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Markov-Decision-Process-Assisted Consumer Scheduling in a Networked Smart Grid

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ABSTRACT Many recently built residential houses and factories are equipped with facilities for converting energy from green sources, such as solar energy, into electricity. Electricity consumers may input the extra electricity that they do not consume into the smart grid for sale, which is allowed by law in countries such as Japan. To reduce peak-time electricity usage, time-varying pricing schemes are usually adopted in smart grids, for both the electricity sold to consumers and the electricity purchased from consumers. Thanks to the development of cyber-physical systems and advanced technologies for communication and computation, current smart grids are typically networked, and it is possible to integrate information such as weather forecasts into such a networked smart grid. Thus, we can predict future levels of electricity generation (e.g., the energy from solar and wind sources, whose generation is predominantly affected by the weather) with high accuracy using this information and historical data. The key problem for consumers then becomes how to schedule their *purchases from and sales to the networked smart grid* to maximize their benefits by jointly considering the current storage status, time-varying pricing, and future electricity consumption and generation. This problem is non-trivial and is vitally important for improving smart grid utilization and attracting consumer investment in new energy generation systems, among other purposes. In this paper, we target such a networked smart grid system, in which future electricity generation is predicted with reasonable accuracy based on weather forecasts. We schedule consumers' behaviors using a *Markov decision process* model to optimize the consumers' net benefits. The results of extensive simulations show that the proposed scheme significantly outperforms the baseline competing scheme.

INDEX TERMS Smart grids, Markov decision process, scheduling algorithms, time-varying systems.

I. INTRODUCTION

Electricity systems for a smart world (also known as smart grids) [1]–[3], in which *information and communications technology* (ICT) is applied to provide consumers with electricity in a more intelligent, stable and efficient manner, are attracting increasing attention. A smart grid includes a variety of components, such as smart meters (which automatically record the amounts of electricity consumed and deliver the data to a control center), smart appliances, and renewable energy resources (where new green energy sources have been integrated into the smart grid).

State-of-the-art studies on smart grids have addressed various aspects of these systems, such as electrical power conditioning and the control of the production and distribution of electricity, from the standpoints of the overall smart grid system, the electricity provider and the consumers. System-oriented research primarily focuses on smart control centers, smart transmission networks, and smart substations, as well as security and other similar concerns. In other words, such studies focus on each component of the smart grid system and optimize them individually. For example, wireless sensor networks (WSNs) [4] can be used to enhance the generation, delivery, and utilization of electricity to improve smart grid operations [5]. By contrast, provider-oriented studies primarily focus on time-varying pricing schemes to optimize a defined objective function, e.g., to reduce peak-time electricity consumption under certain constraints. Support for high peak-time electricity consumption requires a high sunk cost (initial investment), but this is usually only needed for a specific period of time. Finally, consumer-oriented studies primarily focus on the optimization of a defined utility function (such as the minimization of the overall cost) under certain assumptions regarding the smart grid.

An increasing number of recently built residential houses and factories are equipped with facilities for converting energy from green sources, such as solar energy, into electricity and to store that electricity for current and future use or sale. The amount of electricity generated may exceed the consumer's own demands or even the available electricity storage capacity when conditions are favorable. Electricity consumers can sell this excess electricity to the smart grid, which is allowed by law in countries such as Japan. Usually, the smart grid owner sets time-varying prices for the sale of electricity to consumers and the purchase of electricity from consumers to reduce peak-time electricity usage and to encourage consumers to sell electricity during peak times. Consumers decide whether to sell their electricity at specific times based on the current storage status, time-varying prices, and expected future electricity generation and consumption. The key problem for consumers is how they can optimize their behaviors (whether and when to sell their generated electricity or purchase electricity from the electricity plant, and in what amounts).

Data mining, especially big data mining, can help to predict future levels of electricity generation based on historical data and predictions of future weather, seasons, etc. Thanks to the development of cyber-physical systems as well as advanced communication and computation technologies, current smart grids are typically networked, and the available weather forecasts are becoming increasingly accurate. Since weather is the dominant parameter affecting the amounts of electricity generated from solar and wind sources, we can utilize, e.g., weather forecasts to predict the expected future levels of electricity generation with high accuracy. However, even with the ability to predict the amount of electricity that will be generated in the near future, the question of how best to schedule *purchases from the smart grid* and *sales to the smart grid* at each decision time to optimize the overall benefit to electricity consumers remains a non-trivial problem. Moreover, the ability to predict future levels of electricity generation and consumption is still imperfect. To our knowledge, no such optimization scheme has been proposed to date.

In this paper, we study such a smart grid, in which electricity consumers are able to generate their own electricity from solar power or other sources. The amount of electricity generated primarily depends on the weather. Weather forecasts, etc., are integrated into each consumer's control system to help predict the amounts of electricity expected to be generated in the coming few days. We jointly consider the predicted amounts of generated electricity (subject to uncertainty and disturbances) and consumed electricity (subject to uncertainty), the current electricity storage status and the time-varying pricing scheme set by the smart grid owner (including both purchase and sale prices). A *Markov decision process* (MDP) model is used as a tool to help optimize consumers' behaviors with the defined objective of maximizing the consumers' benefit. The *dynamic programming* and *branch-and-bound* [6] algorithm design paradigms are applied to reduce the computational complexity. The results of extensive simulations are reported, which indicate that the proposed mechanism outperforms other competing schemes. The proposed management scheme can be implemented in each consumer's energy generation system to promote better smart grid utilization and attract consumer investment in new energy generation systems. Overall, the contributions of this paper are as follows:

1) Weather forecasts, etc., are integrated into the smart grid system to help predict future levels of electricity consumption to improve smart grid utilization and attract consumer investment in new energy generation systems. The uncertainties in the estimated levels of future electricity generation and consumption due to non-perfect prediction are also considered in the proposed scheduling scheme.
2) An MDP model is used as a tool to schedule consumers' behaviors to maximize their benefits. The dynamic programming and branch-and-bound algorithm are used to reduce the computational complexity.
3) Extensive simulations conducted for performance evaluation are presented, and the results show that the proposed scheme can achieve better performance than the baseline competing scheme in typical scenarios.

The remainder of this paper is organized as follows. We first discuss related work in Section II. Then, we describe the smart grid system and the pricing scheme in Section III. We introduce how we use the MDP to optimize consumers' behaviors in Section IV. We report experimental investigations of the proposed scheme's performance in Section V. Finally, concluding remarks are provided in Section VI.

II. RELATED WORK

Smart grids [1]–[3] include a variety of operational components and devices for energy measurement, including smart meters, smart appliances, and renewable energy resources. Various state-of-the-art schemes consider electrical power conditioning and the control of electricity production and distribution from the standpoints of the overall system, the electricity provider and the electricity consumers. System-level studies (such as [7]) primarily focus on smart control centers, smart transmission networks [5], and smart substations, as well as security [8] and other similar concerns. For example, with regard to transmission, wireless sensor networks [4] can be applied to enhance the generation, delivery, and utilization of electricity in a smart grid. In [5], such a system was studied in which sensors were used to improve the performance of the smart grid. One important issue from the provider's point of view is that of time-varying pricing, which can help to increase the provider's net profit while decreasing the sunk cost. From the consumers' perspective, many works [9]–[11] have attempted to minimize the overall cost or maximize some defined utility function.

Many researchers have investigated various pricing schemes, in which different pricing policies are applied to help optimize a defined objective in typical scenarios [10], [12]–[15]. Specifically, [10] assumed the existence of two-way communication between the smart grid and the consumers and developed a real-time pricing algorithm to benefit both the smart grid owner and the electricity consumers. In [13], a scheme was proposed for electric vehicles (smart grid consumers) to assist in decisions regarding when to buy electricity from the smart grid by predicting future electricity prices. In [14], peak-time electricity consumption was controlled by means of dynamic pricing with distributed load management.

Regarding the use of weather forecasts in smart grids, the related studies can be classified into research on the prediction of future electricity generation, such as [16] and [17], and research on scheduling schemes using such prediction results [18], [19]. In [18], the use of weather forecasts in a smart grid was investigated, but the accuracy of the weather forecasts was not considered. In [19], a methodology was presented for the optimal operation of a smart grid to minimize power flow fluctuations at interconnection points by considering the forecasted errors in isolation.

Similar to the smart grid system discussed in this paper, *vehicle-to-grid* (V2G) systems are emerging, in which electricity stored by vehicles can be sold to the smart grid. Hybrid vehicles and battery-powered vehicles are becoming increasingly popular because of their environmental friendliness, lower operation costs, and decreased fuel dependency, as well as preferential governmental policies and other factors. They also offer an opportunity for V2G power. V2G power [20] is primarily intended to address certain unusual cases, such as the need to satisfy peak power demands to stabilize the grid. Many studies have been conducted related to V2G power [21]–[25]. Several typical works are as follows. In [21], an aggregator was proposed to provide grid-scale power by making use of the distributed power of electric vehicles. The authors of [24] studied a unidirectional V2G power scheme and proposed an aggregator algorithm to maximize profit by combining the capacity of many EVs. The authors of [25] studied how to integrate V2G power to balance the unpredictable nature of wind power to ensure the stable and reliable operation of a power system.

Markov decision process [26] is a tool that provides a mathematical framework to assist in decision-making when the potential outcomes are subject to randomness. The outcome of such a process depends on the current state of the system and the actions chosen by the decision-maker. The MDP approach offers good performance for addressing various problems in which decision-making is required, such as cooperative multimedia transmission [27], dynamic pricing [28], and video frame transmission [6].

Unlike the related studies discussed above, this paper considers a system in which weather forecasts from the internet are used to predict future levels of electricity generation in a networked smart grid. An MDP model is used as a tool to optimize consumers' behaviors with the objective of maximizing their overall benefit while considering forecast errors and potential fluctuations in users' future electricity consumption.

III. SYSTEM OVERVIEW

This section provides an overview of the electricity system concept for the networked smart world (namely, the smart grid system), in which electricity consumers can also generate electricity. We first introduce the pricing model designed by the electricity plants, including the prices at which they sell electricity to consumers and the prices at which they purchase electricity from consumers. The assumptions made concerning electricity consumers' electricity generation and consumption are mentioned at the end of this section.

A. SYSTEM OVERVIEW

We study the electricity system of a networked smart grid, in which most buildings (including residential houses and factories) are equipped with facilities for converting solar energy or energy from other green sources, such as biogas, into electricity. Some capacity for electricity storage is associated with such an electricity generating system to allow the generated electricity to be stored for self-use or sale. A monopoly market is considered, in which there is only one electricity plant.[1] However, the government enforces certain political regulations, e.g., an electricity plant will be fined or even forced to shut down if it cannot provide sufficient electricity, as we discuss in greater detail later. Green electricity from solar power, wind power, etc., has enormous social impacts on society; hence, the government typically assists in the establishment of such energy sources in terms of the initial investment, etc., to promote the development of the necessary facilities, such as the equipment for converting solar energy into electricity. The smart grid is networked, and thus, weather forecasts from the internet, etc., can be utilized for smart decision-making.

Fig. 1 shows an illustration of such a system, in which the electricity plant generates electricity and the electricity is transmitted via the electrical grid (smart grid). The electricity plants and the grid are owned by the monopolistic electricity provider; in this paper, we use a single electricity plant to denote this situation. We divide users into three categories: always-insufficient consumers such as large factories (who demand more electricity than they can generate), always-sufficient consumers (who always generate more electricity than their demands), and other consumers (such as certain residential consumers). Each consumer has an electricity storage unit with a maximum storage capacity, where the additional

[1] This is usually the case in countries such as Japan or China, where there is only one electricity provider in a given geographical area, e.g., the electricity in the Tokyo area is provided by Tokyo Electric Power Company.

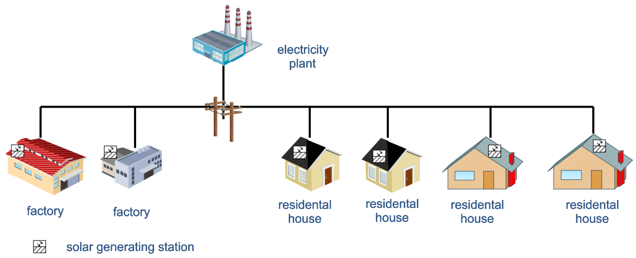

FIGURE 1. **Illustration of an electricity system for the smart world.**

electricity they generate can be stored for future use or for sale to the grid. This electricity storage is directly related to the initial investment and affects the system performance.

B. PRICES SET BY THE ELECTRICITY PLANT

We assume that the electricity plant has a maximum capacity C_{max}, where C_{max} denotes the plant's maximum output. In other words, the electricity plant cannot generate more electricity than C_{max} throughout the year. C_{max} is related to the initial investment, i.e., a larger C_{max} requires a larger initial investment or sunk cost. C_{max} is typically larger than the amount of electricity demanded.

1) SALE PRICES OF THE ELECTRICITY PLANT

The available electricity resources are generally insufficient in situations such as summer in Tokyo, where most of the nuclear power stations have been shut down since the East Japan earthquake in 2011. To reduce peak-time electricity usage and limit the electricity usage of consumers who use large amounts of electricity, elastic prices are usually adopted instead of flat prices.[2] According to this elastic pricing scheme, prices are determined by the amount of electricity consumed and the time period. We denote the electricity usage of user i during time period t (time is divided into multiple discrete periods to simplify the formulation and calculation) by $v_{i,t}$ and the corresponding price by $p_{v'_{i,t},t}$. Here, $v'_{i,t}$ denotes the amount of electricity purchased from the electricity plant, i.e., the amount of electricity consumed minus the amount of consumed electricity self-generated by the consumer. We divide the time and amount of electricity usage used in the pricing scheme into discrete phases. Within each phrase, the prices are the same. Moreover, the prices are bounded by government policy in this monopolistic electricity market. The prices assigned by the electricity plant are defined as follows:

$$p_{v'_{i,t},t} = p_0 + \epsilon \lceil min(\frac{v'_{i,t}}{v_0}, \frac{v_{max}}{v_0})\rceil f_t \quad i \in U \tag{1}$$

where $p_{v'_{i,t},t}$ represents the electricity price when user i purchases an amount of electricity equal to $v'_{i,t}$ from the smart grid during time period t. p_0 is the base price, and ϵ is a constant weight parameter. $\frac{v'_{i,t}}{v_0}$ determines the weight of the amount of electricity consumption; users must pay more money for higher electricity consumption with respect to the base consumption, v_0. Note that this term is bounded by $\frac{v_{max}}{v_0}$, i.e., all users who consume v_{max} or more pay the same electricity price. f_t is the term representing the smart grid's 'business' in the time domain, which takes a positive integer value. Peak time corresponds to a larger f_t, whereas a smaller f_t indicates that the electricity plant is not very busy. U denotes the set of consumers served by the electricity plant.

[2]Our scheme is not specific to any particular pricing scheme, i.e., the proposed scheme also functions in systems in which other types of pricing schemes are adopted.

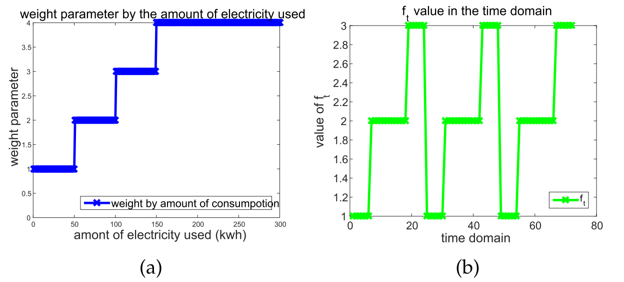

FIGURE 2. **The weight parameters depending on the amount of electricity consumed and the weight profile in the time domain. (a) Amount of electricity consumed. (b) Weight in the time domain.**

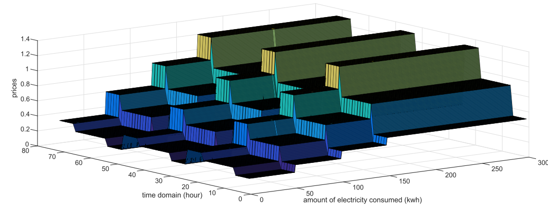

FIGURE 3. **Illustration of the prices defined by the electricity plant for $p_0 = 0.1$ and $\epsilon = 0.1$.**

Fig. 2 (a) illustrates a typical set of weight parameters defined based on the amount of electricity consumed, where v'_0=50 kWh and v_{max} is 150 kWh. Fig. 2 (b) shows the weighting profile in the time domain, where time is divided into three phases. From 0:00 am to 6:00 am, the amount of electricity expected to be consumed is the least, and hence, this time period has the lowest weight. The period of 18:00 to 24:00 is assumed to be the busiest, and thus, the corresponding weight is the highest. Note that these pricing specifications can be modified as needed and that our algorithm does not make any assumptions regarding when the peak time occurs. We assume that this trend holds daily throughout the year. Also note that the time priority can also be modified without affecting the feasibility of the proposed algorithm. Fig. 3 shows an illustration of the final elastic electricity prices adopted by the electricity plant, where the weight parameters based on the amount of electricity consumed and the weighting in the time domain are the same as those shown in Fig. 2. From this figure, we can observe that the electricity prices vary significantly depending on the time and the amount of electricity purchased. Note that no units are assigned to the figure to make the model more applicable to different scenarios, considering that the units could differ as a result of currency differences between countries.

In this monopolistic electricity market, the government assumes the responsibility of supervision and certain agreements are established between the government and the electricity plant, such as $C_{supply} - C_{needed} \geq 0$.[3] If the electricity plant cannot meet this requirement, it will be fined a large amount of money; hence, the electricity plant must invest properly to handle peak-time electricity usage.

2) PURCHASE PRICES OF THE ELECTRICITY PLANT

Consumers can also generate electricity, and the amounts of electricity they generate may exceed their own demands. Hence, users may also put electricity onto the market for the electricity plant to purchase. The electricity plant would like to purchase users' excess electricity during peak periods to avoid a situation in which the amount of electricity supplied is lower than the amount of electricity demanded. The ability to purchase electricity from consumers can also lower the initial investment required of the electricity plant. Therefore, the electricity plant may increase its purchase prices during peak times to attract more electricity sales. Electricity consumers are thus motivated to sell their excess electricity at higher prices if the prices vary in time. We assume that the prices at which the plant purchases electricity from users are defined as follows:

$$p'_t = p'_0 + \epsilon' f_t \tag{2}$$

where p'_t represents the purchase price of electricity at time t, p'_0 is the base price, and ϵ' is the weight parameter for the time factor. f_t is the same function introduced in Eq. (1). This purchase pricing scheme is a simplified version of the sale pricing scheme, in which the quantity purchased is not considered. Generally, purchase prices are lower than the prices set in Eq. (1). Otherwise, consumers might sell electricity purchased from the electricity plant directly back to the electricity plant and make a profit from the price difference, which is obviously not reasonable in a mature market. Note that we do not consider cases in which large government or policy compensations exist since in the presence of such incentives, compensation of this kind will disappear.

C. ELECTRICITY CONSUMERS

The amounts of electricity generated by consumers depend on the season, weather, and time of day. For example, more electricity may be generated during daytime compared with that generated during the night if the system in question converts solar energy into electricity. The amount of electricity generated is also related to the initial investment or the sunk cost. The initial investment determines the maximum amount of electricity that a user can generate when all other conditions remain the same. Note that the initial investment is usually bounded by the limitations of residential houses or factory buildings, etc. The generated electricity can be stored in the electricity storage unit, but the volume of that storage is limited by E_i, where E_i denotes the maximum amount of electricity for user i that can be stored in that user's electricity storage. The amount of electricity stored in user i's electricity storage at time t is denoted by $e_{i,t}$ and must satisfy $0 \leq e_{i,t} \leq E_i$. The amount of electricity generated by user i at time t is denoted by $g_{i,t}$, where $g_{i,t}$ is determined by the initial investment (sunk cost), the season, the weather, the time of day, etc., as mentioned. $M_{i,max}$ denotes the initial investment of user i.

For an always-insufficient consumer, i.e., for big user i, $\sum_{t=1}^{T} v_{i,t} >> \sum_{t=1}^{T} g_{i,t}$, where T is the time horizon considered. Such consumers can use their own generated electricity during peak times or high-price periods. Always-sufficient consumers will sell $\sum_{t=1}^{T} g_{i,t} - \sum_{t=1}^{T} v_{i,t}$ during peak times with a proper storage. It can be easily proven that these are the best strategies for these two types of consumers.

We therefore focus on the remaining consumers, such as certain residential consumers who can generate more electricity than their demands only in certain cases, i.e., a home user i for whom $v_{i,t} < g_{i,t}$ only sometimes. Correspondingly, the amount of electricity sold by such a user i at time t is denoted by $a_{i,t}$. $a_{i,t}$ may be 0, which means that consumer i does not sell any electricity. Because the purchase prices are assigned by the electricity plant in a time-varying manner, consumers must decide when to sell their excess electricity to maximize their benefits. Consumers prefer to sell their electricity when the electricity they are generating is sufficient for their near-future usage and during high-price periods. Consumers must consider the status of their storage, the amount of electricity expected to be generated in the near future, etc., for optimal scheduling; this problem is non-trivial and is the focus of this paper.

Overall, the smart grid system considered in this paper includes an electricity plant, electricity consumers, consumers' electricity storage units and their various home appliances. Consumers can choose when to purchase electricity from the electricity plant and how much to purchase. They also decide whether and when to sell the electricity stored in their storage units considering their expected future electricity generation, their storage status, etc. Regarding their future electricity generation, consumers may rely on weather information (by integrating weather forecasts into their management systems, although weather forecasts are not 100% accurate) and other such tools. This prediction problem is quite novel and interesting by virtue of the development of cyber-physical systems and network communication technologies. This paper further investigates this problem to seek better system efficiency and higher overall benefits for consumers. We hope that systems of this kind may attract more consumers and promote the development of green energy generation systems.

[3]Other regulations are also possible; however, we consider only this typical one in this paper.

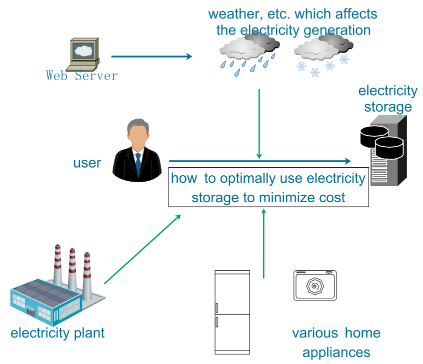

FIGURE 4. **Illustration of the factors affecting user decisions.**

1) ELECTRICITY CONSUMPTION MODEL

We assume that consumers are wise and rational. In other words, consumers will strive to use their home appliances during time periods of low 'business' (low prices) as much as possible to reduce their overall cost. Regarding consumption, there are two cases: one is that the consumers possess complete information about their future home appliance usage, and the other is that the consumers only have knowledge about the distribution of their future electricity consumption. Different home appliances may have different properties in terms of when they are used, e.g., the refrigerator must always be turned on, whereas in principle, the washing machine could be used at any time during the day, although consumers may prefer to wash their clothes at a specific time. The amount of electricity $v_{i,t}$ consumed by consumer i is thus assumed to consist of two components[4]: the base consumption and the flexible electricity consumption. In other words, $v_{i,t} = v^0_{i,t} + v^1_{i,t}$, where the base electricity consumption during time period t is denoted by $v^0_{i,t}$ and $v^1_{i,t}$ denotes the flexible electricity consumption during the same time period. The probability that the flexible electricity consumption of user i will be equal to a certain value of $v^1_{i,t}$ is calculated as $\frac{1}{\delta_{i,t}\sqrt{2\pi}} e^{-\frac{(v^1_{i,t}-\mu_{i,t})}{2\delta^2_{i,t}}}$ [29], where $\delta_{i,t}$ is the corresponding standard deviation and $\mu_{i,t}$ is the corresponding expectation value of the distribution, which is time-varying and can be determined based on historical data.

2) ELECTRICITY GENERATION PREDICTION

$H_{i,t}$ is a positive integer and represents the maximum electricity generation capability of user i. The number of possible values of $H_{i,t}$ is assumed to be H^0. Sunny weather conditions during daytime lead to a large $H_{i,t}$, whereas $H_{i,t}$ may be smaller in the evening. The function $g_{i,t} = (q + rand * q^1) * H_{i,t} * \epsilon^g$ is used to represent the amount of electricity generated, where q is the base value of the generated electricity; $rand * q^1$ is the additive variable for electricity generation, where $rand$ denotes a random number between 0 and 1 and q^1 is a constant value; and ϵ^g is a weight parameter.

The remaining variable to be considered is the weather, and weather forecasts can be used for this purpose with high prediction accuracy. The prediction accuracy at time t for the weather at time t' is assumed to be $w_{i,t,t'}$ ($t' \geq t$), and the corresponding predicted amount of generated electricity is $g'_{i,t,t'}$. Note that a larger $t' - t$ leads to a lower prediction accuracy for the predicted amount of electricity generated at t', as illustrated by the following equation:

$$w_{i,t,t'} = w_0 - \epsilon^w(t' - t) \tag{3}$$

This equation indicates that the prediction accuracy is assumed to be a linear function of the time difference, where ϵ^w is a positive weight parameter. The true weather may be different from the prediction; we assume that the remaining probability is shared equally among all other possible weather conditions (i.e., $\frac{1-w_{i,t,t'}}{H^0-1}$)).

Note that this paper focuses on how to schedule users' behaviors rather than how to perform weather prediction and that our algorithm is also suitable for use with other prediction accuracy models. We normalize the amounts of electricity generated, consumed and purchased as percentages of the electricity storage capacity to simplify the formulation.

IV. FORMULATION

This section introduces the objective function, which is designed to maximize the long-term net benefit to electricity consumers. We then explain how to use an MDP model to solve this indeterministic optimization problem. Fig. 4 shows all the factors that affect users' decisions.

A. OBJECTIVE FUNCTION

In this system, the benefit to electricity consumers is the revenue earned by selling electricity to the smart grid minus the expense of purchasing electricity from the electricity plant and the initial investment. Maximizing this quantity is equivalent to maximizing electricity consumers' net benefit. Hence, the objective function can be expressed as follows:

$$\text{maximize} \sum_{i \in U}(\sum_{t=1}^{T}(a_{i,t}p'_t - v'_{i,t}p_{v'_{i,t},t}) - \phi M_{i,max}) \tag{4a}$$

$$\text{subject to } a_{i,t} \leq e_{i,t}, \quad i \in U, \ t = 1, \ldots, T \tag{4b}$$

$$e_{i,t} \leq E_i, \quad i \in U, \ t = 1, \ldots, T \tag{4c}$$

$$p'_t \leq p_{\cdot,t}, \quad t = 1, \ldots, T \tag{4d}$$

In this equation, $\sum_{t=1}^{T} a_{i,t}p'_t$ is the revenue earned by selling electricity to the smart grid. $v'_{i,t}$ is the amount of electricity purchased from the smart grid, and $\sum_{t=1}^{T} v'_{i,t}p_{v'_{i,t},t}$ represents the cost to electricity consumer i of purchasing electricity from the smart grid. If the electricity consumer does not need to purchase any electricity from the electricity plant, then $v'_{i,t} = 0$. $\phi M_{i,max}$ represents the sunk cost for electricity consumer i that is allocated to the time periods

[4]Our algorithm is not specific to any particular model of consumers' electricity consumption; it works just as well with other models. This model is simply chosen as an example for this paper.

$t = 1, \ldots, T$; this sunk cost is assumed to be linearly proportional to the capacity $M_{i,max}$, with a proportionality coefficient of ϕ. Constraint (4b) indicates that a consumer cannot sell more electricity than the electricity contained in that consumer's electricity storage unit, and constraint (4c) states that the amount of stored electricity cannot exceed the storage capacity. Finally, constraint (4d) ensures that the prices at which electricity is sold are no higher than the prices set by the electricity plant for electricity sales. In all of the above notation, t is the time period index.

B. OPTIMIZATION FACTORS

Consumers usually explore all potential options before deploying their electricity generation systems, which means that $M_{i,max}(i \in U)$ is usually fixed; hence, this quantity is not considered in the optimization. Thus, the decisions that consumers can make to maximize their benefits are when to purchase electricity (affected by time-varying sale prices), when to sell their excess electricity (affected by time-varying purchase prices), how much electricity to purchase and how much electricity to sell. The weather conditions, the season, etc. affect the amount of electricity that is expected to be generated in the near future. If the amount of electricity to be generated is expected to be insufficient for their own use, consumers may choose to keep their electricity instead of selling it. Otherwise, consumers can choose to sell their excess electricity during a high-price period since the amount of generated electricity exceeds their own usage. Moreover, the amount of electricity remaining in storage affects consumers' scheduling decisions, e.g., if a consumer's storage unit is almost full, that consumer may be more likely to sell even when the purchase price is not as favorable. However, future amounts of electricity generation and consumption cannot be known exactly, and thus, the problem of scheduling users' behaviors while considering this uncertainty to maximize the users' net benefit is non-trivial.

C. Markov DECISION PROCESS

An MDP is a finite-horizon (H) recursion process, in which a leaf node of the recursion tree marks the end of the decision process.[5] For each state s_t at time t, there are multiple possible actions, and each possible action leads to different future states. Note that each time index t denotes a different time period, as discussed above. The action that leads to the largest average objective value will be chosen as the best strategy at time t. There are four important factors involved in an MDP, namely, 1) the state space, 2) the action space, 3) the state transition probabilities, and 4) the benefit function. Fig. 5 presents an illustration of such an MDP. Below, we define each factor listed above for the problem of interest and demonstrate how consumers can use an MDP model to make decisions.

[5]Note that always-insufficient consumers can be classified into this category.

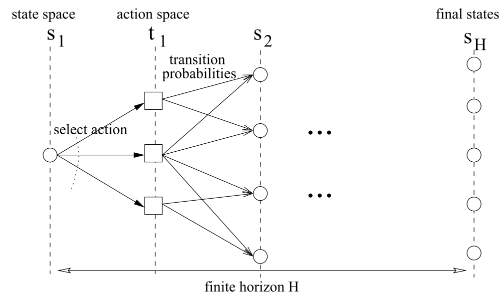

FIGURE 5. **Illustration of a Markov decision process.**

1) STATE SPACE

We define the state of user i at time t as $s_{i,t}$, which represents the status of that user's storage. To reduce the complexity of the MDP, we use a coarse status scale to limit the total number of possible states, in which the unit is defined as the percentage $x\%$ (e.g., x=10) of the total storage capacity. Thus, $s_{i,t} = \lfloor \frac{e_{i,t}}{x\% * E_i} \rfloor$. The compensation is incremented correspondingly with each integer-valued downward shift. Note that this percentage $x\%$ could be replaced with some other constant value depending on the specified requirements in terms of computational complexity and the consumers' sensitivity to the granularity of the state space.

2) ACTION SPACE

An action is defined in terms of the quantities of electricity to be sold and/or purchased during time period t. Since the unit of the state space is $x\% * E_i$, the unit of electricity sales is also assumed to be $x\% * E_i$. This again limits the number of possible actions and reduces the complexity to some extent. Thus, the possible actions $A_{i,t}$ of user i at time t are defined by the possible combinations of how much to sell and how much to purchase, i.e., $A_{i,t} = (a_{i,t}, v'_{i,t})$, where $a_{i,t} = 0, \ldots, \lfloor \frac{e_{i,t}}{x\% * E_i} \rfloor$ and $v'_{i,t} = 0, \ldots, \lceil \frac{E_i}{x\% * E_i} \rceil$. The latter means that the set of feasible actions must satisfy constraints (4b) and (4c). $a_{i,t} = 0$ means that no electricity will be sold. Note that at any given t, either $a_{i,t} = 0$ or $v'_{i,t} = 0$; otherwise, it is obvious that the action is not optimal.

3) TRANSITION PROBABILITY

To define the transition probability, we need to know two factors: the electricity consumption of the home appliances and the future electricity generation. Recall that electricity consumer i can generate an amount of electricity $g'_{i,t,t'}$ $(t' \geq t)$ at time t' with prediction probability $w_{i,t,t'}$, where the prediction is made at time t. Then, based on whether a user's energy consumption is known or unknown, we can calculate the transition probabilities for action $A_{i,t}$ for two cases when the decision is made at time t_0:

Case 1: If the system has full knowledge of the user's energy consumption $v_{i,t}$, then the transition probability can be expressed as follows:

$$T_{s_{i,t+1}}(s_{i,t}) = T_{min(0,s_{i,t}+g'_{i,t_0,t}+v'_{i,t}-v_{i,t}-a_{i,t})}(s_{i,t}) = w_{i,t_0,t} \quad (5)$$

where this equation indicates the state transition and $s_{i,t+1} = min(0, s_{i,t} + g'_{i,t_0,t} + v'_{i,t} - v_{i,t} - a_{i,t})$.

Case 2: When full knowledge of the user's energy consumption $v_{i,t}$ cannot be obtained, there are many possible amounts of electricity consumption, defined in terms of a base consumption $v^0_{i,t}$ and a flexible consumption $v^1_{i,t}$, with probability $\frac{1}{\delta_{i,t}\sqrt{2\pi}}e^{-\frac{(v^1_{i,t}-\mu_{i,t})}{2\delta^2_{i,t}}}$. Then, the transition probability can be expressed as follows:

$$
\begin{aligned}
T_{s_{i,t+1}}(s_{i,t}) &= T_{min(0,s_{i,t}+g'_{i,t_0,t}+v'_{i,t}-v^0_{i,t}-v^1_{i,t}-a_{i,t})}(s_{i,t}) \\
&= w_{i,t_0,t}\frac{1}{\delta_{i,t}\sqrt{2\pi}}e^{-\frac{(v^1_{i,t}-\mu_{i,t})}{2\delta^2_{i,t}}} \qquad (6)
\end{aligned}
$$

4) OPTIMAL POLICY

Before introducing the optimal policy, we must define the benefit of each action. The benefit is defined as the user's net benefit, i.e., the revenue earned by selling electricity minus the costs paid to purchase electricity. This quantity can be calculated as $B_{s_{i,t},A_{i,t}(s_{i,t+1})} = a_{i,t}p'_t - v'_{i,t}p_{v'_{i,t},t}$. If, at the end of the recursion process, the amount of stored electricity is larger than 0, then an additional benefit is added by assuming that the remaining electricity can be sold at the peak-time price.

The optimal policy θ is the series of actions that leads to the maximum benefit over the lifetime of the MDP. Let θ^* denote the maximum benefit, given the current state $s_{i,t}$. $\theta^*(s_{i,t})$ can be defined recursively as follows: a chosen action $A_{i,t}$ in state $s_{i,t}$ leads to state $s_{i,t+1}$ with transition probability $T_{s_{i,t+1}}(s_{i,t})$ and benefit $B_{s_{i,t},A_{i,t}(s_{i,t+1})}$. Then, $\theta^*(s_{i,t})$ exhaustively searches for the optimal action $A_{i,t}$ given state $s_{i,t}$, which can be expressed as follows:

$$
\theta^*(s_{i,t}) = max_{A_{i,t}}\sum T_{s_{i,t+1}}(s_{i,t})[\theta^*(s_{i,t+1})+B_{s_{i,t},A_{i,t}(s_{i,t+1})}] \qquad (7)
$$

The running time of the MDP is decided by the depth of the horizon H and the number of states at each time instance. The dynamic programming and branch-and-bound approaches can be utilized to calculate the optimal policy. The current weather forecast degrades over an increasing time horizon, which limits H. Moreover, the status normalization strategy introduced in Section IV-C1 helps to reduce the numbers of possible states and actions. Hence, the complexity of the MDP can be kept sufficiently low to allow decisions to be made in a *real-time* manner.

V. EXPERIMENTS

To verify the performance of the proposed scheme, extensive simulations were performed. This section presents the setup and results of these simulations for comparison with other schemes. Note that our scheme does not require any specific parameters and that electricity prices tend to differ between countries. We used the following simulation settings, in which it was assumed that each storage unit could accommodate almost one day of electricity usage, to investigate the scheduling performance. This assumption is consistent with typical products currently on the market, such as the *ZEN Urban PowerBank*,[6] which can supply users with at most one day's total electricity usage.

A. SIMULATION SETUP

Each day is divided into two time periods, i.e., peak (8:00 am$\sim$20:00 pm) and off-peak (20:00 pm$\sim$8:00 am) time periods. Consumers purchase (or sell) electricity from (or to) the smart grid at the prices defined in Eq. (1) and (2), with default parameter values of $v_0 = 5$ (off-peak) and 20 (peak), $v_{max} = 150$, $p_0 = 2.8$, $p'_0 = 0.5$, $\epsilon = 0.5$ and $\epsilon' = 0.4$. The weights f_t that are used are 5 and 3 for peak and off-peak time periods, respectively. Note that the highest sale price is lower than the lowest purchase price to avoid consumers selling electricity purchased during an off-peak period back to the grid at peak-time prices. The possible weather conditions are divided into *sunny*, *normal*, and *rainy*, with probabilities of 0.5, 0.3, and 0.2 (determined based on the climate), respectively. We assume that the accuracy of weather predictions deceases as the prediction horizon becomes longer. The weight parameters $H_{i,t}$ ($i \in U$) corresponding to the *sunny*, *normal*, and *rainy* weather conditions are 5, 4, and 3, respectively. The parameters applied to calculate the expected electricity generation are $q = 40$, $q^1 = 50$, and $\epsilon^g = 0.2$. The daily weather predication accuracies are assumed to be (0.95, 0.9, 0.85) for the three coming days.

B. SIMULATION RESULTS

The proposed scheme (denoted by *MDP*) was compared with the *optimal* and *greedy* schemes. In the *optimal* schemes, weather predictions are assumed to be 100% accurate, and the results of this scheme serve as the upper bound on possible performance since it is impossible for the predictions to be any more accurate. The *optimal* scheme also uses the MDP approach for decision-making. The *greedy* scheme serves as the baseline for comparison. In the *greedy* scheme, consumers sell their electricity during peak times when they are expected to have a surplus at time H based on their predicted future levels of electricity generation and consumption and their current storage status. When the storage status is negative, in the *greedy* scheme, the minimum amount of electricity necessary to ensure that the storage status is non-negative will be purchased. After decision-making, if the remaining electricity is greater than the storage capacity, consumers will sell any electricity that exceeds their storage capacity. If the remaining electricity is negative, consumers will purchase the minimum amount of electricity to ensure that the storage status is non-negative. Each set of simulation parameters was simulated 200 times (with 10 decisions (T = 10), or 5 days, in each set), and the results were averaged (the Y axis indicates the consumers' overall benefits in all figures presenting the results).

[6]http://www.zenenergy.com.au/

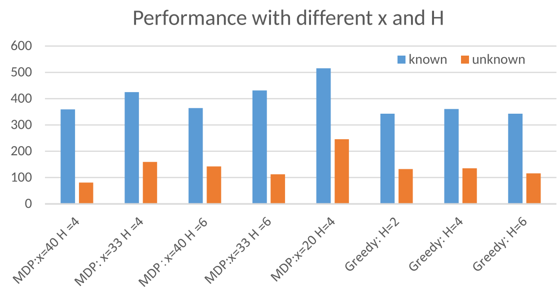

FIGURE 6. **Performance comparison of the *MDP* scheme with different *H* values and different numbers of states.**

Let us first consider the impacts of the MDP factors (the action/state unit size x and the time horizon H). The results are shown in Fig. 6. From this figure, we can observe that considering more states leads to slightly better results, at the cost of a higher computational complexity, for the *MDP* scheme. A longer decision horizon H also leads to better performance, but the prediction accuracy degrades over time, which decreases the performance. Consequently, the results are only slightly better with a longer time horizon H. Regarding the *greedy* scheme, the overall performance does not vary considerably as H increases for similar reasons. The adopted dynamic programming greatly shortens the running time of *MDP* scheme. When $H = 4$ with 6 states, the total running time is around 52.1% of the case without using dynamic programming and this time cost can be shortened to 43% when $H = 6$ with more repeated calculations.

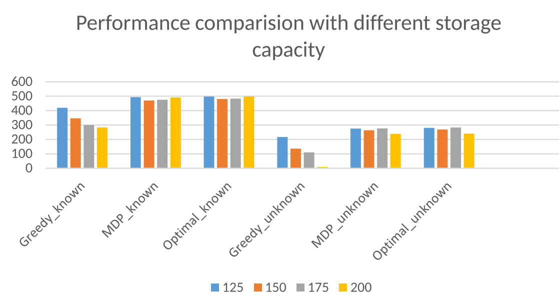

FIGURE 7. **Performance comparison of the *MDP* scheme with different storage capacities.**

For simulations considering both known and unknown levels of future energy consumption, we adopted a horizon of $H = 4$ with 6 states in total. The results are shown in Fig. 7, Fig. 8 and Fig. 9. Fig. 7 shows the performance achieved with the storage capacity treated as a variable (X axis). We observe that the proposed *MDP* scheme greatly outperforms the *greedy* scheme, regardless of whether the future electricity consumption is known or unknown. The superiority of the proposed scheme can be attributed to the decision-making method, which accounts for the expected levels of future electricity generation and consumption as well as the current storage status and uses an MDP model

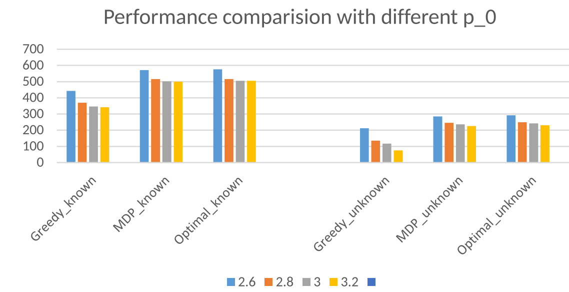

FIGURE 8. **Performance comparison of the *MDP* scheme with different p_0 values.**

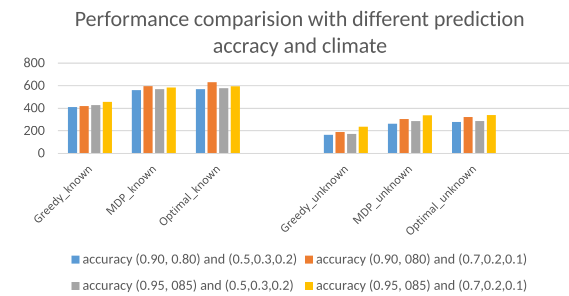

FIGURE 9. **Performance comparison with different prediction accuracies and weather probabilities. The notation (x,y,z) indicates the independent probabilities of *sunny*, *normal*, and *rainy* weather conditions.**

to optimize consumers' behaviors based on this information. The *MDP* scheme performs slightly less well than the *optimal* scheme because of the imperfect weather predictions. Note that the initial states of the simulations with different storage capacities were different; thus, no direct comparison can be made between them.

The effect of the prices at which the consumers purchase electricity from the smart grid was also investigated, as shown in Fig. 8, which presents the results for various p_0 values. We observe that as the prices increase, the overall benefit decreases. However, the previously observed trend holds, i.e., the *MDP* scheme is far superior to the *greedy* scheme and only slightly worse than the *optimal* scheme.

The results obtained for different weather prediction accuracies for the two coming days and different weather situations (affecting electricity generation) are shown in Fig. 9. In this figure, the notation (i, j, k) indicates the independent probabilities of *sunny*, *normal*, and *rainy* weather conditions. In other words, (0.5, 0.3, 0.2) means that for each day, *sunny*, *normal*, and *rainy* weather conditions are assumed to occur with probabilities of 0.5, 0.3, and 0.2, respectively. We observe that as the prediction accuracy decreases, the performance degrades, since inaccurate weather forecasts can mislead the decision-making process. When the probability of *sunny* weather increases, the amount of electricity generated during a given period becomes larger, leading to a higher overall benefit. The proposed *MDP* scheme outperforms the *greedy* scheme in all cases.

VI. CONCLUSION

This paper focuses on a networked smart grid system, in which consumers can generate their own electricity and predictions of future levels of electricity generation can be calculated with reasonable accuracy based on weather forecasts, etc. An MDP model is used to optimize consumers' behaviors (their *purchases from the smart grid* and *sales to the smart grid*) during each specific decision period to maximize their net benefits considering various factors. The results of extensive simulations show that the proposed scheme significantly outperforms the baseline competing scheme.

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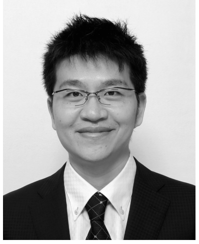

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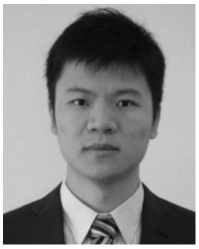

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