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DEMAND RESPONSE BASED REAL-TIME SCHEDULING FOR HOUSEHOLD ELECTRICAL APPLIANCES

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ABSTRACT: This work carries a novel method that uses demands response strategies to develop and evaluate the consumer's perspective through a computational experiment approach. The price of electricity is assumed to be a time-varying parameter. The proposed method describes an optimization model that adjusts the hourly load level of consumer with response to hourly electricity prices. This approach has a home energy consumption simulator and a demand response mechanism obtained through optimization, particle swam method, and an integrative computing platform that combines the home energy simulator and MATLAB together for demand response development and evaluation. A lot more number of demand response strategies are developed and evaluated through computational experiment technique. This work investigates and compares characteristics of different demand response strategies and how they are affected by dynamic pricing tariffs, seasons, and weather. A simple bidirectional communication device between the power supplier and the consumer enables the implementation of the proposed model.

KEYWORDS: Energy consumption, demand response, dynamic electricity price, modelling, simulation, smart grid.

1 INTRODUCTION

Now-a-days it is expected that the achievement of energy conservation can be significantly accelerated by integrating smart, energy-efficient appliances into a "smart" electricity grid. Basically, smart appliances will be no longer merely passive devices that drive energy productions but active participants in the electricity infrastructure for energy optimization and increased compatibility. A key function for the smart appliances within the smart grid framework is the demand response (DR). Demand response (DR) refers to deliberate load reductions during system needed times, like periods of peak demand or heavy market price. Due to reduced consumption and increased generation, for both system's supply and demand to evenness, DR can be a source that counter balances or defers the need for new generation, transmission, and/or distribution setup. The best basic DR packages are structured to maintain system reliability and prevent blackouts. But nowadays, DR has evolved into a more dynamic resource that can also provide price extenuation and auxiliary services to utilities and grid workers. This work holds a summary of four types of DR based on their purpose and use: financial, emergency, auxiliary services, and peaking alternative. In general, DR includes all intentional modifications to electricity timing of energy usage, the level of instantaneous demand at critical times, and consumption patterns in response to market prices. At the same time, DR is a component of smart energy management, which includes distributed renewable resources and electric vehicle charging. Nevertheless, there exist many challenges in developing price-responsive DR strategy for a residential consumer, such as the quandaries faced in accurately estimating the energy consumption of a house and the development a DR algorithm in dynamic price setting. A key function for the smart appliances within the smart grid framework is the Demand Response (DR). The North American Electric Reliability Corporation has defined response as “changes in electricity usage by end-use customers from their normal consumption patterns in response to change in the price of electricity, or to incentive payments designed to induce lower electricity use at time of high wholesale market prices or when system reliability is endangered.” On a whole, around two types of DR available. They are curtailable DR and price responsive DR. In curtailable DR, an end-use customer agrees to curtail under certain circumstances in response to dispatch by the Load Serving Entity (LSE), aggregator, or the system operator and the customer receives an explicit payment for curtailing load. In price-responsive DR, an end-use customer is exposed to time-varying (dynamic) rates and does not receive an explicit payment as compensation for curtailing load. This article presents a mechanism to develop and evaluate a price-responsive DR strategy through a computational experiment approach.

A mechanism to obtain energy consumption of a residential house by using professional building simulation software. Through this method, one can “build” a simulated house that is similar to a practical one. The simulation uses standard commercial building materials defined in the software library and real-life weather data available at an approach of using regression technique to model home energy consumption based on the energy consumption obtained from the home energy simulation software. Therefore, it is possible to model the energy consumption of a residential house more accurately for complicated energy usage and weather conditions. A method to develop optimal DR algorithms based on the regressed household energy consumption model and conventional optimization and particle swam techniques. An integrative computing platform that combines the home energy simulator and MATLAB together for DR development and evaluation. A detailed comparison study focusing on characteristics advantages and disadvantages of different DR policies for both real-time and day-ahead binding customers. The paper is organized is such a way that Section II, heat transfer issues and the techniques used in a home energy simulator to estimate energy consumption of a residential house. Section III gives a computational experiment system that combines home energy simulation and dynamic electricity prices for DR evaluation. Section IV illustrates how to use the computational experiment strategy to develop different DR policies based on optimization approach, particle swarm method, and a heuristic algorithm. The performance of different DR policies is evaluated in Section V. Final section of the paper holds the conclusion.

2 RELATED WORKS

Navid-Azarbaijani et al, (1996) found the problem of scheduling ON/OFF switching of residential appliances under the control of a Load Management System (LMS).The scheduling process is intended to reduce the controlled appliances’ power demand in accordance with a predefined load reduction profile. The conventional practices in this area are shown to be special cases of the PWM technique. The basic premise of this paper is that the existing scheduling tools available to the LMSs are not systematic and, as such, not flexible enough to allow realization of general LRT function. The important advantage of LMS technology is to provide insight to various types of errors which arise in the scheduling process. The major drawback of this paper is that it does not involve substantial data collection or significant commitment of computing resources. T. J. Luiet al, (2010) research shows that the energy conservation can be significantly accelerated by integrating smart, energy-efficient appliances into a “smart” electricity grid. It is important to recognize and keep in mind the three levels of smart grid DR that must be developed and coordinated on a large scale in order to realize benefits from the smart grid. The second level of smart grid DR involves understanding the present usage of and coordinating the responses from all the smart appliances and other smart DR products (e.g., solar panels, electric vehicle supply equipment, and soon) in a given home. The third level of smart grid DR involves knowing the potential, and coordinating the response from, hundreds to millions of homes. This method as of now is implemented only in industries. Tung T. et al, (2010) investigated the problem of scheduling power consumption with time-varying prices that are known causally to consumers. Using stochastic dynamic programming, we have derived optimal policies and the algorithms to find a series of price thresholds. The scheduling problem is naturally cast as a Markov decision method. Procedures to find decision thresholds for both non interruptible and interruptible loads under a deadline constraint are then developed. The computational cost of the proposed scheduling is reasonably low for moderate time horizons, which arguably is the common case for hourly power pricing. The Main advantage of Markov decision process Algorithms is to provide reliable data on the power usage profiles. The drawback of this algorithm is that implementation cost is high.

M Hashem Nehrir et al (2010) presents a comprehensive central DR algorithm for frequency directive, while diminishing the amount of manipulated load, in a smart micro grid. Simulation providing ancillary services for future smart micro grid can be a challenging task because of lack of conventional Automatic Generation Control (AGC) and spinning reserves, and expensive storage devices. Thus, increased attention has been focused on Demand Response (DR), especially in the smart lattice environment. The central DR strategy is based on communication between the utility control center and the responsive loads and has been shown to be stable up to a latency of 300 ms. The main advantage of DR algorithm based on deviation in frequency regulation it makes an optimal decision.The drawback of demand response Algorithm is that the system runs slowly. Duy Thanh Nguyenet al, (2011) in their research DR is treated as a public good to be exchanged between DR purchasers and venders. Purchasers need DR to improve the reliability of their own electricity-dependent businesses and systems. Venders have the measurements to significantly modify electricity request on invitation. Microeconomic theory is applied to model the DRX in the form of pool-based market. In this market, a DRX operator (DRXO) collects bids and offers from the buyers and sellers, respectively. The DRX concept can be considered an implicit market in which DR is a separate commodity to be traded through a virtual pool. Most importantly, this theory brings together DR buyers (i.e., TSO, retailers, distributors, each with their own reasons to demand some DR from time to time) and sellers (i.e., customers through the aggregators) under a common DRX "umbrella". The DRX market-clearing scheme has an advantage of rewarding customers better by allowing them to deal with multiple buyers in a competitive way. Such a reward and competition based scheme can motivate customers to participate in DR programs more actively than in the past. This system is prize to found losses. Jesus M. Latorre et al, (2011), found that wind energy represents a strongly increasing percentage of overall power construction, but wind normally does not follow the typical demand profile. Demand side management measures intend to adapt the demand profile to the situation in the system. Wind production rates are of less importance during high demand hours when implementing programs whose solely objective it is to reduce demand peaks. The impact of an increased installed wind capacity on operation and the cost savings resulting from the introduction of responsive demand are measured. Besides, results from the different implemented demand response options are compared. Major drawback of this is high cost.

Masood Parvania et al, (2011), stated that any system operators around the world are challenged by the problems associated with integrating intermittent resources into the grid. As one of the possible solutions, Demand Response (DR) is expected to play a major role for mitigating integration issues of intermittent renewable energy resources. The proposed method is in the mixed integer linear programming format. This work presents the LRDR program which aims to procure load reduction from DR resources. The proposed model take into account the effect of load recovery by contributors. To disclose the features of the planned method, numerous mathematical studies are conducted on the IEEE-RTS. The results shows that the integrating load reduction in the energy market makes significant economic and technical benefits for the system. It has some drawbacks like mixed integer linear programming format method is very difficult and cost is high.

Zhong Fan et al, (2012), work proposes a distributed framework for demand response and user adaptation in smart grid networks. In particular, the concept of congestion pricing in internet traffic control is used and this shows that pricing information is very useful to regulate user demand and hence balances network load. Both analysis and simulation results are presented to demonstrate the dynamics and convergence behavior of the algorithm. Based on this algorithm, then a novel charging method is proposed for Plug-in Hybrid Electric Vehicles (PHEVs) in a keen grid, where operators or PHEVs can adapt their charging rates according to their preferences. This paper is just a first stepping stone towards distributed demand response. Regarding the overall PHEV charging architecture, there could be a commercial entity called Energy Service Company (ESCo) that acts as an intermediary between a large number of PHEVs and the grid. The advantage of dynamics and convergence behavior of the algorithm is adapted to the price signals to maximize their own benefits. The major disadvantage of this algorithm is that it is Unsecure.

3 FIXED PRICE METHOD

Cost estimation is an important parameter for strengthening enterprise cost management. The reasonableness and accuracy of estimation is the key in determining their profitability, attractiveness and maintainable development. The cost estimation and control in Chinese railway transportation equipment's manufacturing industry can reduce the waste of resources in labor power, material and financial and enhance their skill level even the whole manufacturing. Although the level of cost control and management has been improving, it has not break down the dominating status of post-costing .This rough costing method not only reflect the real resources consumption during production, but also affects measurement and reports of other managing information, so it cannot meet the needs of cost management in manufacturing at this stage. In this work the method of the process cost estimation based on working procedure for conquering the shortcomings and limitations of cost accounting, Activity Based Costing (ABC) and Enterprise Resource Planning (ERP) cost checking, which is based on the cost checking of Chinese traditional railway transportation equipment's manufacturing industry is proposed. Make the process of products as the basic cell in estimating costs which forms the model of process-based cost estimation more carefully and analyze the process cost of the transmission gear in a locomotive enterprise [1]. The relative theory and method has important reference to the cost calculation in the process of other products life cycle.

3.1 ACCOUNTING COST ESTIMATION

There are some methods of accounting cost estimation in common use. The high-low method of cost estimation is direct way to determine the variable cost and fixed cost. The main idea of high-low method of cost estimation is to confirm unit variable cost to the cost variance of the highest point and the lowest point cost of volume of business history in relevant range. And fixed cost can be got by subtracting variable cost from total cost. Scatter diagram is a useful means of cost estimation using graphic method. It is more efficient especially together with the use of other methods of cost estimation [2]. That method is to draw the historical cost data points on the coordinate diagram and to determine the cost pertinence. Least-squares regression analysis is to develop the observation data into a cost estimation formula using mathematical methods. Its idea is to minimize the sum of vertical variance between actual cost values and estimated values of each observation point .Accounting prior-cost estimation is generally based on statistical result of historical cost data [2]. It considers only the factor of the volume of business generally, and lacks of affirmatory conditions. So the estimated result is imprecise.

3.2 ACCOUNTING COSTING

Product costing makes product as the basic cell in calculating the cost, such as particular product or batch of products, or a particular manufacturing process. The costing method is called manufacturing costing method within the range of manufacturing.

3.3 COST STRUCTURE

The cost structure of manufacturing cost method includes direct materials direct labor and manufacturing overhead. Direct materials cost is the cost of main raw materials applied to a particular product. It depends on the consumption number of unit material. And it can be identified simply by multiplying the consumption number of raw materials and its unit cost. Direct labor cost is the cost of labor applied to a particular product. It can be obtained by multiplying the direct labor time and wage rate. Manufacturing overhead includes all manufacturing cost besides direct materials and direct labor. It is used directly for production, but it fails to be credited directly to a particular product cost. Most elements of manufacturing overhead do not have direct relationship to processing of the product. In actual production costing, if the workshop produces only a product, the manufacturing costs can be reckoned directly in production cost of the product, otherwise the manufacturing cost is reckoned in various products respectively ruled by reasonable allocation method [3].There are a lot of methods to assign the manufacturing cost. Some of them are commonly used, such as proportional distribution of the production hours, proportional distribution of worker's wage, proportional distribution of machine hours and proportional distribution of annual planning.

3.4 COSTING METHODS

The manufacturing costing methods can be divided into costing method, job order costing method and process costing method. The category costing method is a calculating cost method which considers the assortment as cost objectives to collect and allocate production costs. The costs are distributed between finished product and goods in process. This method is suitable for volume-produce of one step production and multistep produce calculating costs according to production steps on management. The job order costing method is to collect production costs in accordance with the batch or order form and mainly used in single and small batch production. This method sees each product or each batch as the cost objective to calculate the costs. The calculating cycle of cost consistent with its life cycle and the production costs are collected in different batches [4]. The process costing method is to calculate product costs based on production steps and species of goods to collect and allocate production fees applying for continuous, large and multi-step producing industrial enterprises. In the light of different situation, it can be divided into similar steps, the proportion of law equivalent units, and gradually carried forward sub-step.

3.5 COSTING PROCESS FLOW

Identify cost objectives and cost projects. For manufacturing, the cost objectives include product category, product job order and product process.

- Audit various expenditures and costs strictly. Determine the costs included in products.
- Accumulate and allocate on productive expenses elements. Allocate on various costs according to projects among different products.
- Accumulate and allocate auxiliary production costs.
- Accumulate and allocate manufacturing overhead. For the allocation of manufacturing overhead, you should pay more attention on selecting the distributing standard.
- Distinguish the costs between work-in-process and finished product.
- Calculate the total cost and part cost of the finished goods

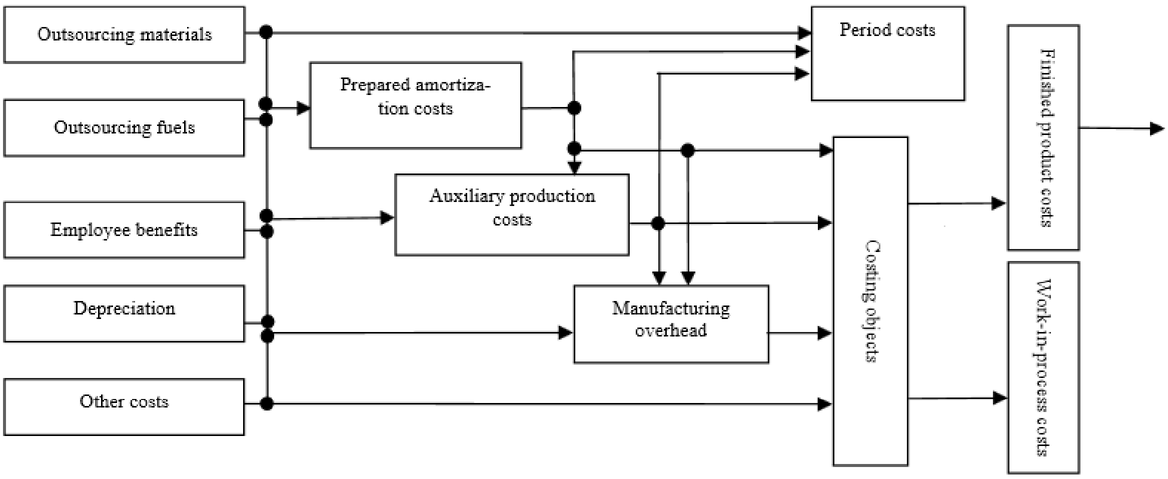

Fig. 1. Block Diagram showing Product Cost Estimation

Accounting cost method is based on a total quantity and calculate unified distributing rates of manufacturing overhead to allocate the manufacturing overhead. The main purpose is to create cost-sharing on a unified basis. But with the increasing complexity of manufacturing costs, they cannot show the causal relationship between output and costs, objectively using every kind of distribution norms, which lead to results coarse relatively. In addition, this is post-costing method, which only tells you the costs occurring in each project, cost overruns or savings, and the reason is unclear, the responsibility is unknown. So it cannot control cost effectively [5].

3.6 Cost of Electricity Machine (C_D)

The formula of calculating the technology and process cost of machine electricity material is shown in equation (1)

$$\mathrm{cd} = \sum_{i=1}^{k} \left(\frac{\mathrm{PE}\times\mathrm{SD}}{60}\right) \mathrm{Tji} \times \eta_{\mathrm{i}} \qquad (1)$$

Where, C_d- the electricity cost of machine, yuan.

T_j- mobile hours of one-piece, min.

P_E- rated power of the electrical motor, kw
η_i-the load coefficient of the electrical motor,
It's efficiency, η= 0.5 - 0.9
S_D - electricity price per hour, yuan/kw·h.

3.7 Cost of Tools (C_{DA})

The formula of calculating the technology and process cost of tools is

$$C_{da} == S_{dap} \times T_j \qquad (2)$$

Where, C_{da}=the cost of tools, yuan.

S_{dap}=is the average cost of using tools per minute while the Machine is working, yuan/kwh.

4 HOME ENERGY CONSUMPTION-SIMULATION

4.1 HEAT TRANSFER IN A RESIDENTIAL HOUSE

In Modelling Energy Consumption of a Residential house, the amount of energy consumed by the Heating, Ventilation, and Air-Conditioning scheme (HVAC) is the most dominant part and is related to heat transfer. The heat load that a HVAC has is o mainly generated in three ways: conduction, convection, and radiation. For a residential house, conduction heat transfer results from internal and ambient temperature differences, such as the conduction through exterior walls and the roof. Convective heat transfer occurs as wind blows over exterior walls, windows, and the roof and also through velocity induced by temperature differences between surfaces and the fluid. Both convection forms are presented in regards to internal heat loads too. Heat radiation may include heat produced by internal loads, such as refrigeration, appliances, and people. Heat gain (and loss) also occurs through the introduction of outdoor air. Hence, for a practical house, computation of the heat loads in terms of the three heat transfer modes is very complicated. In addition, to accurately capture changes in temperature and solar loading throughout a day, calculations must be repeated hour by hour using practical weather and solar load data.

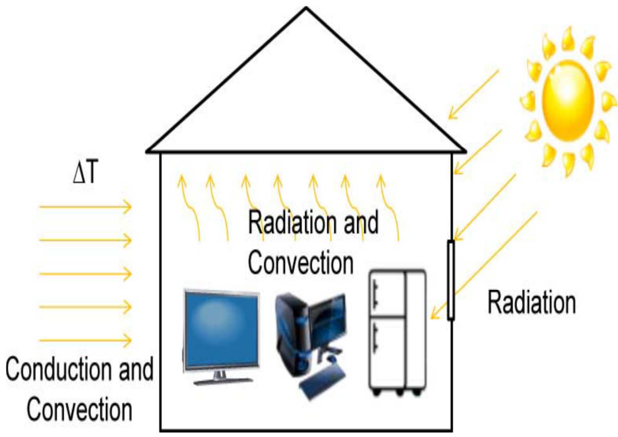

Fig. 2. HVAC heat load sources

In most conventional DR studies the heat loads of a residential house is primarily computed based on 1) approximate heat transfer equations, 2) an equivalent rectangle configuration for a residential house, and 3) a house model without detailed consideration of doors, windows, building materials and internal heat load shown in fig (2).This work uses building simulation software eQUEST as a virtual test bed to determine home energy consumption. The software is x up-to-date, unbiased simulation tool that predicts hourly energy use of a house over one year given hourly weather information and a description of the house and its HVAC equipment . It can use real-life weather and solar data for a specific geographic by assuming that transition from one steady state to another can be achieved immediately. The roof is constructed by using standard built up roof construction. The roof is pitched at 25 and the attic has R-32 insulation. Doors location. Hence, one can estimate changes in the electrical load of a practical house throughout a year, certain days within the year, or certain time period of a day. The software is a steady-state simulation program having a large simulation time step, such as minutes, and does not consider short-term transient and windows are added when appropriate [6]. A garage is created, but is no fair conditioned. Fig 2 shows the front view of the house. The location for the model is Springfield, IL, USA.

4.2 QUICK ENERGY SIMULATION TOOL (EQUEST)

The Quick Energy simulation tool, or eQUEST, allows users with partial simulation experience to develop 3D simulation models of a particular construction design. These replications incorporate construction site, alignment, wall/roof building, window belongings, as well as HVAC systems, day-lighting and various control policies, along with the skill to evaluate design options for any single or combination of energy upkeep measure(s). eQUEST (Version 3.60) is a public domain tool developed by James Hirsch Associates for Southern California Edison (SCE 2007) and is based on the DOE-2.2, the latest versos of DOE-2 (GBS 2007a)[7]. The main differences between DOE-2.1E and 2.2are enhanced geometric representations (support of multifaceted convex polygons), a newly developed HVAC system concept, and additional HVAC components and features (SRG et al. 1998). This free energy simulation tool enables all functionalities of theDOE-2.2 simulation engine and supports conformance analysis with Title 24 California energy code (California Energy Commission 2006).

5 DEMAND RESPONSE AND DYNAMIC PRICE

5.1 DYNAMIC ELECTRICITY PRICE

Electric utility companies typically use hourly Real-Time Price (RTP) or day-ahead price (DAP) structure in their dynamic pricing programs. In North America, Ameren Focused Energy, serving about 2.4 million electric customers in Illinois and Missouri, has very detailed RTP and DAP tariffs posted on their website since June 1, 2008 for both day-ahead and real-time markets. The day-ahead market produces financially binding schedules for the production and consumption of electricity one day before the functioning day. The real-time market resolves any differences between the amounts of energy scheduled day-ahead and Real-Time Pricing (RTP).

5.2 RESULTS ON DYNAMIC ELECTRICITY PRICE

The peak demand reductions observed for 80 such programs, grouped by the type of rate and the use of enabling technologies. In general, Critical Peak Pricing (CPP) and Peak Time Rebate (PTR) rates resulted in greater demand reductions than Time of Fuse (TOU) rates [8]. Enabling technologies generally increased the demand reductions. A 2011 paper on the subject of dynamic pricing showed that, of 109 pricing programs from 24 different utilities, the median peak demand reduction was 12%. For those programs that used enabling technologies, the median peak demand reduction was 23%. While most of these were pilot programs and used various implementation approaches (e.g., different experimental structures, Varying rates, on-/off- peak time periods, participant enrollment approaches, use of control groups, etc.), they generally shows similar price responsiveness from consumers shown in fig 3.

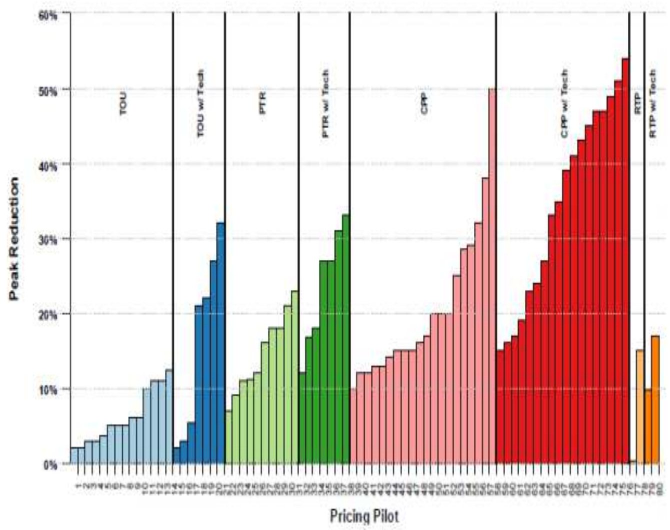

Fig. 3. Demand reductions during peak hours

5.3 REAL TIME PRICING (RTP)

Tariffs based on Real-Time Pricing (RTP) do not charge preset components but apply different retail prices for different hours of the day and for the different days in order to be frequently aligned with wholesale prices. RTP programs have the advantages of increasing the demand responsiveness and of improving the market efficiency. Many experts, indeed, made clear declarations in favor of RTP. One of the supporters is Ray Gifford (chairman of the Colorado Public Utility Commission) who observed “if retail electricity prices reflected the cost of power, a demand-side reply would take the market back to evenness, diminishing both high prices and unpredictability” (see Fauquier and George 2002). Severin Bornstein (director of University of California Energy Institute) argued that “electricity markets will suffer from chronic difficulties until end-users become more active participants” (reported in Bushnell and Mansur 2002). RTP has, indeed, many attractive features (Wolak2001, Bornstein and Holland 2003, Doucet and Kleit 2003). For instance, RTP. Dynamic Electricity price method using in RTP days high price rate may occur at a moderate temperature day.

5.4 Delay Ahead Pricing (DAP)

During 1998-2000, the California Power Exchange operated a day-ahead hour-by-hour auction market. This market ran each day to determine hourly wholesale electricity prices for the next day. By 7 a.m. each day, generators and retailers submit a separate schedule of price-quantity pairs for each hour of the following day. The power exchange assembled these schedules into demand and supply curves and established the equilibrium point by the intersections of these curves. We focus on this (day-ahead) market since it contains the majority of trades. Hourly day-ahead market data are available from the University of California Energy Institute Plots of prices and quantities. They exhibit annual, weekly, and daily seasonal components. The biggest volume of trades of each day is registered during the high-demand period from 9 a.m. to 5 p.m. Day-ahead price for the hottest, medium, and low temperature days and corresponding DAP during those day.

6 Proposed Dynamic Price Method

The hardware design is integrated with a machine learning algorithm to achieve dynamic price response. Collectively considers both interests from the electricity supplier side and the customer side shown fig 4. The integrated computational experiment system consists of three parts: 1) home energy consumption simulation, 2) dynamic electricity price, and 3) demand response methods. The integrated system starts with a specification of home appliance usage strategy, which includes thermostat setting of HVAC units and when to use dishwasher, dryer, electric stove, etc. Then, energy consumption of a residential house is simulated for a practical weather pattern during a year or a day, including temperature, humidity, solar radiation, etc., at a location [9]. The results generated by the home energy simulator are loaded in to a MATLAB-based energy cost computation subsystem, based on which a new DR policy is generated. The updated DR policy is loaded into the home energy simulator and the process is repeated until an acceptable policy is reached. Fig 5 shows the flowchart of the computational experiment system.

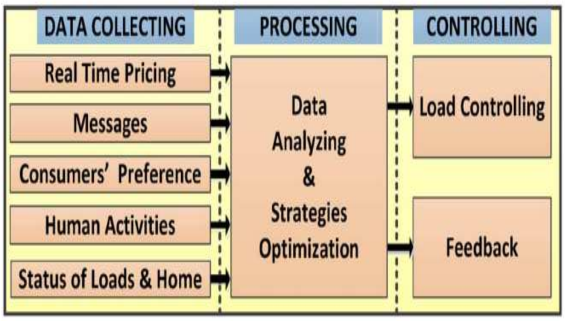

Fig. 4. Block diagram for dynamic price method

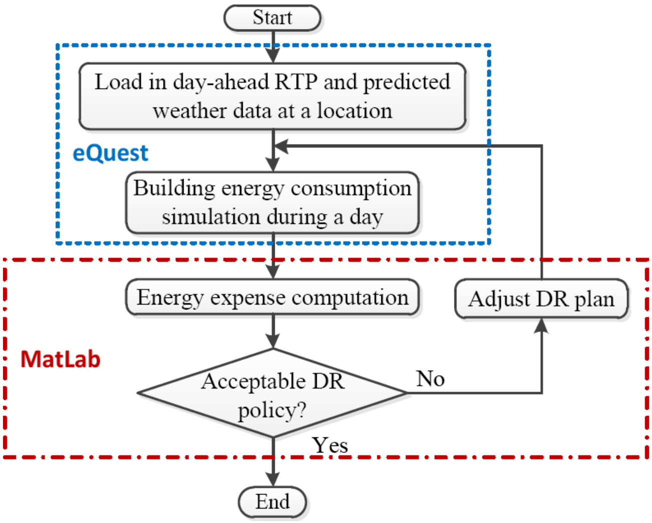

Fig. 5. Flow chart of integrative computational experiment system

6.1 PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle Swarm Optimization (PSO) is an intelligence optimization theory was developed by Eberhart and Kennedy in 1995. The principle of this algorithm was inspired from the aging behavior of birds and fish schooling, and the two scholars were applied this phenomenon to overcome the problems associated with search and optimization. In this algorithm, several cooperative birds are used, and each bird, referred to as a particle, each particle hovering in the space has its own suitability value that mapped by an objective function and velocity movement. Each particle exchanges information obtained in its respective search process [10]. The typical process of optimization the particles are of a PSO particle. The movement of particles impact by two variables; the Pbest that used to store the best position of each particle as an individual best position, and the Gbest that found by comparing individual positions of the particle group and stock it as finest position of the swarm. The particle swarm uses this process to move towards the best position and continuously it revise its direction and velocity, by this way, each particle quickly converge to an optimal or close to a global optimum.

The standard PSO method can be defined by the following equations;

$$v_i(k+1) = w\, v_i(k) + c_1 r_1.(p_{best} - x_i(k)) + c_2 r_2.(g_{best} - x_i(k) \qquad (3)$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \qquad (4)$$

$$i = 1, 2\ldots, N$$

Where *xi* and *vi* are the velocity and position of particle *i*, ;*k* represents the iteration number; *w* is the inertia weight; *r*1, *r*2 are random variables and their values are uniformly distributed between [0,1]; *c*1*, c*2 represents the cognitive and social coefficient respectively. *p*best*, I* is the individual best position of particle *i*, and *g*best is the swarm best position of all the particles.

$$p_{best} i = x_i\, k$$

$$f(x_i\, k) > f\,(p_{best} i) \qquad (5)$$

Where, *f represents* the objective function that should be maximized.

6.2 BASIC PRINCIPLE OF PSO

The basic functioning code of this method can be explained as follows;

Step 1. (PSO Initialization): Particles are usually initialized randomly following a uniform distribution over the search space, are prepared on grid nodules that shelter the search space with equidistant points. Initial velocities are taken randomly.
Step 2. (Fitness Evaluation): Evaluate the fitness value of each particle. Fitness evaluation is conducted by supplying the candidate solution to the objective function.

Step 3.(Update Individual and Global Best Data):Individual and global best fitness values (pbest,i and gbest) and positions are updated by comparing the newly calculated fitness values against the previous ones, and replacing the pbest, i and gbest as well as their corresponding positions as necessary.
Step 4. (Update Velocity and Position of Each Particle): The velocity and position of each particle in the swarm is updated.
Step 5. (Convergence Determination): Check the convergence standard. If the convergence standard is encountered, the process can be ended; else, the repetition number will increase by 1 and go to step 2.

6.3 TOPOLOGY OF PSO

The inclusion of the local ring topology as part of a standard algorithm for particle swarm optimization comes with a warning, however. Given the sluggish junction of the best1 model, more function evaluations are required for the improved performance. This is especially important on unimodal utilities, where the fast junction of the gbest model combined with single minima in the feasible search space results in quicker performance than that of the l best swarm with its limited communication.

6.4 PSO ALGORITHM

1: Initialize particle position: $T_{buf}(m)\in[t\ min,Tmax]$

2: Initialize particle speed: $T_{buf}(m)\in[-\Delta t, \Delta T]$,m=1…,m

3: {Calculate initial fitness values for rallparicles} fitness (m)=f (T_{buf}(m),m=1….M

4: T^G←T(k);if fitness(k)=max{fitness(m),m€[1,M]}T^(m)←T(m);

5: do

6:{Update velocity for all particles}T(m)=Tuff(m)+c1.rand(0,1)[T(m)-buf(M)]+C2.RANDO(0,1)[TG-T BUF(m)]

7: Update position for all particles} T(m)=T_{bu}f(m)+T(m)

8: if T (m) out of boundary→ boundary handling T(m)

9: {Calculate fitness values for rallparicles} fitness (m)=f(T(m),m=1,…..M

10:TG←T(k);iffitness(k)=max{fitness(m),m€[1,M]} T(m)←T(m);ifT(m)>T_{buf}(m)

11: T_{buf}(m)←T(m);T_{buf}(m)←T(m)

12: While maximum iteration or a stop is not reached

13: Output global optimal solution T^G

7 RESULTS & DISCUSSIONS

Electric utility companies typically use hourly real-time price (RTP) or day-ahead price (DAP) structure in their dynamic pricing programs. In North America, Ameren Focused Energy, serving about 2.4 million electric customers in Illinois and Missouri, has very detailed RTP and DAP tariffs posted on their website since June 1, 2008 for both day-ahead and real-time markets. The day-ahead market produces financially binding schedules for the production and consumption of electricity one day before the working day. The real-time market resolves any alterations between the amounts of energy scheduled day-ahead and the real-time load, market member reoffers, hourly self-programs, self-curtailments and any changes in general, real-time system conditions. Fig 6 demonstrates Ameren's RTP and DAP in summer 2011 for its residential customers as well as temperature associated with those days that the RTP or DAP prices occurred. The figure shows that: 1) a high price rate may occur at a moderate temperature day [figs. 7 and 8], 2) the electricity price of an extremely hot day does not mean a high electricity price day [figs. 9 and 10], and 3) real-time price fluctuates more than the day-ahead price.

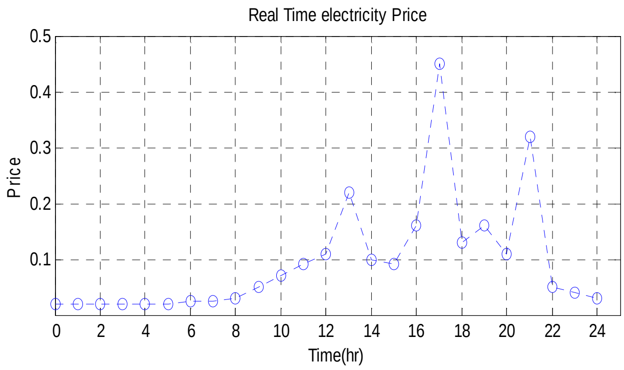

Fig. 6. Highest RTP Tariff in a summer day

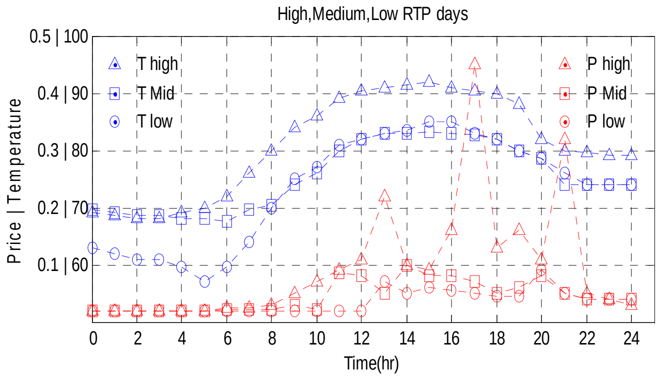

Fig. 7. High, Medium & Low RTP and their corresponding temperatures

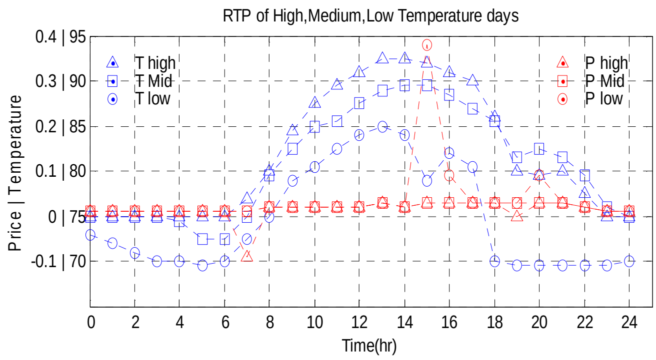

Fig. 8. High, Medium, and Low temperature days and Corresponding RTP during those days

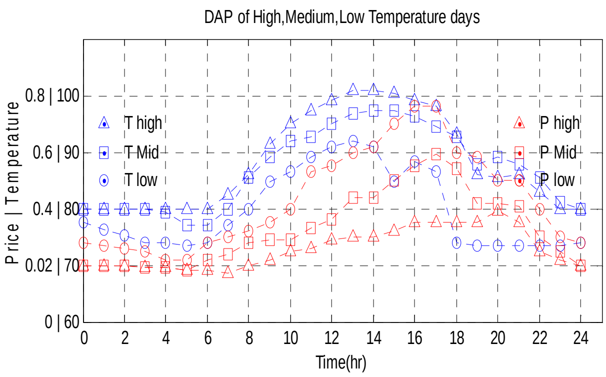

Fig. 9. Day-Ahead Price for High, Medium, and Low days and corresponding temperature

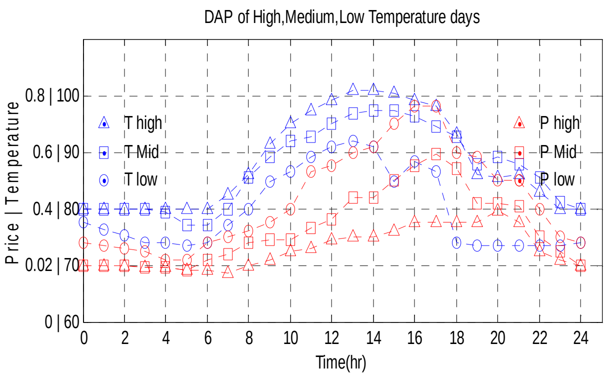

Fig. 10. Day-Ahead Price for High, Medium, and Low days and corresponding DAP during these days

The Proposed Dynamic Electricity Price method is simulated by using MATLAB. In this method, end-use customer is exposed to time-varying (dynamic) rates and does not receive and explicit payment as compensation for curtailing loads. DR clearly reduces the energy consumption of the HVAC during peak hours using either RTP or DAP tariff structure. In terms of cost saving, DR is more effective for RTP binding loads than DAP binding loads. In terms of total cost, DAP is more economical but requires load binding one day before actual use of energy. Thus, a customer may need to take the risk of financial loss if the actual load level is lower or higher than the day-ahead binding load level fig 11&12.

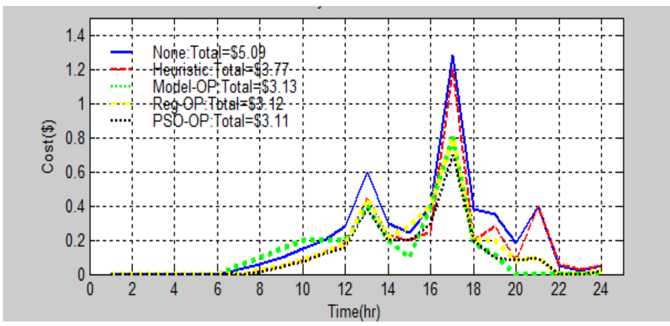

Fig. 11. Hourly and cost based output for RTP

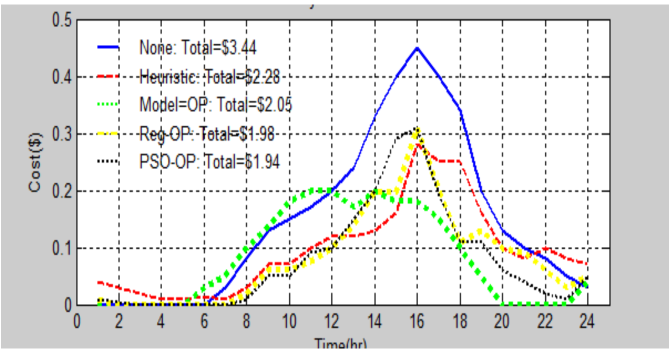

Fig. 12. Hourly and cost based output for DAP

For all the four algorithms, DR clearly reduces the energy consumption of the HVAC during peak hours using either RTP or DAP tariff structure. For DAP tariff structure, HVAC energy consumption could still be high during actual utility peak hours because DAP tariff may be inconsistent with the real-time load demand. For the heuristic algorithm, a "nine-point" thermostat setting at 71 , 72 , 73 , 74 , 75 , 76 ,77 , 78 , and 79 is used, in which 71 and 79 are the thermostat settings corresponds to PR ^{min} and PR ^{max} during a day respectively.

8 CONCLUSION

This work presents a computational experiment approach to develop and investigate demand response strategies for a typical residential house. In price-responsive DR, an end-use customer is exposed to time-varying dynamic) rates and does not receive an explicit payment as compensation for curtailing load. However, it is also found that the real-time market could be cheaper than the day-ahead market for a number of days. For all the four DR algorithms, the demand response clearly reduces HVAC energy consumption during the peak hours using RTP or DAP tariff structure. In general, optimization-based DR algorithms are more efficient than the heuristic DR algorithm. However, demand response based on Model-OP, Reg-OP, and PSO-OP requires detailed price information of a day, which is usually not available for RTP tariff structure, giving the heuristic algorithm an advantage in this perspective. This method has an efficiency of 88%. Residential demand forecast can thus be a future work scope required for demand response implementation.

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