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ENERGY MANAGEMENT SYSTEM FOR SMART GRID CONSUMERS WITH ADVANCED USAGE INFORMATION

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ABSTRACT
This paper presents an online energy management system based on a virtual energy provisioning (VEP) concept. VEP is a novel demand side management inspired by the lean supply chain technology. It aims to control the process of energy generation, delivery, and consumption under the mechanism called "order-then-production" principle. This means electricity should be ordered by end consumers in advance before actually produced and delivered. The utility company, after aggregating consumers' advance demand information, can decide an optimal generation and distribution scheme to meet the actual need. In this paper, the VEP principle and its impacts on smart grid systems will be discussed.

KEY WORDS
Virtual energy provisioning, demand side management, advance demand information, smart metering

1. Introduction

Reliable and efficient delivery of electric power is essential to our daily life. The power grid is regarded as healthy and robust only when all demands are consistently satisfied and the interruption is kept at a minimum level. Based on today's knowledge, we are still not able to find a globally optimal algorithm to control many complex and dynamic systems like the electrical network [1]. The situation becomes more complicated as wind power and solar photovoltaic (PV), which are highly intermittent energy resources, are penetrating into the energy infrastructure. The growing market of Plug-in Hybrid Electric Vehicles (PHEV) creates additional complexities in the loading condition. Quite often we have to make a trade-off between the energy efficiency and reliability. In reality the priority is often given to the reliability in order to satisfy the demand requirement. Even with that, it is estimated that the annual losses due to power interruption exceed $80 billion in the U.S. [2]. Therefore, initiatives must be taken to rejuvenate the power grid so that the network reliability and efficiency can be warranted.

Smart grids are enabling technologies with the objective to sustain high reliability, self-healing, full controllability, and optimal asset management. Compared to its predecessors, smart grids have several unique features including demand side management (DSM), distribution automation, asset management, distributed energy generation, and smart metering [3]. Obviously the energy infrastructure embedded with these features can significantly improve the reliability, efficiency and security.

DSM is the key to the effective implementation of the smart grid concept. Many studies have been carried out to seek new DSM methods and apply them to existing networks for achieving power efficiency, energy conservation, and demand responsiveness. These studies include load shifting [4], direct load control [5], dynamic pricing [6], smart metering and appliances [7], and virtual energy buffers [8]. In addition, new communication technologies [9] are proposed to support the distribution automation and the DSM function.

Besides these techniques, a viable approach to improve the demand responsiveness is to build a close loop supply chain mechanism, which spans generation, transmission, distribution, and consumption, into the electricity production process. As a first step to create such a new management model, Jin and Mechehoul [10] proposed an online energy reservation system called Online Purchase Electricity Now, i.e. the OPEN system. The idea is to treat the electricity as a purchasable commodity allowing consumers to order or purchase energy by providing advance demand information through the Internet. The utility company, after consolidating the advance demand data, can decide an optimal generation and distribution scheme to meet the consumer needs. In other words, consumers place order based on their needs, and then consume exactly what they ordered. The lead time, i.e. the time between the order and the actual consumption, allows the utility company to prepare an optimal generation and delivery scheme.

Based on the work in [10], the purpose of this paper has twofold: 1) providing detailed backgrounds and additional justifications for the development of the virtual energy provisioning concept; and 2) discussing the implications, benefits, and challenges during the preliminary implementation of the OPEN system.

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The remainder of the paper is organized as follows. Section 2 discusses the similarities between the manufacturing enterprise system and the energy production system. Section 3 shows the architectural framework of the OPEN system and examines the necessary operational conditions. In Sections 4 and 5, the technical aspects and the impacts on smart grids will be elaborated, respectively. Section 6 concludes the paper with some remarks on future research.

2. Virtual Energy Provisioning Concept

2.1 Manufacturing Supply Chain System

Inventory is often defined as a batch of goods or materials held in the stock for customer order and purchasing. It is widely used in manufacturing enterprise systems for which the finished goods or products are temporally kept in a warehouse before they are shipped to the retailers who will further sell them to customers. Figure 1 depicts a typical manufacturing supply chain system in which the production is driven or pulled by customers' advance demand orders. Upon receipt of the orders, the manufacturer began to fabricate goods which will be temporarily stored in the inventory before delivered to the customers. This type of supply chains are called "order-then-production" model.

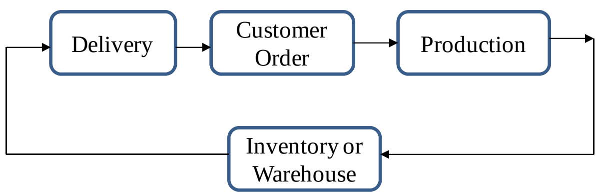

Figure 1. A manufacturing supply chain model

An inventory system consists of three key variables: the customer's order quantity, the inventory level (i.e. the available goods), and the lead time which is the time lapse between the order placed by the customer and the actual product receiving time. Obviously, the inventory serves as a spare parts buffer from which the manufacturer is able to deliver the goods to the customers in a timely manner upon the arrival of orders.

2.2 Virtual Energy Supply Chain System

Many similarities can be found between a manufacturing enterprise system and an energy production system. In the former, goods are produced and sold to the end customers, and the inventory is used as a buffer to mitigate potential back-orders due to uncertain demands. Similarly, electricity is generated by power plants or wind farms, and it is further delivered to the end consumers via the transmission/distribution lines. Power interruptions or outages will occur if the load exceeds the generation. The problem can be mitigated or partially resolved if large scales of storage systems can be created between the generation and the loading lines. Research is undergoing to develop conversion or storage technologies using fuel cells, batteries, and super-capacitors [11]. At present, commercially large and inexpensive storage systems or technologies are still not popular for home, business, and industry applications.

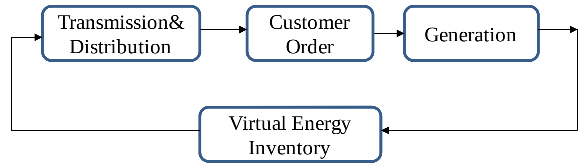

Figure 2. A virtual energy supply chain model

Motivated by the manufacturing inventory model, a virtual energy provisioning (VEP) concept is proposed for the substitution or enhancement of physical energy storage systems. As shown in Figure 2, VEP aims to achieve the same purpose as the physical storage system which behaves similarly as a product inventory system. The working principle of a virtual energy inventory is described as following. The utility company will implement an online database in which individual account will be assigned to each consumer. Consumers can log-on and access their web-based account via desk-tops, laptops, and mobile devices. They will further place advance demand orders based on the estimated usage. These orders represent the future electricity usage in hourly, daily, weekly or monthly bases. The utility company, after aggregating all consumers' orders, can decide an optimal generation and distribution scheme to meet their future needs. Just like a manufacturing supply chain system, this managed order-then-production mechanism acts as a virtual energy supply chain system by delivering the power to end users over the planning horizon.

3. System Implementation

3.1 System Architecture

Different architectures can be devised to implement the virtual energy supply chain concept. The system configuration presented here was originally in [10], and it is called Online Purchase Electricity Now, or simply the OPEN system. It is built upon a hybrid architecture integrating existing utility infrastructure with the Internet platform. Figure 3 shows the high-level configuration of the hybrid architecture.

Given the ubiquitous Internet technology, the deployment of the OPEN system only requires some additional hardware and software components. The key hardware component is the smart meter which supports the data communication between the consumer and the supplier. In fact, the meter used in the OPEN system only needs the one-way communication function by transmitting user's consumption data to the database, while the consumption data and the pricing information can be shown in the database accessible through the Internet. Utility data are primarily in a short message or packet format, representing hourly or daily power consumptions. Since the transmission of these utility data is not time-critical, Internet-based TCP/IP (Transmission Control Protocol/Internet Protocol) should be sufficient and reliable to handle the delivery task. Such communication facilities will be relatively easy to implement by directly integrating the smart meter with the Internet or the wireless communication meshes [10, 12]. Therefore, dedicated broadband utility communication infrastructure or network is not needed for the OPEN system, saving implementation costs.

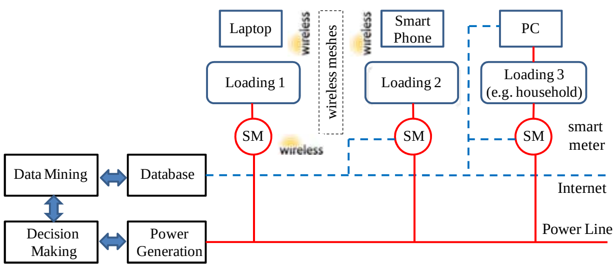

Figure 3. Hybrid architecture for OPEN system

Software applications for the OPEN system include an on-line database, a data mining engine, and a decision making tool. The database solicits the advance usage orders in a regular fashion, and also stores the historical consumption data constantly transmitted from the smart meter via the Internet. The data mining engine is capable of forecasting the future load by synthesizing consumers' order with their historical usage. The decision-making tool will determine the optimal energy generation and distribution plan based on the load forecasting data. All these functions are located at the utility side.

3.2 System Operational Conditions

Consumer participation is the key to the effective operation of the OPEN system. Various incentive packages can be devised so that consumers will participate in the program and input demand data through the online platform. The studies in [13] show that financial incentives, when appropriately implemented, will motivate consumers to participate in the energy management system. For example, the supplier can design customized energy portfolios to accommodate different users' consumption patterns. In that way, consumers can choose the best usage portfolio to minimize their monthly bill. In addition, monetary credits or energy discounts could be rewarded to consumers whose order data are equal or close to their actual usage. In the next paragraph we discuss a set of statistics metrics to assess the consumer performance, based on which various types of incentives can be designed to reward the participants.

Ideally we expect that the consumer orders exactly match the actual consumption. It is difficult, however, for consumers to achieve such a performance outcome. Therefore, incentive programs should be designed in a way that a consumer will obtain a higher financial reward if his or her actual usage is closer to the order. Three main factors need to be taken into account when we assess the consumer order data: 1) the deviation between the order data and the actual consumption; 2) the variation between the order and the consumption; and 3) any large deviation at a particular instant time. In [14], three composite indexes are proposed to capture these criteria

$$q_1 = \frac{1}{m}\sum_{i}^{m}(x_i - y_i) \tag{1}$$

$$q_2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - y_i)^2 \tag{2}$$

$$q_3 = \max\{(x_i - y_i)^2 \;\; for\ i = 1, 2, \cdots, m\} \tag{3}$$

Where, x_i is the actual usage at time i and y_i is the original order, and m is the sample size. Equation (1) calculates the mean error between the order data and the actual usage. The result is able to indicate whether the ordered quantity is always below or above the actual usage. Equation (2) measures the mean variation between the order and the usage. Equation (3) aims to identify the largest discrepancy between x_i and y_i for all i. The target value for q_1, q_2, and q_3 is zero. Obviously, the consumer whose performance metrics are close to the target should receive the financial reward or his/her electricity rate will be reduced depending on the proximity to the target value.

The second assumption for the OPEN system is that dynamic pricing is an effective means to regulate user's consumption behaviour. Since uncertainty is always involved in the prediction, it could grow beyond the control when millions of consumers' demand data are aggregated. Studies [9, 10] have shown that dynamic pricing is an effective mechanism to control and minimize the demand uncertainty. Like an adaptive controller, dynamic pricing establishes a feedback control loop between the suppliers and their consumers, and bring the actual demand close the generation per the game theory [15]. Eventually, a long-term balance between the generation and consumption will be reached, even if less accurate demand orders were provided by the consumers.

4. System Technical Aspects

4.1 Internet Centered Power Grid Systems

Information technology is a mainstay in supporting the operation of the VEP concept. Information such as consumer orders, consumptions, pricing, and generation capacities are also exchanged between the network participants including the generators, transmission & distributors, traders, and end consumers. The Internet provides a ubiquitous, yet cost-effective, communication platform to support the real-time and off-line information exchange in a seamless manner. Originally from [16],

Figure 4 graphically explains a communication model built around the internet technology.

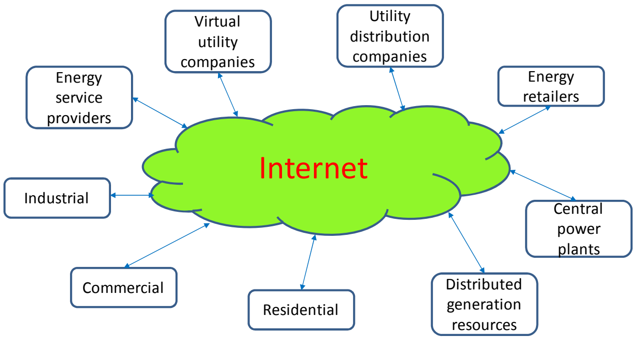

Figure 4. Internet based future grid systems

4.2 User Interface Design

In our virtual energy provisioning system, user interface behaves like a bridge between users and service provider. Similar to an online shopping webpage, users can easily browse their previous electricity usage data, input new usage plan, and other related consumption information, such as number of persons living in a house, appliances information etc. Hence, to design an interactive, functional, and user-like interface is very important.

Our designed interface consists of four components. 1) User Information. When the new user logs into the system, he/she needs to set up an account (e.g. user name and password) and input their personal information including the number of persons in their house, major appliances, air conditioner model for example. This information will be stored in our database, which will be very useful for our system to predict their future electricity demand. The above example is taken from residential homes, but same principle can be applied to industrial and business sectors. 2) Visualization. In order to let users make a good plan, it is necessary for the consumer to visualize the previous electricity usage (day by day, week by week, or month by month etc.), usage pattern of the same period in the previous years, and usage pattern of similar household. 3) Search. The major function of "Search" module is to help user search electricity consumption information of their appliances such as air-conditioner and washing machine. For example, the user can input their refrigerator model, the search module will find out the average electricity consumption of this type of refrigerator. This information will be very helpful for users to make an accurate prediction. 4) Feedback. Through feedback component, the system will provide a predicted usage amount to user. Users also can input their estimated amount and give the system a feedback. For example, based on previous usage information, the system will automatically generate an estimated demand for the user. It is up to the user who will modify the recommended usage and submit it to the OPEN system. When the user will be out of town for weeks or take a long vacation, for instance, he/she can input a very small amount of electricity usage. The user feedback plays a very important role to decide the final order amount.

4.3 Data Mining

In our system, data mining module is to predict load for a future period (load forecasting) based on user's previous consumption records, users' personal information (number of families, electronic equipment information, etc.) and user's feedback. Load forecasting falls into different time horizons: long-term forecasting (from one year to ten years), medium-term forecasting (from several months to one-year), short-term forecasting (from one hour to one week) and real-time or very short-term forecasting (in minutes) [17]. Our system focuses on medium-term and short-term forecasting. Although it performs prediction based on a relative short period, it still involves many uncertain variables. Hence it actually is a very challenging task. Our system will choose the best scheme to get a more accurate estimation based on different situations.

For a new user, who moves into a new-build house and there is no previous usage information about this house, data mining module will use personal information (number of persons, appliances) to seek similar houses nearby. The power usage information of these similar houses will be helpful to give a forecasting. For an experienced user, the power prediction will not only depend on personal information, but also depend on the load of the same house in previous weeks and months, and even the previous year. Other factors such as power usage of similar houses in the same period and same area, weather factor, and user feedback also influence the estimation for future consumption.

Many load prediction tools [18-20] have been developed based on probabilistic theories, simulation techniques, and neural networks. These methods are able to obtain an accurate prediction through the integration of historical data with some external factors (e.g. environment or weather conditions). It is anticipated that a more robust prediction can be made if users' feedback is incorporated into the prediction process. In section 5, we will briefly review a Bayesian prediction method, which can automatically adjust our prediction with user's feedback.

4.4 Optimal Decision Making

Decision making strategies can be applied in: 1) optimization techniques to determine the generation and distribution; 2) risk assessment in the presence of generation and load uncertainties; and 3) pricing negotiation and consumer incentives for the participation of OPEN system.

Optimization of generation and distribution requires a model of the market. The state of the market can be described by the load demand and the price. The OPEN system allows the utility companies to visualize a future market based on consumers' demand orders. The pricing elasticity can be utilized to achieve the load shaving when the generation capacity reaches the limits. Markov Decision Process [21] and game theories [22] can be employed for the optimization of the expected value of the profit. Mote Carlo simulation is an effective tool which can be used to validate and verify the results derived from analytical methods.

5. Potential Impacts on Smart Grids

5.1 Distributed Generation Systems

Distributed generation (DG), or decentralized generation, produces electricity from many small energy sources called distributed energy resources (DER) along with the central generation units. In other words, a DG system is a hybrid power grid system interconnected with DER units and substations to supply electricity. The capacity for a DER unit ranges from 3 kW to 10 MW while the capacity for a central generation often exceeds 500 MW. Typical DER equipment includes wind turbines, solar PV, fuels cells, and micro-generators.

Wind turbines and solar PV emerge as promising energy sources to fill the energy gap between the supply and the demand in the next several decades. The output of these renewable DER units, however, is often intermittent due to the stochastic nature of the wind speed and solar irradiation. In particular, the wind speed and solar energy highly depend upon the weather condition, geographical location, and seasons of the year. Therefore, integrating renewable technology into the power grid adds additional variations on top of the load dynamics. The loss-of-load probability must be modeled and analyzed by taking into account the load uncertainty and power variability at the same time. Otherwise the grid reliability and stability will be jeopardized as the more renewable energy resources are connected to the grid.

The proposed virtual energy inventory concept can play a pivotal role in managing DG systems. Built upon the lean supply chain management, the virtual energy inventory system has the capability of aggregating consumers' future demands and further sending the information to the utility companies. The utility companies, after performing data analysis, can pro-actively roll out an optimal generation and distribution scheme to mitigate the variable wind and solar powers. The lead-time between the consumer order and the actual consumption serves as a virtual energy inventory to supply needed electricity to end users.

5.2 Grid Operation and Asset Maintenance

The OPEN system creates a truly interactive environment that allows for real-time communications between the supplier and its consumers. Consumers directly or indirectly participate in the energy forecasting, generation, and distribution via the on-line database. Suppliers are able to update and post the price information on the webpage in a real-time manner, and to guide the consumption behaviour. The system will be more beneficial to situations where a sudden demand change occurs, such as family leaving for vacations or a surge of energy demands due to manufacturing or business ramp-up. Consumers can easily report their reduced or increased power demands through the OPEN system in advance.

The new system also facilitates the integration of PHEV or other electrical apparatus into the grid systems. The charging of PHEV automobiles has a significant impact on the distribution lines because these vehicles consume large amounts of energy [23]. Functions can be built in the OPEN system that allows the PHEV users to notify utility suppliers when and where the charge will be carried out, and how much energy is needed. Therefore, the advance provisioning concept has great potentials and promises for the development of smart grid systems.

The OPEN system can assist the utilities in optimizing asset management based on consumers' demand information. Maintenance activities on transformers and power lines can be scheduled during the time when the consumer demands are low based on the order data.

5.3 Improving Load Forecasting

The OPEN system can also assist the utility companies in making a more realistic load forecasting by combining consumers' past usage with their demand perspectives. Bayesian theorem is able to combine the historical data with the advance orders to forecast the future load. Although the theorem has been widely used in many fields, its application in power industry for predicting the future consumption is still new.

Bayesian prediction methods can be classified into two categories: discrete Bayesian and continuous Bayesian models. In the former, the prior and the posterior distributions are represented by discrete probabilities. In the latter continuous functions are used to model the prior and/or the posterior distributions.

5.3.1 Discrete Bayesian Prediction

The discrete Bayesian model can be applied in the situations where the demand data is characterized by attributes or categorical data. The mathematical expression of the model is given as follow

$$P\{F_i \mid E\} = \frac{P\{EF_j\}}{P\{E\}} = \frac{P\{E \mid F_i\}P\{F_i\}}{\sum_{j=1}^{k} P\{E \mid F_j\}P\{F_j\}} \quad (4)$$

Where

k=total number of events or categories

$P\{F_i\}$=prior probability for F_i with i=1, 2, …, k

$P\{E|F_i\}$=probability for consuming E given F_i

$P\{F_i|E\}$=posterior probability for F_i given E

We use a contrived yet quite realistic data set to explain the application of this prediction technique. Table 1 lists the daily energy consumption for a consumer during 15 days period. The actual consumption of energy, denoted as X, is listed in the second column, while the forecasting, Y, provided by the consumer is shown in the last column. For example, for day 10, the consumer originally ordered 13kWh electricity through the OPEN system, the actual energy consumed by the consumer is 14 kWh.

Table 1
Daily energy usage versus prediction in (unit: kWh)

Day	Actual Usage (X)	Consumer Orders (Y)
1	10	11
2	11	12
3	13	12
4	13	14
5	12	12
6	11	10
7	10	12
8	14	14
9	14	12
10	14	13
11	12	13
12	14	13
13	12	11
14	12	12
15	11	11

From Table 1, we can easily compute the prior probability for X and the result is given as: $P\{X$=10, 11, 12, 13, or 14$\}$=[0.13, 0.20, 0.27, 0.13, or 0.27], respectively. Meanwhile, we are able to estimate the conditional probability for Y given X based on the data in Table 1, and the results are summarized in Table 2. For example, the P$\{Y$=13$|X$=14$\}$=0.5 as shown in the last row. This means the probability for the consumer to order 13 kWh is 50% given that his/her actual consumption is 14 kWh.

Table 2
Conditional probability of $P\{Y|X\}$

		Y				
	kWh	10	11	12	13	14
X	10	0	0.5	0.5	0	0
	11	0.333	0.333	0.333	0	0
	12	0	0.25	0.5	0.25	0
	13	0	0	0.5	0	0.5
	14	0	0	0.25	0.5	0.25

Now the posterior probability for X can be extrapolated base on Table 2 along with the prior probability of X. The result is summarized in Table 3. For instance, the last row of the table shows $P\{X$=14$|Y$=13$\}$=0.67, meaning the probability for actually consuming 14 kWh electricity is 0.67 given that the consumer's order is 13 kWh.

Table 3
Posterior probability of $P\{X|Y\}$

		Y				
	kWh	10	11	12	13	14
X	10	0	0.33	0.17	0	0
	11	1.0	0.33	0.17	0	0
	12	0	0.33	0.33	0.33	0
	13	0	0	0.17	0	0.5
	14	0	0	0.17	0.67	0.5

Given the consumer order, we can further compute the conditional mean demand and the variance based on information in Table 3. For instance, if the consumer's order quantity is Y=13 kWh, then the conditional mean demand and its variance can be estimated as

$$E[X|Y=13] = \sum_{i=1}^{5} xP\{X = x|Y=13\} = 13.33 \text{ kWh} \quad (5)$$

$$\mathrm{var}(X|Y=13) = E^2[X|Y=13] - (E[X|Y=13])^2 = 0.89 \text{ kWh} \quad (6)$$

The illustrative example, though relatively simple, has clearly demonstrated how the discrete Bayesian inference model can be utilized to predict the consumers' actual consumption by synthesizing the historical data with their demand orders.

5.3.2 Continuous Bayesian Prediction Model

If the actual consumption is expressed as continuous distribution functions and demand orders are still discrete data, the forecast can be made based on the Bayesian model for density functions [24]. That is

$$f_X(x|Y=y) = \frac{P\{Y|X=x\}f_X(x)}{P\{Y\}} = \frac{P\{Y|X=x\}f_X(x)}{\int_0^{+\infty} P\{Y|X=x\}f_X(x)dx} \quad (7)$$

When both X and Y are represented by continuous density functions, the Bayesian prediction model can be expressed as

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{f_{Y|X}(y|x)f_X(x)}{f_Y(y)} \quad (8)$$

Where

X=actual consumption, a continuous random variable

Y=consumer demand order, a discrete random variable

$P\{Y\}$=probability for Y

$f_X(x)$ = prior distribution for x

$f_X(x|Y=y)$ =probability density function for x given y

$P\{Y|X=x\}$ =the conditional probability for Y given x

$f_Y(y)$ = marginal distribution for y

$f_{X,Y}(x,y)$ = joint distribution for x and y

$f_{Y|X}(y|x)$ =conditional density function for y given x

$f_{X|Y}(x|y)$ = posterior density function for x given y

6. Conclusion

This paper discusses a new energy management concept, i.e. virtual energy provisioning, allowing smart grid users to order or request electricity via the broadband Internet as if performing an online purchasing action. The idea is motivated by manufacturing supply chain systems where the production is driven by customers advance demand information, while the lead time creates a time buffer for planning the actual production. The new concept enables consumers to "order the electricity they need, and consume exactly what they ordered". The operating principle, system architecture, and the benefits have been elaborated. The preliminary study shows that on-line electricity ordering system is theoretically reasonable and technically implementable. Many research opportunities will open up while implementing the virtual energy provisioning concept. These topics include, but not limit to, consumer performance assessment, load forecasting, consumer incentive programs, dynamic pricing negotiation, and optimal generation planning. As one of further development, we will use actual monitored demand data in order to illustrate the effectiveness of the proposed energy management system.

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