Consumer Energy Management System: Contract Optimization using Forecasted Demand

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***Abstract*—Smart grid initiative is gaining traction around the world, enabling more complexity in the utility contracts designed to revolutionize our society towards more energy efficient and effective. Consumer energy management system (EMS) is important in assisting how consumers participate in the smart grid with the increasing complexity of utility contracts. A web-based EMS was presented in this paper with two novel design features: i) a maximum demand load forecasting ii) maximum contracted demand (MCD) contract optimization. A maximum demand load forecasting based on space-specific regression models of simple latent variables, temperature, number of workdays and employees, was proposed. These regression models were accurate with a mean average percentage error of 4∼8% and robust to different space size of similar nature. The use of simple latent variables enables consumers to input parameters easily through the proposed EMS web-based interface. The Particle Swarm Optimization (PSO) algorithm is especially suitable in dealing with utility contract's interdependent and discontinuous structure. A MCD contract optimization based on the PSO algorithm was then proposed and showed significant savings in the studied cases of 10∼30% improvement over the current MCD contracts and a 5∼12.5% improvement over using the average maximum demand load. The results showed promising potential of the two proposed features in future consumer EMS.**

Keywords-Energy Management System, Load Forecasting, Contract Optimization, Particle Swarm Optimization.

I. Introduction

The world is gradually marching towards a severe energy crisis, what with an ever-increasing demand of energy overstepping its supply. The total installed electricity generating capacity of a system is typically 20 to 30% greater than the predicted peak load in order to provide reserves for maintenance and contingencies [1]. This surplus capacity can be used to pump and store water in elevated reservoirs to be released through hydraulic turbine generators during peak periods. There is loss with any mechanical systems' transfer of energy, so the ideal case is to facilitate the equilibrium in consumption and generations via economical approaches rather than pure physical/mechanical approaches, i.e., effectiveness vs efficiency. Information communication technology (ICT) plays a necessity in the realization of many different programs that aid more effective use of energy [2], [3], e.g., demand response, time of use, peak leveling, etc.

Most industrial and commercial electricity consumers sign a maximum contracted demand (MCD) contract with the electric utilities company, Taiwan Power Company (TPC), in Taiwan. A MCD contract is an agreement between the consumers and the utilities on the maximum demand load that the consumer plans to use for a given time period, if the consumers use more than the agreement load, they are charged a high penalty. The detail of such a contract is described in Section IV and [4]. This type of contract is advantageous in two ways: i) Knowledge of these MCD contracts allow the utilities a better estimate on demand, therefore the utilities can plan more effective electricity generation and transmission infrastructure. ii) The consumers reduce their electricity cost if they use their electricity more effectively under the agreed maximum demand load while not necessarily decreasing their overall electricity consumption, i.e., equivalent production.

Energy management systems (EMS) [1] play a important role for the consumer to manage either energy consumption or cost. An EMS should give recommendations or control energy consumption given the data it collects via sensors, interface or the internet. In this paper, an EMS is proposed with two main contributions: i) an accurate, robust maximum load forecasting and ii) a flexible and scalable MDC contract optimization feature. The proposed EMS has other features such as appliance monitoring, short term load forecasting. These features are out of the scope of this paper, due the length limitation.

This paper is structured as follows: Section II discusses the background, and the implementation for the proposed EMS. In Section III, a proposed maximum demand load forecasting module is formulated and discussed. The output of the forecasted value is then used as a input to the optimization module. Section IV discusses the methodol-

[1]In this paper, the term EMS is referring to consumer side energy management and not utility side EMS. This term is also used as home energy management system (HEMS) or building energy management system (BEMS).

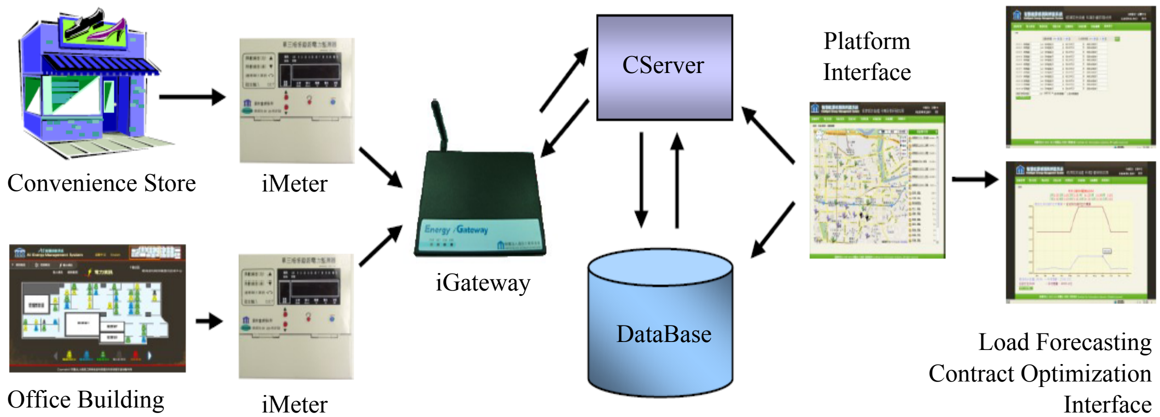

Figure 1: Overview of the proposed energy management system in this paper.

ogy, implementation and experimental analysis for a MCD contract optimization using the particle swarm optimization method. Section V concludes the paper.

II. Web-based Energy Management System

There has been an increase in interest in the research of EMS. An EMS is applied to many different applications, e.g., residential [5], [6], commercial [7], [8] or industrial [9]. An EMS may have one or more of the following features [10]:

- **Data Collection**: to collect real-time interval data from interval meters, sensors, directly from utilities, or other sources from the internet.
- **Reporting and Monitoring**: to automate energy and emissions auditing, to track and display real-time and historical data, includes various benchmarking tools, seeing exactly when and how energy is used, combined with anomaly recognition that can identify savings opportunities.
- **Engagement**: to connect consumers' daily choices with energy consumption, that can be used to offer advice to the occupants, or provide a forum for feedback on sustainability initiatives.

The proposed EMS in this paper presents consumers a way to optimize their MCD contract. System implementation is shown in Fig. 1 and described briefly in the following:

- **Deployment**: The EMS is deployed in 6 convenient stores, a 5000 m^2 office, a 500 m^2 office and 1 university lab. A total of nine spaces.
- **iMeter**: Meters that can measure 4 three-phase power or 12 single-phase power, and the data can transfered via RS-485 ModBus or Zigbee 1.0.
- **iGateway**: A gateway that converts the protocol stack of the iMeter to that of the server and database.
- **Server & DataBase**: Each running on an ASUS RS300-E6 Series servers featuring the Intel 3420 PCH chipset, Intel Xeon 3400 Series Processors, and 4GB memory.
- **Interface**: Web-based user interface. Initial page uses googlemap API to mark each of the deployment locations. Input interface for historical data for forecasting and contractual parameters for optimization.

The EMS features, maximum demand load forecasting and MCD contract optimization presented are shown in the following sections.

III. Maximum Demand load Forecasting

Accurate models for maximum demand load forecasting are essential to MCD contract optimization. Load forecasts can be divided into three categories: short-term forecasts, which are usually from one hour to one week, medium term forecasts, which are usually from a week to a year, and long-term forecasts, which are longer than a year [11]. The problem definition in this paper is more suited using medium term forecasting. Load forecasting methods can be divide into [12]: i) Causal and econometric forecasting methods, identifying the underlying factors that might influence the variable, which is being forecast. ii) Time-series methods that uses historical data as the basis of estimating future outcomes. iii) Artificial intelligence methods such as artificial neural networks, support vector machines, etc.

A. Implementation

Due to the MCD contract structure, the maximum demand load is needed for MCD contract optimization and was forecasted in this paper as an example. For other types of contract optimization, different type of demand can be forecasted using similar method. A causal forecasting method is chosen for this implementation. The proposed maximum demand load model was formulated as follows:

$$D_i = \alpha K_i + \beta L_i + \gamma M_i + \epsilon \qquad (1)$$

where the following variables are defined:

- D_i **maximum load**: The maximum demand load in a non-overlapping 15 minute period starting on the hour. The maximum load can be collected from past bills or utility database.
- K_i **temperature**: Apart from time factors, weather conditions are the most influential variables. Temperature is the most important weather factor with humidity second [13]. The historic or forecasted temperature data can be collected from the Central Weather Bureau database.
- L_i **workdays**: The number of workdays can affect a commercial site of their demand and can be provided by the consumer.
- M_i **employees**: The number of employees can affect the demand, i.e., more employees more demand, and can be provided by the consumer.
- α**,** β**,** γ: the regression coefficient for average monthly temperature, number of workdays in a month and numbers of employees respectively.
- ϵ: a constant.

The regression coefficients and constant can be estimated using historical data. The maximum demand, D_i can then be forecasted from latent variables, P_i, L_i and M_i. Pre-configured global and space-specific maximum demand load models were estimate by the EMS and are suitable for any similar type of commercial space and can be used by the consumer. Specific site training is then optional for the consumer, therefore making easier to use for the consumers. Although model coefficients may be needed to be re-estimated specifically for different types type, i.e., convenient stores with the use of fridge and freezers should have a different model than an office that composes of mainly PCs or an industrial space with heavy machinery.

B. Analysis

Both the global and space-specific regression models were tested for their accuracy and robustness. The accuracy (monthly error over one year) is tested with Mean Absolute Percentage Error (MAPE) defined as:

$$\text{MAPE} = \frac{\sum_{i=1}^{12} |(\hat{E}_i - E_i)/E_i|}{12}. \tag{2}$$

The robustness was tested with a *leave one out* method, where the partitioning of the estimation data and forecasting data can be seen in Table I. Table I also includes the MAPE of forecasting of the three models. It can be seen that a global regression model performs poorly in forecasting with a MAPE=55%, while space-specific models for office and convenient stores have a MAPE of 4% and 8% respectively.

A closer look of the forecasted maximum demand load of for both the global and the space-specific regression models can be seen in Fig. 2(a) and (b) for an office and a convenient store respectively. It can be seen that the maximum demand load is underestimated using global regression model for convenient stores and overestimated for offices.

Table I: FORECASTING PERFORMANCE OF DIFFERENT MODELS FOR DIFFERENT SPACES.

Regression model	Estimation	Forecasting	MAPE
Global	8	1	0.55
Office Space-specific	2	1	0.04
Convenient store Space-specific	5	1	0.08

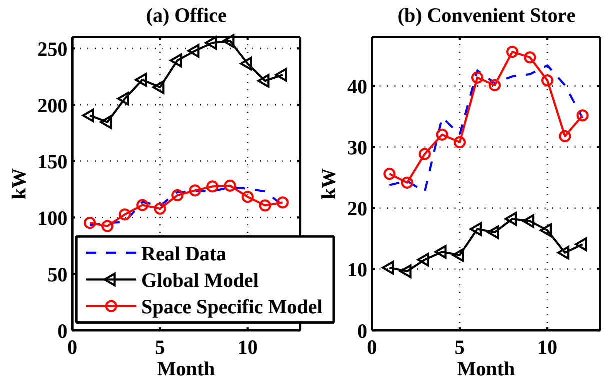

Figure 2: Detail of forecasted maximum demand load values of different models for different spaces.

This is because the latent variables defined in (1) cannot account for different type of appliances used in the space. However forecasting using space-specific regression model, the proposed latent variables can sufficiently forecast the maximum demand load. The forecasted maximum demand load is then used in the contract capacity optimization, describe in Section IV.

IV. MCD CONTRACT OPTIMIZATION

The deregulation and privatization of utility companies has led to dramatic changes in business models, an increased focus on efficiency of operations, and increased focus on reliability of service [14]. Contract optimization of tariff selection was as early as 1992 by Birch et al. [15]. Contracts are becoming more complex [2], therefore requiring more intelligent approaches to contracts from the point of view for all parties: generation [16] , distribution [17], consumer [18].

For problems over real-valued search-spaces, where the classic way of optimization is to derive the gradient of the function to be optimized and then employ gradient descent or a quasi-Newton method. However most utility contracts are not continuous as can be seen in Section IV-A. Another approach towards optimization problems use evolutionary algorithms. These methods do not use the gradient or Hessian matrix so their advantage is that the function to be optimized need not be continuous or differentiable and it can also have constraints [19]. In such cases, algorithmic procedures that take full advantage of modern computer

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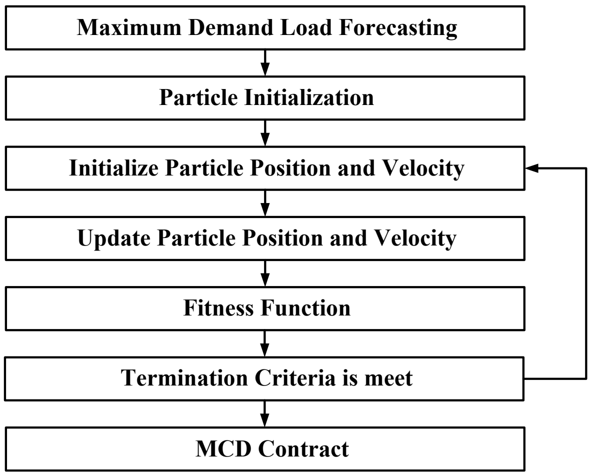

Figure 3: Procedure of MCD contract optimization

systems can be implemented to solve the underlying optimization problems numerically [20]. Popular evolutionary algorithms optimizers for real-valued search-spaces include particle swarm optimization (PSO), differential evolution and evolution strategies . Particle Swarm Optimization was used by Chen et al. to effective optimal demand contract in Taiwan for following advantages [21]: i) fewer parameters to adjust and easier implementation compared to GA, ii) more effective memory capability compare to GA iii) more efficient in maintaining the diversity. The implementation of PSO as illustrated in Fig. 3 on the MCD contract is discussed in the next section.

A. Implementation

Many different type of contracts or programs are offered by utilities, the proposed approach can be implemented for many type contract in a form that can be expressed as the fitness function of the PSO. Here an optimization of TPC's bi-period MCD contract is illustrated. Some notation are define as below:

- T_i^{periods} (kW): The consumers' MCD, a threshold for the $i-$th month determined according to the agreement between the consumers and the utilities for different periods: **peak**, **non**-summer and **off**-peak period.[2]
- $R_{\text{period}}^{\text{season}}$ ($TWD/kW): The rate charged by TPC for **sum**mer and **non**-summer seasons and different maximum contracted demand: **peak**, **non**-summer and **off**-peak.
- D_i^{period} (kW): Consumers' maximum demand load during **peak** or **off**-peak periods for the $i-$th month.
- E_i^{period}: Excess in consumer MCD during **peak** or **off**-peak periods for the $i-$th month.
- P_i^{period}: Penalty paid by consumer corresponding to the given E_i^{period} **peak** or **off**-peak periods for the $i-$th month.

[2]In typical scenarios, only the peak period MCD is selected. MCDs for other periods are only needed in atypical scenarios when these period demands are expected to be greater than the peak MCD.

The fitness function of the PSO is defined as the total cost for the MCD contract:

$$c_i^{\text{total}} = \sum_{i=1}^{12} c_i^{\text{adjust}} + c_i^{\text{basic}} + c_i^{\text{penalty}}, \tag{3}$$

where the adjustment charge for changing the MCD threshold is

$$c_i^{\text{adjust}} = 1670 \max\{(T_i^{peak} - T_{i-1}^{peak}), 0\}, \tag{4}$$

i.e a penalty is only charged for an increase in the MCD. For summer seasons June to September (i=6:9), the basic charge is:

$$c_i^{\text{basic}} = \quad R_{\text{peak}}^{\text{sum}} T_i^{\text{peak}} + R_{\text{off}}^{\text{sum}} \Gamma_i \tag{5}$$

where

$$\Gamma_i = \max\{[(T_i^{\text{off}}) - \frac{T_i^{\text{peak}} + T_i^{\text{sum}}}{2}], 0\} \tag{6}$$

and for other months (i=1:5,10:12), the basic charge is

$$c_i^{\text{basic}} = \quad R_{\text{peak}}^{\text{non}} T_i^{\text{peak}} + R_{\text{non}}^{\text{non}} T_i^{\text{non}} + R_{\text{off}}^{\text{non}} \Gamma_i. \tag{7}$$

The penalty for excess demand is the sum of two the penalty for the peak-period and off-peak period, i.e.,

$$c_i^{\text{penalty}} = \quad P_i^{\text{peak}} + P_i^{\text{off}}. \tag{8}$$

The excess in MCD is defined for the peak period:

$$E_i^{\text{peak}} \quad = \quad \begin{cases} D_i^{\text{peak}} - T_i^{\text{peak}} & \text{if } i = 6:9 \\ D_i^{\text{peak}} - T_i^{\text{peak}} - T_i^{\text{non}} & \text{otherwise} \end{cases} \tag{9}$$

and the off-peak period:

$$E_i^{\text{off}} \quad = \quad D_i^{\text{off}} - (T_i^{\text{peak}} + T_i^{\text{non}} + T_i^{\text{off}}). \tag{10}$$

The penalty for peak time excess demand can then be found for summer period $i = 6:9$ and if $E_i^{peak}/T_i^{peak} \leq 0.1$:

$$P_i^{\text{peak}} = 2R_{peak}^{sum} E_i^{peak} \tag{11}$$

otherwise, if $E_i^{peak}/T_i^{peak} > 0.1$:

$$P_i^{\text{peak}} = R_{peak}^{sum}[0.2T_i^{peak} + 3(E_i^{peak} - 0.1T_i^{peak})]. \tag{12}$$

For the non-summer period $i = 1:5, 10:12$ and if $E_i^{peak}/T_i^{peak} \leq 0.1$

$$P_i^{\text{peak}} = 2R_{peak}^{non} E_i^{peak} \tag{13}$$

otherwise if $E_i^{peak}/T_i^{peak} > 0.1$:

$$P_i^{\text{peak}} = R_{peak}^{non}[0.2T_i^{reg} + 3(E_i^{peak} - 0.1T_i^{peak})]. \tag{14}$$

An additional penalty is charged when off-peak period excess is greater than peak period excess, i.e., $E_i^{off} - E_i^{peak} > 0$, and is defined for summer period $i = 6:9$ and if $(E_i^{off} - E_i^{peak})/(T_i^{peak} + T_i^{non} + T_i^{off}) \leq 0.1$

$$P_i^{\text{off}} = 2R_{off}^{sum}(E_i^{off} - E_i^{peak}) \tag{15}$$

Table II: PRICE OF MCD CONTRACTS IN $TWD

Scenario	Current	Average Load	PSO	Savings from current	Savings from average load
Office	$ 401	$ 290	$ 288	28 %	6 %
School	$ 482	$ 449	$ 444	10 %	5 %
Building	$ 3,790	$ 2,978	$ 2,800	26 %	6 %
Store	$ 500	$ 400	$ 350	30 %	12.5 %

otherwise

$$P_i^{\text{off}} = R_{off}^{sum}[-0.1(T_i^{peak} + T_i^{non} + T_i^{off}) + +3(E_i^{peak} - 0.1(T_i^{peak} + T_i^{non}))] \quad (16)$$

and non-summer period $i = 1 : 5, 10 : 12$ and if $(E_i^{off} - E_i^{peak})/(T_i^{regular} + T_i^{non} + T_i^{off}) \leq 0.1$

$$P_i^{\text{off}} = 2R_{off}^{non}(E_i^{off} - E_i^{peak}), \quad (17)$$

otherwise

$$P_i^{\text{off}} = R_{off}^{non}[-0.1(T_i^{peak} + T_i^{non} + T_i^{off}) +3(E_i^{peak} - 0.1 * (T_i^{peak} + T_i^{non}))]. \quad (18)$$

It can be seen from (3)-(18) that the parameters to be optimized are interdependent and discontinuous. Therefore using a PSO approach is advantageous compare to classic gradient-based optimization methods.

B. Analysis

Using a the above defined fitness function a PSO was carried out. It can be seen that in Table. II, current peak MCD contracts are usually set too high without the computation of maximum demand load forecasting and MCD contract optimization modules. It can also be seen that, using the a 'naive' optimization using the average forecasted maximum demand load is setting the MCD too low. The proposed optimization gives a 10∼30% improvement over the the current MCD contracts and a 5∼12.5% improvement over MCD contracts using the average maximum demand load. It is also noted that under the current contract strucutre, the penalty is really high for adjustment of the MCD as seen by the constant 1690 TWD per every kW increase. This is due to the cost of increasing the limit of the physical infrastructure of current power system being too high and inflexible. However as the smart grid infrastructures advance [3], intermittent and adaptive power systems may lower the cost of varying this limit, thus allowing a more dynamic MCD structure, which can be easily adapted to by the proposed MCD contract optimization module.

V. CONCLUSIONS AND FUTURE WORK

A web-based EMS was presented in this paper with two novel design features: i) maximum demand load forecasting and ii) MCD contract optimization. A maximum demand load forecasting based on space-specific regression models of simple latent variables, temperature, number of workdays and employees, was presented. These space-specific regression models were accurate and robust to different space size of similar nature. The simple latent variables allow consumers to input their parameters easily through the web-based interface. A MCD contract optimization based on PSO was then proposed and showed significant savings. PSO is especially suited and flexible in dealing with utility contract's interdependent and discontinuous structure, and has the potential to be implemented in a distributed computing approach naturally [20]. This allows the scalability of web-based EMS to become a platform based service in the future assisting many people in the time of increasing utility contract complexity as smart grid advances. The next step in our research is to improve the robustness of contract optimization given load forecasting errors.

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