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REAL TIME ENERGY MANAGEMENT IN SMART GRID

by

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(IN)

SUMMARY

The issue of sustainability and eco-friendliness at smart grid causes a challenge to match demand with supply at different levels. We need to improve the existing power grid infrastructure by utilizing intelligent grid-state-aware optimal generation, distribution, and loads. We model the smart grid energy management as a feedback system and analysis of its dynamics from stability, efficiency and user comfort viewpoints. In this paper, we discuss the modelling methodologies to handle large scale power grid problems, solution methods for such large problems and interpretation of these solutions to estimate benefits. Modelling of energy management as the price-setting demand-response mechanism is discussed.

Since even a 1000-customer problem each having 10 appliances with hourly varying time slots and 10 supply side options results in a mixed integer linear program (MILP) with millions of variables, the grid wide optimization is computationally intractable, and convexification techniques and heuristics have to be used.

The model to be presented is an extension of standard MILP formulations, to incorporate aggregation for computational tractability, and extensions to handle constraints such as user comfort, emission limits, and appliance level constraints. The Comfort criterion limits the maximum waiting time to service customer requests. The emission constraint limits the total generation, and possibly its split into categories/locations. A novel feature of our work is modelling of the appliance at a detailed level (major electrical characteristics; power flow, response times, DR variables) and mutual inclusion and exclusion of appliances as constraints and complex inter dependent appliance constraints.

A major feature of this model is the incorporation of *uncertainty*, in an intuitive fashion, using substitutive, complementary and general constraints. The model used is an extension of robust optimization, incorporating information of theoretic concepts to estimate the number of future scenarios covered by the optimization.

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Convexification is used to make the problems tractable, with targeted near real-time response. The convexified model is solved by nested simulation and optimization using Cplex both at consumer and utility levels. Run time of the solution is few seconds at consumer level and few minutes at utility level.

A practical implementation is carried out by connecting the legacy appliance infrastructure with controllable plug load sensors to participate in smart grid activities. We observed benefits of up to 40% of energy saving during the implementation at a campus level network. The result suggests that the model is to create mutual benefit among the consumer and the utility companies with a flat demand curve during a day and the automation of the energy management.

KEYWORDS

Smart energy management, smart plugs, demand response, energy conservation, smart meters, real time analysis of power grid

1. INTRODUCTION:

The issue of sustainability and eco-friendliness at smart grid causes a challenge to match demand with supply at different levels. Even though energy management problem is not new, the concepts of smart grid make it more challenging. Smart grid is a framework for combining the electrical power infrastructure with modern digital communication networks and information technology. Two way communication, customer participation, renewable energies and storage are important features of the smart grid [1]. The smart meter connects the consumer at home or building and utility company as an interface.

The operation of utility and consumers is usually separated. However, we insist that there is possible solution to financial and social advantages for both if they operate together. Energy and demand side management are some of the programs for their interaction. The energy management refers to the process of monitoring real time energy data, controlling the operation of appliances, and conserving energy in a building or city. It is important to consider the operation time and appliance type for energy management, because of the category specific dynamic real pricing (RTP), introduced by utilities. The smart grid requires an important role of consumer in order to achieve energy efficiency and demand response activities. The simulation is conducted based on the assumption of two way communications which is one of the smart grid features and installed smart meter for energy measurement. The response from consumer after solving the optimization model transfers to the utility company as a feedback.

2. RELATED WORK AND CONTRIBUTIONS:

The development of wireless sensor networks, smart appliances and meters causes new optimization problem as it allows monitoring and controlling to the fine grain level (till the appliance level). The energy and demand side management programs are able to be beneficial for both utilities and consumers by interactive and automation. A real time demand response model proposed by authors in [2] minimizes energy bill of the consumer or maximize consumer utility but they considered only one consumer case with simple utility function. Authors in [3] targeted to minimize both energy bill and waiting times with optimal residential power consumption scheduling framework but they have not considered inter appliance constraints.

Even though earlier work in [2, 3, 4] represents few aspects of energy management models, this is the first time to the best of our knowledge to take into account for feedback of consumer in real time, in order to set the price coordinating to DR. The previous models lack the scale of problem and different consumer types.

2.1 Contributions in the paper:

The key contributions in our paper include:

- Modeling of smart energy management system (as shown fig 1) including price uncertainty and analyzes on the dynamics with the stable, efficient, and user-friendly perspectives.
- Detailed level modeling of appliances, containing complex inter dependent appliance constraints.
- Simulation, implementation and analysis of the model, and the results to measure the mutual advantages of consumers and utility companies.

3. SYSTEM MODEL & ARCHITECTURE:

3.1 Optimization Model:

The system model includes the characteristics of electric appliances, consumers and utility. Several features such as the comfort, demand, appliance constraints and participation to DR program affects the bill of consumer. Our goal is to minimize this energy bill of consumer and to maximize utility company's profit. Maximum waiting time to respond to a consumer is restrained by comfort criterion. This is a new development that we include the appliances at a detailed level and those mutual inclusion and exclusion as constraints. The price uncertainty is considered in this model. So, the computation of energy bill/profit is divided into two parts – actual bill till the present time slot and estimated bill based on predicted price and demand for future time slots.

The detailed mathematical model with objective, constraints are as follows:

Objective function: Minimize energy bill: (number of units * price of unit at time t) + (predicted number of units * price predicted at time t)

$$Minimize \sum_t e^t * (\pi_{c,ac}^t) + \sum_t \tilde{e}^t * \tilde{\pi}_{c,ac}^t \qquad (1)$$

Maximize Profit: Revenue (demand *price charged) - Operating cost

$$Maximize(R^t - OC^t) = (\sum_{i=1}^{N} \sum_t d_i^t \pi_{c,ac}^t + \sum_{i=1}^{N} \sum_t \tilde{d}_i^t \tilde{\pi}_{c,ac}^t) - \sum_{j=1}^{M} \sum_t s_j^t c^t \qquad (2)$$

TABLE I

GLIMPSE OF CONSTRAINT SETS IN MODELING

x_a^t -Scheduling vector for timeslot 't' and appliance 'a' w - Waiting cost parameter ; C- segment of consumers (C1, C2, C3) N = Total number of consumers (Integer) M = Total number of generation options (Storage, renewable) (Integer) P – power quantity (kW) ; E – total energy quantity (kWh) π – price; d – demand; e- energy ; Max/Min – Max/Min limits; lim – limit; ac- appliance category;	
$\sum_a \sum_{t=1}^{T} w_a^t * x_a^t \le w_a^{\lim}$ $w_a^{st_a} \le \ldots \le w_a^{et_a} \; \forall a \in A$ $w_a^t \ge 0; [st_a, et_a]$ (3)	*Comfort constraints:* cost of waiting with maximum waiting time; A – Set of appliances t – timeslot of the day; T-total time slots Start time and end time of the job
$price = \pi_{c,ac}^t$ (4)	Real time pricing with predication for category 'c' and appliance category 'ac' with regulatory conditions
$[\sum_{q=1}^{m} z_q \mid (1 - z_q)] - m \ge -BM * y_r$ $\sum_{r=1}^{n} y_r = n - 1$ $y_r \in \{0,1\}$ (5)	*Inter appliance constraints*: BM – Large number y – binary constraints n- number of product terms in SoP form m-num of Boolean var in terms
$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a$ $\forall a \in A, \mu_a^{\min} \le x_a^h \le \mu_a^{\max}$ (6)	*Demand constraints*: Demand to be met per appliance Appliance power limits
$\left[\overline{\pi_{c,ac}^t} - \hat{\pi}_{c,ac}^t, \overline{\pi_{c,ac}^t} + \hat{\pi}_{c,ac}^t \right]$ (7) $\sum \frac{\lvert \pi_{c,ac}^t - \bar{\pi}_{c,ac}^t \rvert}{\hat{\pi}_{c,ac}^t} \le \Gamma$ $Min(\phi\Gamma + \sum \delta_{c,ac}^t)$ $s.t. \phi + \delta_{c,ac}^t \ge \overline{\pi_{c,ac}^t}.e^t$ $\phi \ge 0; \delta_{c,ac}^t \ge 0$	Uncertainty min-max constraints with bounds Γ- *Robustness parameter* *applying strong duality* *dual variables* $\phi, \delta_{c,ac}^t$

Equation (5) illustrates the general constraint specification method defined by consumer for multiple appliances for validity or invalidity in our model. For example, when Appliance A runs, Appliance B cannot work; Appliance types C and D always operate together etc… which can be represented in a truth table form. Equation (6) represents the demand constraints and equation (7) represents uncertainty formulation using robust optimization. Convex polyhedral uncertainty sets are used to specify many kinds of future uncertainties. These are linear constraints that model microeconomic behaviour such as aggregate, substitutive and complementary behaviour for energy demand of appliances.

Some examples of substitutive constraints are:
dem_a0 + dem_a1 + dem_a2 <= 50
dem_a0 + dem_a1 + dem_a2 >= 10

Complementary constraints are:
dem_a0 - dem_a2 <= 15
dem_a0 - dem_a2 >= 2
where dem_ax are uncertain demand variables.

This is more general formulation of Berstimas model [11]. In special cases without break points and liner objective function, it allows to use strong duality and the min-max problem can reduce to linear programming (LP) and results in improvement of solution time.

3.2 System Architecture:

Smart energy management system architecture is depicted in fig-1. Utility can serve 1000's of buildings. Utility has a smart energy manager and each building can have a smart energy managers. The smart meter at any building acts as an interface between the smart energy managers at building and utility. The smart plugs, smart appliances in the building can participate in the real time energy management.

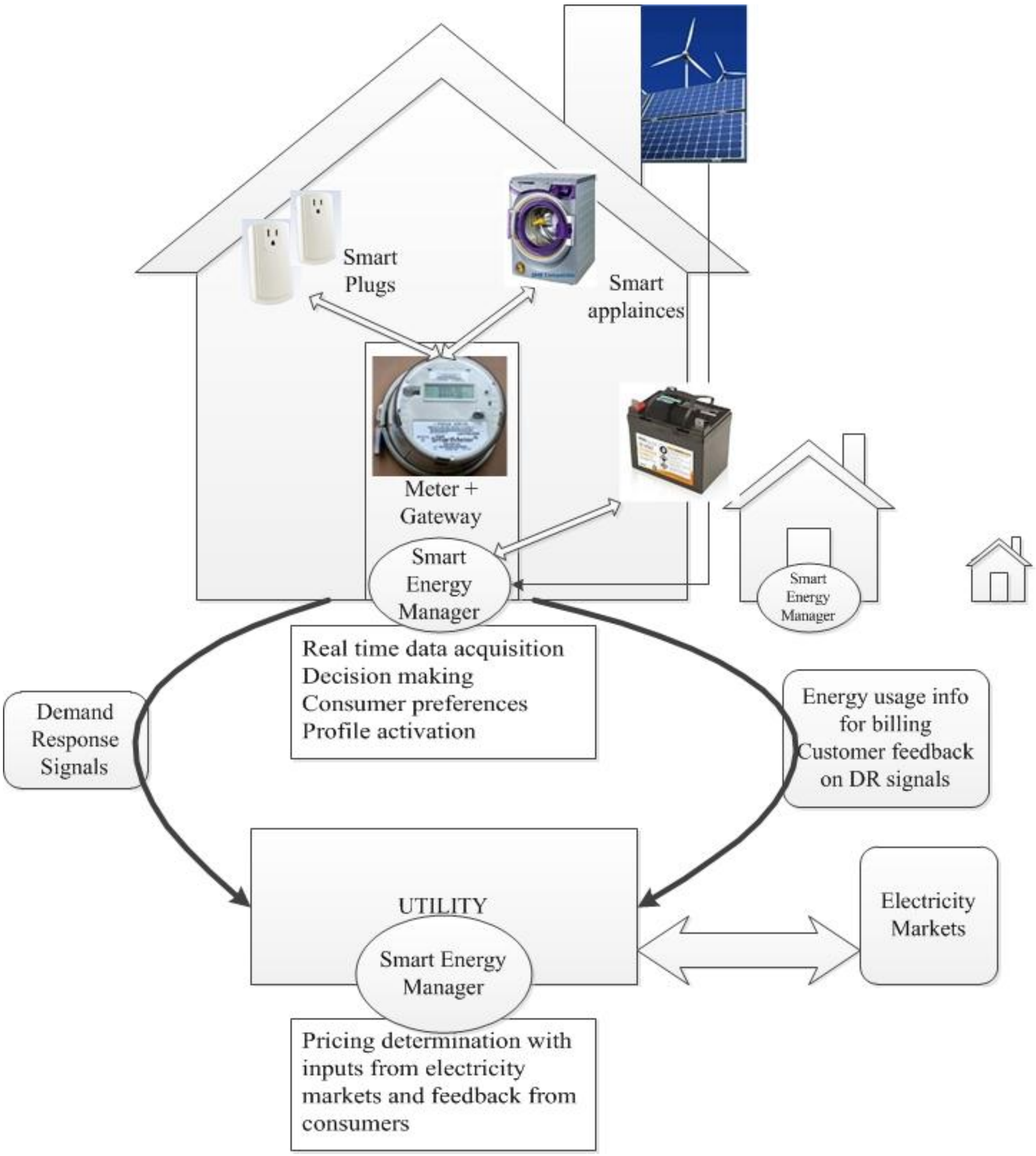

Fig 1: Architecture of Smart Energy Management

The smart meters and smart plugs measure the real time energy consumption and this energy usage information can be sent to utility for load management and billing activities. The real time energy management at any building includes the optimization of energy bill subject to specified constraints and consumer preferences and real time pricing. The optimal operation of appliances, which allows the energy comfort trade off, is resulted by solving the optimization model.

Each consumer operates a number of appliances. This model is tractable even by scaling the numerous generators which serve number of homes/buildings suitable for area/city wise distribution system. The optimization is a MILP, when the metric is linear. The MILP has a great number of variables in the model based on the number of buildings served by the utility company.

Utility can set the price using smart energy management system by considering the real time information sent from the consumers and other parameters from energy markets. Based on this information, utility can send demand response signals to individual consumers and smart energy manager at buildings automatically calculates the load reduction possible based on consumer preferences and specified constraints. This operates in nested simulation model.

4. IMPLEMENTATION & RESULTS:

We convexified the optimization model with objective function and constraints (Table 1). Nested simulation is used to achieve the objective of the optimal operational schedule of energy management. The efficient solution is possible by powerful solvers such as Cplex [5]. So, the model is implemented initially using Cplex and later practically in an enterprise building using smart plugs.

4.1 Cplex implementation:

Basic parameters considered for the implementation are from the reference [2]. We extended further with 1000's of time slots and different cases are considered in running our model using Cplex solver.

- Performance of the solution with u*niform pricing:*

  This was run with 86400 variables, uncertainty of 10000 and 4000 timeslots. At timeslot=1, it took 40000 iterations to solve the model. Then it was run for subsequent time slots. Result of energy consumption is equal to maximum demand value (0.00083) in every time slot. No bias is observed to any of the timeslot due to uniform pricing. So, the demand is fulfilled within the requested timeslot itself. It may push some demand to neighboring timeslot because of maximum hourly limits. Pricing does not have an impact on energy consumption.

- Price is *uniform for some time* with in hour but vary across hours:
  The model was run with 86400 variables with uncertainty 10000 and timeslot=1. Result of energy consumption is varying over 24 hours between 0 to maximum demand (0.00083) in every time slot. But within an hour it has not changed because of equal pricing within an hour. No bias is observed to any of the timeslot within the hour.

- Price variations with *continuous oscillation* consecutively in the neighboring timeslots:
  In this case, price goes up and immediately goes down and then goes up as a continuous oscillation in the consecutive timeslots. Even energy consumption scheduling is also oscillating within the 0 to maximum demand. This was run for 8640 timeslots with uncertainty of 5000 and timeslot=1.

- *Zero uncertainty* in pricing case:
  The robustness parameter (Γ) can be varied. Result of energy consumption is equal to maximum demand value (0.0083) in every time slot. No bias is observed to any of the timeslot. So, the demand is fulfilled within the requested timeslot itself. Pricing does not have an impact on energy consumption as it is a Zero uncertainty case. This was run for 8640 timeslots with uncertainty of 5000 and timeslot=1.

- *100% uncertainty* in pricing case:
  The robustness parameter (Γ) is varied to achieve this case. Result of energy consumption is equal to either 0 or maximum demand value (0.0083) in every time slot. It is observed that the demand is fulfilled in the timeslots with lower price. This was run for 8640 timeslots with uncertainty of 5000 and timeslot=1.

  In last two scenarios, both the cases of oscillating prices and uniform price within hour cases are tested and the same result was observed as earlier.

- *Effect of vary ramp up, down limits:*
  The shifting of demand in consecutive hours is observed. More chance for optimization in the system is observed if higher the limits of allowable ramp/up down. This was run for 8640 timeslots with uncertainty of 5000 and timeslot=1.

In summary from the experiments, we observed the *stability* of the system with *uniform pricing* and *continuous oscillation* consecutively in the neighboring timeslots. In the first case, pricing did not effect on energy consumption and in second case the energy consumption scheduling was oscillating within the 0 to maximum demand. The *sensitivity* of the solution was identified within reliable range and confirms it to be a stable solution when test performed with variation of few parameters including price, demand ramp up and down limits. The analysis demonstrates that our model is proper for real-time implementation. Response time was ranging from few seconds to minutes, which are dependent on the operation of energy management at a building or utility level.

4.2 Practical Implementation:

Sensors such as smart plugs were used at an *initial practical implementation*. The optimization module gave the operational schedule and it was implemented (switch on/off) with the smart plugs. Zigbee smart energy based [10] smart plugs was used for communicating the energy by reading at regular intervals to a wireless gateway (sensing) and by receiving controls from the gateway for automatic control of the attached appliances (actuation). The system was installed in an enterprise building as shown in fig 2. The type of smart plugs used varies based on the type of appliance (15amp / 30amp). In our case, gateway sent the data to the server and smart energy manager is implemented in that server.

The gateway can communicate the sensing information to a server via local area network or to a cloud server using GPRS/3G technologies. To implement similar solution in residential case, the gateway can communicate to a server in the cloud. The smart energy manager can be implemented in a server or in cloud based on the suitability and type of consumer.

Fig 2: Practical implementation with smart plugs

The pattern of energy consumption for various appliances (water heater, water cooler, printer and coffee machine in an enterprise) is shown in fig 3. The pattern observed for several months. The energy management for plug loads resulted in an energy conservation by up to 40%. Automatically turning off the appliances and adjusting the load during peak hours suggested by the optimization module saved the energy consumption. The system enabled to flatten the demand curve over a day with the reduction of the peak load. Please note that we have considered real time pricing with uncertainty in this module. Few more case studies are described and analysed in our earlier work published in [6, 7, 8, 9].

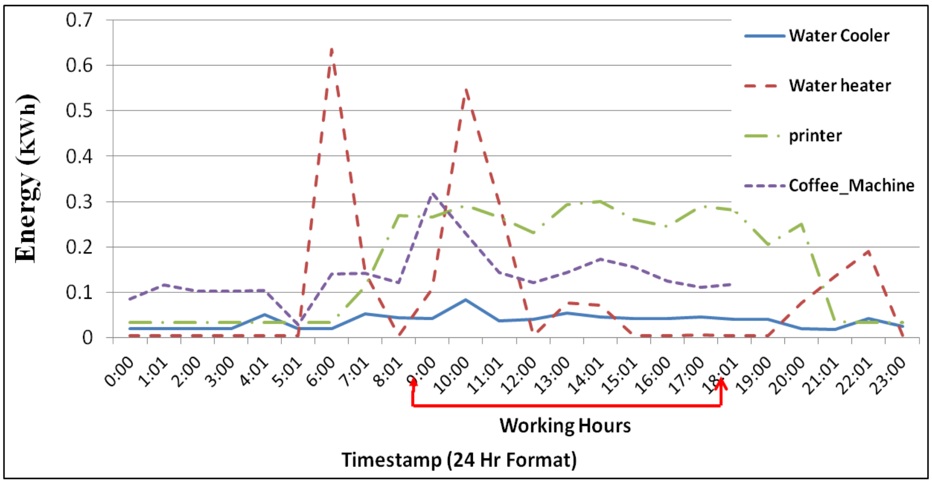

Fig 3: Consumption patterns of break room appliances

5. CONCLUSION:

Modelling of the energy management as a price-setting demand-response mechanism is discussed. Initial results indicate that our model is practical and scalable to an area wide smart grid. This model is giving mutual benefit among the consumers and the utility companies with a flat demand curve during a day and the automation of the energy management. In future, we further develop this model to add renewable energies and continue large scale simulations.

BIBLIOGRAPHY

[1] “The Smart Grid: An Introduction”, U.S. Department of Energy, 2010. Online: www.energy.gov
[2] Conejo, A.J.; Morales, J.M.; Baringo, L, “Real Time Demand Response Model”, IEEE Trans on Smart Grid, Vol 1 no.3, pp: 236-242, Dec 2010
[3] M. Pedrasa, T. Spooner, and I. MacGill, “Coordinated Scheduling of. Residential Distributed Energy Resources to Optimize Smart Home Energy Services”, IEEE Transactions on Smart Grid, Vol 1, Sep 2010
[4] Mohsenian-Rad A.H, Leon-Garcia.A, “Optimal Residential Load Control with Price Prediction in Real-Time Electricity Pricing Environments”, IEEE Transactions on Smart Grid, Vol 1 no.2, pp: 120-133, Sep 2010
[5] IBM ILOG CPLEX [Online].
Available: http://www-01.ibm.com/software/in/integration/optimization/cplex/
[6] Sunil Kumar Vuppala, Kumar Padmanabh, Sumit Bose, Sanjoy Paul, "Incorporating Fairness within Demand Response Programs in Smart Grid", 2nd IEEE international conference on Innovative Smart Grid Technologies (ISGT 2011), Anaheim, California, USA, Jan 17-19, 2011
[7] Sunil K. Vuppala, GNS Prasanna, "Optimal Operational Schedule of Appliances with Energy Comfort Trade off in Smart Grid", International Conference on Operations Research for Sustainable Development in Globalized Environment, The 44th Annual Convention of Operational Research Society of India, Kolkata, January 6-8, 2012
[8] Abhilasha Aswal, Sunil Kumar Vuppala, G N Srinivasa Prasanna,"Smart Grid: Optimization Methods for Demand Response Systems", INFORMS 2011 Annual Meeting, Charlotte, NC, USA, Nov 13-16, 2011.
[9] Sunil Kumar Vuppala, GNS Prasanna, “Closed Loop Feedback System for Demand Response in Smart Grid", International conference on Emerging Automation and Information Technologies for power Industry Growth (PAC2013), CPRI, Bangalore, Apr 19-20, 2013
[10] Zigbee Smart Energy overview. Available online: http://www.zigbee.org/Standards/ZigBeeSmartEnergy/Overview.aspx
[11] Bertsimas, D., Sim, M. “The price of robustness”, Operations Research 2004; 52(1); pg:35-53