DEMAND SIDE MANAGEMENT WITH A HUMAN BEHAVIOR MODEL FOR ENERGY COST OPTIMIZATION IN SMART GRIDS

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ABSTRACT

Demand side management (DSM) is an essential function to schedule and optimize the energy consumption in smart grids. One of the challenges of DSM is how to take the complex human behavior into consideration. In this paper, we apply a special population dynamic model to investigate the performance of DSM algorithms under human behavior effects. Specifically, we adapt the SISa (susceptible-infected-susceptible with autonomous infection) model to describe the population behavior of smart grid customers. The SISa model and the DSM algorithms interact with each other via the recovery probability and the DSM population size. The convergence and the equilibrium of the composite model are studied both analytically and numerically.

Index Terms— demand side management, smart grid, smart meter, human behavior, game theory

1. INTRODUCTION

One of the major objectives of demand side management (DSM) is for utility companies to schedule and optimize the energy consumption of their customers. DSM brings a number of benefits to the grid, such as balancing energy consumption, and reducing peak to average load ratio, etc [1][2]. DSM is especially useful for today's power systems due to the emergence of new heavy appliances (such as plug-in hybrid electric vehicles) and distributed energy sources (such as solar panels) at the customer's side. To address these new challenges, smart grid technologies, such as smart meters and home energy management systems (HEMS), can be applied to develop more effective DSM schemes [3].

With smart meters and HEMS, it is possible to develop autonomous DSM schemes, where energy consumers optimize their own energy consumptions automatically in a distributed manner. This has many advantages, such as high performance, cost-effective implementation, and increased privacy [4] [5]. Nevertheless, one of its severe barriers is the complex human behavior. Human behavior is hard to model and can make the DSM schemes to have dynamics and performance quite different from their laboratory results. Although the impact of human behavior to DSM has attracted great attention, most of the studies happen in management, economics and sociology, where the focus is DSM administration and policy only [6]-[8].

On the technology side, such as designing DSM algorithms under human behavior considerations, a popular way is to apply game theory. Many game theoretic DSM schemes have been developed [9]-[11], which can address the selfish nature of smart grid customers. Nevertheless, the rationality assumption sets a severe limit in dealing with other and more complex human behaviors. For example, many game theoretic schemes, including those in [9]-[11], adopt pricing as an incentive. However, some human behavior surveys suggest that pricing alone is hardly enough [12]. People sensitive to small price changes are usually from low-income population who use less energy and thus have less impact to the grid. In addition, customers may adopt DSM after a sustainability education, or may abandon DSM for convenience rather than price.

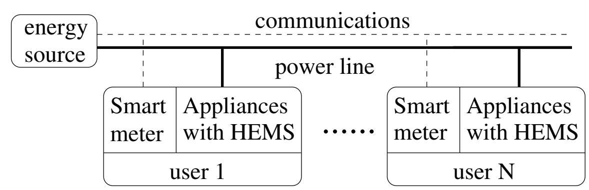

Fig. 1. A smart grid with an energy source and N users.

For large populations, many population dynamic models are extremely effective in addressing the complex human behavior, with many successful results. In this paper, we adapt a special one, the SISa model developed in [13][14], to model the behavior of the DSM population. Based on it, we study the convergence and the equilibrium of both a centralized DSM scheme and a decentralized DSM scheme. The integration of human behavior models and DSM schemes into composite models can give us a more incisive understanding of DSM in practical situations.

The organization of this paper is as follows. In Section 2, we give the DSM system model. In Section 3, we develop and study the composite model. Simulations are conducted in Section 4 and conclusions are given in Section 5.

2. SMART GRID DSM MODEL

Consider a smart grid consisting of one energy source and N consumers or energy users. As shown in Fig. 1, each user has a smart meter with two-way communication capability and is equipped with HEMS to control household appliances. The energy source has a central controller to communicate with the users and to collect their energy usage data through the smart meters. Either centralized or decentralized DSM schemes can be supported in this smart grid.

Let $\mathcal{N} = \{1, 2, \cdots, N\}$ be the user set. Each user $n \in \mathcal{N}$ has a number of household appliances $a \in \mathcal{A}_n$, where $\mathcal{A}_n$ denotes the set of all the appliances of the user n. Each appliance consumes energy $x_{n,a}(h)$ during time $h \in \mathcal{H}$, where $\mathcal{H} = \{1, 2, \cdots, H\}$ is the optimization time horizon. The energy usage (or load) of the whole system during time h is

$$L(h) = \sum_{n \in \mathcal{N}} \sum_{a \in \mathcal{A}_n} x_{n,a}(h). \tag{1}$$

The cost of energy usage is defined as $f_h(L(h))$ which is a function of the energy usage $L(h)$. Each function $f_h(\ell)$, $h \in \mathcal{H}$, is assumed convex. A special example is the monotonically increasing quadratic cost function given in [10], i.e.,

$$f_h(L(h)) = a_h L^2(h) + b_h L(h) + c_h, \tag{2}$$

where $a_h > 0$, $b_h \geq 0$ and $c_h \geq 0$ are time-dependent parameters.

The total energy usage of the whole system is

$$\sum_{h \in \mathcal{H}} L(h) = \sum_{h \in \mathcal{H}} \sum_{n \in \mathcal{N}} \sum_{a \in \mathcal{A}_n} x_{n,a}(h) \tag{3}$$

and the total cost of the system is

$$C(\mathbf{x}) = \sum_{h \in \mathcal{H}} f_h(L(h)) = \sum_{h \in \mathcal{H}} f_h\left(\sum_{n \in \mathcal{N}} \sum_{a \in \mathcal{A}_n} x_{n,a}(h) \right), \tag{4}$$

where

$$\mathbf{x} = \{\mathbf{x}_n | \forall n \in \mathcal{N}\}, \quad \mathbf{x}_n = \{x_{n,a}(h) \mid \forall a \in \mathcal{A}_n,\ h \in \mathcal{H}\}. \tag{5}$$

The DSM problem considered in this paper is to schedule and shift the energy usage profile $\mathbf{x}$ so as to minimize $C(\mathbf{x})$. If $f_h(\ell)$ is monotonically increasing, then minimizing the cost $C(\mathbf{x})$ is equivalent to minimizing the energy usage (3). We assume that each appliance a of the user n consumes a total energy $E_{n,a}$ and can work during time set $\mathcal{T}_{n,a} \subseteq \mathcal{H}$. During each time $h \in \mathcal{T}_{n,a}$, this appliance has an upper bound and a lower bound on its energy consumption, which are denoted as $\gamma_{n,a}^{\min}$ and $\gamma_{n,a}^{\max}$, respectively. This gives constraints on $\mathbf{x}$ as

$$\begin{cases} E_{n,a} = \sum_{h \in \mathcal{T}_{n,a}} x_{n,a}(h), & \\ x_{n,a}(h) = 0, & \text{if } h \notin \mathcal{T}_{n,a}, \\ \gamma_{n,a}^{\min} \leq x_{n,a}(h) \leq \gamma_{n,a}^{\max}, & \text{if } h \in \mathcal{T}_{n,a}. \end{cases} \tag{6}$$

In this paper, we focus on studying the impact of human behavior to DSM by analyzing composite models that integrate human behavior models and DSM schemes together. For the DSM schemes, we directly use those of [10]. Specifically, for centralized DSM, the central controller collects the parameters $E_{n,a}$, $\mathcal{T}_{n,a}$, $\gamma_{n,a}^{\min}$, $\gamma_{n,a}^{\max}$ from all the users and solves the optimization problem

$$\min_{\mathbf{x}} \quad C(\mathbf{x}), \quad \text{s.t.,} \quad \mathbf{x}_n \in \mathcal{X}_n, \quad \forall\, n \in \mathcal{N}, \tag{7}$$

where $\mathcal{X}_n$ is the domain of the optimization variable $\mathbf{x}_n$ defined as

$$\mathcal{X}_n = \{\mathbf{x}_n | x_{n,a}(h) \ \text{satisfies (6) for all} \ a \in \mathcal{A}_n, h \in \mathcal{H}\}. \tag{8}$$

Since the functions $f_h(\ell)$ are convex, (7) is a convex optimization with a unique global minimum. Note that there may have multiple solutions $\mathbf{x}^*$ that can achieve this minimum cost [10].

For decentralized DSM, the elegant game theoretic algorithm developed in [10] is used, which can in fact achieve the global minimum of (7). It has a straightforward distributed algorithm implementation, where each user just adopts the best response strategy to optimize $\min_{\mathbf{x}_n} C(\mathbf{x})$. Note that no human behavior model was considered in [10].

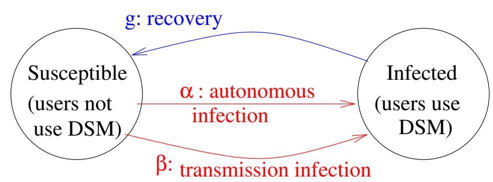

Fig. 2. The SISa (susceptible-infected-susceptible with autonomous infection) model for DSM.

3. INTEGRATE HUMAN BEHAVIOR MODEL WITH DEMAND SIDE MANAGEMENT SCHEMES

3.1. Adapting SISa model for DSM

In the DSM model outlined in Section 2, all users are assumed to follow the same optimization rule and to adopt the optimization results unanimously. However, in practice, users quite often show different behaviors. For example, some users may abandon the DSM when they find it inconvenient to use. Such unexpected human behavior will change the performance of the DSM schemes. The convergence and the optimality of (7) can be different than those derived in [10].

Human behavior is complex to model and analysis. Many methodologies have been developed for it, such as bounded rationality in game theory and descriptive models in behavior science. Population dynamic models, which use succinct nonlinear differential equations to model the interactions among a large population, have the strength of catching the essential interactions while averaging out the variability of the population. The SISa model developed in [13] is one of the examples. As a variation of the well-known disease propagation model ISR (infected-susceptible-recovered), the SISa model is designed specifically for modeling inter-personal propagation of human behaviors, states, ideas, emotions, etc. More importantly, its effectiveness has been verified by real data analysis in [13] (modeling the spread of obesity) and in [14] (modeling the spread of emotions such as content).

Considering the strength of the SISa model for human behavior study, we adapt it to DSM in this paper. We define two states: the *susceptible* state (i.e., not use the DSM scheme), and the *infectious* state (i.e., use the DSM scheme). We use the sets $\mathcal{S}$ and $\mathcal{I}$ to include all the users in each of these two states, respectively. Obviously, $\mathcal{S} \subseteq \mathcal{N}$, $\mathcal{I} \subseteq \mathcal{N}$, $\mathcal{S} \cap \mathcal{I} = \phi$, and $\mathcal{S} \cup \mathcal{I} = \mathcal{N}$.

As shown in Fig. 2, a user in the set $\mathcal{S}$ can autonomously, or spontaneously, switch to the set $\mathcal{I}$, which means adopting the DSM scheme. This happens with probability α, where $0 \leq \alpha \leq 1$. For example, after a sustainability education, each user has probability α to adopt the DSM scheme. In addition, users in the set $\mathcal{I}$ may infect users in the set $\mathcal{S}$, where "infect" means draw from $\mathcal{S}$ to $\mathcal{I}$. For example, a user may adopt the DSM scheme if his friends have already adopted it. This happens with probability β, where $0 \leq \beta \leq 1$. It models the effect of social network behavior. Finally, each user in the set $\mathcal{I}$ has probability g, where $0 \leq g \leq 1$, to switch back to $\mathcal{S}$. For example, a user may find the DSM scheme inconvenient to use and thus abandon it. The parameter g depends on the benefit or cost of DSM.

At time t, let the number of users in $\mathcal{S}$ be $S(t)$ and the number of users in $\mathcal{I}$ be $I(t)$. Then the population sizes evolve according to

$$\begin{cases} \frac{dS(t)}{dt} = -\beta S(t) I(t) + g I(t) - \alpha S(t) \\ \frac{dI(t)}{dt} = \beta S(t) I(t) - g I(t) + \alpha S(t) \end{cases} \tag{9}$$

where $I(t) + S(t) = N$ for any t.

We consider a well-mixed population only in this paper, i.e., each user has equal probability to be in contact with other users. Structured population can be studied by following [14]. The equilibrium of (9) can be obtained by letting $dS(t)/dt = dI(t)/dt = 0$. At equilibrium, the probability for a user to adopt the DSM scheme is

$$P_I = \frac{I(t)}{N} = \frac{1}{2}\left(1 - \frac{\alpha+g}{\beta N} + \sqrt{\left(1-\frac{\alpha+g}{\beta N}\right)^2 + \frac{4\alpha}{\beta N}}\right). \tag{10}$$

As a market penetration problem, in order to get at least NP_I users to $\mathcal{I}$, from (10) we need

$$g < \left(\beta N + \frac{\alpha}{P_I}\right)(1 - P_I). \tag{11}$$

In practice, advertising the DSM scheme can increase α, while increasing social contacts with people in $\mathcal{I}$ results in larger β. By improving DSM performance (i.e., reducing cost $C(\mathbf{x})$), we can reduce g. These parameters can be estimated from smart grid data by following techniques of [13][14].

3.2. Integrating the SISa model with centralized DSM

Let us consider the centralized DSM scheme (7) first. Based on the SISa model, only the $I(t)$ users in the set $\mathcal{I}$ participate in the optimization. Therefore, the cost function (4) is changed to

$$\sum_{h\in\mathcal{H}} f_h\left(\sum_{n\in\mathcal{I}}\sum_{a\in\mathcal{A}_n} x_{n,a}(h) + \sum_{m\in\mathcal{S}}\sum_{a\in\mathcal{A}_m} x_{m,a}(h)\right). \tag{12}$$

Users in $\mathcal{S}$ do not participate in the DSM. If the central controller can still read their energy consumption data $L_m(h) = \sum_{a\in\mathcal{A}_m} x_{m,a}(h)$ through smart meters, it calculates $E_S(h) = \sum_{m\in\mathcal{S}} L_m(h)$ and optimizes

$$C_1(\mathbf{x}_I) = \min_{\mathbf{x}_I} \sum_{h\in\mathcal{H}} f_h\left(\sum_{n\in\mathcal{I}}\sum_{a\in\mathcal{A}_n} x_{n,a}(h) + E_S(h)\right), \tag{13}$$

where $\mathbf{x}_I = \{\mathbf{x}_n | n \in \mathcal{I}\}$. Otherwise, the central controller has to skip $E_S(h)$ and optimizes

$$\tilde{C}_1(\mathbf{x}_I) = \min_{\mathbf{x}_I} \sum_{h\in\mathcal{H}} f_h\left(\sum_{n\in\mathcal{I}}\sum_{a\in\mathcal{A}_n} x_{n,a}(h)\right). \tag{14}$$

In both cases, we have constraint $\mathbf{x}_n \in \mathcal{X}_n, \ \forall\, n \in \mathcal{I}$.

We assume that the recovery probability g is a function of $C_1(\mathbf{x}_I)$. The rational is that the probability that a user abandons the DSM scheme depending on the cost of the scheme. The smaller the cost, the smaller the probability g. Some typical functions can be used, such as linear function $g(x) = \lambda x + \eta$, exponential function $g(x) = \eta(1 - e^{-\lambda x})$, or sigmoid/logistic function $g(x) = \eta/(1 + e^{-\lambda(x-x_0)})$, with appropriate parameters.

In summary, in our composite model, the SISa model (9) affects the cost $C_1(\mathbf{x}_I)$ by changing the user set $\mathcal{I}$, while the cost $C_1(\mathbf{x}_I)$ of (13) affects the SISa model through the parameter g. Since the SISa model evolves at a much slower pace than the optimization (13), in analysis and simulations we can assume that during each iteration of (9) we have time to finish a new optimization (13) and use the optimized cost $C_1(\mathbf{x}_I)$ to update $g(C_1(\mathbf{x}_I))$.

Proposition 1. Assume monotonically increasing cost functions $f_h(\ell)$. For any two subsets $\mathcal{I}_1 \subseteq \mathcal{N}$ and $\mathcal{I}_2 \subseteq \mathcal{N}$, if $\mathcal{I}_1 \subseteq \mathcal{I}_2$, then $C_1(\mathbf{x}_{I_1}) = \tilde{C}_1(\mathbf{x}_{I_1}) \geq C_1(\mathbf{x}_{I_2}) = \tilde{C}_1(\mathbf{x}_{I_2})$.

Proof. If the cost functions $f_h(\ell)$, $h \in \mathcal{H}$, are monotonically increasing, then the optimal values of both (13) and (14) are achieved at the same $\min_{\mathbf{x}_I} \sum_{n\in\mathcal{I}} \sum_{a\in\mathcal{A}_n} x_{n,a}(h)$. Therefore, $C_1(\mathbf{x}_I) = \tilde{C}_1(\mathbf{x}_I)$, which means the energy consumption data of the users in $\mathcal{S}$ can be safely skipped from the optimization. In addition, if $\mathcal{I}_1 \subseteq \mathcal{I}_2$, then $(\min_{\mathbf{x}_{I1}} \sum_{n\in\mathcal{I}_1} \sum_{a\in\mathcal{A}_n} x_{n,a}(h)) + \sum_{m\in\mathcal{I}_2\setminus\mathcal{I}_1} \sum_{a\in\mathcal{A}_m} x_{m,a}(h) \geq \min_{\mathbf{x}_{I2}} \sum_{n\in\mathcal{I}_2} \sum_{a\in\mathcal{A}_n} x_{n,a}(h)$ for all $h \in \mathcal{H}$. Hence $C_1(\mathbf{x}_{I_1}) \geq C_1(\mathbf{x}_{I_2})$. $\square$

Therefore, the more users involved in the DSM, the better the performance.

To analyze the size $I(t)$ of the set $\mathcal{I}$ at equilibrium, from (9), the system can converge to the best case $\mathcal{I} = \mathcal{N}$ if $dI(t)/dt > 0$, which means $g(C_1(\mathbf{x}_I)) < (\beta + \alpha/I(t))(N - I(t))$ for all possible sets $\mathcal{I} \subset \mathcal{N}$. If $g(C_1(\mathbf{x}_I)) > (\beta + \alpha/I(t))(N - I(t))$ for all $\mathcal{I} \subset \mathcal{N}$, then no user participates in the DSM. The system may consist of a mixture of users in both $\mathcal{I}$ and $\mathcal{S}$ otherwise. See Fig. 3 in Section 4 for an illustration of applying these rules to analyze the equilibrium and to determine the equilibrium $I(t)$.

To analyze the optimal cost at equilibrium, we need to use the aggregate load $L(h)$ of (1) as the optimization variable. We assume $L(h) \in [L_h^{\min}, L_h^{\max}]$, which may just be the limit of the energy source's capacity. The aggregate loads of the users in $\mathcal{I}$ and $\mathcal{S}$ are, respectively, $P_I L(h)$ and $L_S(h) = (1 - P_I)L(h)$. The DSM optimization (13) becomes $\bar{C}_1 = \min_{\{L(h), h\in\mathcal{H}\}} \sum_{h\in\mathcal{H}} f_h(P_I L(h) + L_S(h))$, and

$$\bar{C}_1 = \sum_{h\in\mathcal{H}} f_h\left(P_I L_h^{\min} + L_S(h)\right). \tag{15}$$

Next, we use (15) to calculate $g(\bar{C}_1)$ and then $P_I(\bar{C}_1)$ based on (10). Finally, in (15), replacing P_I with $P_I(\bar{C}_1)$, we get

$$\bar{C}_1 = \sum_{h\in\mathcal{H}} f_h\left(P_I(\bar{C}_1) L_h^{\min} + (1 - P_I(\bar{C}_1))L(h)\right). \tag{16}$$

We can find roots of (16) numerically, which is the cost $\bar{C}_1$ at equilibrium. Note that multiple solutions mean multiple equilibria.

As a simple example, let $g(\bar{C}_1) = \lambda\bar{C}_1$ with parameter λ, which means that a user's probability to leave the DSM reduces linearly with the DSM performance. With N large enough so that $\beta N \gg 4\alpha$, from (10) we have $P_I(\bar{C}_1) \approx 1 - \frac{\alpha+\lambda\bar{C}_1}{\beta N}$. If linear cost function $f_h(L(h)) = a_h L(h)$ is used, from (16) we have

$$\bar{C}_1 = \left(\sum_{h\in\mathcal{H}} a_h(L_h^{\min} - L(h))\right) P_I(\bar{C}_1) + \sum_{h\in\mathcal{H}} L(h). \tag{17}$$

The closed-form solution of (17) is

$$\bar{C}_1 = \frac{\left(\sum_{h\in\mathcal{H}} L(h)\right) + \left(\sum_{h\in\mathcal{H}} a_h(L_h^{\min} - L(h))\right)\frac{\beta N - \alpha}{\beta N}}{1 + \frac{\lambda \sum_{h\in\mathcal{H}} a_h(L_h^{\min} - L(h))}{\beta N}} \tag{18}$$

which is the optimal cost at equilibrium.

In the ideal case $\mathcal{I} = \mathcal{N}$, we have $P_I = 1$ and have the minimum cost $C_{\min} = \sum_{h\in\mathcal{H}} a_h L_h^{\min}$. We can easily see that $\bar{C}_1 > C_{\min}$ since $a_h \ll 1$ in practice, which means less market penetration reduces DSM performance. We can also find a lower bound for the performance loss as

$$\frac{\bar{C}_1 - C_{\min}}{C_{\min}} > (1 - a_h)\frac{\sum_{h\in\mathcal{H}} L(h)}{\sum_{h\in\mathcal{H}} L_h^{\min}}. \tag{19}$$

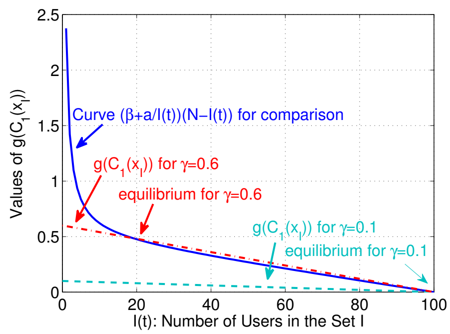

Fig. 3. Derive equilibrium by analyzing $g(C_1(\mathbf{x}_I)) \gtreqless (\beta + \alpha/I(t))(N - I(t))$. Note that $g(C_1(\mathbf{x}_I))$ may not be linear but is monotonically non-increasing in $I(t)$. $N = 100$.

3.3. Integrating the SISa model with decentralized DSM

To implement the DSM (7) distributively, [10] suggested a special pricing scheme that leads to the game $\langle \mathcal{N}, (\mathcal{X}_n)_{n\in\mathcal{N}}, (u_n)_{n\in\mathcal{N}}\rangle$ [15], where the payoff function to be maximized is

$$u_n(\mathbf{x}_n, \mathbf{x}_{-n}) = -\sum_{h\in\mathcal{H}} f_h\left(\sum_{a\in\mathcal{A}_n} x_{n,a}(h) + \sum_{m\in\mathcal{N}, m\neq n} L_m(h)\right). \tag{20}$$

Note that $\mathbf{x}_{-n}$ denotes $\{\mathbf{x}_m | m \in \mathcal{N}, m \neq n\}$. Note also that (20) is similar to (4).

To play this game, each user n maximizes its own payoff by solving $\max_{\mathbf{x}_n} u_n(\mathbf{x}_n, \mathbf{x}_{-n})$. This best response strategy can guarantee the convergence of the game to its Nash equilibrium that equals to the global optimum of (7).

In our case, the game is changed to $\langle \mathcal{I}, (\mathcal{X}_n)_{n\in\mathcal{I}}, (u_n)_{n\in\mathcal{I}}\rangle$. For each user $n \in \mathcal{I}$, the best-response optimization is revised to

$$\min_{\mathbf{x}_n} \sum_{h\in\mathcal{H}} f_h\left(\sum_{a\in\mathcal{A}_n} x_{n,a}(h) + \sum_{m\in\mathcal{I}, m\neq n} L_m(h) + E_S(h)\right). \tag{21}$$

Note that we can remove $E_S(h)$ from (21) if it is unknown.

Proposition 2. With the best response strategy, the game $\langle \mathcal{I}, (\mathcal{X}_n)_{n\in\mathcal{I}}, (u_n)_{n\in\mathcal{I}}\rangle$ converges to the Nash equilibrium which equals to the global optimum $C_1(\mathbf{x}_I)$ of (13).

Proof. This game is a potential game where the potential function is just the payoff function. Since the potential function is concave, the best response strategy (21) converges to the global optimum of the potential function [16], which equals to the global minimum of the centralized case (13). A tricky issue is that because each user knows its own payoff $u_n(\mathbf{x}_n, \mathbf{x}_{-n})$ only, the function $g_n(u_n(\mathbf{x}_n, \mathbf{x}_{-n}))$ may have different values for different users. Nevertheless, such difference will converge to zero. □

Thanks to this proposition, the convergence and the equilibrium performance can be analyzed similarly as the centralized case.

4. SIMULATIONS

In this section, we use simulations to study the proposed composite model, which gives the convergence and equilibrium performance of DSM under human behavior effects. Similar to [10], we simulate a smart grid where each user has appliances with fixed or flexible $x_{n,a}(h)$. $f_h(\ell) = 0.3\ell^2$ for day-time and $0.2\ell^2$ for night-time.

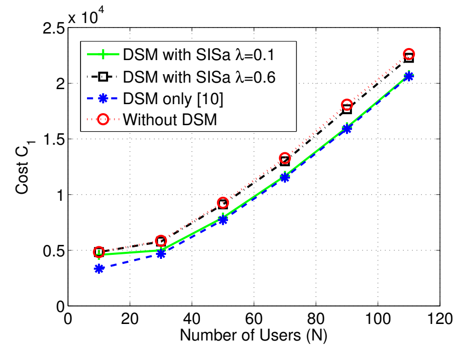

Fig. 4. Performance of centralized DSM schemes.

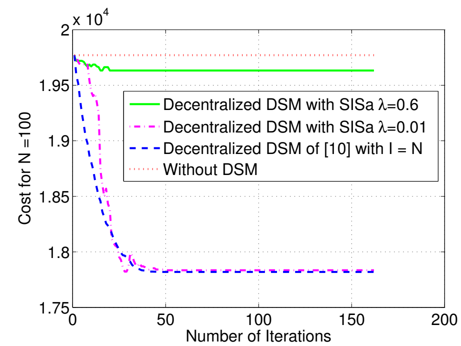

Fig. 5. Convergence of decentralized DSM schemes.

The parameters of the SISa model are $\beta = 0.005$, $\alpha = 0.019$, and $g(x) = \lambda x / C_{\max}$ where $C_{\max}$ is the highest cost. Based on the analysis in Section 3.2, Fig. 3 shows the equilibria under these parameters. It demonstrates that the set $\mathcal{I}$ may have a few users only.

Next, we simulate centralized DSM schemes, both our new composite model and the DSM model of [10]. We run the algorithms for $N = 10$ to 110 users and find their costs. We assume the initial condition $\mathcal{I} = \phi$ for our algorithm and $\mathcal{I} = \mathcal{N}$ for [10]. Note that the cost of [10] is the lowest since it has $\mathcal{I} = \mathcal{N}$. Simulation results are shown in Fig. 4. In addition, we simulate the decentralized DSM schemes, where we compare the convergence of our composite model with the decentralized algorithm of [10]. We set $N = 100$ in this case. Simulation results are shown in Fig. 5.

We can clearly see the impact of human behavior to DSM performance. Under some SISa parameters, the DSM can converge to the global optimum with $\mathcal{I} = \mathcal{N}$. However, under some other SISa parameters, there are only a few users in $\mathcal{I}$ so the DSM performance is extremely worse. On the other hand, the rapid convergence of our decentralized algorithm to equilibrium can usually be achieved.

5. CONCLUSIONS

In this paper, we adapt the SISa (susceptible-infected-susceptible with autonomous infection) model to describe the human behavior in demand side management (DSM) systems. We integrate the SISa model with the DSM algorithms, for both a centralized DSM scheme and a decentralized game-theoretic DSM scheme. Convergence and equilibria of the composite model are studied by analysis and simulations, which demonstrates the importance of addressing human behavior in DSM development.

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