Market-Based Control in Emerging Distribution System Operation

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Abstract—In emerging electrical distribution systems, a multitude of self-interested individual decision makers interacts among themselves and with the power grid. The optimal operation of the grid, according to a set of predefined technical and economic targets, can be achieved by influencing the behaviors of the decision makers with appropriate market signals. The technical feasibility and performance of the system, for example, in terms of line flow limits, network losses, and appropriate voltage profile, can thus be controlled to a certain extent, by market signals. In this paper, we present a conceptual framework for “Market-based Control” for the operation of emerging distribution systems. Characterized by distributed and adaptive control signals over prosumers, market-based control needs to make prosumer benefits aligned with regulator/DSOs concerns, thus satisfying the requirements from both sides. By applying market-based control in network charging, both network and market performances can be improved. The complexity in the environment and in the interactions among players prompt techniques to be derived from complex systems theory. A multiagent model was built up for testing the market control strategies strategy. The concept and applications are illustrated with reference to a standard CIGRE medium-voltage distribution network.

Index Terms—Market-based control, multiagent simulation, smart grids.

I. INTRODUCTION

MERGING smart distribution systems are characterized by massive installations of distributed generation (DG) and storage devices, a maturely developed distribution network with bilateral power flow and DG connection at any location, efficient information transfer through the network, as well as fully liberalized local markets with new functionalities and services [1]. With these additional technical and market possibilities, microplayer-like electricity end users are entitled to behave sometimes as producers, thus making the system even more flexible, which is a challenge for macroplayers like regulators and system operators.

Directly, these flexibilities have made the system more unpredictable, and decision-making problems encountered in the system became dynamic and nonlinear [2]. Alternatively, exploiting extra capacities brought by microplayers [3] may pave the way to smart grids without additional costs of infrastructure upgrading [4], [5]; encouraging the use of renewable generation from the low-voltage side may solve the urge to achieve environmental commitments [6]; localizing at the distribution level the balance of generation and consumption can also relieve the burden of bulk transmission systems and, in the meantime, improve energy efficiency by reducing network losses [7], [8].

All of these system benefits are presumed with cooperative prosumer behaviors. Not necessarily, the prosumer would be an “ideal citizen” [9] who follows a cooperative approach and strives for the global welfare of the systems, because that might involve making sacrifices of his/her own economic benefit or comfort. A more realistic hypothesis is to consider noncooperative prosumers driven by their own utilities and influenced by their social environment. In this respect, efficient market-based operation and control are needed for emerging distribution systems with a large population of autonomous self-interested prosumers to obtain somehow coordinated participant behaviors and optimized global performance.

Many technical and policy dilemmas along with market decision makings encountered in smart distribution systems can resort to distributed market-based control (MBC) problems [10]–[12]: the central control strategy will no longer be a feasible solution with an abundance of control objectives; and, in our case, control objectives could not be directly obtained but only be guided depending on the prosumer decisions in response. MBC applied in distribution systems can thus gain an optimal utilization of distributed resources and represent an efficient strategy for system control through distributed control directly put upon microplayers (the prosumers), and through guided interplay between macroplayers and microplayers (policy decision makers, regulators, retailers, and distribution system operators).

While waiting for the real-world data of fully developed smart distribution systems (which would be useful to adjust the models), multiagent simulation has enabled us to track price-induced system behaviors and evaluate hypothesized scenarios without introducing increased computation complexity [13]. In this paper, we start from the current electricity price structure and emerging necessity of a new strategy as MBC (Section II); and then propose the MBC strategy and through the multiagent model, we observe aggregated performances and emerging properties of distribution systems based on properties and interactions of individual players (Section III). A special focus is placed on the interactions between the social layer of the prosumers and the physical layer of the distribution network.
consider simple models for the network and for each individual prosumer, that are both socially and technically represented; from those simple models, we derive and test MBC algorithms and we provide an example of MCB based on how a DSO can optimize technical performance, such as network losses, by designing proper discriminatory price for usage charging, while keeping the system feasible (Section IV). The simulation results related to a smart distribution system with 14 buses and 1000 prosumers are presented and discussed in Section V.

II. PRESENT AND EMERGING PRACTICE IN PRICING SCHEMES FOR ELECTRICITY

Presently, the final electricity price to consumers is composed by four components: energy, network (T&D), taxes, and VAT [14]. “Energy” covers the price for production and retail profit, and “Network” includes both tariffs from TSO and DSO, basically containing two parts: a fixed price for starting the service (usually referred to as “Connection Charging”) and a unit price according to the amount of energy usage (usually referred to as “Use of System Charging”).

For power injection to the grid (in distribution level), the tariffs are summarized from “Support Schemes,” “Connection Charges”/network access, and “Use of System charge”/network tariffs. The support schemes for DG/RES applied in the EU Member States constitute fixed feed-in tariffs (FIT), price premiums/feed-in premium (FIP) and quota systems based on tradable green certificates (TGCs) [15], [16]. The DG operators have to pay “connection charges” to the DSO in order to obtain network access, subdivided into three main categories: shallow, shallowish, and deep charges [17].

DSOs are allowed to recover certain costs or revenue through network tariff/use of system charges, subject to national network regulation, generally using the method of rate-of-return, revenue/price cap, or yardstick regulation. According to both current practice and emerging situations in setting network tariff [18], [19], three issues have to be considered by the DSO: 1) to allocate the operational costs, 2) to ensure the prices within regulated range, and 3) to encourage the development of local distributed and renewable generations.

The newly adopted Energy Efficiency Directive (2012/27/EU) requires the removal of network tariffs that would impede energy efficiency and/or demand response. Tariffs encouraging customers to shift their peak hour consumption should gain importance. Network tariff structures should incentivize demand response and energy-efficient behavior while providing a stable framework for both customers’ bills and DSO revenues [20].

The existing network tariff setting based only on network costs cannot fulfill the encouragement of distributed generations, or the energy efficiency requirements. A novel method for setting efficient network tariff/usage of system charges is of critical importance in the paradigm shift of traditional distribution systems to smart grid.

In this framework, MBC fits being able to provide a consistent pricing mechanism for power withdrawal and injection, in a context characterized by the widespread use of prosumers. In addition, MBC may favor better control of the DG, more flexible demand response, and incentive local power balancing, and control reverse power flow. The MBC method, may contribute, throughout an innovative approach, to network charges and to obtain good system performance in terms of technical, economic, and environmental indices.

To implement MBC, a proper information exchange between macroplayers and microplayers needs to be implemented, and the widespread use of smart meters with proper functionalities (exchange rate, accuracy, failure rate . . . ) is needed to ensure “real-time” power profiling and information exchange (minimum 15 min routine as the exchange interval, and a minimum 0.5 s reaction intermittent for event-driven data exchange). The prosumers’ responsiveness, on the other hand, can be greatly facilitated by introducing smart home appliances, distributed generation, and storage devices with automatic operation and communication with the smart meter.

III. MARKET-BASED CONTROL

The players in the emerging smart grids may be grouped into two categories: 1) macroplayers and 2) microplayers, characterized by different utilities based on which they perform decision makings. Microplayers are represented by the individual electricity prosumers while macroplayers, like the DSOs, the transmission system operators (TSOs), the retailers, and the regulators provide price signals and technical constraints to the microplayers, which show electrical behaviors related to the devices they own and the smartness of the control of their devices and home systems and driven by their social attitudes, that interact with a physically constrained electricity network (in terms of power flows and network feasibility). Price signals provided by macroplayers to prosumers and power outputs from prosumers to the network constitute the interface between microplayers and macroplayers.

MBC is the design and implementation, by macroplayers, of a set of price signals to prosumers for optimizing global system performance, according to a predefined set of objectives through the induced prosumer behaviors. Final electricity prices to prosumers are directly provided by retailers, and this final price usually contains also components charged by DSO and TSO for connection and network usage. For testing MBC strategy, we choose, as a simple example, the network charges paid to the DSO for the usage of the distribution network, as the control signals, and we consider the DSO as the only macroplayer to execute MBC to optimize the distribution network performance in terms of network losses, considering the constraints on voltage profile and line power flows. The MBC is applicable to the entire set of electricity pricing schemes involving not only network usage charges from DSO but also other components, such as a real-time price from retailers, or even innovative schemes, such as feed-in tariffs, when the increase of local renewable generation or improvement in local emission factors are the considered objectives.

Targeting the control of prosumer behaviors in electricity consumption and generation, normalized charging prices for injecting and withdrawal [ρ, v] (ρ ∈ [−1, l], \( v = \{v_k\}_{k} \), \( \rho_k < 1 \), \( |v_k| < 1 \)) are used as control signals from DSO toward the prosumers; each price couple may be differentiated for each
individual prosumer and each bus of the network (discriminatory pricing). Power output from the prosumer \( k \), \( P_k \), is generated as a result of the prosumer’s reaction to price signals, and pursuing his/her objective of utility in terms of economic benefit (negative cost) and comfort.

\( \mu, \nu \) represents the network usage charging from DSO, where the element values can be positive and negative. For example, in a standard situation with a very limited amount of DG, the consumer will pay network charges \( (\nu_k > 0) \) while the generator, that alleviate network loading, will be paid \( (\nu_k < 0) \). In an opposite situation in which there is an abundance of distributed generation that makes it difficult to keep the systems feasible, we might be willing to pay consumption \( (\mu_k < 0) \) or charge the generation \( (\mu_k > 0) \).

Each individual prosumer is characterized by specific functions in terms of economic and comfort sensitivity, power demand and generation capacity; and those features may be changed and updated through social interactions with other individuals. Macroplayers cannot predict precisely the impacts of his or her pricing decisions with traditional modeling approaches. This would be even more true when we consider price signals related to other macroplayers.

MBC is composed of two mains steps: 1) setting up a proper market structure and 2) regulating, under this structure, prosumers’ behavior toward better global performance (environmental protection, energy and economic efficiency, technical feasibility of the system...). As an example, from the technical perspective, regulation may strive for pursuing better distribution network performance [21] in terms of power quality and reliability, energetic and economic efficiency, or even GHG emission (if regional limits have been set by the regulator) while ensuring network feasibility.

Multiple objectives targeted by different macroplayers may conflict and MBC may become more complicated. The robustness of the “control” must be ensured and checked by proper modeling and simulation tools for ex-ante validation.

The emerging distribution systems are typically complex multilayer complex systems that cannot be modeled with the traditional approaches, and alternative techniques based on complex systems might be considered [22].

IV. MODEL OF DECISION MAKING AND NETWORK IN EMERGING DISTRIBUTION SYSTEMS

A. Network Model and Performance Analysis

The network is composed of a set of nodes to which the prosumers are connected and a set of lines connecting the buses, with a radial structure even though this hypothesis is not strictly necessarily. Each prosumer can inject or withdraw power at a given bus, and the net power injection/withdraw, at bus \( i \), is \( P_i = \sum_{k \in \Pi_i} E_k (P_i > 0) \text{ withdraw}, \Pi_i \text{ set of prosumers connected to bus } i \). The net injection will cause the line flows and voltage profile that are modeled through a standard ac power flow.

We consider a time frame composed of several time intervals (for example, hours) in which the power is kept constant and we analyze the steady-state behavior of the network in terms of line flows and voltage profile, at each interval. Over time, the behavior of prosumers in terms of power injection/withdraw will evolve and so will the underlying network.

We assume that at each time interval, the DSO can provide discriminatory price signals to each individual prosumer and can observe the power injected and withdrawn by each of them. Progressing in the simulation, prosumers update their attitudes by changing their decisions on power injection/withdrawal. Assuming a constant power factor \( \tan \phi \) for each prosumer, the power-flow equations can be written as

\[
\begin{align*}
0 &= P_i - f_i(\delta, V) = \sum E_k^i(\rho_k, \nu_k) - f_i(\delta, V) \quad (1) \\
0 &= Q_i - g_i(\delta, V) = \tan \phi \cdot P_i - g_i(\delta, V) \quad (2)
\end{align*}
\]

where \( \rho_k / \nu_k \) are withdraw/injection prices for the prosumer \( k \).

\( \delta = [\ldots, \delta_i, \ldots] \) and \( V = [\ldots, V_i, \ldots] \) are the vectors of bus voltages and phases and \( f_i(\delta, V), g_i(\delta, V) \) the real and reactive flows over the lines connected to bus \( i \).

B. Prosumer Modeling and Decision Making

Assuming a given degree of control over their power inputs/outputs, for example, to some “smart building” control devices, the behavior of the prosumer would be driven by the maximization of each individual utility function. The individual physiological and social attitude of each prosumer can be characterized with reference to a 2-D space: 1) attitude toward economic benefit \( \mu \), in terms of avoiding cost from consumption or maximizing earning from power injection (economic dimension); 2) attitude toward comfort \( \varphi \), in terms of desire or willingness to use appliances and devices to satisfy his/her living standards (physiological dimension). A prosumer \( k \) is characterized by attitude \( A_k = [\mu_k, \varphi_k] \) by giving different values for the two dimensions (Fig. 1).

The utility a prosumer would get from electricity consumption/generation can be quantified in terms of economic benefit and comfort; and the value of the two terms depends on his/her individual attitudes that determine the power injected/withdrawn.
Considering one time interval, let us say one hour, in which the power is kept constant, we define the power withdrawn \( (E_k > 0) \) or injection \( (E_k < 0) \) as

\[
E_k = d_k - q_k - D_k \cdot [1 - \rho_k \cdot \mu_k \cdot (1 - \varphi_k)] - G_k \cdot [1 - \nu_k \cdot \mu_k \cdot (1 - \varphi_k)]. \tag{3}
\]

The net power injection/withdrawn \( b_k \) is the summation of two terms: one term is the decision on consumption \( d_k \), and the other is the decision on generation \( g_k \). The network power output \( E_k \) from the prosumer is computed by considering reference power values for demand and generation \( \{D_k, G_k\} \), corrected by the price signals weighted on the individual attitude. The two reference power values in this model are constant, without technical interruptions. However, time-varying demands, intermittent phenomena of renewable generation, and the availability of resources highly depending on weather and locations could be considered as well by extending the model and defining the two terms as variables.

The concept of “elasticity” in terms of responsiveness to price is captured by attitude parameters \( \mu_k \) and \( \varphi_k \): in (3), where the coefficient of demand decreases and generation increase are related to the price \( \rho_k/\nu_k \) are \( \mu_k \cdot (1 - \varphi_k) \), thus consisting of the elasticity [23], [24]. In addition, contrary to the usual consumer models based on a “fixed” elasticity, our approach, which the social behavior is explicitly modeled, considers the variation of elasticity due to social interactions and attitude updates.

Taking examples of prosumer attitude positions in the space, if prosumer \( k \) is in position \( A \) (Fig. 1), that means he/she is concerned exclusively with economic benefits: an increase in \( \rho_k/\nu_k \) would cause a decrease (increase) in the power withdrawal. Point \( B \) represents a prosumer that would not change his or her consumption or generation according to a change in price, for the sake of the comfort. Compared with these two situations, points on the dashed line would define price sensitivity with some extent of concerns for economic benefit and comfort. For example, prosumer \( k \), characterized by point \( C \), would decrease his power demand by 0.3 with a maximum price \( \rho_k = 1 \) p.u., considering his or her economic sensitivity; for the sensitivity to comfort, he or she would compromise the consumption decrease by 0.3, which means the final decision on consumption will be decreased by 0.3 (1-0.3) with a maximum price \( \nu_k = 1 \) p.u. Prosumer at point \( D \) on the dashed line, would decrease his or her consumption by 0.7 (1-0.7) with \( \rho_k = 1 \) p.u., and decrease generation by 0.7 (1-0.7) with \( \nu_k = 1 \) p.u.

Conceptually, \( \rho_k \) and \( \nu_k \) can be set independently with each other. We assume \( \rho_k = -\nu_k \) for preventing prosumer arbitrage. The economic benefit \( B_k \) as the negative cost of prosumer electricity consumption/generation can be defined as

\[
B_k = -\rho_k \cdot E_k = \{D_k + G_k\} \cdot \rho_k \cdot (1 - \varphi_k) - (D_k - G_k) \cdot \rho_k. \tag{4}
\]

with the normalized comfort as

\[
C_k = \varphi_k \cdot (1 - \mu_k). \tag{5}
\]

Utility of prosumer \( k \), comprised of these two terms, can be described as a set of vectors

\[
U_k = [B_k, C_k]. \tag{6}
\]

C. DSO Decision Making

MBC strategy from each macroplayer’s view would involve a prediction of the prosumer reaction, as the control strategy, that may only be effective by aligning prosumer utilities and behaviors with the macroplayer’s objective. From the microplayers’ view, MBC results in instantaneous power injection/withdraw based on personal attitudes toward comfort and price responsiveness. A schematic representation of MBC by DSO is provided in Fig. 2.

Social welfare, in the society of local prosumers (connected to the considered network), is the total economic benefit (in terms of negative cost incurred by the prosumer in power consumption/generation) of all prosumers: \( \sum_{k=1}^{K} B_k \).

In the MBC, the macroplayer wants to maximize the network performance \( O_m \) (\( m \) indicating for the index of different objective indices) and for that need also to consider, predicting the social welfare, in terms of total prosumer economic benefits, which will drive the prosumers’ behaviors. The MBC can be exerted and formulated only considering and weighting these two aspects. Hence, an objective function \( J(\rho, \nu) \) is constructed by weighting direct network performance terms (network losses) and an indirect social welfare term. To the network performance indicator \( O_m \), a weight \( \alpha_m \) is provided while the estimated (by the DSO) welfare of the prosumer \( k, B_k' \), is associated with a weigh \( \beta \) uniform for all prosumers \( \sum_{m=1}^{M} \alpha_m + \beta = 1 \).

Selling and buying prices for each prosumer \( \{\rho, \nu\} \) are the decision variable to be selected as inputs to prosumer society. Market-based operation from the macroplayer’s point of view can be formulated as an optimization problem under the constraints of the distribution network

\[
\max_{\rho, \nu} J(\rho, \nu) = \sum_{m=1}^{M} \alpha_m \cdot O_m + \beta \cdot \sum_{k=1}^{K} B_k
\]

s.t. 

\[
\begin{align*}
& P_i - f_i(\delta, V) = 0 \\
& Q_i - g_i(\delta, V) = 0 \\
& V_i^{\min} \leq V_i \leq V_i^{\max} \\
& S_j \leq S_j^{\max}
\end{align*}
\]
where the constraints expressed the real power nodal balance, the voltage, and line flow limits.

In formulating its objective, the DSO would choose $\beta$ in the range $0 \leq \beta \leq 1$ ($1 \geq \sum \alpha_m \geq 0$). If $\beta = 0$ ($\sum \alpha_m = 1$), the DSO would not consider prosumers’ benefits in his or her decision making; if $\beta = 1$ ($\sum \alpha_m = 0$), the DSO disregards its own objective in favor of the benefits of the prosumers. The choice of $\beta$ is dependent on the structure of the society; thus, a proper choice of value in reality cases would be based on an analysis of the local prosumer society.

D. Interplay Between the DSO Decision and Individual Behavior of the Prosumer in the Presence of Social Dynamic

Restricted knowledge on the behavioral patterns of prosumers is one of the most challenging factors for regulators and decision makers in the smart-grid environment. The behavior of each individual is affected by the behaviors of other individuals with whom he/she might get in touch in society. We model this considering, for sake of simplicity, that each prosumer may know the utilities of a set of prosumers within his/her social networks and, at each time step, they can make decisions of moving toward the most rewarding adjacent position.

Fig. 3 represents a simplified attitude space with nine possible options in terms of attitudes and utility vectors (the two values in the brackets are $L_k$ and $C_k$ of the utility vector). Pursuing greater benefit, prosumers continuously update their attitudes through their social interactions with other prosumers so that the overall set of prosumers’ attitude dynamically changes over the time. In updating their attitudes, prosumers will evaluate and compare rewards with others by their own function that can be weighted with their attitudes to economic benefit and comfort ($\mu_k$ and $\varphi_k$) as

$$\Delta R_k = A_k \cdot \Delta U_k = \mu_k \cdot \Delta B_k + \varphi_k \cdot \Delta C_k.$$

(8)

Possible moving directions of prosumers on the attitude space are marked with arrows. When multiple moving directions are identified for an attitude position, real-time movement will be decided randomly (irrationally) among these possibilities with one unit of step ahead; $(\mu_k^{t+1}, \varphi_k^{t+1}) = (\mu_k^t \pm 1, \varphi_k^t)$ stands for horizontal updates and $(\mu_k^{t+1}, \varphi_k^{t+1}) = (\mu_k^t, \varphi_k^t \pm 1)$ stands for vertical updates in their attitude spaces.

Three nodes on the space are identified with no intentions of moving their attitude position, $(\mu_k^t, \varphi_k^t) = (\mu_k^t, \varphi_k^t)$. In position O, prosumers have the unrealistic property to show no sensitivity to both economic benefit and comfort; once moving his or her attitude from this original point (to any other random position) will never choose to come back under the attitude updating rule. Position A (highest consideration for price) and B (highest consideration for comfort) are typical for a prosumer that will never choose to change his or her attitude since $\Delta R_k$ will never be positive.

With a new position in the attitude space, in the next time step, prosumer $k$ will decide their power injection/withdrawn $E_k^t$, according to $\mu_k^{t+1}$ and $\varphi_k^{t+1}$, and with the current prices $[\mu_k^{t+1}, \varphi_k^{t+1}]$:

$$E_k^{t+1} = D_k \cdot [1 - \rho_k^{t+1} \cdot \mu_k^{t+1} \cdot (1 - \varphi_k^{t+1})] - G_k \cdot [1 - \nu_k^{t+1} \cdot \mu_k^{t+1} \cdot (1 - \varphi_k^{t+1})].$$

(9)

In MBC, DSO would need to consider the prosumers’ reactions (under prediction), as the control strategy that in the long term may only make sense if the individual expectations, attitudes, and utilities are taken into account. From the DSOs, MBCs are executed by instantaneous power injection/withdraw and power sensitivity to prices.

Prosumer attitudes can be predicted according to previous power injection/withdraw patterns in terms of

$$E_k = D_k \cdot [1 - \rho_k \cdot \mu_k \cdot (1 - \varphi_k)] - G_k \cdot [1 - \nu_k \cdot \mu_k \cdot (1 - \varphi_k)].$$

(10)

$$\mu_k \cdot (1 - \varphi_k) = \frac{(D_k - G_k - E_k)}{(\rho_k - D_k - \nu_k \cdot G_k)}.$$

(11)

It has to be noted that actual power outputs from prosumers will not necessarily be identical as predicted, since prosumers keep updating their attitudes in social interactions. The prediction of the prosumers’ attitudes of prosumers, enables an estimation of their economic benefits $B_k'$ as

$$B_k' = \{D_k + G_k\} \cdot \mu_k \cdot (1 - \varphi_k) \cdot \rho_k^2 - (D_k - G_k) \cdot \rho_k.$$

(12)

V. MARKET-BASED CONTROL PERFORMANCE: ILLUSTRATIVE EXAMPLE

To conceptually illustrate the MBC, we developed an agent-based simulation platform in which two interacting layers have been considered (Fig. 4): 1) the physical layer of the distribution grid and 2) the social layer of the prosumers. Spatially, prosumers connected to the same node of the grid are connected with each other as a neighborhood, and socially they are connected within social networks (prosumers marked with the same color). Power-flow equations are coded in Matlab, using the backward forward sweep method [25]; while interactions of the physical–social layer and among agents (macroplayers and microplayers) are implemented in Netlogo (a flowchart is reported in Appendix A). In this case, the macroplayer is the DSO that we assume is able to fix the network charges, assuming a given set of objectives and considering the prosumers’ behavior under
a market-based approach. The results of network performance in terms of network losses are compared with alternative pricing schemes for network charges.

We consider a standard medium-voltage distribution network (CIGRE TF C6.04.02, see Appendix B and [26]) with 14 buses, 13 lines (radial system), 1000 prosumers, and about 6 MW of max demand and about 8 MW of max generation (disregarding weather conditions). Prosumers are initially distributed in the attitude bidimensional space with coordinates generated randomly.

We assume a fully implemented smart distribution system with bidirectional real-time information exchange between end users (prosumers) and the DSO.

Through modeling the interacting players (DSO and Prosumers) over the distribution network, the simulation is capable of capturing individual behaviors that affect power injections/withdrawal and the interactions with the decision making of the DSO. Technical and economic performance for both individual players and macroplayer (DSO) under various pricing methods are compared.

Three different methods for charging network cost are considered:

- **Uniform pricing (UP)**: providing common price signals all over the network, computed from averaged network cost.
- **Nodal pricing (NP)**: providing price signals to each individual node, computed from network cost introduced by power withdraw or injection on the node [27], [28].
- **Discriminatory pricing (DP)**: providing price signals to prosumers according to MBC.

Discriminatory pricing is computed mainly from (7) in Section III and is affected by the behavior of the prosumers in terms of their attitudes and the structure of the distribution network (in terms of line flow limits and operational constraints—voltage profile).

We compare the outcomes of three methods on our platform with respect to:

- technical performance (network losses);
- economic performance (prosumer economic benefit, DSO revenue).

The economic benefit of the prosumer, defined as the costs/income from power consumption/generation along with the comfort, define the prosumer’s utility. The DSO benefit here is defined as the revenue from the wheeling service on the distribution network.

In the DSO decision making, the objective is limited to the minimization of the network losses and a value of $\beta = 0.35$ is chosen.

Both technical and economic performance are tracked over a fictitious time frame in which, at each time interval, prosumers interact accordingly among themselves and with the network making decisions at the same time with the DSO. The trend converges to an average value after a given number of interactions.

### A. Technical Performance Analysis

Different pricing methods provide different performance as illustrated in Fig. 5. After the social dynamic of the prosumers stabilizes (about 50 time steps), DP obtains the best performance in terms of least network losses. The use of DP can be extended to consider peak-hour demand alleviation and offpeak generation limiting.

At the same time, other network performances, such as voltage profile and line flows, can also be ensured under DP.

In Fig. 5, under DP, some spikes appear in the curve. The spikes are due to the features of multiagent simulation. Simulation time in MAS is discrete while, in the real world, the interactions are continuous. At each time step, a sequence of actions has to be defined and fixed in advance. As in our case, the prosumers would react to and make decisions with the given price sets from DSO. The DSO’s decision on price sets, on the contrary, is computed from the behaviors of prosumers in the last simulation time frame, making these price sets not fitting any more in the next time step when prosumers have updated their...
attitudes. With proper prediction of prosumer-adapting behaviors based on enough historical data of an evolving prosumer society, these spikes might be eliminated.

In the initialization of the MBC, we need to consider: 1) the distribution of the prosumer population on the attitude space and 2) the initial prices set by the DSO.

DSO can be aware of the attitudes of the local population of prosumers, through experience or sociological studies. That would provide the starting scenario for the allocation of prosumers on the attitude space (Fig. 4 upper layer) and the starting losses at time $t=0$ of Fig. 5. In the example considered, since no sociological identification was possible to be done on a real social sample, the distribution has been chosen randomly, for the sake of simplicity.

For the “price setting” dimension, initial prices are set randomly; in the first iteration, the power behaviors of prosumers are induced by the initial prices, since we have no information of the system status and cannot apply the MBC in the first iteration. In the MBC perspective, the prosumers first react to the initial process inducing the corresponding network power flows, then the DSO sets prices for the next iteration and, again, the prosumers would make power-output decisions according to the prices given.

Fig. 6 illustrates the exploitation of local generation to match local demand; DP is capable of minimizing network losses while controlling voltage profile and line overload using less generation resources from prosumers.

B. Economic Performance Analysis

Distribution systems are natural monopolies, and the DSO is usually unwilling to hand over operational rights to decentralized generator owners and turn to a passive regulating pattern of managing distribution networks. Moreover, the rising complexity of distribution networks introduced by high penetration of DGs usually brings in increased operational cost for DSOs. Though reduced network losses may cover part of this cost, new mechanisms and incentives are still needed by DSOs to accommodate additional private DGs [29]. DP can also help the DSO in increasing its revenues pushing toward smart grid with a relieved concern for cost. Fig. 7 illustrates network pricing, in arbitrary monetary units, and the DSO revenues under various pricing schemes. UP and NP pricing compared with DP pricing, both showed a lower level of charging with few benefits (or even negative in the case of UP). Even increasing the network charge price did not seem to increase the DSO profit. (UP shows decreased revenue while increasing network pricing, and NP revenues seem more or less unchanged.)

The DSO, with reference to the considered application of MBC, obtains operational revenue equal to the net balance between the money received after paying and getting paid to/from the prosumers. In Fig. 7, we compare the normalized price for network usage and operational revenue of the DSO by applying different network usage charging methods.

Comparing Figs. 7 and 8, we can see that although DP provides, in general, higher prices for network usage, the prosumer economic benefits from DP still dominate over the other two charging methods. In other words, the DP is beneficial to the
DSO and, at the same time, to the prosumers. In addition, prosumer economic benefits grow along time (Fig. 8) and with the increase in the DSO operational revenues, showing the alignment between them (Fig. 9).

Compared with UP and NP, DP provides higher social welfare (prosumer economic benefits) as shown in Fig. 8. At the same time, the prosumer utility terms of economic benefit and comfort are not affected, in the DP, by an increase of the DSO operational revenues.

C. Robustness of MBC

We analyze the robustness of the MBC with respect to the decisions of a macroplayer like the retailer, and to a different social pattern of the prosumers.

Electricity price to end users typically includes the following components: electricity price (at the source), dispatching and balancing costs (TSO level), and distribution network charges (DSO level); the retailer would decide the electricity price and then charge the other components on behalf of the relevant entities. A 24-h demand profile is considered, and the hourly electricity prices are decided by the retailer according to the total demand of the considered distribution system at that hour. We want to assess the robustness of MBC with respect to different choices on the ratio of peak electricity price with reference to the DSO network charges, represented by the variable of “rp” computed from the retailer price in the peak hour divided by the maximum DSO network charge.

The retail prices are given in each time step of the 24-h scenario equal for all of the customers. The change in retail price (Fig. 10) does not affect the technical performance of the network (losses, voltages, and overflows). For economic performance, it does affect the DSO revenues (our objective is not to improve DSO revenue); while the prosumers’ economic benefit and comfort are not harmed.

Aggregation refers to the phenomenon of a set of prosumers showing similar attitudes, as measured by the values of $\mu_k$ and $\gamma_k$, after a process of social interaction in which they compare their utilities with other prosumers and update their attitudes. Repeating this interaction, commonly, prosumers would aggregate within a small distance on the attitude space, known as the “oneness” [30] of social behaviors.

The aggregation is driven by the responsiveness of the prosumer to the difference of their utilities with those of other prosumers they use as comparison in updating the individual attitudes. Changing the threshold of the utility difference that activates updating the behavior produces different societal aggregation. The proposed MBC is tested with different social behaviors in terms of aggregation to compare a different social environment. In Fig. 5, the simulation was undertaken with a more aggregated society (small activation threshold 0.1); while in Fig. 11, we increased the activation threshold (from 0.1 to 1), considering a less aggregated (more scattered) society.

Fig. 11 shows the network losses as a technical performance under different electricity prices under a less aggregated society; the base case of network losses under DP in aggregating society is also included as a reference; as we can see, DP still shows a dominating method to minimize losses.

The simulation undertaken shows that if we consider together the choice in terms of price from the retailer and different prosumer society, the outcomes of the DP are still consistent with the presented results.

VI. CONCLUSION

In emerging electricity distribution systems, the overall system performance is related to the interplay of macroplayers...
(regulator, DSOs, retailers) and microplayers, such as prosumers with different global or individual goals and utilities. The global utilities pursued by the macroplayer in terms of environmental control, energetic efficiency, or technical feasibility of the network can be pursued by providing proper price signals to the microplayers and devising strategies that would align the global goals with the individual utilities. The approach needs to be dynamic, and discriminatory in terms of pricing, overcoming the usual static regulatory framework, and taking into account the social characterization of the prosumers and their dynamics.

To choose a proper regulatory strategy, comprehensive models of emerging distribution systems that are able to incorporate social and technical layers are needed and can be used to test ex-ante the strategies.

The MBC proposed in this paper, considering both electric and social behaviors, manages self-interested distributed decision makers by simultaneously optimizing multiple objectives in terms of network and market performance and seems a promising way to go toward.

APPENDIX A

The main blocks in realizing the simulation of the multilayer complex distribution system are shown in Fig. 12.

The bottom-level power-flow calculation is implemented in Matlab. Components in the middle block are simulated as agents in Netlogo, and the upper-level block is the user interface to configure the environment for simulation and interactive running.

APPENDIX B

The study case of this paper is based on the MV distribution benchmark developed in CIGRE TF C6.04.02 [26], the original network derived from a German network as following Fig. 13, simplified and standardized as in Fig. 14.

REFERENCES


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