A Review on Demand Response: Pricing, Optimization, and Appliance Scheduling

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Abstract

The evolution of conventional electric grid into Smart Grid (SG) has enabled utilities as well as consumers to reap fruits due to its time varying price mechanisms. The utilities can acquire benefits by improving stability of grid, lessening blackouts and brownouts, knowing better their consumers power needs and not investing into new infrastructures. On the other hand consumer can also reduce electric bills, gain incentives by installing renewable energy sources and exporting energy to the main grid and attain improved services from utility. Demand Response (DR) is one of the most cost effective and reliable techniques used by utilities for consumers load shifting. In this paper, we are presenting a review of several DR techniques with a specific view on pricing signals, optimization, appliance scheduling used and their benefits. A comprehensive performance comparison is also prepared with the help of multiple criteria of SG paradigm.

Keywords: Smart Grid; Demand Response; Appliance Schedule; Optimization

1. Introduction

Information and Communication Technologies (ICTs) are being used in typical electric grid to enhance it into a Smart Grid (SG). These ICT services include but not limited to intelligent and autonomous controllers, advanced software for data management, and two-way communications between power utilities and consumers. Two of the key objectives in SG are the enhancement of its stability in stressed periods from utility perspective and electricity cost savings from consumers point of view. To achieve these goals, one of the major concepts is Demand Side Management (DSM) that includes all activities which target to the alteration of the consumers demand profile, in time and/or shape, to make it match the supply, while aiming at the efficient incorporation of renewable energy resources. Demand Response (DR) is a subset of DSM with energy-efficiency and energy-conservation programs. The US Department

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of Energy defined DR as “a tariff or program established to motivate changes in electric use by end-use consumers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized”1. DR is one of the most cost effective and reliable techniques used by utilities for consumers load shifting. Appliances are scheduled in response to various time varying price signals in a cheaper time slot to achieve maximum cost savings in the electric bill. As the research and development of DR is evolving day by day, this review provides a summary with their key characteristics. Moreover, our contribution complements the existing surveys by presenting: a) an overall objective of each study b) pricing signal used c) appliance scheduling (AS) type and d) a detailed classification regarding renewable energy and storage energy used, underlying unwarranted assumptions, uncertainties handled, scalability, forecasting techniques, communication requirements, maximum possible delay in appliance operation, appliance types and at last but not least benefits gained by both consumers and utilities.

2. Related Work

In recent years, there has been an extensive research effort on the DR and AS for electricity cost savings, reducing peak to average ratio and enhancing grid stability while maintaining user comfort. The objectives of2, are to reduce consumer energy bills, peak to average power ratio and carbon emissions. Two types of energy management schemes; Optimization based Residential Energy Management (OREM) and In-Home Energy Management (iHEM) are proposed and compared. In OREM, a Linear Programming (LP) model whose objective is to minimize the total cost of electricity usage at home with the help of optimal appliance schedules. Aim of the iHEM is to save the electricity cost while not degrading the consumer comfort too much. The purpose of3 is to formulate a practical optimization model for a household to determine the optimal scheduling of home appliances under Time of Use (ToU) electricity prices. The main contribution of3, is the consideration of inconvenience level and formulation of the problem as Mixed Integer Non-Linear Programming (MINLP) rather than Mixed Integer Programming (MIP). It minimizes the cost with an incentive offered to the consumer during peak times. In4, the objective is to design a scheduler to optimize the energy use of an entity for a fixed time horizon so that consumers can obtain the maximum savings in their monthly electricity bills by knowing future price predictions of electricity. An optimal energy scheduling framework is proposed in which full user preferences and generic electricity pricing schemes are considered. A complete DSM framework is proposed in5, that uses two most common DR strategies AS and power storage to enhance the consumer benefits. To gain full advantage of the DR, an autonomous scheduler is also proposed in this study that schedules appliances and power storage devices with the help of Smart Meter (SM) and load aggregator. The main objectives of6 are to ensure adaptive learning and add more intelligence in the system to reduce cost, and peak load. A hybrid intelligent system based on unsupervised learning is proposed to optimize the user comfort with respect to energy consumption by learning occupancy preferences and patterns. A novel system architecture and control algorithm, called “Green Charge (GC)” is proposed in7 that manages renewable energy, Battery Energy Storage (BES) and grid energy in buildings. It lessens electricity bills by combining on-site renewable generation with energy storage that stores electric energy during low-cost periods and then use this stored energy during high-cost periods.

3. REVIEW AND PERFORMANCE COMPARISON OF DIFFERENT DR PAPERS

In this section, we summarized and organized six latest research results in a novel way that integrates and adds understanding to the field of DR and made a comparison among them. At the end of this section, we will provide a cogent summary according to diverse criteria like scheduler type, electricity pricing schemes, optimization problem type, renewable energy sources used, uncertainties handled or not, communication requirements, forecasting techniques and appliance types etc.

3.1. Autonomous Appliance Scheduling for Household Energy management

In8, a computationally feasible and automated optimization-based residential load control framework is proposed that uses Real Time Pricing (RTP) combined with Inclining Block Rate (IBR). Aim of8 is to minimize the households electricity payment and waiting time by optimally scheduling the operation and energy consumption of each appliance,
while maintaining user comfort. Every house is assumed to be equipped with SM that has built in price predictor and energy scheduler. Real time electricity prices are relayed to SM by utility via a Local Area Network (LAN). Then, energy consumption scheduling vector of appliances are formulated for complete planning horizon $H$. User inputs the appliances start/stop times within the planning horizon, their minimum/maximum power needs and limit of power in each planning horizon slot with the help of an interface (like In Home Display (IHD), smart phone or Energy Management System (EMS)). In addition to the above mentioned user constraints, a frustration based waiting cost is also included in the objective function that increases with waiting time and vice versa. A multi objective linear optimization problem is formulated that minimizes cost of electricity as well as waiting time of appliance operation. Now, energy scheduler determines optimal choices of all appliances operation according to the user provided data. These choices are then implemented on appliance in the form of ON/OFF commands with specified power levels over wired/wireless Home Area Network (HAN) among appliances and SM. This is the case when electricity prices are known ahead of time for planning horizon. If electricity prices are partially known for some planning horizon then price predictor in SM is used to predict the unknown prices. In this situation, the optimization problems cost minimization objective is further decomposed into two parts; one that is known at that specific time and the other that is predicted. Energy scheduler also solves and implements this optimization problem in the same way as in the first case when electricity prices are known ahead of time.

In addition authors in $^8$, also presented that their proposed optimization-based residential load control framework can be extended with slight modifications in diverse directions like Appliances with Discrete Energy Consumption Level, Interruptible and Un-interruptible Residential Load, Availability of Multiple Retail Electricity Sources, Avoiding Load Synchronization, Announcing the Scheduled Consumption Back to the Utility, Handling Load Reduction Requests, Residential Electricity Storage and Accommodating Changes in Users Energy Needs.

Simulations show that average electricity bill as well as peak to average ratio reduced 25% and 38% simultaneously. At last but not least, they studied the impact of adopting IBR, Scheduling Control Parameter, Price Announcement Horizon and Price Prediction and Number of Users on their proposed framework.

3.2. Appliance Commitment for Household Load Scheduling

The primary objective of $^9$ is to reduce electricity bills for next 24 hours subject to constraints on user comforts and meeting the predicted hot water requirements. User comfort in $^9$ is defined by the limits of hot water temperature and three types of loads are considered: Controllable Thermostatically Controllable Appliances (C-TCAs), Controllable Non-Thermostatically Controllable Appliances (Non-TCAs) and non-controllable.

A novel appliance commitment algorithm is proposed in $^9$ that schedules a C-TCA Electric Water Heater (EWH) on the basis of electricity price and consumption forecasts. Authors in $^9$ formulated energy consumption scheduling as a nonlinear optimization problem, however, they transformed it to a set of linear constraints and linear optimization problem. They solved it with the help of linear-sequential optimization-enhanced, multi loop algorithm. This algorithm is fundamentally an exhaustive search algorithm, so the solution is optimal and always solvable.

EWH thermal model was defined with the help of thermal capacitance and thermal resistance. They estimated these parameters from ASHRAE handbook and statistical regression models. Hot water consumption is predicted from the historical data. In this optimization problem price forecast, range of thermostat settings, characteristics of electric water heater and demand for hot water are used to model the objective function and constraints. They used the two step scheduling process: day ahead scheduling and real time adjustments, to find the solution.

In day ahead scheduling, on the bases of electricity price and hot water usage forecasts EWH estimated ON time duration for the next 24 hour period is determined. Price threshold is found from the sorted (monotonically increasing) electricity price curve where it intercepts with total EWH ON time. When electricity prices are lower than this threshold value, EWH would be ON otherwise it would be OFF. Now the constrained optimization problem is solved and compared to the control law of the heater that was earlier determined without any optimization. If there is no violation of user comfort band then these schedules are as it is accepted and total payment is calculated. On the other hand, if violations exist then subdivide the time horizon at point where first violation has occurred. Then repeat this process for the complete 24 hours period. Real time adjustments are made on the bases of updated information of electricity prices and hot water usage. The two-step approach provides adjustments for the uncertainties by updating real time prices and hot water usage of a house. If user gives more flexible limits of temperature then higher savings would be possible.
The simulations in\(^9\) revealed that the algorithm can be optimally used to automatically generate schedules based on different cost and comfort settings. The authors in\(^9\) also claimed that appliance commitment problem is better than agent based approaches and their approach also handles uncertainties which may appear from energy forecast and hot water consumption prediction.

### 3.3. Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home

The aims of\(^10\) are to minimize the energy expenses of each appliance in Smart Home (SH) with the help of optimal AS that uses real time energy prices and at the same time conforms to the target trip rate. In\(^10\), they tackle stochastic characteristics of consumer energy consumption pattern, BES and renewable generation. In addition, Variable Frequency Drive (VFD) concept and limit on the total load demand are salient features included in this work. In\(^10\), a three step algorithm is proposed and its final solution is found by stochastic optimization.

A SM is assumed in SH that is capable of receiving energy price forecasts from utility and generating schedules along with other tasks for home appliances. In the first step a LP based deterministic scheduling algorithm is used to minimize the expense of electricity from grid, Photo Voltaic (PV) and BES. Constraints related to total load, power consumption of appliances in an interval, BES capacity, solar power limit and its utilization are formulated for first phase of optimization. A feasible LP based schedule is found in the first step. In the second step, a systematic trip rate driven stochastic offline scheduling algorithm is proposed to derive the desired energy adaptation variable. The probability that the home power network trips out during a time interval is defined to be the trip rate. In this phase, operation schedule are generated for a given set of household appliances with desired trip rate to handle the uncertainties in energy consumption and runtime of household appliances with the help of some probability distribution function. In this offline scheduling algorithm, it is assumed that all its inputs are known a priori. As a result, the offline operation schedule is optimum at that moment. But as the system becomes operative the energy consumed by household appliances and the energy produced by the solar panels strays from the values utilized to optimize the offline operation schedule. Thus, the optimality of the offline operation scheduling is lost and the online operation needs fine tuning to compensate for the optimality loss. So, in the last step the online runtime scheduling is invoked that can effectively handle the uncertainty in the energy generation from the PV system. Appliance operation scheduling in\(^10\) also speeds up the creation of the desired operation schedule by exploiting parallelism in the computing process. Simulation results of\(^10\) show that the proposed energy consumption scheduling scheme achieves up to 41\% monetary expenses reduction when compared to the traditional scheduling scheme that models typical appliance operations in traditional home scenario. Moreover, execution time of proposed scheduling algorithm in\(^10\) is within 10 seconds, which is fast enough for household appliance applications.

### 3.4. An optimal power scheduling method for demand response in home energy management system

The objectives of\(^11\) are to reduce electricity bills and peak to average ratio of demand curve. In\(^11\) a general architecture for EMS in a HAN is presented and then an efficient AS method is proposed. In\(^11\), they classify the problem to be a non-linear problem and solve this using Genetic Algorithm in MATLAB.

EMS comprises of Advance Metering Infrastructure (AMI), SM, Home Gateway (HG), Energy Management Controller (EMC), smart appliances and IHD. AMI is responsible for two way communication, collecting and transmitting consumption data between SM and utility and relaying price information back to the SM from utility. HG is used to acquire price signals and control signals from utility company and send load forecasting information to the utility company. In\(^11\) home appliances are divided into two broad categories; Automatically Operated Appliances (AOAs) and Manually Operated Appliances (MOAs). AOAs are further classified as interruptible appliances whose operation can be stopped and non-interruptible appliances whose operation cannot be stopped.

As HG receives DR signal from the utility, it creates optimal schedules of appliance on the basis of information received from user and utility. An IHD is used to input appliances ON/OFF requests, AOAs length of operation time, appliances start and stop time, operation time interval and power consumption of appliances. MOAs are not included in this optimization process because their usage cannot be predicted in advance. In order to generate optimal appliance schedules, the IHD sends all these parameters to HG. Users always require minimum delay in their appliances start time. An optimization problem is formulated in\(^11\) based on the parameters entered by user via IHD that optimizes power consumption scheduling matrix and a delay time rate (DTR). The value of DTR is between 0 and 1. Zero means
Table 1. Comparison of DR Techniques based on Selected Quality Criteria

<table>
<thead>
<tr>
<th>Technique Objectives</th>
<th>Scheduler</th>
<th>Pricing Scheme</th>
<th>Optimization</th>
<th>Assumptions</th>
<th>Renewable Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Minimize energy bill, appliance waiting time and PAR,</td>
<td>Manual</td>
<td>RTP combined IBR</td>
<td>LP</td>
<td>Future pricing parameters are known for the users ahead of time</td>
<td>PHEV as a BES used</td>
</tr>
<tr>
<td>2. Minimize energy bill and user discomfort</td>
<td>Automatic</td>
<td>RTP</td>
<td>Converted-Linear</td>
<td>Temperature band is uniform, Mean error of 10% is assumed in forecasted price</td>
<td>Not used</td>
</tr>
<tr>
<td>3. Minimize energy bill by consumer reward</td>
<td>Automatic</td>
<td>TOU</td>
<td>NLP</td>
<td>Power consumption profile in each house is assumed to be the same</td>
<td>Not used</td>
</tr>
<tr>
<td>4. Minimize energy bill and PAR</td>
<td>Manual</td>
<td>RTP combined with IBR</td>
<td>Non-linear</td>
<td>Nine kinds of AOAs and 16 operation per day for them</td>
<td>Not used</td>
</tr>
<tr>
<td>5. Minimize energy bill and user discomfort</td>
<td>Automatic</td>
<td>RTP, FIT and Net Sale/Purchase</td>
<td>Linear</td>
<td>Convex cost function, PV generation is able to meet 50% of its load requirement</td>
<td>PV</td>
</tr>
<tr>
<td>6. Minimize energy bill and user discomfort</td>
<td>Manual</td>
<td>RTP</td>
<td>Linear stochastic</td>
<td>Solar power is cheaper than grid</td>
<td>PV and BES</td>
</tr>
</tbody>
</table>

no delay and 1 means maximum allowable delay. The price mechanism used in this study is real time price combined with IBR. In this pricing scheme, if a user consumes more energy than a predefined threshold value then price of the electricity goes higher than normal price. This combined pricing scheme prevents rebound peaks, which otherwise might appear, in off peak periods. Appliances optimal start time the only unknown parameter in this optimization problem is determined to reduce energy cost and DTR.

The authors in\textsuperscript{11} have shown in their simulation results that real time pricing of electricity combined with IBR has alleviated rebound peaks in off peak periods. They further deduce that electricity cost and average DTR formed a pareto optimal frontier where if we try to reduce electricity cost, DTR goes high and vice versa. They also observed that an average saving of 12.68 cent daily along with reduction in peak to average ratio of 5.22 to 3.37 is possible with their devised algorithm. The authors with the help of simulations in\textsuperscript{11} also revealed that their proposed algorithm is still effective in the case of combing AOAs with MOAs.

3.5. Autonomous Appliance Scheduling for Household Energy Management\textsuperscript{12}

This work’s goals are not only to minimize the energy consumption level, but also reduce energy bills and ensure minimal user discomfort with the help of AS. These goals can be achieved with the help of renewable energy and DSM techniques. EMSs benefit consumers to lower their electricity bills, as well as utility to reduce their peak power demands. In\textsuperscript{12}, energy management savings for a house with standard appliances and PV arrays installed on its rooftop are presented. The strategy is to purchase as little energy as possible from grid while export as much energy as possible to grid.
The authors in[12] proposed linear programming based autonomous AS algorithm for a house with the help of an intelligent Smart Scheduler (SS) and load clustering. They also proposed various energy pricing frameworks (Real time, Feed in tariff and Net sale/ net purchase). The basic principal behind SS is that it calculates and stores the hourly probabilities of appliances in the house for a specific time horizon (an year) on the basis of historical usage data of appliances while taking into consideration features like day of the week, weather conditions, degree of penetration of the appliances and occupancy level of the house. The SS can estimate the house hold usage of certain appliances by monitoring hourly probabilities of those appliances. Most preferred ToU for an appliance is when it has highest probability. SS monitors individual household load consumption and at the same time confines the appliance aggregate load at a predefined limit. It also ensures that the appliances are scheduled in off-peak periods so that consumers can achieve maximum reduction in their electricity bills. SS has two way communication capabilities and can issue commands like start, stop, pause and resume to the appliances.

Appliances having similar ToU probabilities and load profiles are assigned the same cluster. Each cluster has a peak load limit, reaching that, further appliances operations are not allowed in that time slot. An appliance, that has been disallowed two time slots consecutively, is given higher priority. In next time slot, these higher priority appliances are scheduled first to reduce the user discomfort. If at any time slot, a higher priority appliance asks for activation and there is not enough power capacity with that cluster, then a lower priority appliance needs to be paused.

Flexible schedules are automatically generated for appliances at time slots where they have highest ToU probabilities by incorporating some tolerance value. SS assigns tolerance value on the basis of priorities of the appliances. It is quite possible that some appliances may be scheduled in an improper time slot due to poor tolerance value assigned by SS. In that case, a frustration cost is included in the objective function of the optimization problem to handle the discomfort bore by user.

Simulations in[12] show energy savings for a prosumer with the help of autonomous AS algorithm by considering different pricing signals. The authors in[15] compared their proposed algorithm with the house that has neither installed any RES nor made schedules and show that their proposed scheduling algorithm is a viable solution to residential consumers power management.

3.6. Demand Response for Residential Appliances via Customer Reward Scheme

In[13], an incentive based DR scheme for residential distribution system is proposed in which consumers are rewarded on the bases of how much amount of load they shed and how much improvement in feeder voltages is caused by them during peak periods. The proposed scheme doesnot depend on cost of electricity consumption.

In[13], first of all a detailed consumer survey is conducted to take their inputs and preferences to participate in the proposed DR. In the later stages, the results of these surveys are used to design various indices for the load control algorithm. Five types of indices related to consumer priority, satisfaction, and flexibility are proposed in this research work. Houses are ranked according to the effects they made on the feeder voltages. Rewards depend on the willingness of the user to participate in the scheme and are calculated on daily basis.

The load control algorithm is implemented in two hierarchical levels; at the first level the SM (primary controller) regulates the feeder voltage in an acceptable range and at the second level main controller prevents overloading of the transformer. Everyday at the start of the time horizon SM sends the appliance state and power data to the main controller that calculates voltage level at each house. Aggregate power and voltage of the network at each house are checked to insure that they are kept within standard regulatory limits in every 2 minutes. Offline load flow studies are performed to acquire the appropriate load adjustments in the case that the power level and/or voltage at each house are violated. The offline load flow is an iterative process that selects multiple sets of loads for adjustment in that time step. The criteria indices, house rankings and decision values are calculated in all iterations of the proposed algorithm[13]. The load of that house is identified and chosen to shed; whose decision variable has maximum value for load adjustment. After shedding this load the power and voltage levels are re-computed and if violations exist then another load is identified and shed. This process continues until the power and voltage levels stabilize in the permissible range. All selected appliances for adjustments are saved and signals are sent at to relevant SMs. If loads are adjustable, then some adjustments in the parameters of these appliances are made for 15 minutes to reduce the load. On the other hand, if loads are non-adjustable then these are switched off for 4 minutes. This process is repeated for whole day and at the end of the day rewards to the consumers according to the proposed formula in[13] are calculated.
The authors made critical assessment of consumer reward scheme according to their designed criteria indices, evaluation of cost coefficient, implementation and operation of this scheme, its scalability and prevention from consumers misuse of the scheme. They also presented in\textsuperscript{13} that this scheme can effectively shave the network peak for several years, before the feeder transformer needs to be upgraded.

4. Comparison and Analysis of All Techniques

A comparison of six DR techniques with respect to quality criteria is shown in table I. Overall, there is no single criterion available that can evaluate the best technique among them. So, we took multiple criteria to assess and compare these techniques.

Reduction in energy bills is the most common objective of these techniques\textsuperscript{1−6} whereas user comfort is just behind this objective. Minimization of peak to average ratio is the goal of\textsuperscript{3,4} that also brings stability in the smart grid. The least common objectives are greenhouse gas emissions and customer direct incentives. Automatic schedulers are proposed in technique\textsuperscript{1,2}, while manual schedulers are suggested in\textsuperscript{3−6}. A variety of pricing schemes are designed and used in these techniques. A vast majority utilizes real time pricing\textsuperscript{1−5} and time of use pricing\textsuperscript{6}. Net sale and net purchase\textsuperscript{1} and feed in tariff\textsuperscript{1,4} are the least popular price structures in these techniques.

Nearly all of the techniques formed are linear or its derivative form\textsuperscript{1,2,4}. PV or BES is able to supply 50% of the total needs of the house load as supposed in\textsuperscript{5}.

A vast majority included and handled electricity prices and consumptions forecasting. Communication infrastructure is a basic requirement of these DR techniques. Almost all studies have used three types of appliances i.e deferrable and interruptible, deferrable and non-interruptible, non-deferrable and non-interruptible.

Table 2. Comparison of DR Techniques based on Selected Quality Criteria

<table>
<thead>
<tr>
<th>Technique</th>
<th>Users</th>
<th>Forecasting</th>
<th>Communication</th>
<th>Requirement</th>
<th>Max Delay</th>
<th>Benefits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Multiple users (10)</td>
<td>Real-time price prediction at the user side</td>
<td>WHAN is used</td>
<td>SM with energy scheduler and price predictor</td>
<td>User defined</td>
<td>25% reduction in EC and 38% reduction in PAR Over 20% in EC</td>
</tr>
<tr>
<td>2</td>
<td>Single User</td>
<td>Energy and hot water FC</td>
<td>Thermostatic Signal to control appliance</td>
<td>Modeling of equipment</td>
<td>Temperature of water may low</td>
<td>Shave the network peak for almost 11 years 26.06% in EC and 35.44% reduction in PAR 10.92% in EC</td>
</tr>
<tr>
<td>3</td>
<td>Multiple users</td>
<td>Consumer survey is used</td>
<td>SM and main controller are used</td>
<td>Consumers survey prior to connection</td>
<td>4 minutes or switch off for 15 minutes User defined</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Multiple users</td>
<td>Not used</td>
<td>Too much communication involved</td>
<td>HEMS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Single User</td>
<td>Energy and Load FC</td>
<td>Smart scheduler uses 2 way communication</td>
<td>TOU probabilities of appliances</td>
<td>2 time slot (12h)</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Single User</td>
<td>Energy FC</td>
<td>SM is used to communicate</td>
<td>VFD and capacity limited energy drives</td>
<td>Instead of delay new trip rate used</td>
<td>24% to 44.1% in EC</td>
</tr>
</tbody>
</table>
Finally, table II classifies all the survey papers according to the scalability of the proposed method, forecasting technique used, level of communication requirement, other peculiar requirements, maximum possible delay in the appliance operation, categorization of appliance and benefits gained.

5. Conclusion

In this paper, we have presented a survey of recently published research in the domain of DR. We provide an extensive review on pricing signals and AS schemes used with respect to multiple criteria. The maximum electricity cost saving (24% to 44.1%) was achieved in 6, while 38% reduction in peak to average ratio was possible in 1. The simulation results of 3, showed that network peak can be shaved for almost 11 years that benefits utility by not requiring any update in their infrastructure.

References