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***Abstract*—According to the Department of Energy, demand response provides an opportunity for end-users to play a significant role in the efficiency, reliability, resilience, and sustainability of a power grid. This is made possible owing to the existence of storage devices and diversity of energy sources at the customer level and the advent of the Internet of Things . Social influences and psychological traits of consumers affect their behavior and decision-making. Consequently, there is a necessity to bring the influences of humans, organizations, and societies on the power system together through computational social science into a cyber-physical-social system. Hence, in this paper, we introduce our development of an artificial society of the social demand response of a power system, a well-known approach in computational sociology based on a bottom-up approach, starting from theory. We assume that consumers can engage in demand response to fulfill two aims: save their cost or enhance the sustainability of a power system. The literature concerning sustainability-based demand response is limited to only considering CO_2, NO_X, and SO_2. In addition to NO_X, and SO_2, we examine the impact of power systems on water pollution, disability-adjusted loss of life year, and exergy in demand response, and provide an environomic-based social demand response. We show that when the level of satisfaction and cooperation of end-user is low, the marginal level of load shaving and improvement in sustainability cannot be fulfilled.**

***Index Terms*—Demand Response; Power Systems; Cyber-Physical-Social Systems (CPSS), Computational Social Science.**

I. Introduction

The balance between electricity supply and demand at every instant of time is the core problem of power system operation and planning [1]. When the supply of the electricity is insufficient, the demand of end-users is expected to reduce to satisfy the power balance. In addition, the intermittency of renewable energy raises hurdles for power system operation. Hence, there is a need of Demand Response (DR) to mitigate this problem. DR has many benefits for consumers, the utility, and the community as a whole. On the one hand, consumers engage in the DR program to decrease their electricity bills and environmental emissions. Although a few studies consider air pollution as an incentive for power system DR programs, there is no discussion of water pollution and Disability-Adjusted Loss of Life Year (DALY)[1]. Hence, in this paper, we address this problem. The electric utility, on the other hand, aims to overcome the intermittency of renewable energy, shift system peak loads, decrease generation backup, flatten out the daily loads, and decrease the exergy. In the thermodynamic cycle of power plants, the exergy, the energy accessible to be used, is decreased. Hence, the power plants with a higher value of exergetic efficiency have priority in the DR program. That is important from a sustainability point of view while it is ignored in the literature. Hence, in this paper, we address this second problem.

In DR programs, aggregators recruit flexible commercial, residential, and industrial customers who are willing to shift their load Advanced metering facilities and bidirectional communication infrastructure make customers able to engage actively in DR schemes. Besides, according to the U.S. Energy information, 38% of the total electricity consumption is devoted to residential customers, who form the largest sector [2]. Hence, the decision-making of costumers and their behavior is critical. The decision-making of consumers is tight with their level of satisfaction and cooperation. A high level of satisfaction and cooperation of customers make them compliant to participate in a DR program. The involvement of the active end-users implies that a power system is a cyber-physical-social system, not the conventional cyber-physical system. That is due to the diversity of the energy sources, and the engagement of social entities, the Internet of Things, and the Internet of energy into the traditional centralized operation mode [3]. Since the customers are an integral part of a power system, there is a need for computational social science to model their behavior, by including insights from psychology, social and cognitive sciences [4]. DR programs influence the human habits, activities, and mental states of customers and vice versa. On the other hand, the level of satisfaction, cooperation, flexibility, and other social features of consumers affect the sustainability, stability, reliability, and resiliency of a power system. Without considering the social behavior of customers, DR programs may never fulfill their intended purpose and face failure in practice.

In this paper, we assume that the motivations of the end-users in participating in DR programs are two-fold: either to improve the power system's sustainability or to make savings. Based on this assumption, we developed a method that will motivate end-users to participate in DR by keeping their satisfaction at the highest level while meeting the desired marginal level of load shaving. The contributions of this work are summarized as follows:

- We model the dynamic levels of satisfaction, cooperation and social diffusion of active end-users. We provide an artificial society based on theories from social, cognitive and neuroscience to model the social behaviors of consumers.

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[1]The DALY measures life loss from premature death and years of living with a lousy quality of life due to health problems related to the pollution produced by power plants.

- We provide a new framework for the DR program to decrease the air and water pollution, and the DALY.
- We take the exergy and the thermo-dynamical cycles of energy into consideration for the DR schedule. We consider the overall chemical exergy of the fuel in the DR program to increase power system sustainability.

II. Model property

We propose an environomic-based (thermodynamic, environmental, and economic) model of social DR. Figure 1 provides the framework of our proposed model. We developed an artificial society to model the social behavior of consumers as active end-users. The incentive of these consumers to participate in a DR program is environomic-based. To reach various aims of DR,i.e, peak load shaving, frequency stability, and sustainability , the role of consumers as active end-user is inevitable. The participation of the consumers in a DR schedule depends directly on the level of their social cohesion. Social cohesion consists of the level of cooperation, the community's empathy, which influences to what extent the people of a community are willing to participate in a DR program [5]. In addition to the social cohesion, the emotion of the people, i.e, the level of their satisfaction is significantly important and can influence their willingness to participate in a DR program [6], [7]. Hence, there is a need to consider the level of satisfaction (emotion), and cooperation of the people in the DR study. However, in the literature, the main optimization considered is minimizing the cost of power generation or the emissions while ignoring the social science aspect of DR. We introduce a new objective function of social well-being. As we discuss in the next section, a decrease in cost and emissions can lead to an increase in social well-being. A social DR program aims to achieving the maximum level of community well-being.

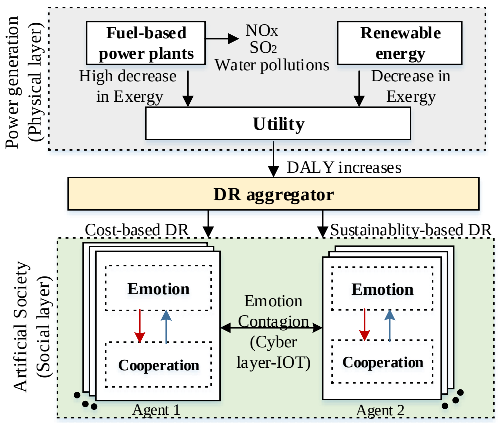


Fig. 1: The proposed framework of an environomic-based social DR.

To model the satisfaction, emotion and cooperation of the community and their effect on a DR program, we propose to use an artificial society, which has generally been recognized as a promising method in sociology. Specifically, we build an artificial society based on theories from psychology, social and neuroscience. We use the bottom-up approach in modelling, where we build our model from the theory, not top-down, from the data. We have based our model on Barsade's theory [8] of emotional contagion and use the absorption model of emotional spread to model the collective behavior and community emotion as proposed in [6], [7]. We adopt the term of emotional spread ,or influence, from here on, as the word contagion can be misleading in explaining the spread. According to Barsade, group emotion is viewed as a combination of personal feelings [8]. A high level of satisfaction and cooperation of the consumers is associated with a high level of their participation in DR programs. In addition to model the emotion (here, satisfaction) and cooperation, we consider the social diffusion inside a community based on diffusion neurons in neuroscience. The people in a community are connected to each other through mass media platforms and other communication devices. Note that the cyber layer comprises the social media platform that supports the exchange of information between the end-users, which consists of the social diffusion of dissatisfaction among them. Social diffusion means that the high level of satisfaction of one consumer has a positive effect on that of other consumers and vice versa. In a DR program, there is a trade-off between social well-being, community resilience, sustainability, economic, reliability, and frequency stability.

The literature considers three different motivations, i.e., cost, frequency, and emissions, for the initiation or involvement in DR programs. For instance, [9], [10] consider decreasing electricity cost as an incentive to motivate consumers to participate in a DR program. Frequency stability as ancillary service is another motivation to initiate a DR program. A few papers have suggested DR based on emission. It targets wealthy people who are concerned about environment degradation. In this paper, the incentives of consumers to participate in a DR program are a decrease in the electricity cost or an increase in sustainability. Most papers dealing with the sustainability aspect of a DR program aim to decrease the emission of CO_2. Here, we consider three indexes of sustainability, i.e., pollution, DALY, and exergy, which have a high effect on social life. One of the primary aims of sustainability is to decrease air and water pollution. Nowadays, coal accounts for about one-quarter of the world's total primary energy supply, and it is estimated that its share will not change substantially until 2030. Coal-fired power plants release fly ash, bottom ash, resulting in severe water pollution [11]. In addition to water pollution, we consider air pollution by NO_x and SO_2. The second index of sustainability, i.e., DALY, investigates the effect of power plants on the physical health [12]. The third index of sustainability, exergy, which is ignored in the literature, is considered. From an exergetic point of view, it is electricity rather than steam that should be used when calculating the performance of a power plant. Although energy only converts from one form to another, the exergy can decrease. As a result, various types of outputs have different values. The outputs with higher quality or exergy per unit energy are desirable. Using exergy-based indicators in DR-program increase the effectiveness of energy resource use in power systems.

III. Environomic-Based Social DR

In this section, we develop an optimization model for environomic-based social DR. For the electric utilities, the motivation to initiate DR programs is to achieve a specified marginal level of load shaving, Ξ, and to enhance sustainability. For the end-users, the motivation to engage in a DR program is cost rebates or environmental preservation. Hence, the objective function of the problem is to minimize the level of dissatisfaction of the end-users with DR. The proposed model can be expressed in the following way:

$$\textbf{Min} \sum_t R_{tn} \tag{1}$$

$$R_{(t+1)n} = \frac{h(R_{tn})}{\varpi^{rr}}(\hat{R}_{tn} - R_{tn})\varkappa^t + R_{tn}, \tag{2}$$

$$\begin{aligned}\hat{R}_{tn} = \underbrace{\varpi^{rr}(\frac{\sum_m \gamma^R_{tnm} R_{tm}}{\sum_m \gamma^R_{tnm}})}_{Social\ contagion} + \underbrace{\varpi^{cr}(1 - C_{tn})}_{Cooperation} \\ + \underbrace{\varpi^{pr}(1 - (\frac{\sum_i 0.5\alpha_{\Delta t_i} \hat{d}_{\Delta t_i n}}{\bar{C}}))}_{Rebate} + \underbrace{\varpi^{sr}(1 - S_t)}_{Sustainability},\end{aligned} \tag{3}$$

$$\begin{aligned}S_t = \underbrace{\frac{\varpi^1}{\overline{S}^1}\sum_k(\kappa^{NO_x}P_{tk} + \kappa^{SO2}P_{tk})}_{NO_x\ and\ SO_2\ emissions} + \underbrace{\frac{\varpi^2}{\overline{S}^2}\sum_k \kappa^w P_{tk}}_{Water\ pollution} \\ + \underbrace{\frac{\varpi^3}{\overline{S}^3}\sum_k \kappa^{NO_x}\varrho^{NO_x}P_{tk}}_{DALY} + \underbrace{\frac{\varpi^4}{\overline{S}^4}\sum_k \frac{P_{tk}}{\eta_k}}_{Exergy}\end{aligned} \tag{4}$$

$$C_{(t+1)n} = -\kappa(R_{(t+1)n} - R_{tn})\varkappa^t + C_{tn}, \tag{5}$$

$$d_{tn} = \tilde{d}_{tn} + \sum_i \hat{d}_{tin}, \tag{6}$$

$$\sum_i \hat{d}_{tin} \leq (1 - (1 - C_{tn})R_{tn})\tilde{d}_{tn} \tag{7}$$

$$|(\frac{24 d_{tn}}{\sum_t \tilde{d}_{tn}}) - 1| \leq \Xi_n, \tag{8}$$

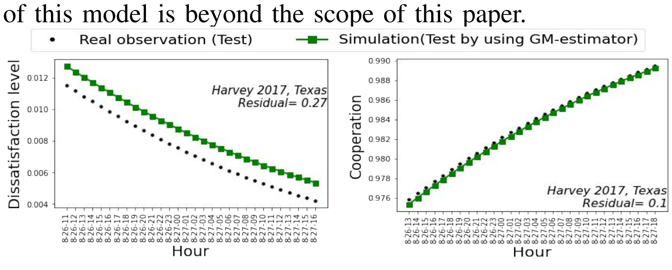
$$\sum_k P_{tk} - \sum_n d_{tn} = 0, \tag{9}$$

$$0 \leq P_{tk} \leq \bar{P}_k, \tag{10}$$

In Eq. (1), R_{tn} is the dynamic change of the level of dissatisfaction of the consumers and prosumers (consumers who own distributed energy resources) over time *t* and for load *n*. That is obtained by Eq. (2). $h(R_{tn}) = (\frac{\sum_m \gamma^R_{tnm} R_{tm}}{\sum_m \gamma^R_{tnm}})$ denotes the social influence of dissatisfaction , ϖ^{rr} denotes weighting factor of social contagion, *t* denotes the time, *n* denotes the load, $\varkappa^t$ denotes the time coefficient such that $\varkappa^t \leq \frac{1}{n-1}$, and $\hat{R}_{tn}$ denotes the amount of the effect of dissatisfaction diffusion on the active consumers and prosumers, which in turn is a function of cooperation, peak time rebates of the price of electricity, and sustainability. It is obtained in Eq. (3). ϖ^{rr}, ϖ^{cr}, ϖ^{pr}, and ϖ^{sr} are weighting factors. ϖ^{pr} and ϖ^{sr} in the Eq. (3), can get value between 0 and 1. A value of 0 for ϖ^{pr} and ϖ^{sr} indicates that the consumers are uninterested in cost-saving DR and sustainability-based DR (inelastic loads) while a value of 1 for these parameters indicates that the consumers are entirely interested in cost-saving DR and sustainability-based DR. Here, γ^R denotes the emotional spread, which is the weighted dissatisfaction of each agent based on [6]. The social diffusion is discussed in detail in [7]. The dependence between the emotion and cooperation is discussed in [13], [14]. Rebate (peak time rebates of the price of electricity), $\alpha_{\Delta t_i}$, motivates the shift of the load from time t_{i-1} to time t_i, denoted as Δt_i. Here, $\hat{d}_{\Delta t_i n}$ and $\bar{C}$ are the load shifting. Because the number of end-users participating in DR to achieve enhanced sustainability may not be sufficient, there is another type of motivation, i.e., rebates of the price of electricity. In this case, when the end-users save cost, their level of satisfaction is increased and, in turn, they are willing to engage in DR. The price of electricity depends on their initial level of satisfaction (to electric utilities) and cooperation. In the case study, we will further investigate this topic. S_t, in Eq. (3) consisting of four terms is obtained by Eq. (4). κ^{NO_x} (Kg/MW), and κ^{SO_2} (Kg/MW) are linear coefficients associated with the amount of NO_x, and SO_2 emissions particular to each power plants. κ^w (Kt/MW), and η_k are coefficients of water pollution and exergetic efficiency, respectively. Note that, κ^w is the release of effluents from the fuel combustion residue per MW [15]. P^u_t denote the power produced by various types of power plants. ϖ^1, ϖ^2, ϖ^3, and ϖ^4 are weighting factors getting value between 0 and 1. $\overline{S}^1$, $\overline{S}^2$, $\overline{S}^3$, and $\overline{S}^4$ are maximum value of air pollution, water pulsations, DALY, and the exergy generated by the power plants, respectively. Let us express the related terms in per units. The first term of Eq. (4) is associated with the air pollution and SO_2, and NO_x emissions [12]. The second term is related to water pollution [11]. The third term is related to DALY. These terms consider the effect of the power plants on the physical health of the community. The last term is associated with exergy. Renewable energy has a higher level of efficiency. i.e, η_k [12]. In this plan, some end-users are willing to shift their demand to the hours that enhance the sustainability indexes. Hence, because these end-users have contributed to the enhancement of sustainability by shifting their demand, their satisfaction level is increased and their aim is fulfilled. The level of cooperation of the end-users to participate in a DR program is obtained by Eq. (5), where $\tilde{d}_{tn}$ denote the predicted load of end-users. κ, $\in$ [0,1], is the dynamic speed factor of the cooperation. The final demand after shifting d_{tn} is obtained by Eq. (6). It is noted that if $\alpha_{ti} \geq 0$, $\hat{d}_{tin} \geq 0$ and vice versa. We set the value of $\hat{d}_{tin}$ to 0 at all hours to account for inelastic loads. The maximum amount of load shifting from t to other time of day is obtained by Eq. (7). The constraint related to satisfying the marginal level of load shaving, i.e., Ξ_n, is obtained by Eq. (8). The power balance, and he real power maximum value of the kth type of power plants, $\bar{P}_k$, are defined by Eqs. (9)-(10). Noted that $h(R_{tn})$, ϖ^{rr}, $\hat{R}_{tn}$, R_{tn}), $\varkappa^t$, γ^R, ϖ^{rr}, ϖ^{cr}, ϖ^{pr}, ϖ^{sr}, C_{tn}, S_t, ϖ^1, ϖ^2, ϖ^3, ϖ^4, η_k, and Ξ_n take values within the interval [0 1]. Besides, 0 means the lowest level of variables (e.g., dissatisfaction, cooperation) while 1 is their highest level.

IV. Case Study

We verified our model first by checking that our model outputted the expected patterns from the literature. Specifically, we verified our computational model outcomes in Case Study 1 below with those from [7]. While the power system's cyber and physical components are well-modeled, the social component poses modeling challenges. In terms of the social component, traditional social science has relied heavily on surveys to quantify social behavior. However, new tools, such as natural language processing, machine learning algorithms, computer-text analysis tools, and social media, can be utilized today [16], [17]. The social model is calibrated using social datasets obtained through appropriate social sensing. The social model's parameters are then estimated. Figure 2 illustrates the validation of the social behavior in social demand response, namely dissatisfaction and cooperation. We gather and analyze data collected from Twitter and power utility companies regarding hurricanes Harvey and Irma. We conduct tenfold cross-validation in order to validate the social behaviors in terms of socio-technical dependencies. Social constraints and behaviors, understandably, are nonlinear. As a result, the linear approximation of the social behavior reduces the model precision. Nonetheless, we use a linear and simple model of socio-technical constraints in this work to keep the model simple, and hence to avoid introducing additional social features and to focus on the concept. The detailed validation of this model is beyond the scope of this paper.



(a) End-users dissatisfaction **(b)** End-users cooperation

Fig. 2: The level of dissatisfaction and cooperation of the end-users during Hurricanes Irma and Harvey.

There are three active consumers participating in DR. Consumers 1 and 3 are interested in DR based on price, while consumer 2 is interested in DR based on emission reduction, that is, sustainability. The level of dissatisfaction and cooperation of Consumers 2 and 3 is assumed to be 0.5 (medium level), while those of Consumer 1 is equal to 0.45. The marginal level of load shaving is considered to be 0.2. The sustainability-based factors of various power plants, i.e., Ultra Super-critical Coal (USC), Natural Gas Combined Cycle (NGCC), Wind turbine (WT), and Solar thermal panel (STP). are provided in Table 2.

TABLE I: The sustainability-based factors of various power plants

Units	Air pollution (kg/MW)		Water pollution (kt/MW)	DALY (DALY/kg)	Exergy (%)
	κ^{NO_x}	κ^{SO2}	κ^{w}	ϱ^{NO_x}	η_k
USC	0.0928633	0.154772	0.2459	0.0000014	34
NGCC	0.01166079	0.01548	0.2459	0.0000014	32
WT	-	-	-	-	59
STP	-	-	-	-	90

The result of the DR schedule for the three types of consumers is shown in Figure 3. This figure displays the dynamic change of the level of dissatisfaction and cooperation, the predicted demand, and the demand after shift for 3 active end-users. According to this figure, because the DR for Consumers 1 and 3 are price-paced with approximately the same initial values, the dynamic change of their level of dissatisfaction and cooperation have the same trends. We can observe they shave the predicted load, especially for an hour after 20, and the flat load curve is obtained by shifting the demand based on price. For the hour the electricity price is high, the price–based DR increases the level of satisfaction of customers who participate in this program. The final demand of the Consumer 2 is shifted to an hour that electricity is produced by renewable energy to fulfill sustainability goals.

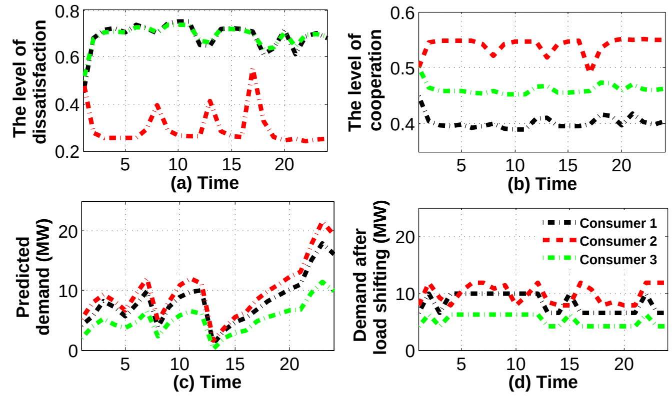


Fig. 3: The results of the environomic-based social DR: a) the level of dissatisfaction. These patterns are consistent with the discussions given in [7]; b) the level cooperation. These patterns are consistent with the discussions given in [18]; C) the predicted demand; and D)the demand after load shifting. These patterns are emergent effects provided by the model outcomes showing the effect of behavior of the costumers.

The consumers, by shifting their load to hours that renewable energy generates electricity, induce the maximum sustainability index as much as 0.754. The NO_x and SO_2 emissions are equal to 23.569, and 39.282 Kg, respectively. The effluents for water pollution is equal to 62.411 kt. The amount of Disability-Adjusted Loss of Life Year (DALY) and exergy is equal to 3.299 $\times 10^{-5}$ DALY, and 1254.93 MW, respectively. DR cost for utility as much as 993 \$. Each of the end-users 1, 2, and 3 participate in DR as much as 3.365, 3.617, 2.254 MWh. The average level of dissatisfaction of consumers increases to 0.559 to reach the marginal level of load shaving that is 0.2. When the marginal level of load shaving forced by the utility is increased to 0.5, the average level of dissatisfaction of consumers decreases to 0.518.

Table II provide various outputs of environomic-based social DR for different initial values for the dissatisfaction, R_0 , and cooperation, C_0 , of active end-users, and motivation price factor (Υ) (to encourage the end-users to participate in cost-based DR), and the marginal level of load shaving Ξ_n. Note that we use $\Upsilon\alpha_{ti}$ instead of α_{ti} in Eq. (3). Here, S is a sustainability index showing the capacity of used renewable energy. Utility cost is the cost that utility should spend to motivate costumers to participate in the DR program.

Because the marginal level of load shaving for emission-based DR, i.e., Ξ_2, is decreased from 0.9 in Case 1 to 0.5 in Case 2, the index of sustainability, S, is reduced by 2.54%. As expected, all of sustainability metrics, i.e., NO_x, SO_2, water pollution, DALY, exergy, are increased. When $\Xi_{1,3}$ decreases from 0.5 to 0.2 in Case 3, the level of dissatisfaction of the end-users increases. Furthermore, because of the high level of limitation, they cannot participate freely in DR to save more cost. As a result, they participate less in DR. Utility cost decreases in this case. Different communities and

TABLE II: The average level of dissatisfaction, and cooperation, sustainability indexes, and utility cost for various scenarios. In case 1, Ξ_2 is equal to 0.9 while that of other cases is equal to 0.5.

Case	Inputs				Outputs							
	R_0	C_0	Υ (Cost increase rate)	$\Xi_{1,3}$	R	S	Utility cost ($\times 10^3$ \$)	NO_x (Kg)	SO_2 (Kg)	Water pollution (Kt)	DALY ($\times 10^{-3}$ DALY)	Exergy (MW)
1	0.1	0.9	1	0.5	0.398	0.824	1.605	21.448	35.747	56.794	0.030027	1207.397
2	0.1	0.9	1	0.5	0.399	0.803	1.564	22.206	37.01	58.801	0.031088	1223.485
3	0.1	0.9	1	0.2	0.439	0.782	0.855	22.983	38.306	60.86	0.032176	1240.208
4	0.5	0.1	1	0.2	-	-	-	-	-	-	-	-
5	0.5	0.1	1	0.3	0.68	0.775	0.98	23.246	38.743	61.554	0.032543	1243.248
6	0.5	0.1	2	0.2	0.664	0.777	1.53	23.161	38.602	61.33	0.032425	1242.942
7	0.9	0.1	2,3	0.2	-	-	-	-	-	-	-	-
8	0.9	0.1	4	0.2	0.613	0.765	2.938	23.639	39.398	62.596	0.033094	1252.563

societies have different cultures and characteristics, influencing the level of dissatisfaction and cooperation. When the level of dissatisfaction and cooperation of end-user is as low as 0.5 and 0.1 in case 4, the marginal level of load shaving of 20%, cannot be fulfilled by the proposed motivation price. In this situation, the utilities should increase the marginal level of load shaving to 30%, i.e., Case 5, or they must increase the motivation price by 20%, i.e., Case 6, to reach their aim. Case 6 costs more for utilities. As we can see, the social behavior of end-users also affects the cost of utilities and, therefore, the economic aspects of power systems. When the level of dissatisfaction of people is high, the situation even worse. The utility must increase the motivation price by at least 40% to fulfill its aims (appropriate load shaving).

Our simulation results demonstrate emergent patterns - collective behaviors - that cannot be predicted by the individual agent rules. Note that this paper does not discuss how to increase consumer cooperation or satisfaction. Rather than that, we discuss how to incorporate dissatisfaction and cooperation into DR while taking environmental constraints into account. We model social behavior in the DR because consumer willingness and participation in the DR are contingent on their social behavior. In other words, when end-users' social behavior is ignored, the optimal results of DR are different than when end-users' social behavior is considered. To help readers grasp the concept, we included a simple case study in the paper. The social behavior's trends derived from our model output were consistent with the expected trends discussed in the literature. The social DR model proposed here can be easily applied to large-scale power systems. The proposed model enables us to understand DR better and develop new hypotheses for testing in real-world scenarios.

V. Conclusions

In this paper, we leverage an artificial society based on the computational social science approach to model the behavior of active end-users who participate in the DR. It shows the potential of using computational social science in power system operation. The inherent feature of each end-user consists of the level of satisfaction and cooperation. These features can bring both economic and sustainability benefits for the utility and the society as a whole. In addition, these features make the community more resilient. In the environomic-based social DR, some consumers participate in DR to increase the peak time rebates of the price of electricity. Other consumers participate in DR to decrease air pollution, water pollution, DALY, and exergy. The engagement of end-users in DR depends not only on incentives, such as increased rebate and sustainability but also on the degree of satisfaction, customer cooperation, and social diffusion.

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