Stochastic Unit Commitment in Smart Grid Communications

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Abstract - There is growing interest in renewable energy resources and smart grid. Since most renewable sources are highly intermittent, they can induce significan fluctuation on the supply side of the power grid. On the other hand, the use of smart meters and smart appliances in the smart grid can cause significan uncertainties on the demand side as well. Unit commitment scheduling of power generation systems is an important issue in smart grid communications to coordinate energy demand and generation. In this paper, we study the stochastic unit commitment problem in smart grid communications. Hidden Markov models (HMMs) are used for renewable energy resources. The stochastic power demand loads are modeled by a Markov-modulated Poisson process (MMPP). We show that, under reasonable conditions on the smart grid, structural results can be derived for the unit commit problem, which make the solution practically useful. Simulation results are presented to show the effectiveness of the proposed schemes.

Keywords - Unit commitment, renewable energy, smart grid, power demand loads

I. Introduction

Recently, there is growing interest in obtaining energy from sustainable resources, such as wind, solar and hydro [1]. Most renewable energy sources are highly intermittent in nature and often uncontrollable, which can induce significan fluctuation on the supply side of the power grid. *Smart grid* technologies can facilitate these renewable energy solutions, by coordinating and managing dynamically interacting power-grid participants [2]. A smart grid is an intelligent electricity network, which can reduce power demand peaks, encourage manufacturers to produce “smart” appliances to reduce energy use, and sense and prevent power blackouts by isolating disturbances in the grid [2]. How to use information and communication technologies, such as advanced metering, and bi-directional communications is a major challenge in the smart grid to save energy, reduce cost and increase reliability.

The use of smart meters and smart appliances in the smart grid, which are an emerging class of energy users, can cause uncertainties on the demand side [3]. Therefore, it is a challenging task to guarantee that power demand load and power generation remain balanced, which is very important for system reliability. A mismatch between the supply and demand could cause a deviation of zonal frequency from nominal value [4], and power outages and blackouts may occur, when it gets severe. Unit commitment scheduling of power generation systems is an important issue to effectively coordinate energy demand and generation in order to minimize cost and greenhouse gas emissions, and to avoid blackouts in the grid [5].

In order to effectively model renewable energy, the successive-time state transition probabilities need to be known [6, 7]. Weibull, Rayleigh, lognormal or Gamma probability distribution functions (PDFs) are often used to predict the magnitude of the wind speed or solar radiation. However, these theoretical PDFs assume independence of successive wind speeds or solar radiation levels [8], which may not be realistic in practice. Therefore, finite-stat Markov models have been widely accepted in the literature as an effective approach to characterize the correlation structure of the renewable energy outputs [6, 7]. Considering Markov models may enable substantial performance improvement over the schemes with memoryless models. Moreover, it is generally assumed that the renewable energy system state is known perfectly in previous work. However, meteorological instability and complex system dynamics (e.g., wind turbine or solar cells malfunction) make it difficul to fully observe the system state. Therefore, hidden Markov models (HMMs) are more efficien in modeling renewable energy systems [9, 10].

In this paper, we study the stochastic unit commitment problem in smart grid communications. HMMs are used for the renewable energy resources. The stochastic power demand loads are modeled as a Markov-modulated Poisson process (MMPP). Costs, reliability and pollutant emissions are considered in the scheme. We model the operational cost of the utility grid as a convex function of instantaneous power consumption, so as to reflec the fact that each additional unit of power needed to serve demand become more expensive as the total power demand increases. We then formulate the unit commitment problem as a partially observable Markov decision process (POMDP) multi-armed bandit problem [11, 12]. A value iteration method and a structural results method are presented to solve the problem. The value iteration method works well for a smart grid with a small number of generation units. For a large smart grad with a variety of different generation units, the value iteration-based solution can become computationally intractable. Therefore, we further present structural results for this problem. We show that, under reasonable conditions on the smart grid, structural results can be derived for the the unit commit problem, which are trivial to implement and make the solution practically useful. Simulation results are

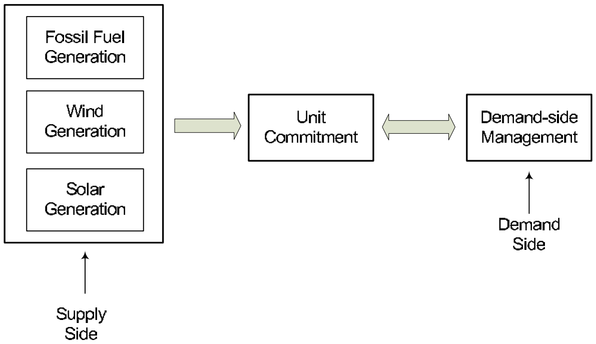

Fig. 1. The relationship among supply side management, demand side management, and unit commitment.

presented to show the effectiveness of the proposed schemes.

The rest of the paper is organized as follows. Section II introduces the system models. Section III describes the formulation and solutions to the unit commitment problem. Section IV presents the simulation results. Finally, we conclude this study in Section V.

II. SYSTEM MODELS

In this paper, we consider that solar panels, wind turbines and traditional fossil fuel power generators are integrated into the smart grid. Since both renewable resources highly depend on weather conditions, it is possible that power fluctuation occur. Therefore, fossil fuel power generators are also used in order to mitigate or even cancel out the fluctuations

In the smart grid, *demand-side management* (DSM) programs are also implemented by utility companies to reduce and shift power consumption at the customer side. Therefore, two kinds of energy users exist in the smart grid: traditional energy users, and opportunistic energy users, who introduce uncertainties on the demand side.

The relationships between supply side management and unit commitment, and demand side management and unit commitment are illustrated in Fig. 1 [13]. Both the status of the generators and the status of the demand side determine which units will be committed. In turn, unit commitment affects demand, which produces a feedback loop, and is different from the traditional one-way affect that the demand side has on unit commitment. The power generation units need to be integrated together using smart grid communications in order to serve the stochastic demand loads while satisfying economic, reliability and environmental criteria. Therefore, it is critical to optimally schedule these units, considering stochastic demand loads, costs, reliability and pollutant emissions.

A. Generation Unit Model

Assume that there are G_w wind turbines, G_s solar panels and G_f fossil fuel power generation units in the smart grid, for N units total. In this paper, *wind power* and *solar power* mean the electric power generated by wind turbines or solar panels rather than the input wind power or solar radiation power. *Wind turbine* and *solar panel* may mean an individual energy generation unit or a cluster of such units as a farm, depending on the context under consideration. We consider that the time axis is divided into equal time slots, which correspond to the time intervals between two decisions.

Let the state of a generator n, $n \in \{1, 2, \ldots, N\}$, be $s_k^{(n)}$ at time slot k. Each state represents the power supply level of generator n. The power supply of each generator can be divided into L discrete levels. The power supply state space $\mathbb{S}$ includes all the power supply states $\{s_1, \ldots, s_L\}$. The state of renewable energy generator n, evolves according to a L-state firs order Markov chain with state transition probability matrix $J^{(n)}$, which is described as follows:

$$J^{(n)} = \left(s_{ij}^{(n)}\right)_{i,j\in\mathbb{S}}, \text{ where } s_{ij}^{(n)} = P\left(s_{k+1}^{(n)} = j | s_k^{(n)} = i\right).$$

The observation of selected generator n's power level state is denoted as $y_k^{(n)}$ at time slot k, which belongs to a finit set $\mathbb{M}_n$ indexed by $m^{(n)} = 1, \ldots, M_n$, and $|\mathbb{M}_n|$ denotes the number of possible observations of the generator n's power generation level state. If generator n is picked at time k, and the system state $s_k^{(n)}$ equals to i, the probability of observation m obtained from generator n is denoted as:

$$b_i\left(a_k = n, y_k^{(n)} = m\right) = P\left(y_k^{(n)} = m | s_k^{(n)} = i, a_k = n\right), \tag{1}$$

where $i \in \mathbb{S}$, and $m \in \mathbb{M}_n$. Defin the observation matrix as:

$$B_s^{(n)}\left(y_k^{(n)} = m\right) = diag[b_1(a_k, m), \ldots, b_L(a_k, m)]. \tag{2}$$

B. Power Demand Model

The stochastic power demand is modeled by a Markov-modulated Poisson process (MMPP). MMPPs have been extensively used for modeling the processes in various applications, such as multimedia applications [14, 15]. MMPP can qualitatively model the time-varying arrival rate and capture some of the important correlations between the inter-arrival times while still remain analytically tractable.

The MMPP for modeling power demands consists of a Q-state Markov chain. Let the state of the demand arrival rate be d_q, $d_q \in \mathbb{D} = \{D_1, D_2, \ldots, D_Q\}$, where Q is the number of demand state levels. The arrival power demand resides in state d_q for a mean time of $1/r_q$ with rate d_q. In the proposed scheme, the MMPP is specifie by the infinitesima generator matrix GM as follows [16]:

$$GM = \begin{pmatrix} -r_1 & r_1 & & & \\ & -r_2 & r_2 & & \\ & & \ddots & \ddots & \\ & & & -r_{Q-1} & r_{Q-1} \\ r_Q & & & & -r_Q \end{pmatrix}. \tag{3}$$

Since matrix GM models a continuous-time Markov chain, we use *uniformization* [17] to obtain the equivalent discrete-time transition probability matrix T for the stochastic power demand as follows [7]:

$$T = \frac{GM}{\vee + I}, \tag{4}$$

where $\vee \geq \min_q(|[GM]_{q,q}|)$ (i.e., $\vee$ is greater than or equal to the absolute value of the minimum diagonal element in GM) and I denotes an identity matrix. The observation probability matrix of the hidden Markov chain for power demand state can be obtained based on the conditional probability function of the actual demand states and observation states.

C. Cost Model

In order to minimize costs and greenhouse gas emissions, and to avoid blackouts, we consider utility costs (UCs), customer interruption costs (CICs) and pollutant emission costs (PECs) in our scheme.

At time slot k, let unit n be selected (i.e., $a_{k+1} = n$), based on the history information $Y_k^{(a_k)}$. The instantaneous cost $C\left(x_k^{(n)}, n\right)$ incurred at time k is as follows [1, 18]:

$$\begin{aligned} C\left(x_k^{(n)}, n\right) &= \underbrace{UC_k^{(n)}\left(x_k^{(n)}\right)}_{utility} + \underbrace{CIC_k^{(n)}\left(x_k^{(n)}\right)}_{interruption} \\ &\quad + \underbrace{PEC_k^{(n)}\left(x_k^{(n)}\right)}_{pollution}, \end{aligned} \tag{5}$$

where $x_k^{(n)} = \left(s_k^{(n)}, d_k\right)$, which includes the state of generation unit n and the demand state at time k.

Utility costs $UC_k^{(n)}$ include the average costs associated with the required investments and operations of the chosen generator n during the time slot k, when a renewable energy generator is chosen. If a fuel generator is chosen, the utility cost for purchasing power at time k can be calculated as: $UC_k^{(n)}\left(s_k^{(n)}, d_k^{(n)}\right) = p_k \times \varphi(p_k)$ where p_k is the power purchased at time k, and $\varphi(p_k)$ is the power price. If only one fuel generator is chosen at time slot k, $p_k = d_k^{(n)}$. Function $\varphi(\cdot)$ is an increasing, differentiable convex function, which reflect that each unit of additional power needed to satisfy increasing demand becomes more expensive to obtain and make available to the consumers.

Customer Interruption Cost $CIC_k^{(n)}$ is directly related to the type of customers and the duration of interruptions (i.e. the length of time slot k), which is define as follows:

$$CIC_k^{(n)} = \begin{cases} F(\Delta), & \Delta > 0, \\ 0, & \Delta \leq 0, \end{cases}$$

where Δ equals to the power demand subtracting to the power generated from generator n at time slot k. $F(\Delta) = \sum_{z=1}^{Z} f_z(\Delta_z)$, where $\Delta = \Delta_1 + \cdots + \Delta_z$. Function $f_z(\cdot)$ is the CIC in customer sector z, and Z is the number of customer sectors.

With the increasing concerns about environmental protection, stricter regulations on pollutant emissions have been introduced, often including financia penalties associated with emissions (e.g., carbon credits), as well as non-financia costs associated with environmental damage, which is represented as financia penalties as well in our model. There are no pollutant emissions for renewable energy generation systems. The amount power generators must pay depends on fuel consumptions p_k, which can be calculated as follows [1]:

$$PEC_k^{(n)} = \alpha + \varepsilon \times p_k + \gamma \times p_k^2, \tag{6}$$

where α, ε, and γ are the coefficient approximating the generator emission characteristics.

The total expected discounted cost over an infinite-tim horizon is given by:

$$J_\mu = E\left[\sum_{k=0}^{\infty} \beta^k C\left(x_k^{(n)}, n\right)\right], \tag{7}$$

where β is the discounted factor, which models the fact future cost is worth less than immediate cost, because the future is less certain. The objective is to fin the optimal stationary policy $\mu^* = \arg\max_{\mu \in \eta} J_\mu$ to minimize the cost in (7).

In the proposed scheme, the number of scheduled units at each time slot is determined by the renewable energy generation situation and the total power demand loads. For simplicity of the presentation, we assume that one generation unit (either a renewable energy generation unit or fuel generation unit) will be chosen at each time slot. Note that it is straightforward to generalize the model to picking more than one generation unit.

III. FORMULATION AND SOLUTIONS TO THE STOCHASTIC UNIT COMMITMENT PROBLEM

A. Formulation of the Stochastic Unit Commitment Problem

The decision on which generation units are chosen should not totally depend on the current observation values, since the renewable energy generation units' states are only partially observable. According to [19], the above POMDP multi-armed bandit problem can be re-expressed as a fully observable multi-armed bandit problem in terms of the information state, which means optimal units can be chosen based on the information states.

The information state of a generation unit refers to a probability distribution over the unit's states. The entire probability space (the set of all possible probability distributions) is referred to as the information space. For an arbitrary unit n, the information state at time k is denoted as $\pi_k^{(n)}$. If unit n is chosen, a new observation $y_{k+1}^{(n)}$ is obtained at time $k+1$. Its information state at that time $\pi_{k+1}^{(n)}$ can be recursively updated by the hidden Markov model state filte known as the *forward algorithm* with the new observation [20].

For our proposed scheme, the optimal policy has an *indexable rule* [11], meaning the units' Gittins indices $\gamma^{(n)}\left(\pi_k^{(n)}\right)$ $(n \in \{1,\ldots,N\})$ are used to choose the appropriate unit at time k. Furthermore, the optimal policy at time k is that the unit with the largest reward Gittins index at that time should be selected. In the following, we present two possible methods to compute the Gittins index.

B. Solutions to the Stochastic Unit Commitment Problem

A value iteration algorithm can be used to solve the above unit commitment problem. An elementary coordinate transformation is introduced to transform the value function with a parameterized retirement reward to the value function of a standard POMDP. The near-optimal Gittins index $\gamma_H^{(n)}(\pi^{(n)})$ for an arbitrary unit n is given by the finite-dimensiona representation in [20].

In this subsection, we show that, under reasonable conditions on the cost vector C, state transition probability matrix U (i.e., $J \otimes T$) and observation probability matrix B of each generation unit in the smart grid, the Gittins index in our problem can be monotone increasing in the information state (with respect to the monotone likelihood ratio (MLR) ordering [12]). Therefore, if at a given time the information states of these N generators are MLR comparable, then the optimal policy is to simply pick the generator whose information state is smallest in terms of the MLR ordering. The definitio of MLR ordering used in this paper is described as follows.

Definitio III.1. *MLR Ordering.*

Assume that each generation unit includes the same number of states. Namely, $\mathbb{X}_1,\ldots,\mathbb{X}_N$ are equal to $\mathbb{X}$.

1) *Let π_1 and π_2 be two information state vectors. Then, π_1 is less than π_2 with respect to the MLR ordering – denoted as $\pi_1 \le_r \pi_2$ if $\pi_1(i)\pi_2(j) \ge \pi_2(i)\pi_1(j), i < j, i, j \in \mathbb{X}$.*
2) *A function $f(\cdot)$ is MLR increasing if for all $\pi_1, \pi_2 \in \mathbb{X}$, $\pi_1 \le_r \pi_2$ implies $f(\pi_1) \le f(\pi_2)$.*
3) *Let $\pi^{(1)}, \pi^{(2)}, \ldots, \pi^{(N)}$ denote the information states of N units. Then they are said to be MLR comparable if for any $n, \widetilde{n} \in \{1,\ldots,N\}$, either $\pi^{(n)} \le_r \pi^{(\widetilde{n})}$ or $\pi^{(n)} \ge_r \pi^{(\widetilde{n})}$.*
4) *Given MLR comparable information states of these N units, denote the smallest information state (with respect to MLR ordering) as $\min\{\pi^{(1)},\ldots,\pi^{(N)}\}$ with index $\arg\min\{\pi^{(1)},\ldots,\pi^{(N)}\}$.*

In the following, we present the conditions on the parameters C, U and B of an arbitrary generation unit, where its Gittins index $\gamma(\pi)$ is monotone in information state π with respect to the MLR ordering.

Theorem 1. *Consider the following assumptions for each generation unit:*

Assumption 1. *Costs satisfy $C(i) \le C(i+1)$.*

Assumption 2. *State transition probability matrix U is totally positive of order 2 (TP2), i.e., all its second order minors are non-negative. That is, determinants*

$$\begin{vmatrix} u_{i_1 j_1} & u_{i_1 j_2} \\ u_{i_2 j_1} & u_{i_2 j_2} \end{vmatrix} \ge 0 \text{ for } i_2 \ge i_1, j_2 \ge j_1.$$

Assumption 3. *Symbol probabilities satisfy $(b_{i,m})_{m\in\mathbb{M}} \le_r (b_{i+1,m})_{m\in\mathbb{M}}$ for $i = 1,\ldots,|\mathbb{X}|-1$.*

Then the Gittins index $\gamma(\pi)$ of each unit is MLR increasing. Therefore, if the information states of the N units are MLR comparable, then the optimal policy μ^* is to pick the unit with the smallest information state with respect to MLR ordering at each time slot, namely, $a_k = \mu^*\left(\pi_k^{(1)},\ldots,\pi_k^{(N)}\right) = \arg\min\left(\pi_k^{(n)}\right), n \in \{1,\ldots,N\}$.

In the following, we show that under some reasonable conditions on the matrices of each generation unit in the smart grid, the generation system meets the above three assumptions. Assumption 1 shows that for an arbitrary generation unit, the cost in state i is less than or equal to that in state $i+1$. Due to continuity arguments, if the state of a unit is $x_i, 1 \le i \le X$ at time k, then at time $k+1$, it is reasonable to assume that it is either still in state x_i, or, with a lower probability, in the neighboring states x_{i+1} or x_{i-1}. Therefore, in our proposed scheme, each unit can be modeled as a X-state Markov chain with diagonally dominant tridiagonal transition probability matrix U, where $u_{ij} = 0$ for $j \ge i+2$ and $j \le i-2$. According to [21], a necessary and sufficien condition for tridiagonal matrix U to meet Assumption 2 is that $u_{i,i}u_{i+1,i+1} \ge u_{i,i+1}u_{i+1,i}$. Several common observation probability models for the generation units that satisfy Assumption 3 are listed as follows:

1) Each unit measures the target in quantized Gaussian noise.
2) Observation probabilities die geometrically fast with the error between the reported observation y and the real state x.
3) The value the unit reports is never more than one discrete value away from the true value. Therefore, B matrix is the following $X \times X$ tridiagonal matrix:

$$\begin{pmatrix} p_1 & 1-p_1 & 0 & 0 & \cdots \\ \frac{1-p_2}{2} & p_2 & \frac{1-p_2}{2} & 0 & \cdots \\ 0 & \frac{1-p_3}{2} & p_3 & \frac{1-p_3}{2} & \cdots \\ 0 & 0 & 1-p_4 & p_4 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

When vector C, matrix T, and matrix B of each generation unit meet all of the three assumptions in Theorem 1, the Gittins index $\gamma(\pi)$ is monotone increasing. Therefore, if the information states of the N units are MLR comparable, the optimal policy is to pick the unit with the smallest information state with respect to MLR ordering.

IV. Simulation Results and Discussions

In this section, we consider the following simulation scenario to evaluate the proposed scheme's performance. There are wind turbine generators (WTGs), photovoltaic systems (PVs), and conventional fossil-fuel generation systems (FFGSs) in the smart grid. Each generator includes two power supply level states {high, low}, and there are two demand load states {peak, off-peak}. The utility cost of wind turbines is lower than that of solar panels, and higher than that of fossil fuel generators.

The wind speed state transition probability matrix, taken from [22], was calculated from the average frequency of transitions of real wind speed data gathered at Tangiers, Morocco. The state transition probability matrix of cloud coverage is define following to [7, 23]. Therefore, the power supply level state transition probability matrices of the WTG, PV and FFGS are as follows:

$J^{(1)} = \begin{pmatrix} 0.756 & 0.244 \\ 0.279 & 0.721 \end{pmatrix}$, $J^{(2)} = \begin{pmatrix} 0.850 & 0.150 \\ 0.150 & 0.850 \end{pmatrix}$,

$J^{(3)} = \begin{pmatrix} 1.000 & 0.000 \\ 0.000 & 1.000 \end{pmatrix}$.

Power demand loads are determined by two Poisson processes, one for peak hours and another for off-peak hours, where the inter-arrival times between two requests are exponentially distributed with a mean of 1 hour and 12 hours, respectively. Assume the demand in each request is 100 kWh/h. The corresponding power demand load state transition matrix is define as:

$T = \begin{pmatrix} 0.700 & 0.300 \\ 0.400 & 0.600 \end{pmatrix}$.

Their observation matrics are define as:

$B_s^{(n)} = B_t^{(n)} = \begin{pmatrix} 0.900 & 0.100 \\ 0.100 & 0.900 \end{pmatrix}$, where $n = 1, 2, 3$.

The price of electricity differs for peak rate 9.9 cents/kWh and off-peak rate 5.1 cents/kWh [24] and that of solar power is 80.2 cents/kWh [25] in Ottawa, Canada. The price of wind power is set to 20.5 cents/kWh. The cost matrices are as follows in \$/h: $C^{(1)} = (20.5, 25.5, 890.5, 1.7)$, $C^{(2)} = (80.2, 85.2, 950.2, 6.7)$, $C^{(3)} = (309.9, 314.9, 1075.1, 26.1)$. Each cost element includes utility costs, customer interruption costs and pollutant emission costs.

We firs run simulations to compare the costs of the proposed scheme with and without considering the dynamic power demand loads and an existing scheme that does not consider (hidden) Markov models for modeling renewable energy resources [26]. Fig. 2 shows the average cost within the firs 20 hours of the simulations of the smart grid of different sizes. In these simulations, we use the same three kinds of units mentioned earlier. The results show that the proposed scheme has the lowest cost compared to the existing scheme and the proposed scheme without considering the demand loads. The results also show that the cost of the proposed schemes and existing scheme decreases when the number of available units in the smart grid increases from 3 to 18. The reason is that there are more units that can be selected, so low-energy units can be avoided when demand is high.

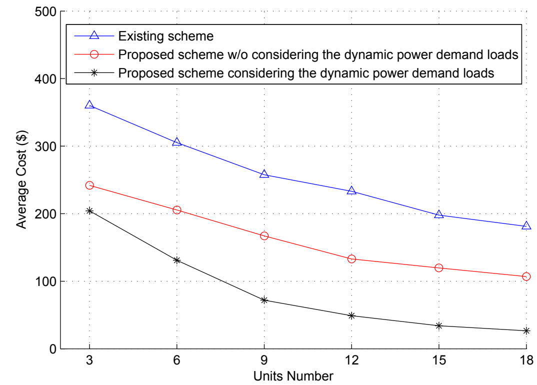

Fig. 2. Average costs of three schemes with varying units in the smart grid.

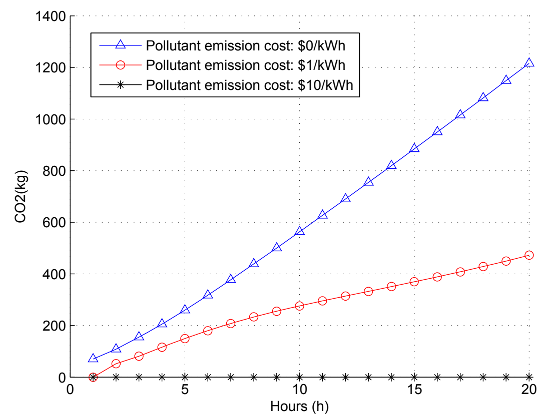

Fig. 3. CO_2 emissions in hours.

Different values of pollutant emission costs are also used in the simulations to analyze how they affect the CO_2 emissions in the smart grid, since reducing pollutant emissions is the main motivation for employing renewable energy generation. We understand that the higher the pollutant emission cost, the greater the chance that renewable energy generators are scheduled. In our paper, the CO_2 emission is set with 0.6999 kg/kWh [27]. Fig. 3 shows that CO_2 emissions increase with the reduction of the pollutant emission costs.

Simulations are performed to compare the computational efficien y in the proposed scheme using the structural results method (SRM) and the value iteration algorithm (VIA). Table I shows the computation time spent in the proposed scheme in the off-line and on-line parts, as the total number of unit types in the smart grid varies from 2 to 50. For the value iteration algorithm, the on-line computation time is of the same level as that of the structural results method. The table

TABLE I
THE COMPUTATION TIME OF THE TWO METHODS IN THE PROPOSED DISTRIBUTED SCHEME.

Method	2 types	4 types	20 types	50 types
SRM (off-line)	0	0	0	0
SRM (on-line)	0.0427s	0.0576s	0.2337s	0.5960s
VIA (off-line)	0.03s	8h1m22s	unfeasible	unfeasible
VIA (on-line)	0.0379s	0.0531s	-	-

also shows that the off-line time is the dominant part for the value iteration algorithm. The computation time dramatically increase when the number of unit types changes from 2 to 4: from 0.03 seconds to more than 8 hours. In the structural results method, a *quicksort* algorithm with MLR ordering is used to sort the units by current information states. The off-line computation time for the structural results method is always equal to 0, since the method is only used for on-line unit scheduling. The computation time of the structural results method slightly increase with the increasing type of the units in the smart grid. This shows that the structural results are practically useful in the smart grid.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented a distributed stochastic unit commitment scheme in smart grid communications. In the proposed scheme, the most suitable generation unit is dynamically scheduled based on the intermittent renewable energy power generation situations, stochastic power demand loads, utility cost, reliability and pollution emissions of the generation units. Hidden Markov models and a Markov-modulated Poisson process were used in modeling renewable energy resources and the power demand loads, respectively. We formulated the unit commitment problem as a POMDP multi-armed bandit problem, and its optimal policy can be chosen using Gittins indices. A value iteration method and a structural results method were used to solve the problem. Simulation results showing that our scheme can decrease costs and greenhouse gas emissions were presented. Future work is in progress to consider system reliability in the proposed framework. Mathematical programming method will be also used to evaluate the impact demand response on unit commitment problems and to pursue optimal price-assigning strategy.

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