority	User-time preference
Washing Machine	6	2100	1	10:00 – 20:00
Tumble dryer	1	1200	3	10:00 – 22:00
Dish washer	6	1900	2	08:00 – 19:00
Electric vehicle	1	1000	4	1:00 – 5:00

The cost functions were taken to be constant in this setup, i.e., a regular Real-Time Pricing (RTP) signal. Hourly prices for electricity for the Scandinavian electricity market [155], considering the first week of February 2016, were used in these experiments. The prices were as shown in **Figure 6.5**.

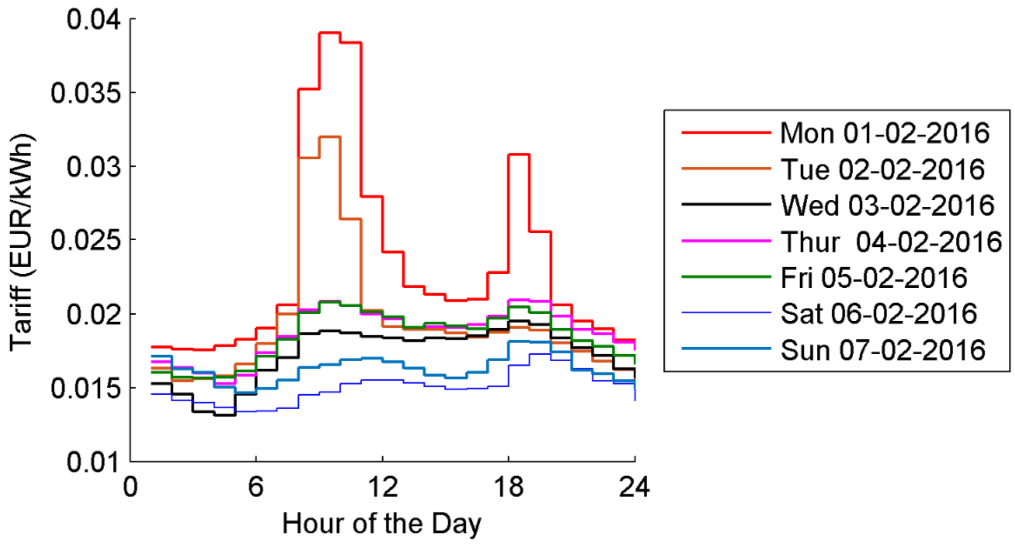
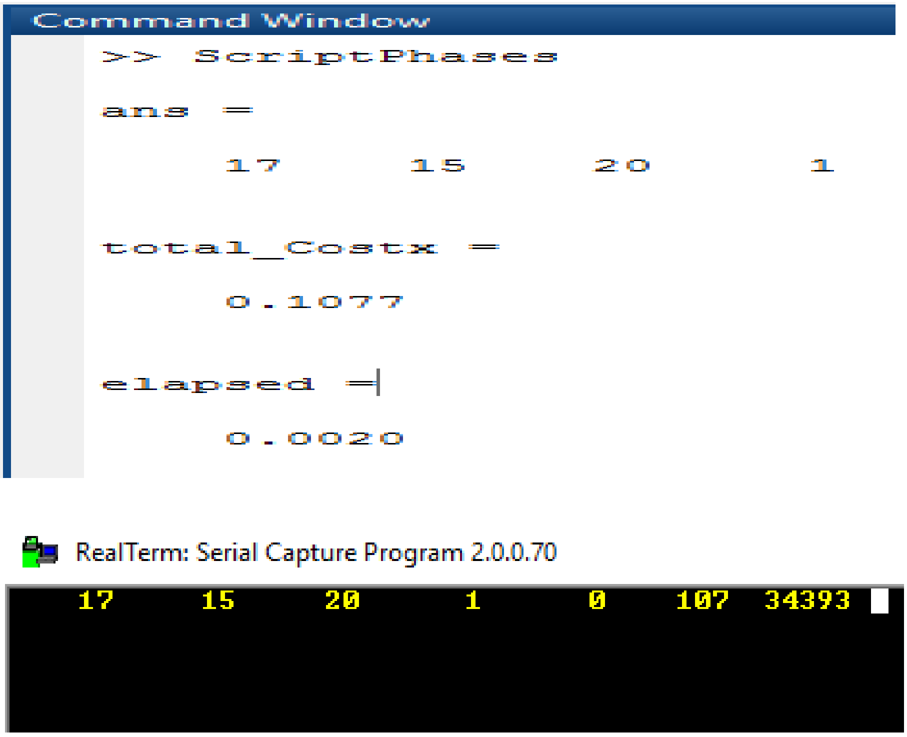


Figure 6.5. Electricity Tariff (Hourly system price) from the 01/02/2016 to 07/02/2016. Data taken from Nordpoolspot [155].

Hourly system prices as shown in **Figure 6.5** were utilized by the heuristic algorithm for scheduling the appliances to obtain cost and processing time for both the embedded processor implementation and MATLAB© based implementation. Optimization was carried out once every 24 hours in these tests for a one-week duration only (Monday to Sunday), with a specific hourly system price that corresponds to each day of the week. After simulation, the obtained results indicate that total consumption cost for both the MATLAB© based experiment and the embedded processor implementations were effectively the same, and both within 0.0042% of the optimal achievable cost when compared with test results for an exhaustive search method in section of chapter 5 (Section 5.3.1). A snapshot of one day of optimization is shown in **Figure 6.6**. In terms of power consumption, it is observed that there is no disparity in the power distribution as both schedules start appliances in the same time slots. However, the solving time (in seconds) between them varies somewhat, which is to be expected given the disparity of the processing platforms. The extent to which the solving time differs with an increase in the number of appliances (and changes to other configuration settings) was also tested.



(a)

(b)

Figure 6.6. Screen shot of the simulation results obtained in MATLAB© (a) and embedded processor (b), showing a snapshot of the scheduled appliance start times (hours), total cost (euro in (a) and cents in (b)) and simulation solving time (seconds in (a) and μs in (b))

6.5.2 Computational time evaluation

Two different scenarios have been investigated, and the results for each compiled to provide a clearer picture of the scalability and worst-case performance of the embedded implementation.

Scenario 1: Different household configuration with increase in number of appliances and appliance configuration: solving time was further tested with an increasing number of appliances, each with a different household configuration (C1 to C5). Real-time hourly prices across the same period of 5 days (Monday – Friday) as employed in Section 6.5.1. The number of appliances is increased from 4 to 10 across the five different household configurations, as shown in **Table 6.2**. Results illustrate that the solving time mostly increases with the increase in number of appliances, as expected – but that the appliance configuration also influences the results. Comparing the results of the embedded processor implementation to the MATLAB© based implementation, we observed that the solving time (in seconds) again shows an expected disparity. However, the point to note is that it can be observed that the trend of computation times is similar across the configurations for both implementations. In particular, the computing time increase between 5 and 10 appliances is of approximately the same relative order of magnitude in both cases.

Table 6.2. Solving time for MATLAB© based experiments and embedded processor implementation across different configurations with increase in number of appliances.

No of appliances	**Household Configuration**	**Average CPU solving time (seconds)**	
		MATLAB©	***Embedded system***
5	C1	0.00233	0.00802
6	C2	0.00185	0.00850
7	C3	0.00215	0.00880
8	C4	0.00209	0.00970
10	C5	0.00272	0.01290

Scenario 2: Worst case appliance scheduling scenario: The worst-case solving time performance for the embedded processor implementation and the MATLAB© based implementation can be tested by forcing the scheduling time window such that appliances are scheduled to operate anytime within the course of the simulation period (24 hours), as opposed to a user-defined time window. In this last experiment, 10 random appliances with representative time and energy requirements were scheduled using the hourly real-time prices for Saturday and Sunday the 6^{th} and 7^{th} February 2016 respectively. The optimizer was run for 10 times each day and **Table 6.3** summarizes the average obtained execution times, max/min execution times and standard deviation in execution times in each case. From this table, it can be observed that for embedded implementation, both the maximum and average execution times were at the sub-millisecond level, with very small standard deviation. This indicates that even for 10 controllable appliances, for a typical horizon configuration of 24 hours the heuristic is extremely efficient.

Table 6.3. Relative solving time for PC-based experiment vs Embedded processor implementation under worst-case scheduling scenario.

Metric	PC-Based IDSS	Embedded Processor IDSS
Mean	0.004295	0.017985
Max	0.005100	0.018500
Min	0.004000	0.001720
Standard Deviation	0.000327	0.000919

Combining results from **Table 6.2** and **Table 6.3** and assuming scheduling is performed once every minute, then an average processor utilization of less than 1.1×10^{-5} % will be consumed. This utilization figure is, in effect, negligible for all practical purposes and the heuristic scheduling algorithm would seem a good candidate for implementation on a smart meter.

6.6 Summary

In this chapter, a prototype embedded system implementation of a residential load scheduling system using the proposed heuristic algorithm has been described and tested on a small-embedded processor, and the prototype implementation validated against IDSS Implementation on MATLAB©. Test results indicate that the heuristic algorithm is efficient enough to be co-located on a small smart meter with limited processing power without any difficulties. In the next chapter, evaluation of the heuristic algorithm from the utility side perspective will be explored, considering multiple households and smart meters with heuristic deployed as a part of an embedded intelligent Decision Support System (IDSS) to respond to utility DSI event signals.

Chapter 7

7 Evaluation of the Proposed Heuristic Algorithm Part 2) Utility Viewpoint

7.1 Introduction

The scheduling algorithm proposed in Chapter 4 of this thesis was extensively tested from the consumer viewpoint in Chapter 5; it was found to produce near-optimal results under a wide variety of operating conditions and pricing models. However, the end consumer of energy (householder) is not the only stakeholder in the overall context of this thesis. In the preceding Chapter 6, it was demonstrated that the heuristic seems to be efficient enough to be mounted on a small microprocessor and potentially rolled-out en-masse within a smart meter/AMI installation. The focus of the current chapter falls upon investigating the behaviour of multiple instances of the algorithm responding to price signals driven principally by wholesale energy prices and unexpected events affecting the wider grid. It investigates the combined decision-making ability of the heuristic algorithm in response to DSI events signalled by a utility company – the other principal stakeholder in this situation - when the primary focus of each individual heuristic is upon minimization of end-consumer economic costs. Hence, in this chapter, medium-scale simulations of the impact of utility pricing schemes on a roll-out of residential DSI will be presented. Furthermore, the extent to which a heuristic algorithm for household load scheduling can help shift aggregated demand in response to normal and stringent DSI prices will be explored.

Electric utilities are incorporating DSI approaches in their energy networks, principally to handle increased levels of uncertainty arising from renewable energy production and related regulatory requirements. DSI can be implemented by using implicit price-based schemes such as TOUP, RTP and 2TP tariffs for end consumers, but may also incorporate (explicit) DSI programmes in response to external or unexpected effects on the wider grid [2]. Although (traditionally) DSI pricing schemes have mainly focused upon industrial end users of energy, the push towards a smarter grid opens new opportunities to involve residential consumers in explicit DSI; one way this may be implemented is to encourage shifts in residential load by using ‘transient’ pricing signals provided in real-time by the utility company. The goal is to provide an extra ‘push’ during a DSI event to encourage the shift of energy consumption away from a particular time period on a particular day, by transiently adjusting prices away from tariff norms for DSI participants (registered customers). This provides a specific, targeted, and surgical attempt to reduce the load factor of the electricity system when a contingency occurs [168],[169]. In this chapter, the effects of multiple households using the proposed residential heuristic algorithm for scheduling smart appliances is explored from this utility planning and DSI perspectives.

7.2 Background on Utility planning.

Insufficient investment in the ageing electricity infrastructure network has limited the capacity to meet the increasing system loads [170]. This has placed an additional responsibility on utilities to incorporate DSI approaches in their energy networks to reduce peak loads and better match capacity with demand. From the consumer side, scheduling of controllable loads (such as smart appliances) with the help of an IDSS can help to achieve consumer DSI participation and can assist with DSI for utility event handling. Utility planning refers to efficient operations in electricity generation, transmission, and distribution. This is based on proper management of base load and peak load, as well as various energy resources for electricity generation [171]. The major goal of utility planning is to create a flexible plan that allows adjustments in response to uncertainty of growing and changing system demand. Distributed generation (DG) is an emerging option for solving distribution system capacity problem. Many utility planners apply an integration cost adder to calculate the cost of new distributed renewable capacity. These include the cost of balancing supply, forecast errors, and other costs related to variable generations in power system [172].

Additional mechanisms such as ancillary services (AS) [173]-[175] are also needed to regulate supply and demand while also responding to contingencies, for example during a sudden loss of transmission of electric power from utilities to the consumers. AS has potential benefits for consumer demand response participation. Such benefits include the availability of reliable resources to system operators and the flexibility to manage uncertainty events as a result of increasing integration of renewable generations to the grid [175] etc. These are aimed at enhancing energy system efficiency and help to prevent grid instability. In conjunction, utility companies can ensure proper planning, implementation, and monitoring of DSI activities designed for efficient utilization of the existing infrastructure network while reducing the cost of grid upgrades. **Figure 7.1** below presents an example hierarchy of the common utility planning objectives that includes the provision for sustainable development as well other attributes adopted by many utilities.

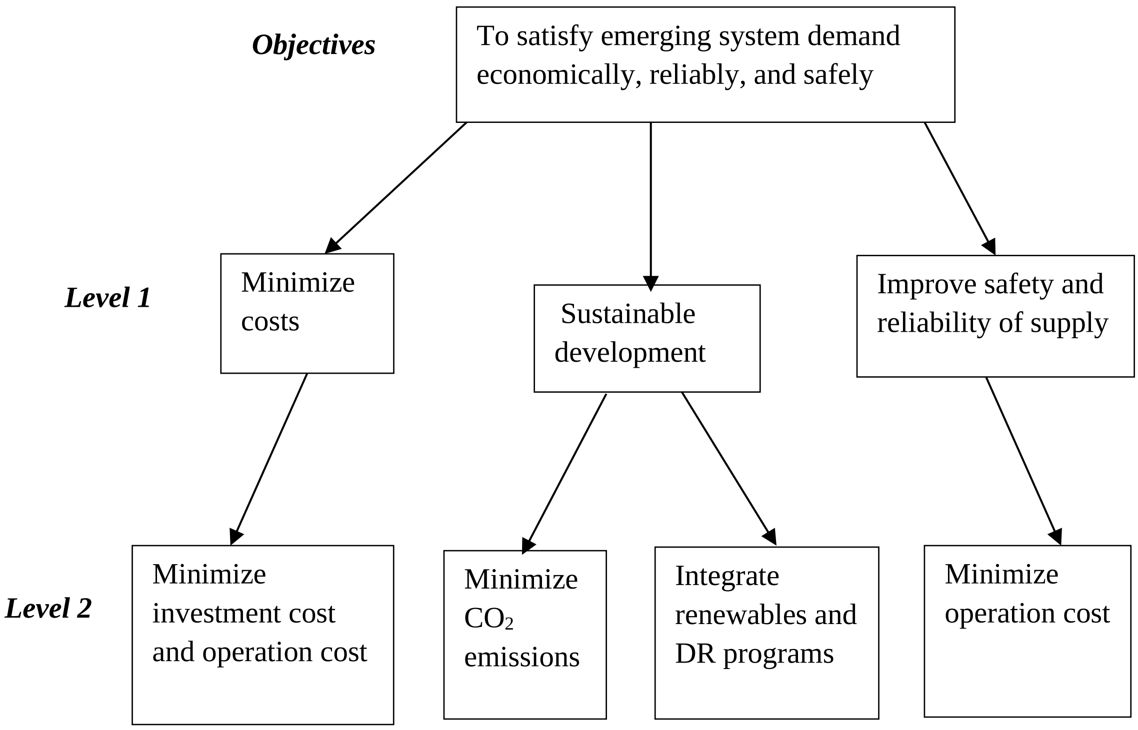


Figure 7.1. Example of the hierarchy for utility planning objectives [176]

7.2.1 Assumptions for Utility planning

During the planning processes, assumptions are made by utility to facilitate the planning at different stages. These assumptions include, but are not limited to, unidirectional load flow, electric load as passive demand, high cost of consumer load etc. However, utilities mostly adopt the 'peak planning method' such that the best alternative plan is found when it meets the expected peak load at minimum cost [176]. This implies that when a capacity limit is exceeded, both customer and utility costs increase to a sufficient value to justify the investment plan. Therefore, the utility planner evaluates the network performance by making use of all the distribution network information such as component rating, layout etc., together with the forecasted peak loads as the static inputs to determine when to activate an event. DSI events are typically limited in number and duration, and are triggered by utilities based on the following criteria [170]:

- During emergency conditions at the generation, transmission, and distribution levels such as the sudden loss/unplanned outage of a generator or transmission line.
- Surpassing of an economic threshold based on spot prices.
- During extreme weather conditions such as high or low temperatures that may increase loads on the system.

To respond to the emergency, heuristic scheduling algorithm could be deployed in smart meter/AMI installation at residential buildings to provide scheduling advice and recommendations based on DSI prices. Hence, from the utility perspective, load management is an important mechanism for efficient planning and operations.

7.2.2 Development of Utility plan

The utility plan can also be referred to names such as Electric resource plans (ERP), Integrated resource plans (IRP), Long-term procurement plan (LTPP) etc. The utility planning process is complicated by growing uncertainty due to resource availability, load growth, regulatory and environmental concerns as well as the competition in the various sectors of the power market [177]. In particular, the unknown nature of the future system load at the initial building of the system is a major concern. Subsequently, utility cannot afford to overbuild the system upfront for every possible load increase for many years [178]. Development of utility plans that minimize the interruption of system loads during unexpected DSI events requires balancing processes and criteria that the utility personnel must follow to ensure grid stability. Utility planning process is analogous to many other planning procedures and can be classified into five different generic stages as in [179], which includes data and information gathering; forecasting and performance assessment; problem identification and formulation; evaluation prioritization; and approval. Amongst the aforementioned stages, load forecasting is one of the key segments to achieving an economic balance on the system loads [179]. Utilities utilize peak load forecasting methods [180], [181] such as load-curve based algorithms, diversity factor, Valender correlation etc., to produce near estimates of the energy demand based on the assumptions in Section 7.2.1.

Availability of load forecast incorporated in the utility plan would enable the network planner to perform routine assessment and analysis of the distribution system. This is done to estimate if the performance of the system meets the utility's criteria in terms of capacity of demand required by customers, safety, reliability etc. More so, there is need to prioritize the planning process in the course of emergency events to address other planning problems such as improvement of power quality, peak demand reduction etc. The rest of the planning process would include the utilization of modelling, simulation, optimization, and analytical tools to develop and evaluate various planning alternatives. As such, there is absolute need for empirical knowledge of the planning processes and stages by the utility planner for various planning criteria and tools.

7.2.3 Utility planning tools

Utility planners can utilize a set of commercial software packages to plan and analyse basic functions such as load flow, contingency analysis, reliability assessment in the modelling and simulation of utility planning requirements. Considering the capacity issues, the related costs may be determined by positive sequence power flow diagrams [182]. The power flow tool must be capable of estimating the energy costing, simulating the load characteristics and load increase over time. Software packages such as PowerFactory, CYMDIST distribution system analysis etc., have different interface options and are efficient in running simulation algorithms designed for the planning and DSI event activation. The interface options include but not limited to utility custom tools, MATLAB, distributed management system, SCADA etc. The use of the planning tools is to determine the economic value of the planning options.

7.2.4 Utility incentive/pricing programs

For utility planning processes that use analytic tools, the utility planner would first asses the available resources about demand expectations and then select the appropriate pricing program. Generally, two categories of DSI pricing programs exist as previously described in Chapter 3 (Section 3.2.2) of this thesis. There are the price-based programs that motivate customers to change their consumption behaviour in line with the dynamic pricing; and the incentive-based programs that rewards the customers for reducing energy usage on certain periods of the day in response to the DSI request [99]. The incentive-based programs can be configured to achieve a specific goal such as peak reduction during transmission congestion, which in turn, diversify the impacts of DSI on grid operations. However, as has been discussed, utility companies use pricing-based programs such as Critical Peak Pricing (CPP) [183], Real time pricing (RTP) [184]-[186], Time of use pricing (TOUP) [187], etc., to influence consumers to adapt to their tariff structure aimed at achieving an aggregated demand that matches the needs of the power generation. With the help of Advanced Metering

Infrastructure (AMI) - a two-way communication medium - utility company are able to advertise pricing-based signals and receive consumption details for electric billing purposes through a smart meter. The billing is based on measured demand and represents the actual energy consumption by customers. With the pricing-based programs, in particular CPP, utilities offer customers discounted rates of energy tariff throughout the year. In return, they have the opportunity to charge higher prices for energy consumed during the CPP event days. The price of electricity is higher during CPP events (i.e., periods of high-energy use with stringent prices) while the CPP rate offers standard tariff during all other times (non-CPP event days). This pricing program is beneficial to participating customers that voluntarily reduce energy usage on the CPP event days. Importantly, utilities are only allowed to invoke a certain number of CPP events in a given period (within a year/season) specified on the contract. An example is the CPP event advertised by Southern California Edison (SCE), which limits events to between 9 and 15 times per summer or maximum total of 60 hours per year [188]. Utility notifies customers of any planned event no later than 3.00pm the day before the event through different communication forms such as emails, telephone, fax etc.; and request they reduce energy usage during a certain CPP event period. In some cases, residential customers do not require acknowledgement of event notification and customers may decline to participate with or without penalty. However, customers may also participate in other DSI programs for additional incentives. Interestingly, although price-based programs account for only a small portion of the total DSI resource base, more utilities offer some types of it to customers than the incentive-based programs [189].

Automated Demand Response (Auto-DR) [190] in the form of an IDSS is highly desirable for consumers to respond to DSI requests from the utility. This would encourage customer participation in DSI events by automating the load scheduling process and hence, eliminating the need for manual intervention. In the course of an event, the pricing signal is sent to customers via the internet to the Energy Management System (EMS) or other devices such as the AMI, helping to reduce load in accordance with the DSI strategy/technique.

7.2.5 Literature - Utility planning algorithms

Researchers have considerable publications on different planning frameworks for the utility side management. Recent works [191],[192] present the utility planning processes and provide the survey of utility plans and procurement practices. In addition, there are studies relating to integration of renewable costs into utility planning (e.g. [182], [193],[194]). The pitfall is that the costs of integration are applied traditionally due to inability of most analytic tools to capture the details of system operation and transmission. As such, the integration costs are inaccurate in terms of managing the unpredictable nature of the renewable generations and therefore lacks uniformity in certain development factors. However, there exist a few literatures on electric utility planning with emphasis on decentralized smart home appliance scheduling during demand response events. Reference [195] proposes a distributed algorithm for customers and the utility company to compute demand schedules and optimal prices. This is such that the utility company use varying prices to coordinate DR to the benefit of the overall system. The authors in [196] illustrate how to use an existing utility data to predict customers demand management behaviour. Specifically, they showed the calibration of the of the estimated customer cost function to help in the design of efficient demand management contracts. In [197], a dynamic game along with a distributed algorithm was proposed to demonstrate the interactions between the utility company and its subscribers, which eventually leads to economic point. This chapter explores the performance of the heuristic algorithm on the aggregate household electricity consumption during DR events.

7.3 Motivation

Various DSI implementation strategies such as, peak load curtailment for unexpected DR events [198],[199], direct load control [200] and price responsive demand [201] have all been employed in the past few years for reducing peak demand. However, such techniques have limitations in terms of the required ability of the utility company to control the residential smart appliances remotely. As a result, utilities are adopting pricing-based mechanisms to encourage residential customers to conserve energy and reduce peak demand. One of the barriers to enabling a critical investigation to different pricing schemes and their subsequent appraisal for use in future smart grid has been the complexity of the residential load-scheduling problem, which (as previously discussed) is known to be NP-hard [129]. The principal goal of the heuristic is to minimize a resident's electricity bill in the presence of varying utility price signals within a reasonable computational time. Consequently, the utility company could adjust the pricing signals and energy capacity provided in each timeslot to help plan their actions. Therefore, the use of the near-optimal and extremely low-overhead heuristic algorithm proposed in this thesis opens a pathway for further investigations. Utility can provide the cost function for electricity (e.g., CPP during a DSI event) to the residential energy users 24 hours in advance via the AMI to the smart meter. These prices are then used by the IDSS equipped with the proposed heuristic algorithm (co-located on the smart meter) to respond to DSI events, while reducing peak consumption. Further evaluation of the proposed heuristic algorithm in terms of cost savings due to DSI and power shifts from peak to off-peak period during DSI event is the main motivation of the simulation study described in the following section.

7.4 Experimental studies

Numerical studies were conducted to investigate the aggregated performance of multiple instances of the heuristic algorithm in response to events affecting the utility side and manifesting as dynamic fluctuations in the pricing signals offered to customers. Two sets of experiments were considered, each with two scenarios that addresses a specific DSI event. The first experiment evaluates the total resident's cost while the second experiment evaluates the power distribution for the given scenarios. In the first scenario, 'normal' DSI procedures were assumed, and hourly RTP pricing structures that reflect the cost of electricity during the course of a number of days were assumed to be sent to each heuristic algorithm. In the second scenario, 'stringent DSI prices' which are modified pricing structures that aim to reduce electricity demand at specific times during the course of DSI event days were assumed to be sent to each heuristic algorithm. Ten heterogeneous residences with smart appliances and smart meters equipped with the heuristic algorithm were considered, and the aggregated demand was measured during the course of eight simulated days for both experiments. Representative configurations of the number and type of appliances and individual appliance constraints were employed. The number of appliances in a residence was varied between four and ten. The impact upon aggregated and individual household costs was also calculated in both experiments. **Figure 7.2** displays the baseline RTP signals, and the magnification of prices applied during stringent events.

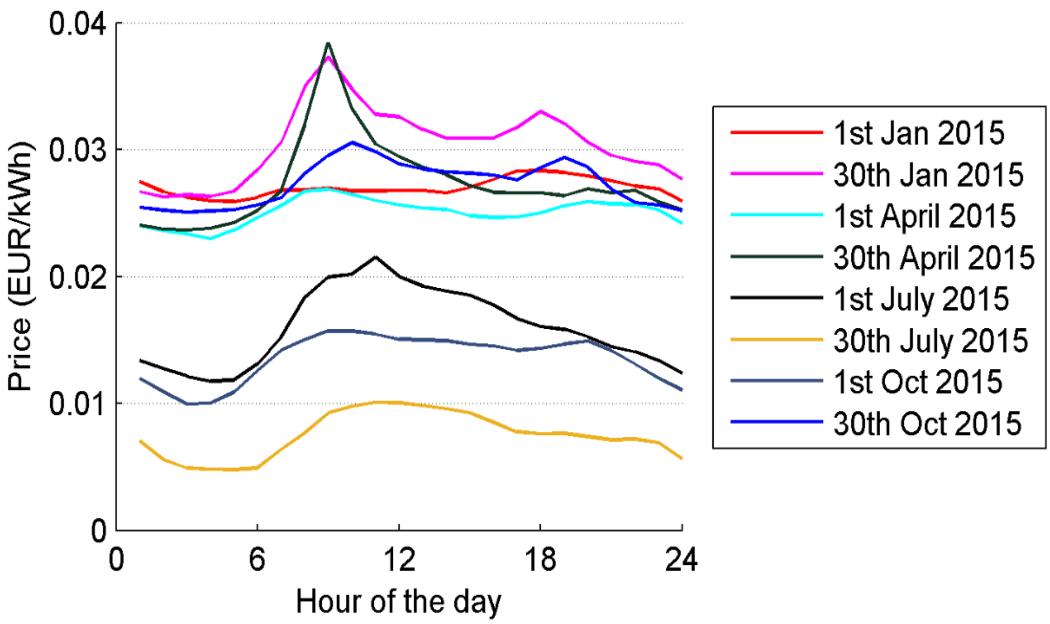


Figure 7.2. Example of hourly RTP of electricity used in simulation, showing the plot for 1st and 30th day of the representative months of the season. Data taken from Nordpoolspot [155]

7.4.1 Experimental data and configuration

Baseline hourly electricity pricing data from Nordpoolspot [155] was used for the basic RTP signals and prices were used across four months in 2015 (1st and 30th days of January, April, July, and October), representing samples of the four seasons of the year (winter, spring, summer, and autumn). RTP data used in this simulation was arranged in such a way that both normal and stringent DSI prices have the same average total tariff. For stringent DSI event simulations, peak periods were defined for each day (6 AM until 11 AM, and 5 PM until 11 PM). The prices for the peak periods of each stringent DSI event day were fixed at the highest cost of electricity during that particular day, and the tariff for the remainder of the off-peak hours was scaled appropriately such that the average price for both a normal and stringent day remained the same. This configuration corresponds to a situation in which the utility is pre-notified of, say, a loss of contracted peak power supply and re-schedules its prices to effect DSI while ensuring that customers receive the same average price.

7.4.2 Experimental results: Residents' electricity cost

This experiment evaluates the optimized costs of fulfilling the residents' energy demand for the appliance scheduling. Results obtained for the aggregate energy costs for both normal and stringent DSI event days across all households is presented in **Table 7.1**. Corresponding aggregate results for all households DSI event days are shown in **Table 7.2**. From Table 7.I, it can be observed that the household average total cost of €1.2964 was incurred for normal DSI event days as compared to €1.2502 obtained for stringent DSI event days. This indicates that, for the pricing models employed, lower costs were achievable (on average) across the households during stringent DSI event days. However, it may be observed that 2 individual households (Houses 4 and 7 respectively) incurred greater costs during stringent DSI event days despite the average total cost of all households being lower. These factors should be kept in mind when utilities consider the impact of price schedules to achieve DSI participation. From the results in Table 7.2, there is only one (day 30th July) where the aggregate total cost for Stringent DSI event was higher than the Normal DSI event. In addition, since the heuristic has low overhead, alternate scenarios can quickly be considered, adding an opt-in/opt-out opportunity to residents when DSI events result in changes to nominal RTP schedules seems advisory.

Table 7.1. Comparison of household average total cost on all DSI event days for normal and stringent events

Households with 8 DSI Event days (2015)	DSI Events (Normal) Household Average Total Cost (EUR/kWh)	DSI Events (stringent) Household Average Total Cost (EUR/kWh)
House 1	1.0461	1.0445
House 2	0.9068	0.8811
House 3	1.1671	1.0994
House 4	1.1831	1.1953
House 5	1.3102	1.1924
House 6	1.2060	1.1724
House 7	1.4131	1.4299
House 8	1.4117	1.3134
House 9	1.5528	1.4791
House 10	1.7670	1.6945
Mean	**1.2964**	**1.2502**

Table 7.2. Aggregate total cost of DSI event days for all households under normal and stringent events

DSI event days (2015)	Normal DSI Events Household Total Cost (EUR/kWh)	Stringent DSI Events Household Total Cost (EUR/kWh)
1st January	2.0532	2.0195
30th January	2.2561	2.1230
1st April	1.8949	1.8831
30th April	1.9912	1.8405
1st July	1.1983	1.0998
30th July	0.5146	0.5179
1st October	0.9963	0.9867
30th October	2.0593	2.0315

7.4.3 Experiment results: Power distribution

In this experiment, the distribution of power consumption of the appliance schedule is examined to determine the differences in the on-peak and off-peak energy consumption (in kWh) for each DSI event day with normal and stringent DSI prices. **Figure 7.3** displays the results obtained for the aggregate electricity demand for both normal and stringent DSI event days. From the figures, visually it may be observed that for both normal and stringent days, the consumption follows the wholesale electricity price, but the price differences have had a marked impact on the distribution of power consumption.

a)

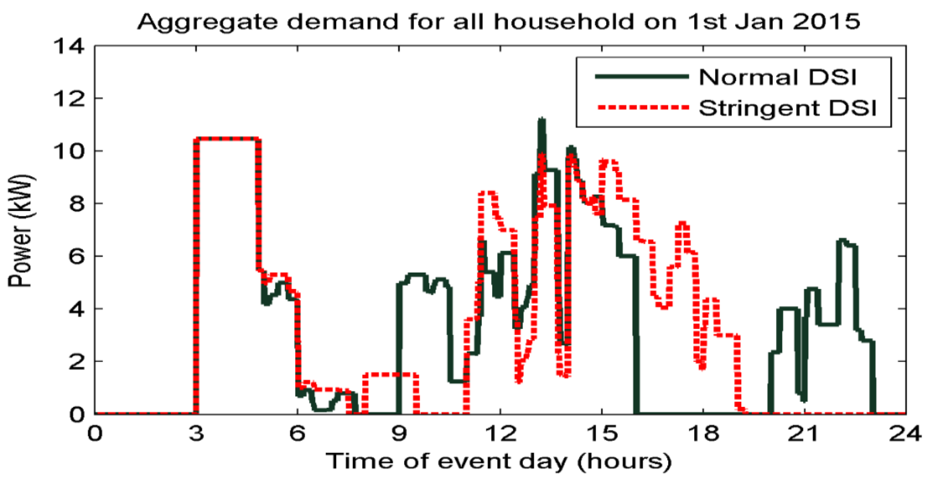
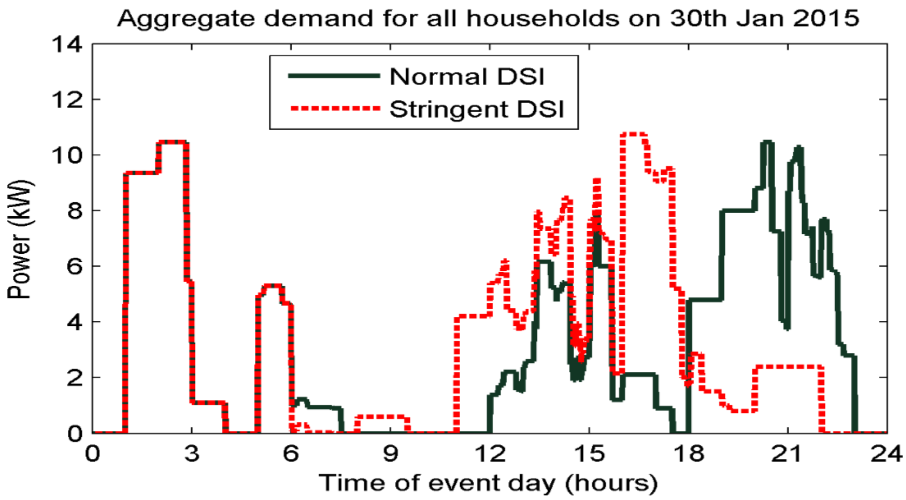
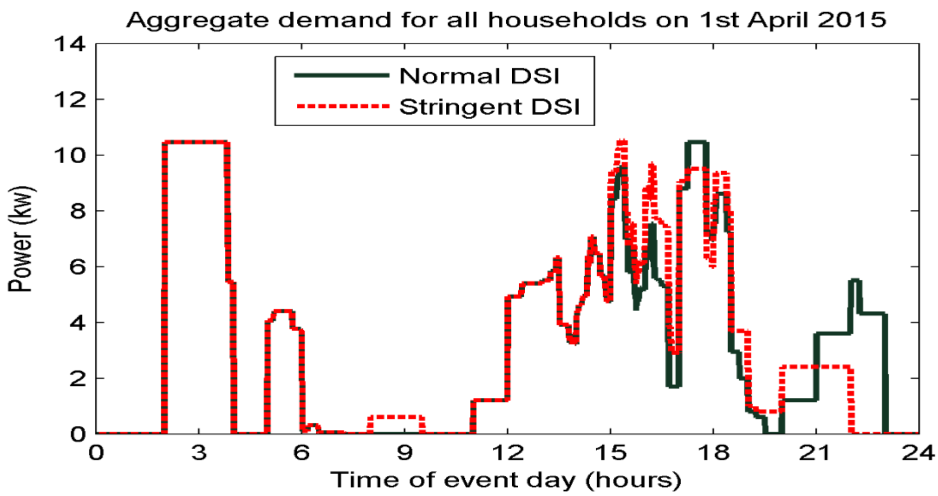


Figure 7.3 Cont.

b)



c)



d)

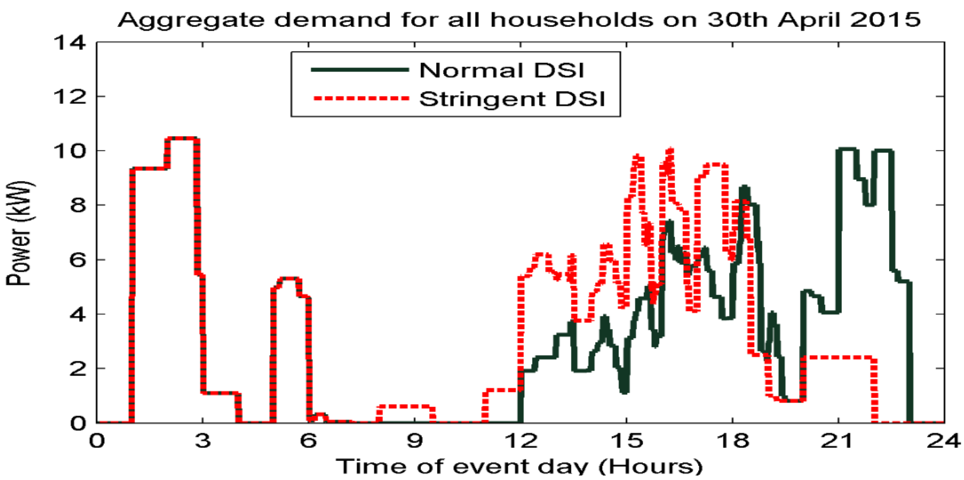
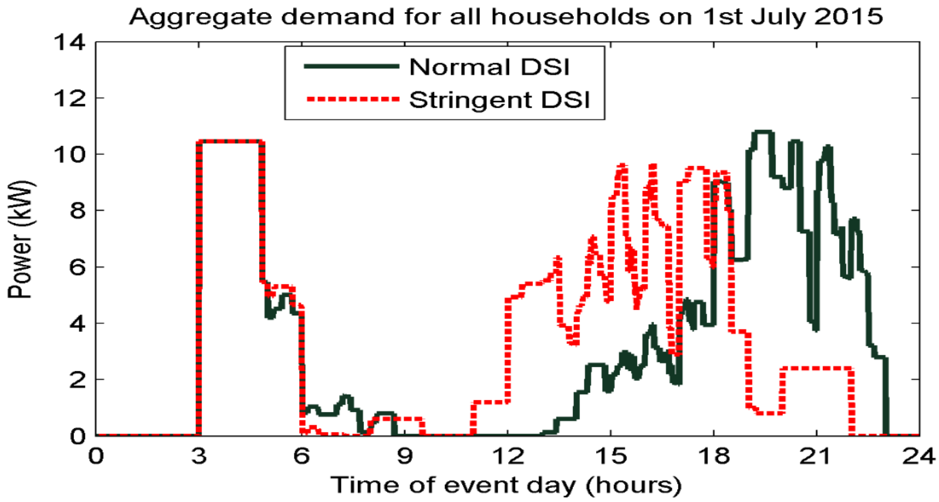
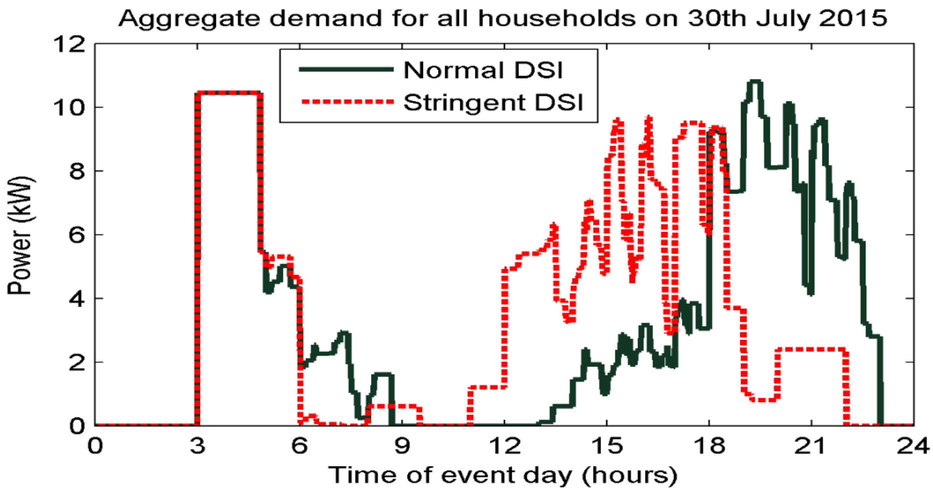


Figure 7.3 Cont.

e)



f)



g)

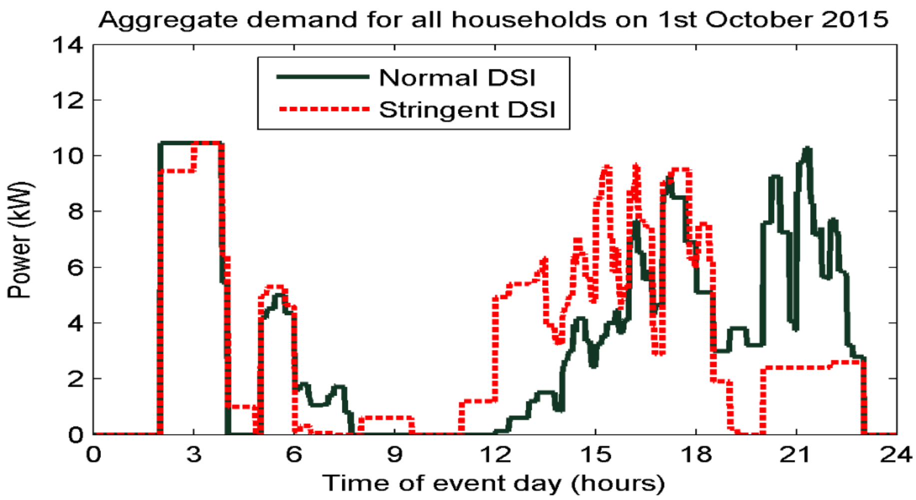


Figure 7.3 Cont.

h)

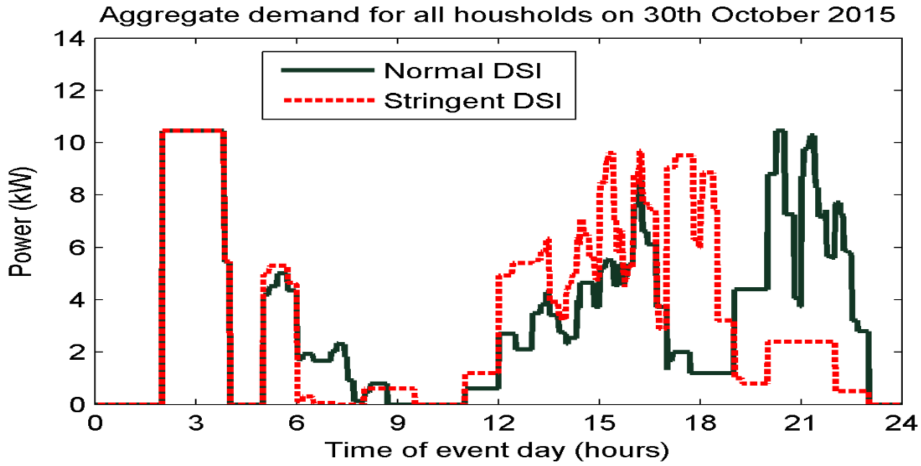


Figure 7.3. Aggregate demand for all households (a to h) over the course of the day with Normal and Stringent DSI events.

Although the normal prices were set to follow the wholesale cost of electricity (and hence implement DSI), the desired effect during stringent days is to shift additional power from peak to off-peak periods. To investigate this aspect further, peak, and off-peak energy consumption was calculated and is shown in **Table 7.3** below. From the table, it can be observed that the desired effect has been achieved for each simulated day. On average, 2.65 kWh was shifted away from peak periods. This corresponds to an average of 40% consumption shifted away from peak periods. The largest absolute reduction in peak consumption occurred in the summer with 4.15 kWh for the 30th July, while the largest relative (%) reduction occurred on 30th January with a 56.76% shift. The smallest absolute peak power reduction is seen on the 1st April with 0.44 kWh; this also corresponded to the smallest relative reduction at 10.76%. Nevertheless, a 10% shift in power consumption from on-peak to off-peak periods remains a considerable asset for a utility to call upon. Overall, the result confirms that the approach employed can be used for general DSI and to encourage shifts away from peak periods during DSI events. The results also suggest that the proposed heuristic algorithm can be effective in reducing aggregate peak demand when employed in a decentralized fashion.

Table 7.3. Aggregate on/off peak power consumption for normal and stringent DSI event days

Event Day	Normal DSI Total power Consumption (kWh)		Stringent DSI Total power Consumption (kWh)		Reduction in peak period consumption (kWh)	Reduction in peak period consumption (%)
	On peak	Off	On	Off Peak		
1st January	3.74	9.31	2.22	10.56	1.52	40.64
30th January	5.92	6.79	2.56	10.13	3.36	56.76
1st April	4.09	8.72	3.65	9.20	0.44	10.76
30th April	5.74	6.92	3.45	9.25	2.29	39.90
1st July	7.52	5.30	3.65	9.05	3.87	51.46
30th July	7.80	5.10	3.65	9.05	4.15	53.21
1st October	6.38	6.45	3.65	9.05	2.73	42.79
30th October	5.33	7.54	3.65	9.05	1.68	31.52

7.5 Summary

Effective utility planning can help to achieve more efficient use of electricity distribution resources and help curtail excessive economic costs from poor utilization of resources. DSI initiatives/programs can also help to react to unexpected or unplanned events on the wider grid. In this chapter, the impact of a cost-minimizing heuristic algorithm when viewed from a utility perspective has been explored. The obtained results were positive in that the use of the proposed heuristic algorithm (in combination with careful pricing structures during DSI event days) could help shift aggregated demand in households with smart appliances. The economic effects on individual households were beneficial (on average), but some households nevertheless experienced slightly increased costs due to differing appliance scheduling configurations across various households. Overall, the test results confirm that the heuristic rapidly responds to DSI pricing signals and produces the desired responses from numerous households in synchronicity, although the choice of price signals plays a major role in the depth and nature of the response. The choice of effective price signals to achieve a specific DSI goal or target is an area that requires further investigation. Details of these – and other – related areas of future work will be described in the final concluding chapter of the thesis.

Chapter 8

8 Conclusions and future work

8.1 Conclusions

This thesis has investigated an important aspect of the implementation of an IDSS for Demand-side Integration in the emerging smart grid. The work in this thesis covered four main subject areas: first, the smart grid and its enabling technologies; second, DSI load management strategies and heuristic scheduling algorithm development; third, embedded processor implementation of consumer IDSS; and fourth, DSI realization from the perspective of Utility planning (moderating the aggregate electricity demand while ensuring consumer benefits in terms of cost savings). For the accomplishment of the thesis requirements from these subject areas, a heuristic algorithm for scheduling residential smart appliances has been proposed and extensively tested. The usefulness of the heuristic algorithm for practical purposes comes from enabling residential appliances to be scheduled greedily, one after the other without backtracking, such that the worst-case computation time is significantly reduced compared to an exact method, at the expense of a potential loss of optimality in the obtained solution. The proposed heuristic algorithm ensures near-optimal scheduling within polynomial time, thus, offers the choice for use in the consumer IDSS to provide scheduling advise and recommendations to residential customers. However, the success of the heuristic scheduling algorithm will likely depend on whether the residential home has the ‘right’ set of smart (schedulable) appliances. To that end, knowledge of the appliance technical specifications (parameters) such as time and power requirements (e.g., length of timeslot, power profiles etc.) as well as decision variable (start time) are imperative to define the problem objective and determine the corresponding scheduling solution. These attributes were taken into consideration in the research study.

The performance of the proposed load scheduling algorithms (heuristic and exact algorithms) was effectively investigated using a generic cost model for electricity prices and a variety of representative smart home configurations. This was deemed necessary in case heuristic is deployed as an IDSS in households across different geographical locations with various dynamic pricing structures. The generic cost model presented in this thesis can be configured for traditional on/off peak pricing, RTP, Time of Use Pricing (TOUP), Two-Tier Pricing (2TP) and combinations thereof. Simulation results indicated that, when compared to an exact algorithm, the proposed heuristic consistently produces results, which are very close to optimal at a fraction of the computing cost. The results also suggest that the proposed heuristic algorithm is very effective across different types of pricing model.

Additionally, a prototype of the heuristic algorithm was implemented on a resource-constrained embedded processor (ARM7-TDMI 32-bit microcontroller). The performance of this prototype was tested and validated against a PC based IDSS implementation. The results indicated that the heuristic algorithm is efficient enough to be co-located on a small smart meter with limited processing power without any difficulties.

Following the good performance of the embedded heuristic algorithm from consumer viewpoint, the performance of such a situation from the perspective of a utility company was also explored as a means to reduce peak consumption. The effects on aggregated electricity demand with multiple instances of the heuristic, considering multiple (heterogeneous) household configurations, were also investigated. Test results confirm that the heuristic can produce a measured and coordinated response to DSI pricing signals in terms of aggregated electricity demand.

The thesis concludes that the proposed heuristic algorithm is a good candidate for the large-scale deployment of residential consumer oriented DSI and could be deployed as a useful and low-cost extension of an AMI in smart grids.

8.2 Future work

A first area of future work is to further evaluate the performance of the heuristic algorithm and its embedded prototype with large-scale Monte-Carlo simulations, employing many households (upwards of 1000 representative houses with up to 100 appliances in each case). In addition, the worst-case computational ability of the exact algorithm may be improved by utilizing pruning techniques (such as branch-and-bound or branch-and-price) which may help to reduce the average-case run-time; this would help create better benchmarks to examine the relative overheads of the heuristic.

The second area of future research is on the effect of pricing signals advertised by the utility service companies and the solution sensitivity. The sensitivity of both the heuristic and exact algorithms in the presence of time-of-use pricing (TOUP) was found to be low with respect to the economic cost but high with respect to the peak power consumption around the optimal solution point; some differences were also observed between the heuristic and exact algorithms. In addition, when multiple instances of the heuristic were present, the effectiveness of the depth of DSI was dependent upon the choice of pricing signals; it is not yet clear what choice of pricing signals would yield the optimal effect. Both aspects need further investigation.

The third area of future work is to integrate Renewable Energy sources (RES) and storage system to the cost function, making it a multi-objective optimization. This will provide a robust evaluation of the heuristic algorithm.

Appendix A: Details of household configurations for different appliance scheduling in section 5.5

A1 Configuration for five appliance scheduling with dynamic pricing

Table A1. Configuration for five appliance scheduling with dynamic pricing [17]

Devices	Input parameters	Household configuration			
		C1 RTP	**C2 RTP/2TP**	**C3 TOUP**	**C4 TOUP/2TP**
Washing Machine	Start time Range	10~20	10~20	10~20	10~20
	Timeslot length(min)	136	161	130	154
	Power	2249.96	2249.96	2249.96	2149.96
Dish washer	Start time Range	9~23	9~23	9~23	9~23
	Timeslot length(min)	82	134	78	87
	Power	1739.96	1880.96	1740.96	1840.96
Tumble dryer	Start time Range	13~23	13~23	13~23	13~23
	Timeslot length(min)	90	120	105	70
	Power	1200	1200	1500	1200
Electric vehicle	Start time Range	1~6	1~6	1~6	1~6
	Timeslot length(min)	120	110	150	120
	Power	1100	1000	2500	2000
Water heater	Start time Range	5~20	5~20	5~20	5~20
	Timeslot length(min)	105	60	90	60
	Power	950	900	700	1000

A2 Configuration for six appliance scheduling with dynamic pricing

Table A2. Configuration for six appliance scheduling with dynamic pricing [17].

Devices	Input parameters	Household configuration			
		C5 RTP	**C6 RTP/2TP**	**C7 TOUP**	**C8 TOUP/2TP**
Washing Machine	Start time Range	10~20	10~20	10~20	10~20
	Timeslot length(min)	135	135	155	135
	Power	1939.96	1899.96	2249.96	1899.96
Dish washer	Start time Range	9~23	9~23	9~23	9~23
	Timeslot length(min)	89	88	132	108
	Power	1720.96	1700	1960.96	1700
Tumble dryer	Start time Range	13~23	13~23	13~23	13~23
	Timeslot length(min)	90	90	90	90
	Power	1100	1000	1100	1000
Electric vehicle	Start time Range	1~6	1~6	1~6	1~6
	Timeslot length(min)	120	120	120	110
	Power	1500	1200	1000	1300
Water heater	Start time Range	5~20	5~20	5~20	5~20
	Timeslot length(min)	90	90	90	90
	Power	900	900	900	900
Electric cooker	Start time Range	6~22	6~22	6~22	6~22
	Timeslot length(min)	75	75	75	75
	Power	600	600	600	600

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