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A Review on Demand Side Management and Case Study Using Optimization Tool

A Dissertation Submitted in Partial Fulfillment of Requirement for the Degree of Bachelor of Science in Electrical and Electronic Engineering

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Declaration of Candidate

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

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ABSTRACT

Utilities around the world are now considering Demand Side Management (DSM) in their strategic planning. The costs of constructing and operating a new capacity generation unit are increasing everyday, which force the utilities to search for another alternative without any additional constraints on customers comfort level or quality of delivered product.

DSM encompasses a broad range of utility initiated activities to encourage end users to willingly modify their electricity consumption without any impact on service quality or customer satisfaction. It was found that an objective function reflecting the user electricity expenses did widely serve the best for both the electric utility as well as the end user. From a utility point of view, benefits are meterized as freed capacity, deferred investment or increased revenues. Other developed target objective functions such as maximizing the load factor or the utility revenues did serve to achieve its targets but without much impact on end user electricity expenses or even increased ones.

Demand side management (DSM) is one of the important functions in a smart grid that allows customers to make informed decisions regarding their energy consumption, and helps the energy providers reduce the peak load demand and reshape the load profile. This results in increased sustainability of the smart grid, as well as reduced overall operational cost and carbon emission levels. Most of the existing demand side management strategies used in traditional energy management systems employ system specific techniques and algorithms. In addition, the existing strategies handle only a limited number of controllable loads of limited types. This research presents a review on different prevalent demand side management strategies and case study based on peak clipping & load shifting technique for demand side management. Simulations were carried out on a load profile which contains a variety of loads in different hours of the day. The simulation results show that the proposed demand side management strategy achieves substantial savings, while reducing the peak load demand of the smart grid.

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CHAPTER 1

DEMAND SIDE MANAGEMENT (DSM)

1.1 Introduction

The worldwide rise in energy demand accompanied by the rise in prices of petroleum products has led to a profound change in the present day energy infrastructure. Academia and industry have evaluated the upgrade to a smart grid as a critical step to address the future energy requirements. Smart grid represents a vision of the future power systems integrating advanced sensing technologies, control methodologies and communication technologies at transmission and distribution levels in order to supply electricity in a smart and user friendly way. The main characteristics of a smart grid are consumer friendliness, resistance for attack, self-healing, hack-proof, ability to accommodate all types of generation and storage options.

The scope of the DSM programs is the planning, development and implementing of programs whose objective is to shape actively the daily and seasonal electric load profiles of customers to realize or achieve better overall system utilization. DSM activity has grown and matured over the past decades. Many utilities have implemented DSM programs on a routine basis and more utilities are considering DSM as a part of their resource planning process. The benefits from applying DSM programs are mutual for both the customer and the utility, utilities will have better utilization of the available system capacity. For customers, the amount of monthly electric bill will be decreased besides the improvement in the electrical service quality. At the heart of the DSM programs, there is a series of measures intended to encourage specific groups of customers to modify their energy usage patterns in a manner consistent with the utility's DSM objectives while maintaining or enhancing customer satisfaction. Different utilities have different programs to be applied on their customers. These programs are different according to the number of participated customers in the program, nature of the targeted load type (commercial, industrial or residential), the revenue from each program and the level of customer satisfaction or reaction towards similar applied programs. These programs can be augmented in five steps: DSM targets, financial and feasibility study, designing of effective programs, program implementation & monitoring and program evaluation.

The main objective of the DSM techniques is the reduction of system peak load demand and operational cost. Although the utilities are capable of offering different incentives to respective customers for direct control over selected loads by grouping the customers' loads, most of the methodologies used do not consider the criteria and objectives independently. Thus, it is difficult to employ these methods for DSM of future smart grids which aim to provide the customers with greater control over their energy consumption.

Energy, transportation, water, public safety, and all other services should be managed in future smart and connected communities (S&CCs) to support smooth operation while providing citizens with a clean, economical, and safe environment. Electricity is the most versatile and widely used form of energy, and ever-increasing global demand for it. In future smart cities, smart grids can boost the quality of energy services for consumers by detecting and addressing power grid faults, improved voltage control, and self-healing. A smart grid is an integrated energy grid infrastructure that handles electricity in a reliable, robust and cost-effective manner focused on a sophisticated cluster of distributed generation systems, renewable energies, energy storage, power generation, transmission, conversion and distribution facilities and circuits. Although smart grids provide many advantages over traditional power grids, smart cities rely heavily on reliable electricity supply, and power outages remain a major challenge. New types of power loads such as plug-in hybrid electric cars that can eventually double the usage of residential users have prompted energy suppliers to need efficient and consistent electricity generation plans. The total power supplied from traditional and renewable energy sources must be higher or equal to the demand of the customer in power networks that include smart grids. There are periods, though, that power generation may not meet demand enough, which may be significantly higher than its expected cost. Owing to severe voltage oscillations that may cause minor or major (even permanent) failures, the power network is at risk during these times. The demand-side management (DSM) is used to control and reduce high demand to increase reliability in smart grids and decrease power outage and voltage fluctuation periods. Demand side control systems are generally used to prevent possible imbalances in electricity grids, delivering financial benefits by using only the cheapest generation sources and reducing the need to build new power plants to meet surging peak demand. Due because of its potential to reduce the expense of satisfying peak demand, demand side management has become an essential function in power management.

1.2 Demand Side Management (DSM)

The term Demand Side Management (DSM) is used to refer to a group of actions designed to efficiently manage a site's energy consumption with the aim of cutting the costs incurred for the supply of electrical energy from grid charges and general system charges, including taxes.

Demand-side management (DSM) or demand-side response (DSR) is the modification of consumer demand for energy through various methods such as financial incentives and behavioral change through education.

Usually, the goal of demand-side management is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak times such as nighttime and weekends. Peak demand management does not necessarily decrease total energy consumption, but could be expected to reduce the need for investments in networks and/or power plants for meeting peak demands.

In particular, instead than production following electricity demand as is currently the case, the DSM concept states that consumers adjust their consumption to reduce the load of the electricity. Each utility desires to avoid additional expenses by installing extra capacity to meet the daily growing electricity demand. One way to achieve this objective is to utilize existing energy efficiently. Therefore, utilities implement DSM programs to manage the energy consumption of the consumers [1]. Thus the most important aims of DSM implementation are the reduction of the cost of electricity by managing energy consumption, environmental and social development, increasing the reliability and reducing the gird issues.

DSM programs contain diverse policies such as:

- Energy efficiency policy (it refers of using a less energy to offer similar or better level of service to the energy consumer in an economically efficient approach),

- Demand response policy,

- Consumers load management policy.

In the residential consumer load management policy, the utility intends to decrease the electricity consumption and to reduce the peak [1].

1.3 Aims & Targets of DSM

- Minimizing maximum demand
- Maximizing load factor
- Maximizing efficiency
- Minimizing operating cost
- Minimizing tariff

1.4 Classification

There are different types of demand side management (DSM) in practice. The six most used techniques of DSM are peak clipping, valley filling, load shifting, strategy conservation, strategic load growth and flexible load shape [2].

➢ **Peak clipping:** This method indicates load cutting, demand reduction in time for a heavy load. This can delay the need for additional generation capacity. The duration of the peak can be reduced by direct load control (DLC), shutdown of consumer equipment, or distributed generation. The net effect is a reduction in both peak demand and total energy consumption.

- **Valley filling:** This method encourages off-peak consumption. Non-peak consumption periods are increased, which is particularly desirable because the cost of production is lower, decreasing the average price and improving the efficiency of the system. Various incentives, such as discounts, motivate certain consumers to change their habits.

- **Load shifting:** This method shifts the workload transfer period of greatest consumption (peak period to period of lower consumption) and moves tip out loads without changing the total consumption. This is also possible with distributed generation.

- **Strategic conservation:** Utilization of this strategy decreases seasonal energy consumption mainly by increasing consumption efficiency and reducing energy waste. This program is quite comprehensive and includes incentives for technological change.

- **Strategic load growth:** controls the increase seasonal energy consumption. The dealership utilizes intelligent systems and processes, extra efficient equipment, and more competitive energy sources to attain their targets.

- **Flexible load shape:** a set of actions and integrated planning between the concessionary and the consumer, subject to the needs of the moment. This approach models consumer loads without affecting the actual security conditions, limiting the power and energy that the individual consumer can use at certain times by installing load-limiting devices.

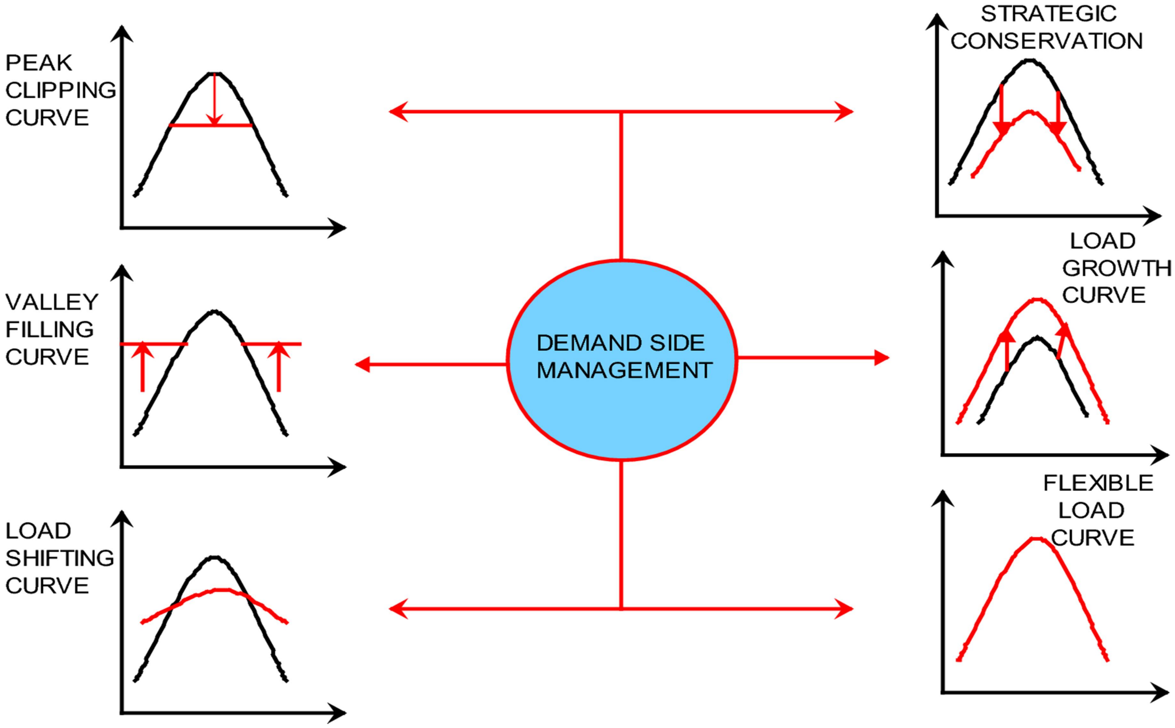

Figure 1.1: Classification of Demand Side Management (DSM)

1.5 Socio-economic aspects of DSM

Reducing energy demand is contrary to what energy suppliers have been doing during most of the modern industrial history. Whereas real prices of various energy forms have been decreasing during most of the industrial era, due to economies of scale and technology, the expectation for the future is the opposite. Previously, it was not unreasonable to promote energy use as more copious and cheaper energy sources could be anticipated in the future or the supplier had installed excess capacity that would be made more profitable by increased consumption.

In centrally planned economies subsidizing energy was one of the main economic development tools. Subsidies to the energy supply industry are still common in some countries.

Contrary to the historical situation, energy prices and availability are expected to deteriorate. Governments and other public actors, if not the energy suppliers themselves, are tending to employ energy demand measures that will increase the efficiency of energy consumption. The socio-economic aspects of Demand Side Management (DSM) can be divided into three aspects.

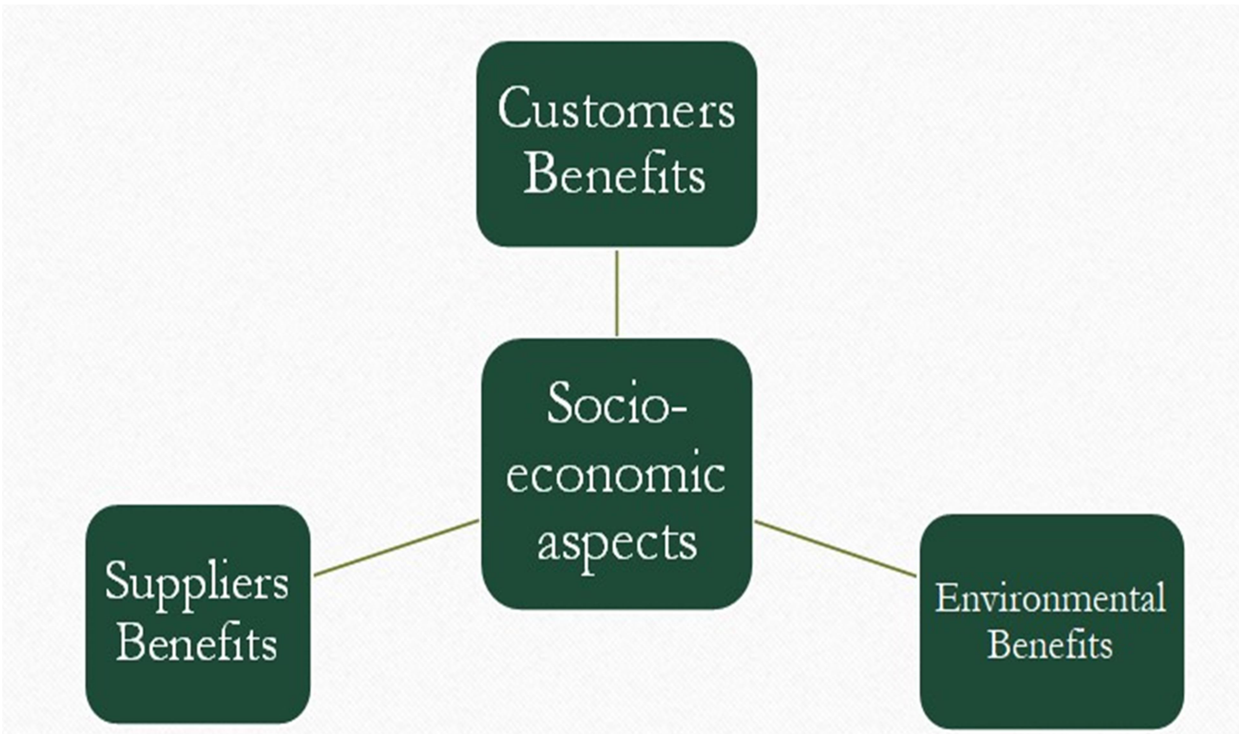

Figure 1.2: Socio-economic aspects of Demand Side Management (DSM)

➢ **<u>Customers Point of View:</u>**

- Electricity demand satisfied
- Reduced electricity bill
- Improved quality of service
- Improved lifestyle & productivity

- **<u>Supplier Point of View:</u>**

- Lower cost of operation
- Reduces need for new power plant
- Improves operating efficiency & flexibility
- Improves customer service
- Improved market
- Reduced dependency on foreign energy sources

- **<u>Environmental point of view:</u>**

- Conserves resources
- Reduces environmental degradation
- Less dependency on fossil fuels
- Reduces global warming

CHAPTER 2

LITERATURE REVIEW

[3] Residents usually preferred that finish their work as soon as possible than less waiting time. These techniques have not taken previous usage pattern consideration, thus have been limited for use in home appliances. In this paper, we propose a system architecture and an algorithm for DSM referred to as user-friendly DSM (UDSM) using ICT. The UDSM is based on time-varying price information considering the following three-fold factors: electricity bill, usage pattern, and rebound peak load. Our proposed algorithm is divided into two steps. In the first step, we formulate the objective function based on electricity bill and usage pattern, and we minimize the electricity bill and maximize the usage similarity. Then, as the second step, we apply a load balancing algorithm to avoid blackout and to minimize rebound peak load. Our algorithm is tested in a real data from Jeju Island's smart grid test site, and experimental results validate the proposed DSM scheme shifts the operation to off-peak times and consequently leads to significant electricity bill saving and user satisfaction ratio. In this paper, we suggest time-varying pricing based DSM system architecture and algorithm considering not only minimize consumption bill and peak load but also maximize user convenience using previous user pattern. Each objective depends on variables which are provided from user and supplier to ICT technologies. Users have previous electricity consumption information about each appliance. It is used to analyze user consumption pattern in database. The supplier provides time-varying pricing information to users. The price information directly affects to reduce consumption bill. When scheduling is contented with two conditions, it is possible that electricity consumption is concentrate in specific time which has the lowest price and higher user convenience. If every home is given the same price information and is running such a DSM algorithm opportunistically utilizing the times with low prices of energy, some peak in energy use can happen at these times. They denote such peak as "rebound peak" [4]. In this result, the load balancing algorithm has to distribute electricity consumption to reduce rebound peak load. In this paper, we consider efficient automated demand-side management system of smart-gird. They design convex

optimization problem to satisfy demand-side management. The first object is minimizing electricity bill. And the second object is following usage pattern. Using convex optimization, we can achieve our objects and certify that it schedule devices by demand-side management. Although electricity bill is not minimal, our proposal approaches near optimal solution. Continuously we will study to reduce peak load for optimization. [5] The increasing presence of wind, solar and other intrinsically intermittent sources of energy into the grid will lead to an erratic change of voltage along a distribution feeder. This phenomenon can lead to over- and under voltages in some nodes of the line. In this paper, consumers will be considered as partially interruptible loads. By curtailing opportune loads, a smoother voltage profile can be obtained. The aim of this paper is to create a curtailment schedule that takes into account both the voltage profile along the line as well as the demands of the consumers. The use of binary particle swarm optimization will be investigated to obtain this demand side management (DSM) system. The intermittent nature of renewable power can lead to voltage fluctuations along a distribution feeder. In extreme cases, it can even lead to under voltages and over voltages in some nodes. It is possible to smoothen this voltage profile (a smooth voltage profile is a profile where the voltage amplitude in each node is near the reference amplitude) by switching applications on or off in well-chosen nodes. A distribution feeder consisting of five consumers, where one of them has a distributed generator installed, is simulated. The data concerning the power consumption in each node, the size of each class and if applicable, the size of the generated power, is randomly chosen as it is seen as the input data of the system. In real life situations this information would be determined using weather prediction models and consumer behavior models. Extensions can be made to the constraints to improve the comfort of the consumers. For instance, in this paper, class one has absolute priority in case of low consumption, as a result, class two will be curtailed to fulfill the voltage constraints. If class one would be switched of in case of very low consumption (less than 5% of the normal consumption) priority can be given to class two, as this means that the consumer is either sleeping or not at home. In order to improve optimization results, subclasses could be created. This means that applications would still have the same boundary constraints, but they can be switched on and off at different times. This would have an immediate impact on the results. This paper presented a methodology to find a curtailment schedule in order to smoothen the voltage along a distribution feeder. A base simulation was tested and the results were discussed. The methodology seems to perform better for the consumer demands, than for obtaining a smooth voltage along a distribution feeder. Better results are expected when the presented extensions are added to the methodology. [6] To meet the fast growing demand of energy, in addition with increased generation, improved efficiency, stability and flexibility, smart techniques need to be adopted that are in compliance with the environment and energy conservation. In this paper, we present an autonomous demand-side energy management to encourage users to willingly modify their electricity consumption without compromising with service quality and customer satisfaction using load forecasting. The projected distributed demand side energy management (DSM) strategy gives each consumer an option to simply apply its best response strategy to current electric load and tariff in the power distribution system. Using NSGA II optimization technique on load prediction, it is obtained that an area-load based pricing method is beneficial for both electric utility and consumer. Finally, simulation results substantiate that the proposed approach can maximize load factor and reduce total energy cost as well as user's daily electricity charges. Short term load forecasting has been adopted to improve the energy efficiency without compromising with consumer's household demand. An hourly peak consumption pattern for the next day is predicted using artificial neural network (ANN) prediction technique. The predicted load profile along with cost function is displayed on the user network. Scheduling is then done for area-load based cost function using NSGA II and hence a comparatively smoother load profile is obtained. This provides freedom and flexibility to each consumer to shift high power household appliances in accordance to the displayed load profile. The consumer's actual energy usage profile would then be used in evaluating the corresponding individual load factor (LF), thus encouraging to adopt load shifting strategy in order to reduce the daily electricity bill by furnishing suitable rebate. This would in return benefit the generating unit by operating at improved load factor. This paper presents a new approach of area-load based pricing which ensures improvement of overall load-factor of area along with energy cost. Area-load required for scheduling is determined using prediction in ANN.

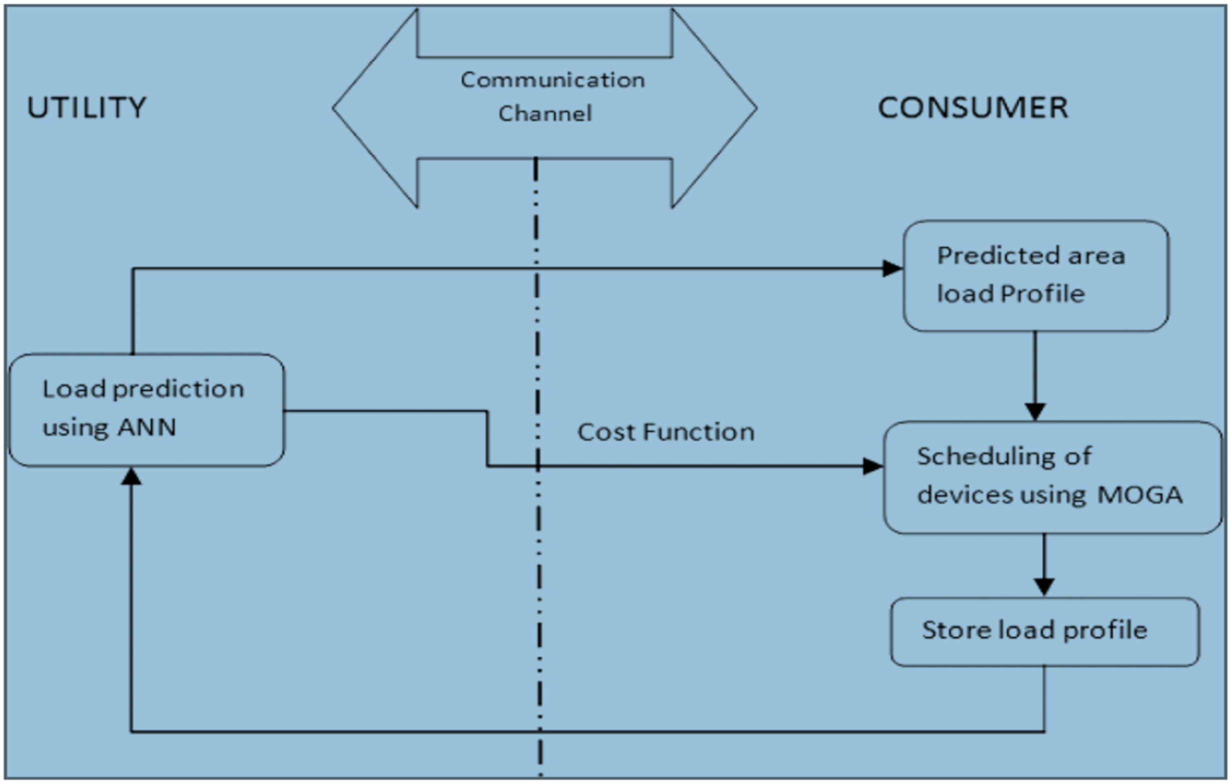

Figure 2.1: Flowchart for DSM using ANN

From simulation results it is observed that area-load based pricing with a continuous cost function results in maximum savings, both in terms of energy cost and load factor. The present work shows decrease in user energy bill and improvement in load factor with scheduling techniques. We plan to study exact cost savings of utility by load factor improvement using cost of generation curves in future works. In this paper, we propose a distributed framework for the demand response based on cost minimization. Each user in the system will find an optimal start time and operating mode for the appliances in response to the varying electricity prices.

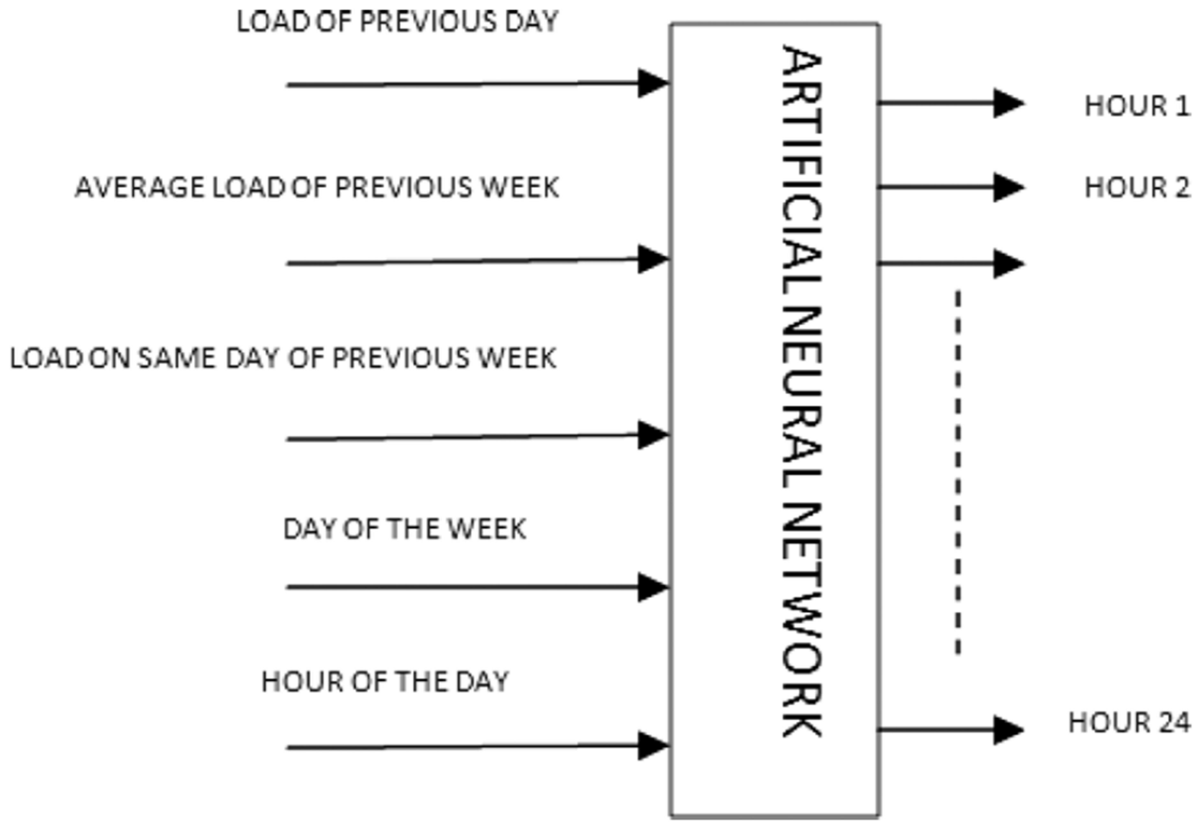

Figure 2.2: TOD strategy using ANN

We model the cost function for each user and the constraints for the appliances. We then propose an approximate greedy iterative algorithm that can be employed by each user to schedule appliances. In the proposed algorithm, each user requires only the knowledge of the price of the electricity, which depends on the aggregated load of other users, instead of the load profiles of individual users. In order for the users to coordinate with each other, we introduce a penalty term in the cost function, which penalizes large changes in the scheduling between successive iterations. Numerical simulations show that our optimization method will result in lower cost for the consumers, lower generation costs for the utility companies, lower peak load, and lower load fluctuations. A “smart electricity system” has moved from conceptual to operational in the last few years. The smart grid has undergone significant innovation, with demand response, being one of the important focus areas. The principal goal of demand response is to reduce the generation cost of electricity by reducing the peak load and shifting peak-hour demand to off-peak hours. Shifting electricity usage to off-peak hours is desired to allow for better utilization of the generated power, and reduce costs to both the consumers and utility companies [7], [8].

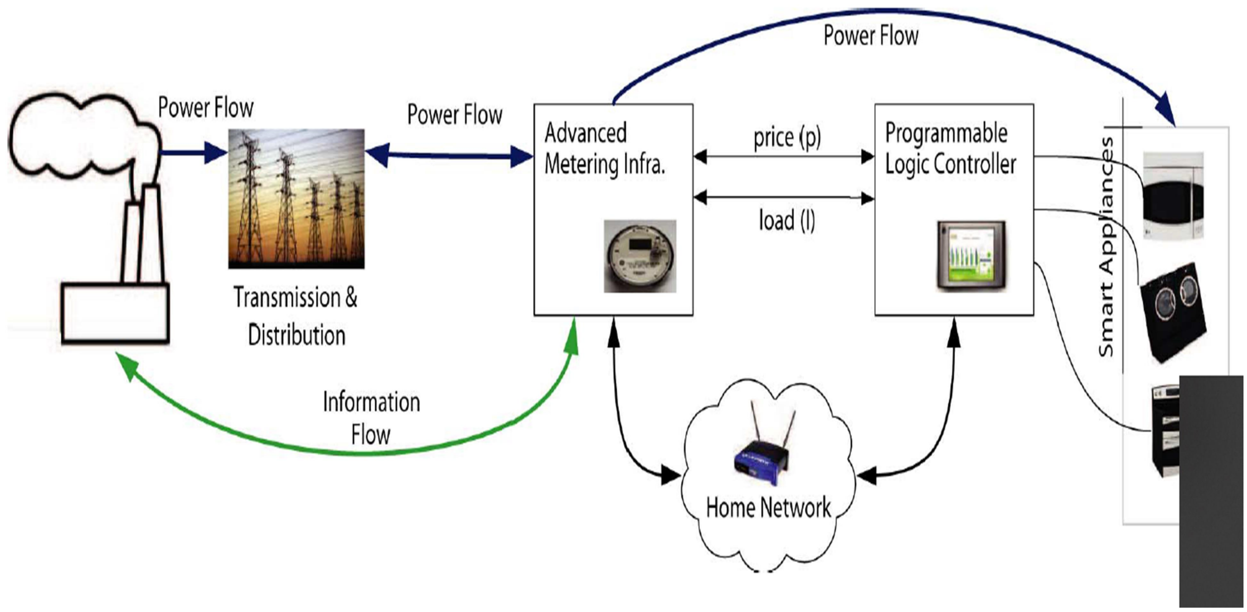

Figure 2.3: Use of AMI & PLC in DSM

With the advent of advanced communication infrastructures that enable a reliable two-way communication between the energy provider and the end-users, it has become feasible for the utility company to provide the consumers with the time-dependent price of the electricity. Consider a power system with one utility company (we refer to the utility company as “the utility” from now on) and users. For each user, an AMI measures the hourly consumption of electricity and communicates this consumption information to the utility. The AMI also communicates the price information from the utility to the users. A PLC is used to send the control signals for each appliance depending on the demand response algorithm and for each user, an EMC facilitates the communication between the appliances and the PLC and schedules the appliances within a home. In order to coordinate the behavior among multiple users and to ensure that above algorithm converges, we modify the cost by imposing an additional penalty term. The use of such a penalty term was first proposed in for tensor field estimation, and later used in for demand response in smart grids with distributed. In both papers, the penalty term was the difference between successive iterates of the variable of interest. Motivated by these ideas, we introduce a penalty on a change of load schedule between two consecutive iterations for each user. However, since we are optimizing over binary matrices, the difference in the successive iterates of these matrices does not necessarily imply small changes in the load schedules between iterations. In this paper, we propose appliance scheduling as a demand response scheme for a smart grid. Unlike the earlier approaches that either select an optimal start time or an optimal energy consumption, our model finds a joint solution by considering all the appliances to be operating in specific modes. Such modeling is also realistic, since it is easier to design appliances that can switch between various modes depending on the energy consumption. We select the optimal price that the utility company has to charge to be proportional to the generation cost. We then propose a distributed framework, where each user independently minimizes his own cost using a greedy approximation. The overall optimal behavior is enforced using the price.

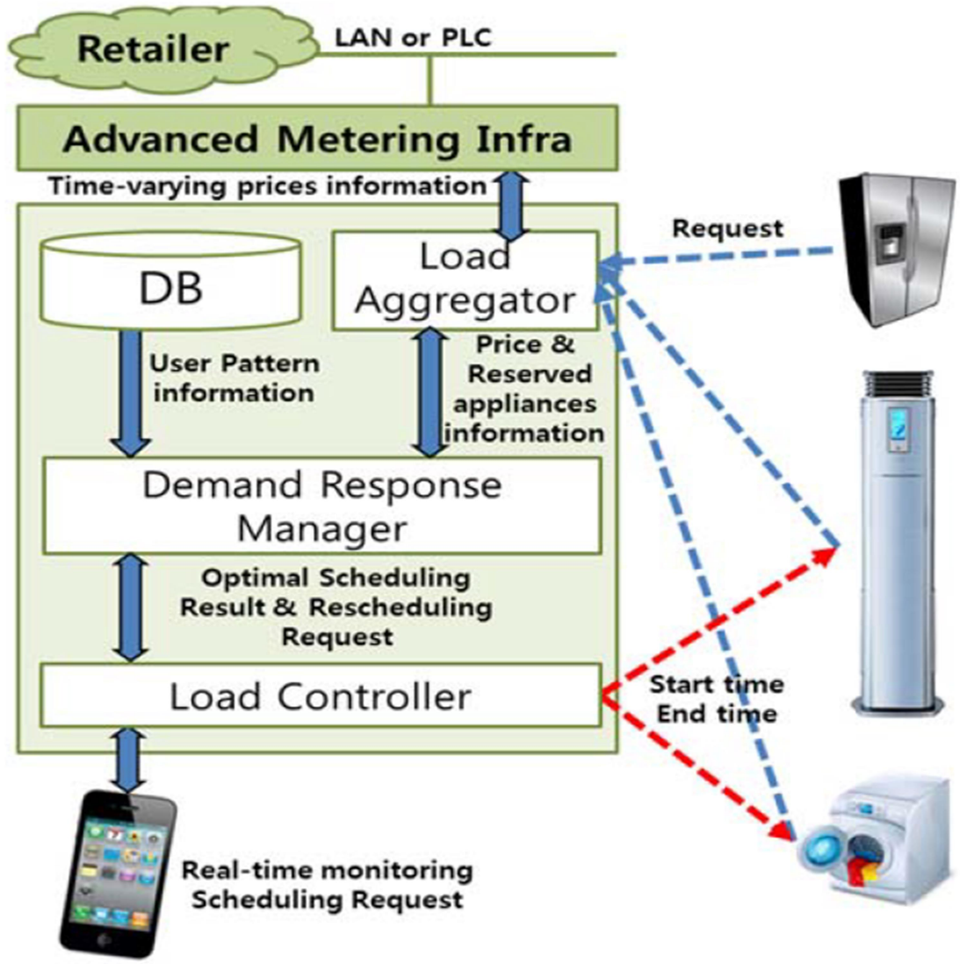

Figure 2.4: Use of AMI & PLC in DSM for real-time monitoring scheduling

[9] Introduction of time of day (TOD) tariff encouraged them to use electricity efficiently. But, residential customers are not exposed to TOD tariff structure so far in India. This makes inefficient use of electricity by residential customers. Non-existence of DSM incentives for residential customers leads to inefficient utilization of devices. This paper mainly focuses on the importance of DSM for residential customers that help distribution utilities to reduce peak load and their operational cost. A case study of DSM implementation on electricity distribution for IIT Roorkee campus is carried out using non-conventional optimization technique. This is an eye opening for Indian utilities which demonstrates their inefficiency due to non-support of residential customers. Scenario of DSM would have been different if utility gives more attention to TOD tariff implementation for residential customers too. Indian economy is growing day by

day due to rapid industrialization and commercialization of urban cities. This leads huge amount of power requirement to cater needs of all categories of consumers across the country. In spite of continued growth in the power generation over the years, Indian power industry is facing problem of power and energy shortage. The all India actual peak demand deficit during the year 2011-12 was 10.6% and anticipated same deficit in near future [10]. Installation of new generation plants is not the economical solution to bridge the gap between supply and demand. To cope up with this situation demand side management (DSM) is the feasible solution. DSM encourages management of loads on consumer side with respect to time and amount of use so that overall system peak reduces. Proper implementation of DSM activities offers great help in managing demand supply balance. Use of time of day (TOD) tariff is one of the activities under DSM that encourages large industrial and commercial consumers to use electricity efficiently. This TOD tariff structure is not available for residential consumers in India which leads to inefficient use of home appliances. Flat rate tariff is used for large residential colonies and educational institutes where there is no restriction on maximum number of units consumed. TOD tariff can be applied to bulk residential consumers, large residential colonies, and large educational premises where mixed loads are used. This avoids unnecessary use of electricity by residential consumers. Approximately 800 devices from all categories of residential consumers e.g. students staying in hostels, faculty quarters, different category of staff and small commercial shops are available for control. Uttarkhand Power Corporation Limited (UPCL), India is providing supply to IIT Roorkee campus at a flat rate of 3.6 Rs. per unit. There is no cap on number of units consumed by individual consumers. This leads inefficient utilization of devices. If TOD tariff would have been implemented to such consumers then that may help utility to reduce their operational cost and also reduce system peak load. Thus, in this paper an attempt has been made to develop load shifting DSM strategy based on TOD tariff that shows utility cost reduction along with reduced system peak. The rest of the paper is organized as follows. Section II presents problem formulation on DSM. Section III provides the details about simulation case study on IIT campus. Simulation results and discussion are presented in section IV. Section V concludes the paper. Load shifting DSM strategy has been simulated for a practical distribution system of IIT campus, India. This strategy reduces utility operational cost and system peak load. TOD tariff implementation for residential consumers has been proposed, that may help utility to reduce their operational cost and system peak. Though it is quite difficult to implement load shifting DSM program to remote rural areas, educated people in urban areas certainly willing to support and participate in this activity. The simulation results are very satisfactory and may be extended for real time implementation. [11] A novel control methodology for automated residential demand-side management (RDSM) is proposed. The methodology utilized the time dimension of consumer power demand to generate a meaningful energy characteristic for each controllable household load. It is supposed that consumer preferences can be reflected entirely within the energy characteristic and hence controlling loads based on energy will result in better outcomes for the consumer. Hence guarantees can be placed on consumer satisfaction, while still near-optimally scheduling the resultant power flows. Simulation results for each second in a day are provided in MATLAB/Simulink for 7 typical New Zealand houses, and show that consumers with electric vehicles can save approximately 17% of their power bill without sacrificing comfort using practical time-of-use pricing rates. Modern power systems are facing new pressures in the distribution, transmission and generation sectors. Climate change legislation has been providing subsidies to promote renewable energy (RE) generation, both centralized and distributed. RE generation tends to vary unpredictably, which adds uncertainty to a supply side which has in the past been mostly deterministic. Also as the uptake of new technologies rises, like electric vehicles (EV) in response to oil price volatility, the traditional demand peak when consumers return home from work promises to lengthen in duration and increase in magnitude. Meanwhile transmission and distribution network operators must manage capital expenditure to cope with increasing capacity requirements. An issue that complicates residential demand control is the unpredictable nature of its elements. Distributed generation (DG) power, the cost of generation and delivery (as indicated by the spot price), and user consumption behave all vary randomly. Many load control algorithms attempt to predict the external factors and use optimizations techniques to schedule loads against these predictions and in a time-of-use pricing environment, load can be deferred for a specific amount of time as the price-breaks are known in advance. These schemes may struggle to adequately incorporate DG if it varies significantly from predictions, and may struggle further when exposed to fully unpredictable, real-time prices. In most cases these schemes are presented considering power consumption in hourly blocks, which may act to mask this effect. In the following sections an algorithm will be introduced in which predictions are replaced with risk-hedging and inter-load cooperation, although this process is managed by each load itself and the operation is hidden from the energy manager. First the concept of state of charge has been defined for controllable household loads and the usefulness of as a control variable has been explored, and secondly a reactive control methodology named Net Energy Stored (NES) control has been presented which controls SC. Simulation results show that the algorithm can be used to save a realistic community 16.9% of their power bill under a real time-of use pricing scheme and as a side-effect reduce the evening demand peak by 29%. If community distributed generation is added, NES control can increase the value of energy it delivers. NES control delivers these cost savings while at the same time placing a guarantee on consumer satisfaction and equitably sharing out a constrained amount of power among a community. Additionally, given NES control does not use any prediction or forecasting in its operation, it is ideal for use in blind real-time pricing schemes and for power systems with large proportions of unpredictable supply. [12] Several pure binary integer optimization models are developed for clustering time periods by similarity for electricity utilities seeking assistance with pricing strategies. The models include alternative objectives for characterizing various notions of within-cluster distances, admit as feasible only clusters that are contiguous, and allow for circularity, where time periods at the beginning and end of the planning cycle may be in the same cluster. Restrictions upon cluster size may conveniently be included without the need of additional constraints. The models are populated with a real-world dataset of electricity usage for 93 buildings and solutions and run-times attained by conventional optimization software are compared with those by dynamic programming, or by a greedy algorithm applicable to one of the models, that run in polynomial time. The results provide time-of-use segments that an electricity utility may employ for selective pricing for peak and off-peak time periods to influence demand for the purpose of load leveling. The models developed allow for inclusion of constraints on both minimum and maximum cluster size by manipulating the input distance matrix and modification of the general optimization models and of the DP algorithms presented are not necessary. Since the solution techniques for the models developed herein have a low-order polynomially-bounded number of operations, updating the results of the models is not excessively time-consuming and new clusters can readily be obtained. The solutions found provide utility managers flexible options for selecting among various objectives, number of clusters of time periods, and cluster sizes. The DP and greedy algorithms were found to be very efficient and they were necessitated for solving larger problems. Cluster analysis is an appropriate methodology for assisting DSM program managers to determine time periods to group and control/price together. Most research in classical statistical cluster analyses is associated with algorithms designed to determine groups according to a heuristic policy as presented in texts such as [13]-[16]. Typically, a "greedy" heuristic where an objective is optimized at each iteration of the clustering algorithm without regards to subsequent choices is employed. Optimization models have selectively been incorporated to perform cluster analyses, such as the work in [17] and [18] where basic linear integer programming (IP) models for a general optimal clustering approach were developed. Summaries of mathematical programming models applied to optimal clustering problems are provided in [19]–[21] and [22] may quickly overwhelm all resources to determine the optimal clusters for aggregation of large data sets. But, for classification purposes for which the data is not necessarily overwhelming, mathematical programming models may be tractable. Computational results and performance statistics for solving the four IP models presented in Section III using both a conventional linear IP solver and the DP and greedy algorithms are now examined. An electric utility company initiated this research by expressing a desire to develop groups of hours during the day that could be considered most similar and appropriate for their implementation of TOU rates and provided data for hourly demand. In Table II is a sample of five observations for the input data set consisting of kWh usage for 93 commercial buildings over each of 24 hours during a day. The average over all observations is 1815 kWh with a maximum of 2543 kWh and minimum of 1017 kWh. Multiplying the demand by the different kWh costs for the time periods may be performed and similar results found. IP models were developed for contiguous clustering of time periods to assist with differential pricing for DSM. Distances, represented as a data matrix on a torus, allow for circularity of a time horizon. DP and greedy procedures with polynomial time complexities were developed for situations where an IP optimization solver may fail. In addition to clusters of time periods, observations may be clustered for differentially controlling groups of customers, and this has been well-studied with statistical cluster analysis, particularly the efficient K-means algorithm of [23] since the number of observations may be large. Current research in progress involves simultaneously clustering both customers and time periods as in the bivariate clustering in [24]. Results will be customer groups that have similar kWh usage and the clusters of time periods that should be considered for differential pricing for each particular customer group. [25] An increasing number of retail energy markets show price fluctuations, providing users with the opportunity to buy energy at lower than average prices. They propose to temporarily store this inexpensive energy in a battery, and use it to satisfy demand when energy prices are high, thus allowing users to exploit the price variations without having to shift their demand to the low-price periods. They study the battery control policy that yields the best performance, i.e., minimizes the total discounted costs. The optimal policy is shown to have a threshold structure, and we derive these thresholds in a few special cases. The cost savings obtained from energy storage are demonstrated through extensive numerical experiments, and we offer various directions for future research. In this paper, we address the problem of organizing energy storage purchases to minimize long-term energy costs under variable demands and prices. This problem involves deciding whether to satisfy demand directly from the grid or from the battery, as well as up to what level to charge or discharge the battery. The resulting optimization problem is complicated by the stochastic nature of price and demand and due to the fact that we aim to minimize the long-term costs. They model the problems a Markov decision process and show that there exists a two-threshold stationary cost-minimizing policy. When the battery level is below the lower threshold, the battery is charged up to it, and the battery is discharged when above the upper threshold. By comparing the costs incurred under this policy with the cost of satisfying all demand directly from the grid, we can show that energy storage may lead to significant cost savings. [26] Demand side management (DSM) is one of the important functions in a smart grid that allows customers to make informed decisions regarding their energy consumption, and helps the energy providers reduce the peak load demand and reshape the load profile. This results in increased sustainability of the smart grid, as well as reduced overall operational cost and carbon emission levels. Most of the existing demand side management strategies used in traditional energy management systems employ system specific techniques and algorithms. In addition, the existing strategies handle only a limited number of controllable loads of limited types. This paper presents a demand side management strategy based on load shifting technique for demand side management of future smart grids with a large number of devices of several types. The day-ahead load shifting technique proposed in this paper is mathematically formulated as a minimization problem. A heuristic-based Evolutionary Algorithm (EA) that easily adapts heuristics in the problem was developed for solving this minimization problem. Simulations were carried out on a smart grid which contains a variety of loads in three service areas, one with residential customers, another with commercial customers, and the third one with industrial customers. The simulation results show that the proposed demand side management strategy achieves substantial savings, while reducing the peak load demand of the smart grid. Smart pricing [27], [28] is a unique characteristic of smart grid made possible by usage of smart metering devices in the automatic metering infrastructure. It could lead to cost-reflective pricing based on the entire supply chain of delivering electricity at a certain location, quantity and period. When smart pricing is used with demand side management, control of the customer's energy usage will be influenced by real-time penalty and incentive schemes at all levels of the supply chain. However, the rationale behind the implementation of demand side management within the context of the smart grid is to promote the overall system efficiency, security and sustainability by maximizing the capacity of the existing infrastructure while facilitating the integration of low carbon technology into the system. renewable energy sources make power dispatch functions in a smart grid challenging. Such a scenario necessitates the use of load control methodologies. Next, the operation of smart grid requires two ways communication between central controller and various system elements. The designed demand side management system should be able to handle the communication infrastructure between the central controller and controllable loads. The last, but not the least, criteria for deciding the optimal load consumption can vary widely. The criteria could be maximizing the use of renewable energy resources, maximizing the economic benefit by offering bids to reduce demand during peak periods, minimizing the amount of power imported from the main grid, or reducing peak load demand. Demand side management has potential to provide many benefits to the entire smart grid, particularly at distribution network level. This paper presents a demand side management strategy that can be employed in the future smart grid. The proposed strategy is a generalized technique based on load shifting, which has been mathematically formulated as a minimization problem. A heuristic based evolutionary algorithm is developed for solving the problem. Simulations were carried out on a smart grid which contains three different kinds of customers' areas. The simulation outcomes show that the proposed algorithm is able to handle a large number of controllable devices of several types, and achieves substantial savings while reducing the peak load demand of the smart grid. [29] This paper describes significant cost saving opportunities for consumers in developing countries by the use of computational intelligence and demand-side-management techniques to mitigate the massive use of diesel back-up during grid outages. Application of load scheduling optimization is investigated during scheduled power outages for statistical distributions of loads and diesel pricing for residential consumer in India under conditions of both a flat-rate and Time-of-Day grid tariff structure. Two load shifting approaches are explored - a casual load shifting out of blackout region and a combined TOD-Outage scheduler. The load types modeled include passive loads and schedulable. Maximum executable peak load at any time is constrained by an aggregate load limit. The maximum diesel savings for consumer due to load shifting can be approximately 40% for a flat-tariff grid to more than 70% for a TOD-tariff grid. Effect of rising diesel prices on the economic benefits of load-shifting is also examined. Demand-side-management (DSM) policies are being formulated by various stakeholders in India and other developing countries. These policies are specifically targeted to overcome large energy demand-supply gaps, to inclusive and reliable power for entire populations. For example, in India, load scheduling has recently been implemented successfully for the agricultural sector. As in developed countries, load scheduling is driven by the utility for peak clipping of demand, load shifting for energy conservation and/or supporting load growth. In this work, our aim is to highlight the urgent need for demand-side management to address one of the major unaddressed challenges for a consumer in a developing country which is the problem of frequent power outages. DSM solutions and policies need to be developed, validated and framed to enable the consumer get reliable power and reduce his dependence on expensive diesel back-up systems. In this study, two kinds of demand-side management techniques to mitigate power blackouts are explored as follows. One, a casual load shift wherein the consumer moves heavy and shiftable loads out of the power outage regions without apriori grid pricing knowledge (such as TOD). The second DSM approach explored uses sophisticated optimization techniques for load scheduling. It must be stated that the analysis is for statistical uncertainties related to planned or scheduled outages and completely uncertain unscheduled outages are not in the scope of this study. Implementation of a load scheduler can be extremely difficult for a consumer in a developing country. The reasons are many including ease of use, availability of controllable loads etc. In India, consumers typically switch off their heavy loads during a power outage and execute them after power is restored. In newer apartment buildings, the heavy load lines are usually a separate circuit (e.g. 15 amps) and the apartment back-up generator simply doesn't provide power to these lines. All heavy and shiftable loads are often connected to the 15 amp line. This technique of casually rescheduling heavy loads results in unexpected peaks for the utility as soon as power is restored. While the actual implementation of the load control and scheduling can be accomplished either by the utility or the end consumer themselves, the aim of the DSM policy needs to be consumer-centric. In other words, the consumer needs to always have the flexibility of load selection and execution without yield controlling to the utility. Use of intelligent load-shifting techniques to mitigate power outages in developing countries shows significant cost savings potential by massive reduction in diesel consumption by load-scheduling. The maximum diesel reduction for the consumer due to load shifting during power outages can be approximately 40% for a flat-tariff grid to more than 70% for a Time-Of-Day tariff grid. The study also showed that the actual savings potential depends on the timing of power outage, duration and the specific load characteristics. As diesel prices increase, the economic benefits of load-shifting are also increase correspondingly. For blackouts of lesser duration the benefits in saving diesel can be as much as 73%. For longer blackouts, the diesel savings is in the range of 20%-30%. DSM policies for developing countries should consider specific approaches to mitigate power outages and provide relief to customers. Clearly, challenges exist in implementation of DSM policies since most consumers in India and frugal markets have outdated appliances that are unintelligent with a severe need to develop low-cost smart network-controllable solutions as a retrofit. [30] The increasing penetration of renewable energy sources, particularly wind power, raises concern about the level of flexibility needed to cope with the inherent variability and uncertainty affecting these sources of energy. Departing from the common conception of providing flexibility using fossil-fuel generators with fast ramp rates, this paper explores the use of demand-side resources. A technique to optimize the balance between the flexibility provided by fast generating units and the flexibility achievable from demand side management (DSM) is presented. This methodology is based on an extended unit commitment optimization that considers both short- and long-term aspects, i.e. operational and investment costs. The methodology is applied to the IEEE RTS (RTS-96), using actual demand and wind profiles from central Scotland. Achieving an optimal flexible generation portfolio is a problem that has been studied for some time [31]. The liberalization of the electricity markets has made this issue more complex because it is necessary to take into account regulatory issues when analyzing the flexibility provided by the different participants of the system in order to optimize the corresponding bid strategies [32]. In a context where more renewable generation is being connected, it has also been shown that when the stochastic nature of wind power is taken into account, rolling commitment strategies would lead to improved economic performance because this would reduce the error on the wind predictions [33]. The consequence, however, is a reduced overall utilization of expensive peaking units. Enhancing the ability of demand to respond to price signals can help markets operate more efficiently resulting in less onerous flexibility requirements. The optimal scheduling of DSM during critical price periods, particularly thermal loads, was explored in [35], resulting in a significant reduction in the need for flexible generation units. Using a security constrained unit commitment approach showed that introducing DSM would reduce both load curtailment (and the corresponding losses of profit or comfort) and the need for investments in grid reinforcements. This paper has proposed an expanded methodology to consider both the short- and long-term operational and investment costs of providing flexibility. This technique is a powerful tool to analyze how demand-side management can be used to meet some of the requirements for flexibility in power systems. Results from its application to the simplified RTS system show that as wind is introduced in the generation mix, more flexibility is required. Provided the corresponding real-time monitoring and control infrastructure is in place, demand side management schemes, such as the aggregation of smart appliances, would not only improve the performance of the system but would also allow the cost effective integration of more renewable energy resources. However, since electricity is an essential good, DSM will be limited. Therefore, in the future, other sources of flexibility, such as storage, will also need to be part of the solution. [35] This paper presents the concept of Dual Demand Management (2DSM) as an evolution of the conventional Demand Side Management concept. 2DSM accounts at the same time on one hand for the local needs, i.e. energy efficiency of the building stock as well as optimization of the local distribution grid and on the other hand for the challenges of the higher level electrical grid arising from the integration of renewable and alternative energy sources. The proposed concept shows the possibilities originating from the interaction of local district heating, heat storage and micro grid technology. Finally the paper shows the development and testing processes required for designing complex multi-domain systems. The goal of the research here introduced is to develop the intelligence needed to manage a multi-grid system at city quarter level. In detail we propose the development of a new concept that we call Dual Demand Side Management (2DSM). The 2DSM as evolution of the standard Demand Side Management (DSM) is designed to meet at the same time the needs of the local systems and the need of the grid infrastructure. Furthermore, 2DSM proposes also to break the direct link between utility request and customer reaction by introducing the concept of a local energy market where the players interact in a peer-to-peer fashion. The implementation of a local electricity markets is the scope of ongoing projects like the NOBEL project funded in the EU FP7 program [38]. The 2DSM market concept will make use of the existing experience but extend the market to other forms of energy like thermal energy. The planning and design of the described energy efficient transition of city quarters requires a holistic approach taking into account the dynamic interplay of multi-physics systems. Thus it is favorable to use simulation tools that are capable to run multi-physics, especially thermal and electric, models of the city quarter. In order to be able to have all the necessary data available a well-defined data structure is required. They propose the development of a City Quarter Information Model (CQIM) as an expansion of Building Information Modeling (BIM) and Building Energy Management system (BEMS) to the city quarter level. he CQIM also comprises representations of the electrical components described by Common Information Models (CIM). The proposed concept Dual Demand Side Management (2DSM) expands the classic Demand Side Management to multi grid systems. 2DSM reaches out to fully exploit the potential in terms of energy efficiency and flexibility arising from the combination of thermal and electrical systems. Furthermore, 2DSM removes the direct link between the utility control and the customer, creating a P2P environment where the local agents may decide to participate to a network request and trade among themselves the best option. On the one hand the energy efficiency of the existing building stock can be improved significantly and on the other the electrical grid can benefit through a higher flexibility. The requirements due to the design and operation of such a multi-domain systems have been introduced. A possible approach to fulfill the requirements based on multi-agent systems has been proposed. Also the challenges in designing such systems have been described as well as possible solutions in terms of simulation tools and testing facilities. [36] In order to keep a proper functional electricity grid and to prevent large investments in the current grid, the creation, transmission and consumption of electricity needs to be controlled and organized in a different way as done nowadays. Smart meters, distributed generation and -storage and demand side management are novel technologies introduced to reach a sustainable, more efficient and reliable electricity supply. Although these technologies are very promising to reach these goals, coordination between these technologies is required. It is therefore expected that ICT is going to play an important role in future smart grids. In this paper, they present the results of our three step control strategy designed to optimize the overall energy efficiency and to increase the amount of generation based on renewable resources with the ultimate goal to reduce the $CO2$

emission resulting from generation electricity. The focus of this work is on the control algorithms used to reshape the energy demand profile of a large group of buildings and their requirements on the smart grid. In a use case, steering a large group of freezers, we are able to reshape a demand profile full of peaks to a nicely smoothed demand profile, taking into the account the amount of available communication bandwidth and exploiting the available computation power distributed in the grid. The result of the freezer use case show that our three step methodology is able to apply global optimization techniques a large group of houses. Both the predictions and planning are performed at each house, exploiting the available distributed computational power available in the grid. Due to the subsequent division of the large optimization problems into sub-problems via a tree structure, a fast scalable system is achieved. Using uniform prices leads to a sort of worst case scenario. Since all individual house controllers try to minimize their own cost, they all optimize to periods with low costs, leading to a shift of demand peaks instead of the desired profile. In other words, addressing each house individually by using different steering signals gives the best results. By choosing a proper tree structure, communication requirements can be kept low. The use of simple price and production patterns lead to small messages to be sent. Although the initial version, as shown in this work, already shows promising results, improvements are still possible and needed. On multiple levels in the tree, better approaches to determine when to stop the planning are needed to reduce the amount of iterations required during planning. Furthermore, by optimizing the way information is encoded during communication, bandwidth requirements can further be reduced. Furthermore, the improved algorithms can be extended to steer a larger fleet of different kind of appliances, including electrical cars and HVAC systems (consumers), microchip appliances (producers) and heat stores/batteries (buffers). Although the same control strategy as presented in this work can be used, different kind of appliances react differently on changes in the price vector. This will influence the amount of required iterations.

CHAPTER- 3

METHODOLOGY

3.1 The Objective Function

DSM has a major role of utility planning and operation. In this section, an optimal based formulation is developed to simulate the implementation process of the DSM program to assess its technical and financial impacts for both utility and users. The objective function is formulated either to control the use of the supply side resources subject to end user demand for power and energy without DSM has a major role of utility planning and operation. In this section, an optimal based formulation is developed to loss of production or comfort, or to improve system performance by increasing load factor and enhance the customer service quality.

The mathematical formulation of the DSM techniques as an optimization problem is taken from a reference paper [37]. The objective is to maximize the system load factor for the utility. The objective function was used for the five DSM techniques, the imposed constraints on the demand type at different time intervals (control variables) differ from a technique to another and depend, also, on the load peculiarities and the power system.

The objective functions are defined as the following:

$$LF_{max} = \left[\left[\sum_{i=1}^{N} \sum_{j=1}^{J} P_{(i,j)} t_{(j)}\right] / \sum_{j=1}^{J} t(j)\right] / \sum_{i=1}^{N} P_{(i,k)}, \quad (3.1)$$

Where,

L.F. = System load factor.

P (i,j)) = Demand of load type i at time interval number j.

N = Total number of load demand types.

J = Total number of time intervals.

The different DSM techniques including the respective objective function and constraints as an optimization problem that we have used are presented below. The description of the method and effect on load shape in addition to means of implementation are also given.

The used methods are:

- Valley Filling
- Load Shifting
- Peak Clipping
- Energy Conservation
- Load Building

1. Valley Filling : Program description and effect on load shape: It entails building of off-peak loads. This is often the case when there is under-utilized capacity that can operate on low cost fuels. The net effect is an increase in total energy consumption, while the peak demand is kept fixed (Fig. 3.1). Consequently, the load factor will be improved. Means of implementation: This can be achieved by **c**reation of new off-peak electric loads such as charging of electric cars and thermal energy storage.

Objective function: The objective function is formulated to maximize the system load factor as follows:

$$LF_{max} = \left[\left[\sum_{i=1}^{N} \sum_{j=1}^{J} P_{(i,j)} t_{(j)}\right] / \sum_{j=1}^{J} t(j)\right] / \sum_{i=1}^{N} P_{(i,k)}, \quad (3.2)$$

Where,

L.F. = System load factor.

P(i,j)) = Demand of load type i at time interval number j.

N = Total number of load demand types.

J = Total number of time intervals.

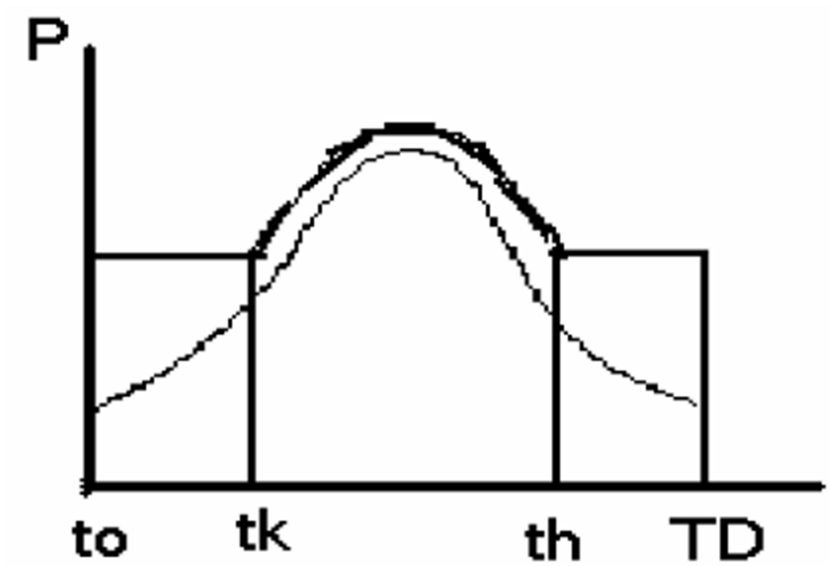

Figure 3.1: DSM using valley filling

The constraints for this technique are written below:

Equality Constraints:

- $P_{new(i,j)} = Pold\ (i,j) \forall \mathrm{tk} \rightarrow th$

Inequality Constraints:

- $P_{new(i,j)} \geq P_{old(i,j)} \forall to \rightarrow tk, th \rightarrow TD$
- $P_{new(i,j)} \leq P(value) \forall to \rightarrow tk, th \rightarrow TD$

Where:

$P_{new(i,j)}$ ⟶ the demand of load type i at time interval j after applying DSM technique.

$P_{old(i,j)}$) ⟶ the demand of load type i at time interval j before applying DSM technique.

The $P_{new(i,j)}$ is not permitted to cross the P (value) which is an extreme limiting value given by the planner. $P_{(value)}$ is an extreme limiting value given by the planner for load demand after applying DSM program. k is the time interval at which the total demand of all load types PTo(k) is maximum.

2. Load Shifting: Program description and effect on load shape: It involves shifting loads from on-peak to off-peak periods (Fig. 8). The net effect is a decrease in peak demand, but no change in the total energy consumption. This effectively, improves the system load factor and decreases the cost of the electricity bill.

Means of implementation: This can be achieved by time of use rates and/or use of storage devices that shift the timing of conventional electric appliances operation.

Objective function: The objective function is formulated to maximize the system load factor as follows:

$$LF_{max} = \left[\left[\sum_{i=1}^{N}\sum_{j=1}^{J} P_{(i,j)} t_{(j)}\right] / \sum_{j=1}^{J} t(j)\right] / \sum_{i=1}^{N} P_{(i,k)}, \quad (3.3)$$

Where,

L.F. = System load factor

P (i, j) = Demand of load type i at time interval number j

N = Total number of load demand types

J = Total number of time intervals.

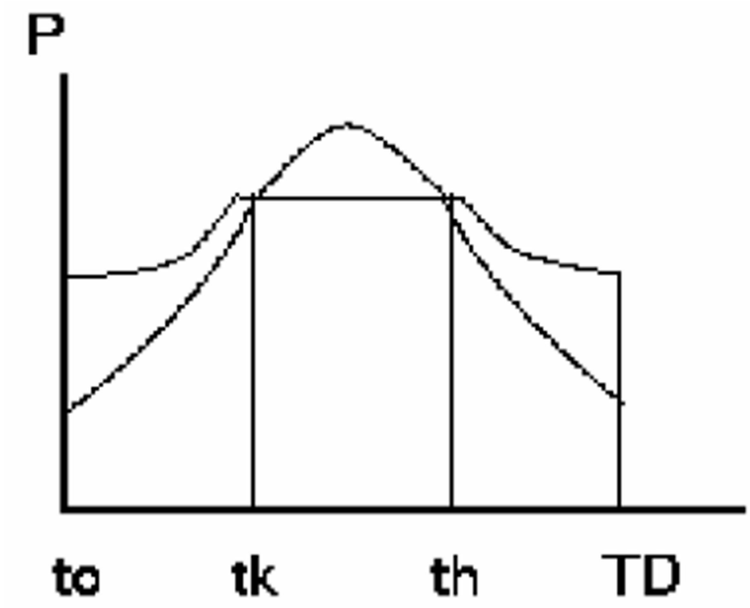

Figure 3.2: DSM using load shifting

The constraints for this technique are written below:

Equality constraint:

- $\sum_{i=1}^{N}\sum_{j=1}^{J} P_{new(i,j)} t_{(j)} = \sum_{i=1}^{N}\sum_{j=1}^{J} P_{old(i,j)} t_{(j)}$
- $P_{new(i,j)} = P(value) \forall tk \rightarrow th$

Inequality constraints:

- $P_{new(i)} \geq P_{old(i)} \ \forall to \rightarrow tk, th \rightarrow TD$
- $P_{new(i)} \leq P(value) \forall to \rightarrow tk, th \rightarrow TD$

Where

$P_{new(i,j)}$: is the demand of load type i at time interval j after applying DSM technique.

$P_{old(i,j)}$: is the demand of load type i at time interval j before applying DSM technique.

The $P_{new(i,j)}$: is not permitted to increase the P(value) which is an extreme limiting value given by the planner.

P (value) : is an extreme limiting value given by the planner for load demand after applying DSM program.

k: is the time interval at which the total demand of all load types PTo(k) is maximum.

3. Peak Clipping: Program description and effect on load shape: Peak clipping refers to reduction of utility loads during peak demand periods (Fig. 9). The net effect is a reduction in both demand and total energy consumption. Therefore, the system load factor is improved and, also, the customer electricity bill is decreased**.**

Means of implementation: Direct utility control on customer appliances or end-use equipment can be carried out to reduce peak demand periods.

Objective function: The objective function is formulated to maximize the system load factor as follows:

$$LF_{max} = \left[\left[\sum_{i=1}^{N}\sum_{j=1}^{J} P_{(i,j)} t_{(j)}\right] / \sum_{j=1}^{J} t(j)\right] / \sum_{i=1}^{N} P_{(i,k)}, \quad (3.4)$$

Where

L.F. = System load factor.

P (i, j) = Demand of load type i at time interval number j.

N = Total number of load demand types.

J = Total number of time intervals**.**

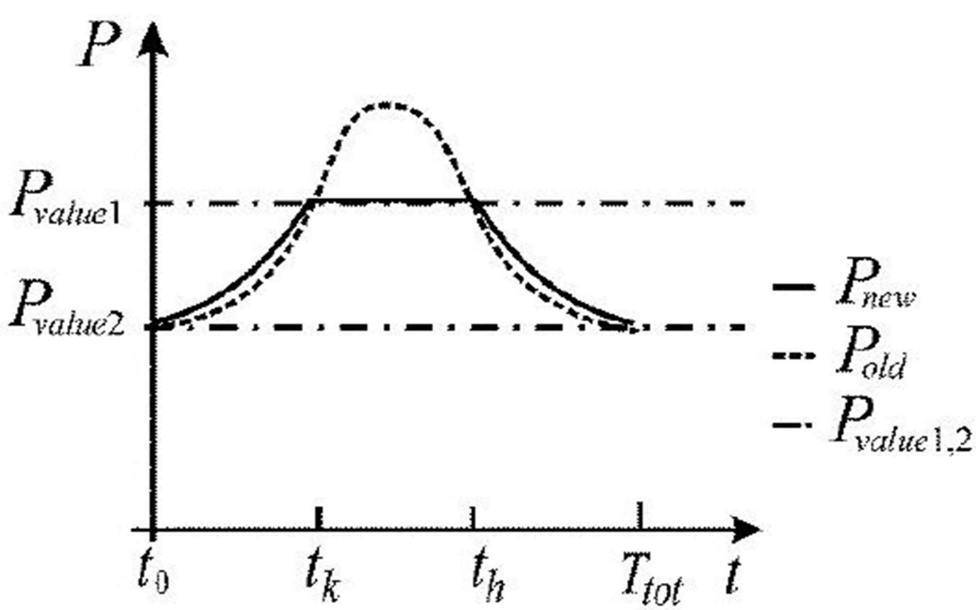

Figure 3.3: DSM using peak-clipping

The constraints for this technique are written below:

Equality constraint:

- $P_{new(i)}$ =$P_{old(i)}$∀to→tk,th→TD

Inequality constraints:

- $P_{new(i)} \leq P_{(value1)} \forall tk \rightarrow th$
- $P_{(value1)} \geq P_{(val\quad)} \forall tk \rightarrow th$
- $P_{new(i)} \leq P_{(value2)}$

Where:

$P_{new(i,j)}$ → the demand of load type i at time interval j after applying DSM technique.

$P_{old(i,j)}$ → the demand of load type i at time interval j before applying DSM technique.

The $P_{new(i,j)}$ is not permitted to exceed the $P_{(value)}$ which is an extreme limiting value set by the supplier.

$P_{(value1)}$, $P_{(value2)}$ are limiting values given by the planner, that depends on the nature of the load and user activity, for load demand after applying DSM program**.**

4. Energy Conservation:

Program description and effect on load shape have clarified the energy conservation technique as an effective mean for reducing the end-users consumption. In such a method, both peak demand and total energy consumption are reduced.

Means of implementation: Appliances efficiency improvement and weatherization are some examples for energy conservation.

Objective function: The objective function is formulated to maximize the system load factor as follows:

$$LF_{max} = \left[\left[\sum_{i=1}^{N} \sum_{j=1}^{J} P_{(i,j)} t_{(j)}\right] / \sum_{j=1}^{J} t(j)\right] / \sum_{i=1}^{N} P_{(i,k)}, \quad (3.5)$$

Where

L.F. = System load factor

$P_{(i,j)}$ = Demand of load type i at time interval number j

N = Total number of load demand types

J = Total number of time interval

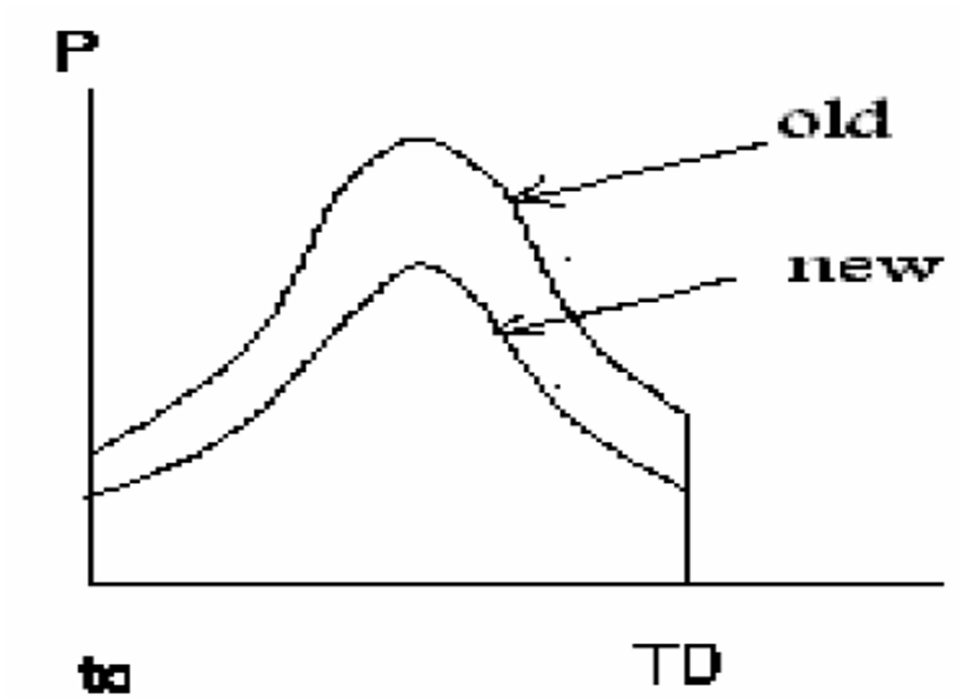

Figure 3.4: DSM using energy conservation

The constraints for this technique are written below:

Inequality constraints:

- $P_{new(i)} \leq P_{old(i)} \forall\ to \rightarrow TD$

5. Load Building:

Program description and effect on load shape: It refers to an increase in overall sales. The net effect is an increase in both peak demand and total energy consumption (Fig. 3.5).

Means of implementation: Load building involves increased market share of loads that can use electric energy instead of fuel. Electric vehicles, industrial heating and electrification may be, also, effective means for load building.

Objective function: The objective function is formulated to maximize the system load factor as follows:

$$LF_{max} = \left[\left[\sum_{i=1}^{N}\sum_{j=1}^{J} P_{(i,j)} t_{(j)}\right] / \sum_{j=1}^{J} t(j)\right] / \sum_{i=1}^{N} P_{(i,k)}, \quad (3.6)$$

Where

L.F. = System load factor.

P (i, j) = Demand of load type i at time interval number j.

N = Total number of load demand types.

J = Total number of time intervals.

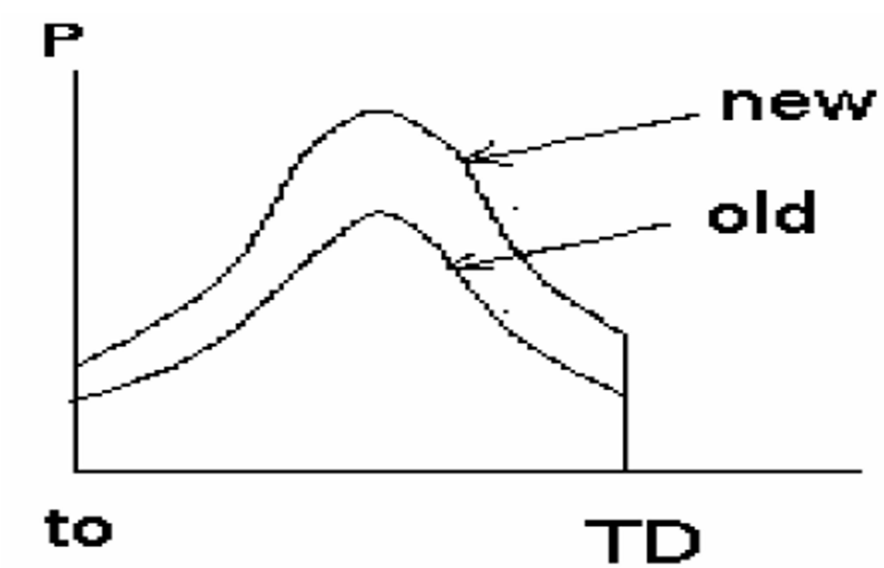

Figure 3.5: DSM using load building

The constraints for this technique are written below:

Inequality constraints:

- $P_{new(i)} \geq P_{old(i)}$ ∀ to → TD

3.2 Solution tool

The different DSM programs was formulated in the form of optimization problems, these problems have to be solved utilizing efficient mathematical tools. The software which was utilized to solve the optimization problem is called the Solver which is a MS excel based tool used to solve optimization problems.

Solver is a free Excel plug-in developed at the University of Auckland[1] that supports optimization and simulation modelling in a spreadsheet using an algebraic modeling language. It is popular in education, the public sector and industry for optimization users because it uses industry-standard modelling languages and is faster than traditional Excel optimisation approaches.

Solver tool adds a text editor to Excel that is used to create a text-based optimization (or simulation) model using a modelling language such as PuLP, AMPL, GAMS or Julia/JuMP. It also provides a tool for naming data on a spreadsheet (and specifying indices for this data), allowing the data to be used in the model. When the model is run, the system automatically reads input data from the spreadsheet and provides it to the model, and then writes the model results back to the spreadsheet.

Solver is used to find an optimal (maximum or minimum) value for a formula in one cell — called the objective cell- subject to constraints, or limits, on the values of other formula cells on a worksheet. Solver works with a group of cells, called decision variables or simply variable cells that are used in computing the formulas in the objective and constraint cells. Solver adjusts the values in the decision variable cells to satisfy the limits on constraint cells and produce the result you want for the objective cell.

We can use Solver to determine the maximum or minimum value of one cell by changing other cells. For example, you can change the amount of your projected advertising budget and see the effect on your projected profit amount.

The main screen of the solver is shown below:

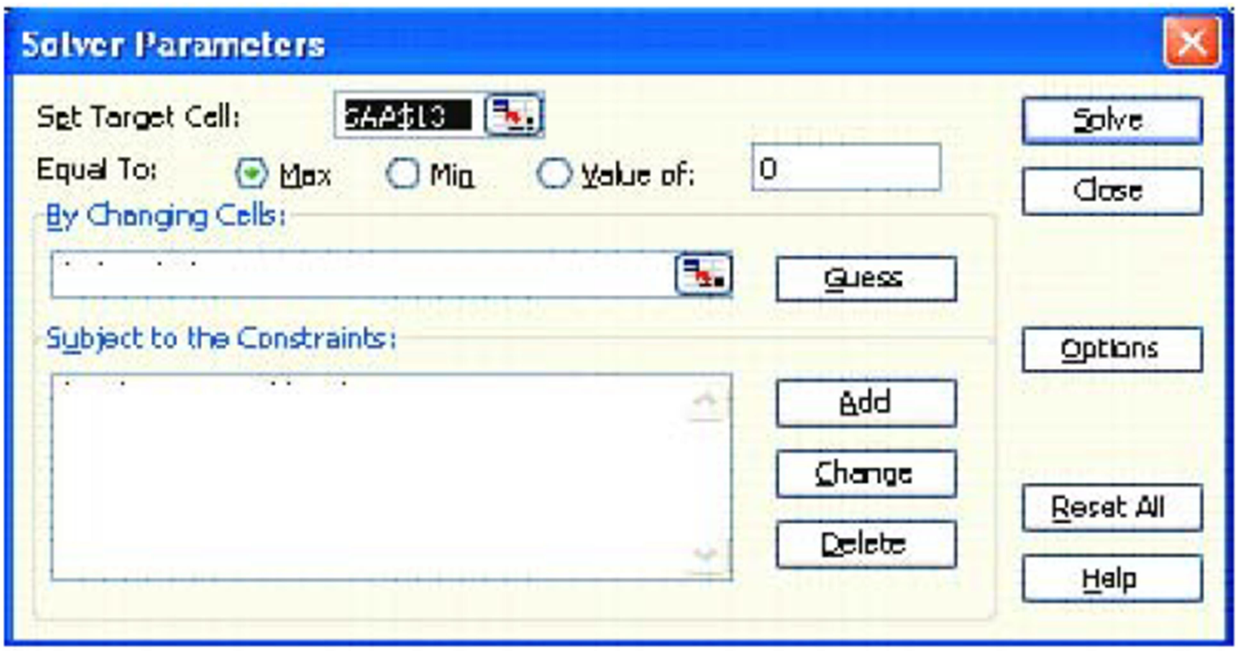

Figure 3.6: Solver tool main screen

In the solver main screen, the objective function is written in the target cell where the constraints and variables to be optimized are written in the changing cells. The objective function and constraints including the problem variables are fed to the program. The goal of optimization is to find the values of a model's variables that generate the best value for the objective function, subject to any limiting conditions placed on the variables.

CHAPTER 4

OPTIMIZATION & RESULTS

4.1 Input Load Profile

We have taken a daily load profile of certain load from a paper [38] and used that to optimize for Load Shifting and Peak Clipping method by using solver tool.

Input:

Time (Hour)	P_{old} (KW)
1	20
2	40
3	40
4	40
5	40
6	40
7	50
8	60
9	70
10	60
11	50

12	50
13	40
14	40
15	80
16	100
17	120
18	100
19	100
20	90
21	80
22	70
23	50
24	20

Table 4.1: Input Load Profile

4.2 Optimization for Peak Clipping:

We have chosen a block in MS Excel and inserted our objective function. In solver tool we have given the input of set objective from that MS Excel block and we choose to maximize the Load Factor.

In the Changing variable cell we have inserted an empty column of Excel sheet.
And in the constraints we have inserted the constraints of Peak clipping.

The constraints that were inserted are as follows:

Equality constraint:

- $P_{new(i)} = P_{old(i)}$ ∀ *to* → *tk*, *th* →*TD*

Inequality constraints:

- $P_{new(i)} \leq P_{value1}$ ∀ *tk* →*th*
- $P_{new(i)} \geq P_{value2}$ ∀ *tk* → *th*
- $P_{value2} \leq P_{value1}$

We have chosen the P_{value1}= 70KW, P_{value2} = 20KW

The main screen of the solver is shown below:

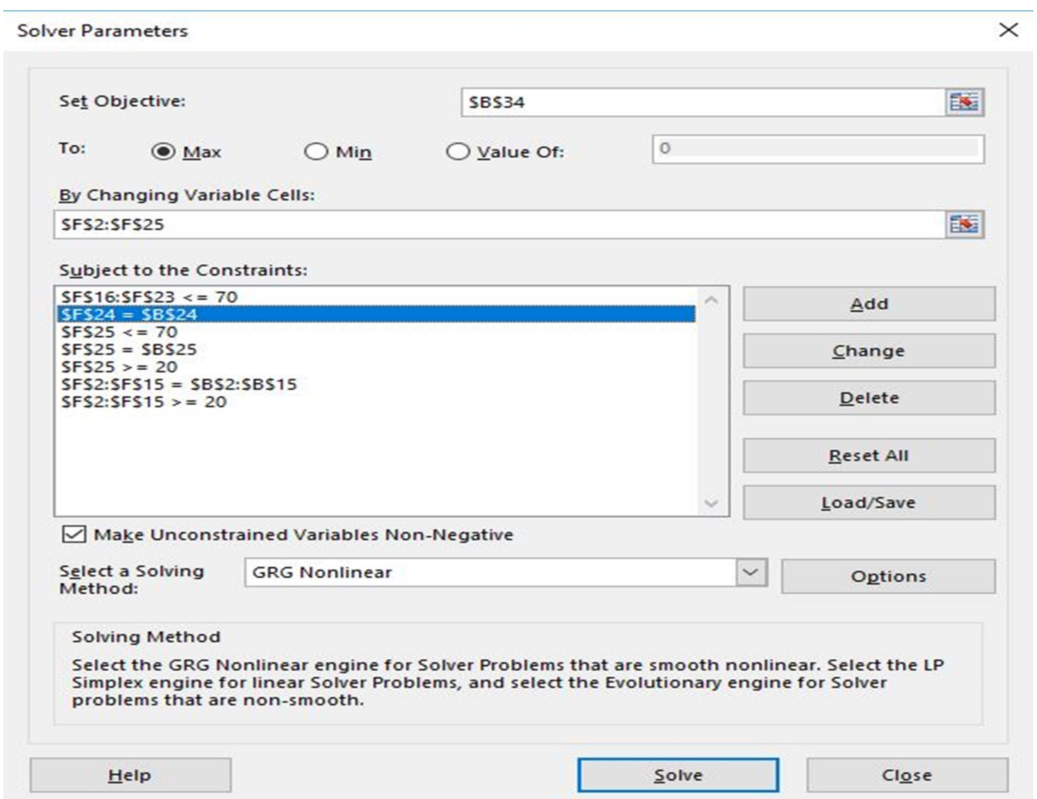

Table 4.1: Solver Constraints

The output from the solver tool is given in the chosen Changing Variable Cell.

Output:

The output table is given below:

Time (hour)	P_{old} (KW)	P_{new}(KW)
1	20	20
2	40	40
3	40	40
4	40	40
5	40	40
6	40	40
7	50	50
8	60	60
9	70	70
10	60	60
11	50	50
12	50	50
13	40	40
14	40	40
15	80	70
16	100	70

17	120	70
18	100	70
19	100	70
20	90	70
21	80	70
22	70	70
23	50	50
24	20	20

Table 4.2: Load Shifting Optimization Results

Load Curve:

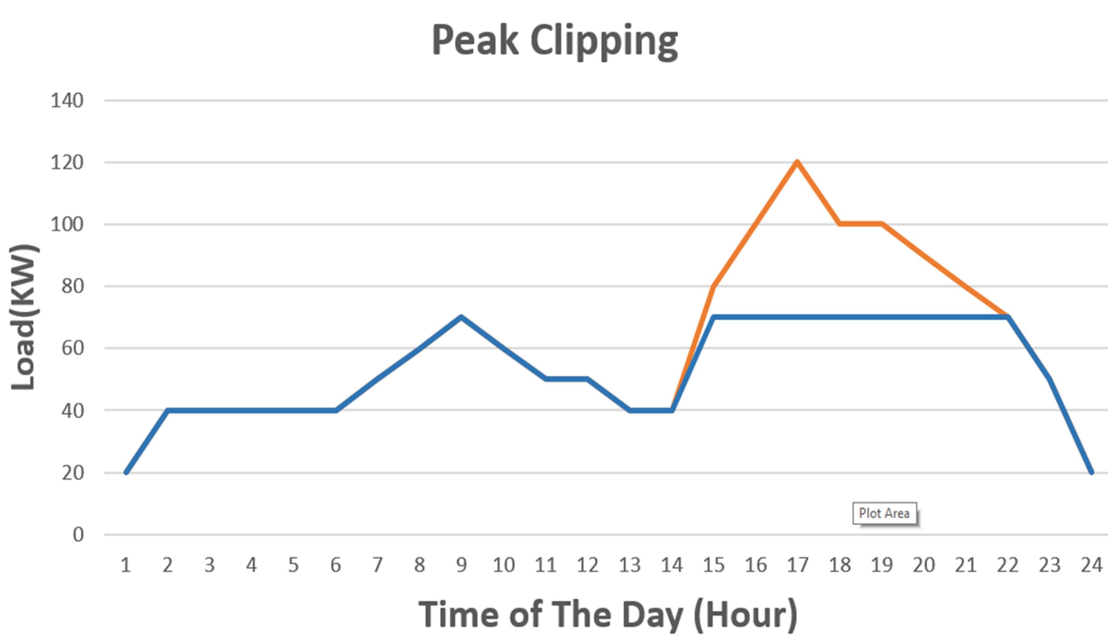

Figure 4.2: Load Curve for Peak-Clipping

4.3 Optimization For Load Shifting:

We have chosen a block in MS Excel and inserted our objective function. In solver tool we have given the input of set objective from that MS Excel block.

And we choose to maximize the Load Factor.

In the Changing variable cell we have inserted an empty column of Excel sheet.
And in the constraints we have inserted the constraints of Load Shifting.

The constraints that were inserted was:

Equality constraint:

- $\sum_{i=1}^{N}\sum_{j=1}^{J} P_{new(i,j)} t_{(j)} = \sum_{i=1}^{N}\sum_{j=1}^{J} P_{old(i,j)} t_{(j)}$
- $P_{new(i)} = P_{(value)}\ \forall\ tk \rightarrow th$

Inequality constraints:

- $P_{new(i)} \geq P_{old(i)}\ \forall\ to \rightarrow tk, th \rightarrow TD$
- $P_{new(i)} \leq P_{(value)} \forall to \rightarrow tk, th \rightarrow TD$

We have chosen the $P_{(value)}$ = 70KW

The main screen of the solver is shown below :

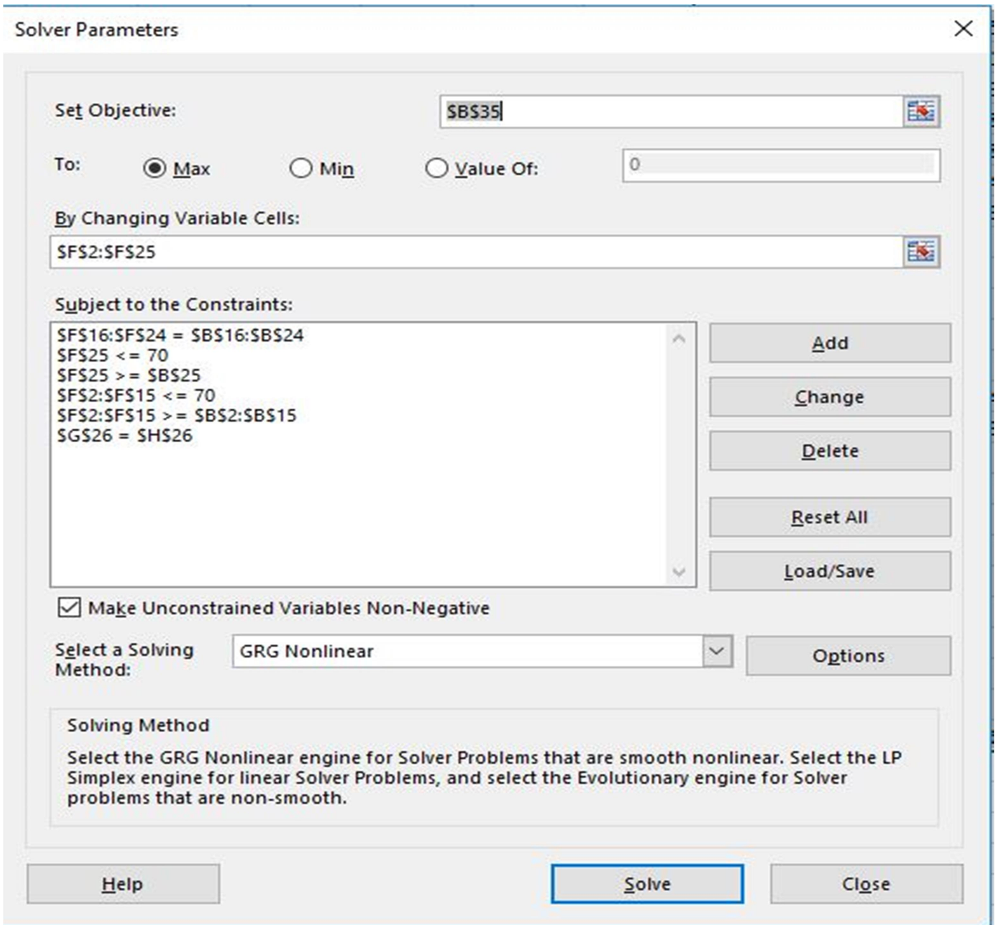

Figure 4.3: Solver Constraints

The output from the solver tool is given in the chosen changing variable cell.

Output:

The output table is given below:

Time(hour)	P_{old} (KW)	P_{new}(KW)
1	20	21.94264565
2	40	43.88529123
3	40	45.8279371
4	40	47.7705828
5	40	49.71322849
6	40	51.65587419
7	50	63.59851989
8	60	70
9	70	70
10	60	70
11	50	70
12	50	70
13	40	65.25439408
14	40	67.13703978
15	80	70

16	100	70
17	120	70
18	100	70
19	100	70
20	90	70
21	80	70
22	70	70
23	50	70
24	20	66.62349677

Table 4.3: Load Shifting Optimization Results

Load Curve:

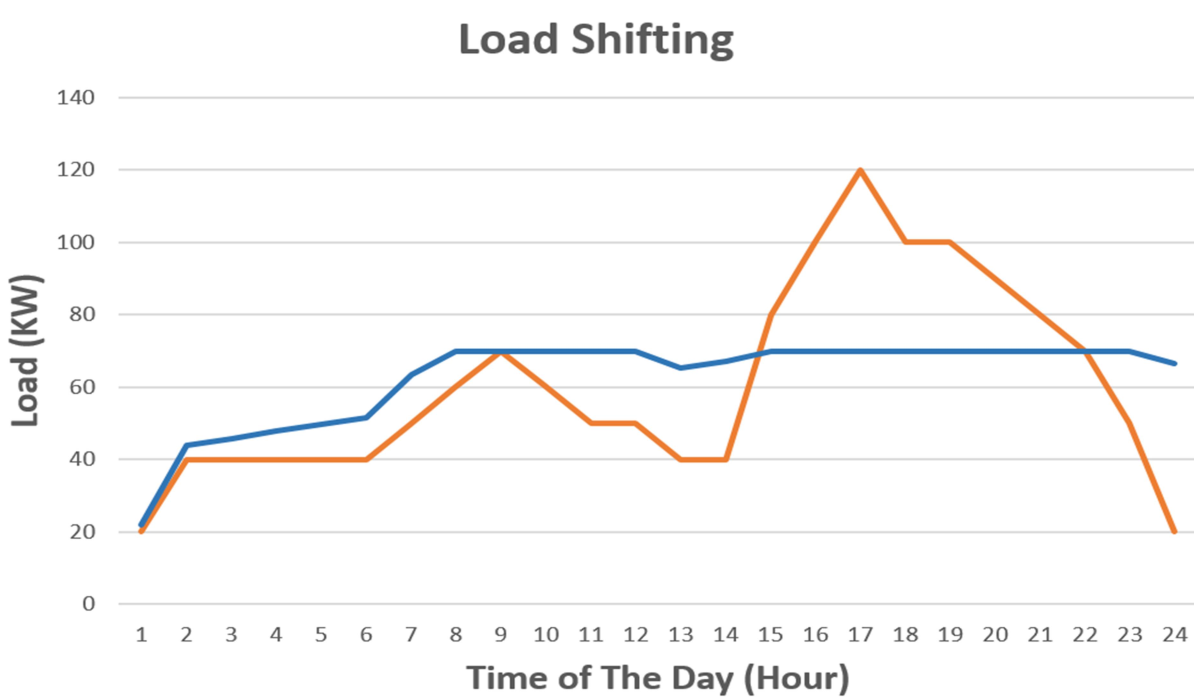

Figure 4.4: Load Curve for Load Shifting

4.4 Cost Estimation:

An industrial plant daily load curve was utilized to clarify the benefits of DSM programs and to substantiate the validity and powerful of the introduced formulations. Results of applying the load shifting and the peak clipping techniques are only shown.

Fig. 4.4 shows the load curve before and after applying load shifting DSM program, while Fig. 4.2 shows the load curve before and after applying peak clipping DSM program. The salient results of the two applications are shown in Table (4.3) for peak clipping & Table (4.4) for load shifting.

The load factor has improved from 0.5066 to 0.74404 for peak clipping program, and to 0.86856 for load shifting program. Besides, the monthly customer bill has decreased by about 2.02% for load shifting program and 12.59 % for peak clipping program. The demand cost was considered to be 87.6 L.E./KW while the energy cost was considered to be 0.1535 L.E./KWH. In the two applications, the objective function was formulated to maximize the system load factor.

Parameter	Before applying DSM	After Peak Clipping
P_{max} (KW)	120	70
Energy (KW/year)	521950	456250
$P_{average}$ (KW)	60.799	52.08333333
L.F	0.506658333	0.744047619
Demand Cost ($)	10512	6132
Energy Cost/Year ($)	29243553.63	25562546.88
Cost/Year ($)	29254065.63	25568678.88
Cost/Month ($)	2437898.802	2130723.24
End User % save		12.59786177

Table 4.4(a): Usage and Cost Estimation Table for Peak-Clipping

Parameter	Before applying DSM	After Load Shifting
P_{max} (KW)	120	70
Energy (KW/year)	521950	532602.8677
$P_{average}$ (KW)	60.7990	60.79941412
L.F	0.506658333	0.868563059
Demand Cost ($)	10512	6132
Energy Cost/Year ($)	29243553.63	29840407.17
Cost/Year ($)	29254065.63	29846539.17
Cost/Month ($)	2437898.802	2487211.597
End User % save		2.025269069

Table 4.4(b): Usage and Cost Estimation Table for Load Shifting

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