A Real-Time Congestion Control Strategy in Distribution Networks

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Abstract—This paper proposes an algorithm for real-time congestion management in a distribution network. It sets up a peer-to-peer market allowing the distribution system operator to inject network charges. This enables him to obtain flexibility from distributed agents with heterogeneous preferences. These network charges vary in real time and are related to the network's congestion. Prosumers minimize their cost function, and find a consensus through alternating direction method of multipliers decomposition. This formulation allows the management of the large number of agents present in the distribution networks only using one price broadcast by the distribution system operator to prosumers. We illustrate with the CIGRE low voltage test case that this strategy is efficient to manage congestion and presents limited sub-optimality compared to the optimal power flow.

Index Terms—Distributed Optimisation, Peer-to-peer, Distribution System Operator, Cost Allocation, Real-Time, Flexibility, Congestion Management.

1 INTRODUCTION

The deployment of Distributed Energy Resources (DERs) alters the management paradigm of distribution networks which will host 99% of new DER infrastructures [1]. Electrical consumption is expected to drastically rise [2] because of new uses – electric mobility, heat pump – exposing it to risks of congestion and non-compliance with voltage limits [3]. However, the violation of thermal constraints can lead to the premature aging of conductors or even to blackouts, which represent a significant additional cost for the Distribution System Operator (DSO). Currently, these constraints are managed through long-term physical network reinforcement [4]. However, the introduction of distributed flexibilities creates a possibility of new management of the network, which is essential to achieve energy transition while limiting the costs of new infrastructures [5]. This transition is facilitated by the widespread deployment of smart meters [6] which enables limited yet bilateral information exchange between DSO and prosumer. But currently, DSOs do not have efficient means of controlling large numbers of agents in real time.

Within the Demand Response (DR) literature, two types of approach stand out. In incentive-base DR programs, agents are offered payments in order to deliver a specific amount of load reduction. In price-based DR programs, consumers voluntarily provide load reductions by responding to economic signals [7]. The purpose of these programs is to match production and consumption. But fluctuating prices rarely reflect the price of using the network and to our knowledge are never used to solve the constraints associated with it.

A new market design focused on the interaction between DSO, aggregator and prosumers, opt-in for prosumers and that satisfies Pareto efficiency was proposed in [5]. The DSO can manage network constraints by buying flexibilities from the agents, but the negotiation mechanism is not suited to real-time application. Alternatively, Steriotis [8] proposed a real-time pricing scheme that offers an easily adjustable level of financial incentives to consumers, by fairly rewarding the desirable consumption changes. But prosumers have to announce their future consumption to the aggregator which can lead to privacy issues. Finally, Lu [9] proposed to handle constraints directly by solving an Optimal Power Flow (OPF) in a distributed manner taking advantage of the radial structure of the distribution networks to obtain an exact relaxation of the problem. Real-time resolution is made possible by warm-starting the algorithm by using the offline scheduling solution as the initial point. However, it does not directly involve prosumers in the decision making. On the other hand, peer-to-peer (P2P) markets are able to process a large number of agents with heterogeneous and private preferences (i.e. renewables, zonal) without increasing the computational complexity [10]. It is the most generic formulation because any market configuration can be expressed as a P2P market [11]. In addition, fluctuating pricing helps with involving prosumers by making them more responsible [12]. A P2P market was proposed in [13] to solve economic dispatch while introducing an exogenous grid price. This provides the system operator with a lever to compel market agents to comply with grid physical constraints. A consumption decrease proportional to the agents' flexibility was observed when price increases. This algorithm is a good candidate but no rule was provided to fix the network charges in advance and the algorithm requires iterative bilateral communication with the SO.

Thus, supposing that a communication network lies on top of the electric grid, we propose a real-time implementation of [13] allowing the DSO to manage congestion in the network using only a broadcast price reflecting the network state. Section 2 presents the P2P formalism and how it can be used to solve electricity markets in distribution networks. Simulation results are presented and discussed in section 3 using a test case relying on the CIGRE low voltage network. Section 4 contains our conclusions and perspectives for further work.

2 METHOD

2.1 Peer to peer market

The general formulation [13] of a P2P market is given in (1). Where $\mathbf{P}$ is the matrix of power trade p_{nm} of agent n with agent m, ω_n is the set of partners of n, f_n is the cost function, p_n is the power exchanged, $\underline{p_n}$ and $\overline{p_n}$ are respectively the minimum and maximum power limits. h_n is a regularization function which condense all network constrains. It is equal to 0 if they are respected and $+\infty$ if they are violated.

$$\min_{\mathbf{P}} \quad \sum_{n\in\Omega} f_n(p_n) + h_n(p_n) \tag{1a}$$

$$\text{s.t.} \quad \mathbf{P} = -\mathbf{P}^T \tag{1b}$$

$$p_n = \sum_{m\in\omega_n} p_{nm} \qquad n \in \Omega \tag{1c}$$

$$\underline{p_n} \leq p_n \leq \overline{p_n} \qquad n \in \Omega \tag{1d}$$

$$\underline{p_n} \leq p_{nm} \leq \overline{p_n} \qquad n \in \Omega \tag{1e}$$

Baroche [13] proposed to replace h by an exogenous terms. These exogenous term would aim not only at allocating congestion-related costs but also at controlling prosumer demand via their sensitivity to energy prices. Hence, h can be replaced by a cost allocation function defined as

$$h_n(p_n) = \gamma \cdot p_n \tag{2}$$

where γ is the network charge fixed by the DSO which represent the network's solicitation.

Problem (1) can be efficiently solved using the Alternating Direction Method of Multipliers (ADMM) [14]. The resulting decentralized negotiation mechanism [13] reads :

$$\begin{aligned}(p_{nm})^{k+1}_{m\in\omega_n} = \underset{(p_{nm})_{m\in\omega_n}}{\text{argmin}} \; & f_n(p_n) + \gamma \cdot p_n \\ & + \sum_{m\in\omega_n} \Bigg[\lambda^k_{nm} \left(\frac{p^k_{nm} - p^k_{mn}}{2} - p_{nm} \right) \\ & + (\rho/2) \left(\frac{p^k_{nm} - p^k_{mn}}{2} - p_{nm} \right)^2 \Bigg] \\ & \text{s.t.} \quad \text{(1c)–(1e)} \end{aligned} \tag{3a}$$

$$\lambda^{k+1}_{nm} = \lambda^k_{nm} - \rho(p^{k+1}_{nm} - p^{k+1}_{mn})/2 \tag{3b}$$

where penalty factor $\rho > 0$ and λ_{nm} is the dual variable associated to the trade p_{nm}. According to [14], supposing cost functions f_n to be closed, proper, and convex is a sufficient condition to ensure convergence of (3).

2.2 Real time implementation using rolling iteration warm start

Convergence of trades $\mathbf{P}$ towards the optimal trades requires a certain number of iterations which depends on the number of agents N_Ω, the cost function f_n and the parameter ρ. The core element of the proposed algorithm is that at each time t_0, agents solve their local problems and enforce their decision with an effective power exchange $p_n^{t_0}$. The DSO then measures the grid state, updates grid cost value and broadcast it at the next time step $t_0 + \Delta t$. For small Δt values, the solution should always be close to the optimal. This concept has already been studied for optimal control and Hours [15] has shown that a well chosen ρ keeps the residuals bounded. Indeed, we can assume that between two close instants, the power $p_n^{*t_0}$ requested by agent n at t_0 is not very different from $p_n^{*t_0+\Delta t}$. Similarly, the cost function $f_n^{t_0}$ should be close to $f_n^{t_0+\Delta t}$. We can therefore find Δt such that the solution of (1) is almost identical at both times. Thus, we propose the algorithm 1.

Algorithm 1: Real time congestion control

```
Result: p_n, ∀n ∈ Ω
while True do
    for n ∈ Ω do
        Get the grid cost via DSO broadcast: γ^t ;
        Get trades from other agents: p^t_mn, ∀m ∈ ω_n ;
        Update dual variable: λ^t_nm ← (3b) ;
        Compute new power exchange: p_n^{t+Δt} ← (3a)
         ;
    end
    DSO computes network charges : γ^{t+Δt} ← (6);
    t ← t + Δt ;
end
```

2.3 Price evolution

The DSO is in charge of maintaining the network's integrity and must ensure that it is not congested. Although the distribution network's state is generally not well known because of the small number of sensors, we will consider that it is observable in real time, for example via an estimator [16].

The DSO determines the most constrained line or voltage

$$l' = \underset{l\in\mathcal{L}}{\text{argmax}} \; I_l / C_l \tag{4}$$

where I_l and C_l are respectively the current and the maximum current admissible in l. Any technique can be chosen to determine the price the network's cost : Machine Learning, Reinforcement Learning, Kalman filter, etc. but even simple solutions can work out as illustrated section 3.

3 TEST CASE AND RESULTS

3.1 Test case

Simulations[1] were carried out using panda power [17] on the single-phase CIGRE European LV distribution network [18]. Fig. 1 shows the network's topology. It is composed of 44 buses, 40 prosumers including 33 with solar panels. To model the power exchanged by each agent, we used the 1 minute time step time series from [19]. For illustrative purpose, agent's power and lines' capacity were adapted. A

1. Test case and algorithm available at gitlab.com/satie.sete/rt-congestion-control/-/releases#1.3

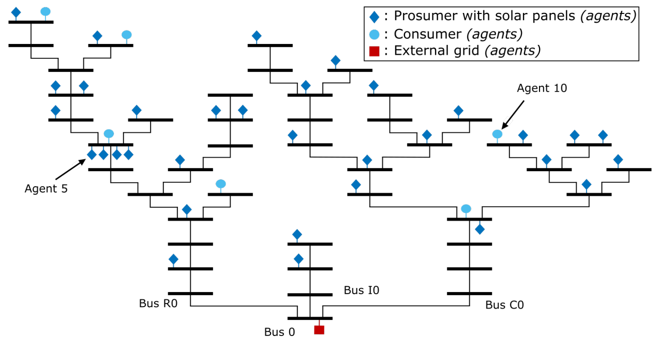

Fig. 1. CIGRE low voltage network 44-bus, with 40 prosumers including 33 with solar panels.

quadratic function is here used for each prosumer (5). However, in a real implementation, each agent is encouraged to implement the cost function f_n^t of their choice which can be the result of an internal cost-saving optimisation [20].

$$f_n^t(p) = -F_n \cdot p_n^{t*} \cdot p + 0.5 \cdot F_n \cdot p^2 \tag{5}$$

where p_n^{t*} is the objective power of the agent n at time t. F_n represents the agent's sensitivity to a price fluctuation γ. The larger F_n is, the less sensitive the agent will be to γ, and the closer the power obtained p_n^t will be to p_n^{t*}. In return, the agent will pay a high price to the DSO when the network is constrained. In this paper we have chosen to use a quadratic function because (3) is efficiently solved by [21].

With the aim of achieving significant price fluctuations, we fixed agents' flexibility between 25 and 200. Only p_n^* changes over the course of the simulation. Agents 0 represents the external grid with infinite power. It is very flexible ($F_0 = 0.1$) and has a zero power objective ($p_0^* = 0kW$). This agent can be used to manage the coordination between TSO and DSO although this is beyond the scope of the article.

As mentioned section 2.3, any technique can be chosen to set the network charges γ^t, we illustrate with a PI regulator :

$$\gamma^t = \max\left[0\,;\left(K_p + \frac{1}{T_i}\int \cdot\, dt\right)\cdot\left(\frac{I_{l'}^t}{C_{l'}^t} - 1\right)\right] \tag{6}$$

where K_p is the proportional gain, T_i the integration constant and γ^t the fluctuating grid cost at time t.

3.2 Time series analysis

The first two panels of Fig. 2 show the evolution of the powers exchanged by agent 10 (not very flexible) and agent 5 (very flexible). *Objective* (b) represents the agent's objective power, i.e. the minimum of its cost function p^{t*}. *Exogenous* (a), *OPF* (c) and *OPF without line limits* (d) represent respectively the power exchanged by applying the Exogenous algorithm, OPF with line limits and OPF without constraints. This legend is common to the first 3 panels. We adopt the producer convention : $p_n > 0$ means that the power is produced by the agent n. Agent 10 being inflexible, the exchanged powers p_n^t are equal to p_{10}^{t*} for all t, contrary to agent 5. Before minute 100, the exchanged powers (c) and (d) are equal because no constraints are active. The exchanged powers are lower than the target because the grid agent pushes self-consumption and forces the most flexible agents to consume less. After minute 100 the curves (c) and

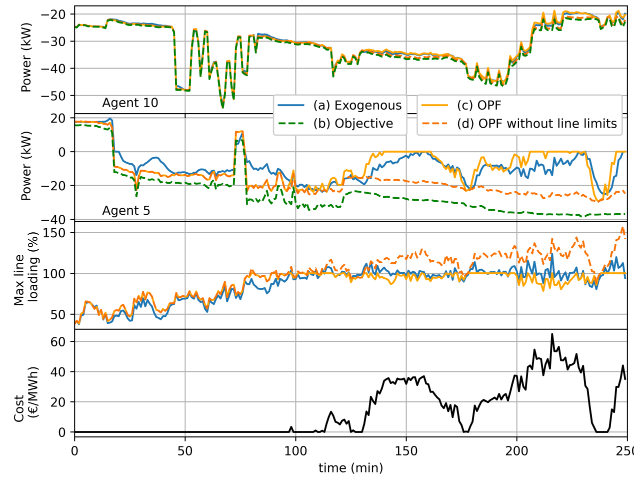

Fig. 2. Evolution of the power, network charges, maximum line loading and network charges γ^t during the simulation.

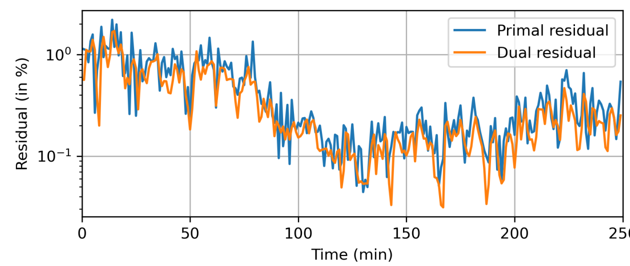

Fig. 3. Primal and dual residual throughout the simulation

(d) differ because the network is constrained. As requested, the power consumption (a) follows the variations of (c), although instantaneous variations are unavoidable.

The third panel represents the evolution of the most saturated line during the simulation for the three algorithms. Without control (d), the network exceeds the thermal constraint from minute 100 and reaches at most 155%. (c) is the strategy that implements the OPF, so it respects the constraints. (a) respects the constraint in spite of slight overruns – a qualitative analysis is made section 3.3. Finally the last panel represents the evolution of the network charges γ^t given by the PI controller. It is null when constraints are inactive.

The primal (7a) and dual (7b) residual expressed as a percentage of the power exchanged during the simulation represent the degree of agreement between agents.

$$r^{t+1} = \left[\sum_{\substack{n\in\omega \\ m\in\omega_n}} (p_{nm}^{t+1} + p_{mn}^{t+1})^2\right] \Big/ \sum_{\substack{n\in\omega \\ m\in\omega_n}} (p_{nm}^{t+1})^2 \tag{7a}$$

$$s^{t+1} = \left[\sum_{\substack{n\in\omega \\ m\in\omega_n}} (p_{nm}^{t+1} - p_{nm}^{t})^2\right] \Big/ \sum_{\substack{n\in\omega \\ m\in\omega_n}} (p_{nm}^{t+1})^2 \tag{7b}$$

Fig. 3 shows the evolution of these residues during the simulation. They never exceed 2%. This means that the evolution of $p^{*,t}$ is slow enough for the algorithm to remain at a reasonable consensus level.

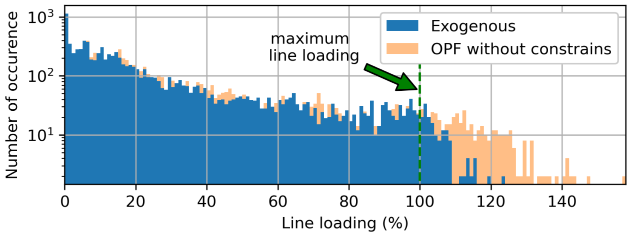

Fig. 4. Histogram of line loading percent for the Exogenous algorithm ($(K_i, K_p) = (0.01, 0.01)$) and the OPF without constrains. Respectively 1.7% and 4.2% of the lines exceed the maximum admissible current. Biggest overflows are 28% and 58%.

3.3 Statistical analysis

The histogram of the line load rating is presented Fig. 4. Over the simulation period (250 minutes), only 1.7% of the lines exceed the maximum admissible current. The biggest overflow is 28% and appeared only once. The network charges are determined by a PI controller (section 2.3). The optimal values of K_p and K_i cannot be known in advance because of the difficulty to characterize the system composed of the network and its agents (whose cost functions are private). We perform an exhaustive search to determine the optimal pair.

Two metrics are proposed : the undelivered power (8a) and the maximum overflow in the lines (8b). For each simulation we have N_Ω (number of agents in the network) values of $P_{\text{not delivered}}$ and $N_\mathcal{T}$ (number of time step) values of L_{overflow}. We choose to represent, for each metric, the median value and the 95% quantile.

$$p^n_{\text{not delivered}} = \frac{\sum_t |p^t_{n,exo} - p^t_{n,OPF}|}{\sum_t |p^t_{n,exo}|} \tag{8a}$$

$$L^t_{\text{overflow}} = \max_{i \in \mathcal{L}} l^t_{\text{i,overflow}} \tag{8b}$$

Fig. 5a shows the median undelivered power for different K_i, K_p pairs. $(K_i, K_p) = (0, 0)$ corresponds to the performance of the algorithm without correction. Without correction, the undelivered power exceeds 7.5% for half of the agents and drops to 4.5% with the best setting. Fig. 5b shows that without correction, the undelivered power is higher than 48% for 5% of the agents. With the best regulation, it drops to 25%. Without corrector, the most overloaded line exceeds 8% of overload half of the time (Fig. 5c). With a corrector, the network is not under stress at all for at least half of the time. Finally Fig. 5d shows that the most overloaded line exceeds 37% of overload 5% of the time. With the best controller, it is reduced to 7.5%.

Fig. 6 shows the influence of flexibility on the average network's charges per MWh. The trend suggests that the more flexible an agent is, the lower the cost. For example, the cost paid by agent 5 is 1.5 times lower than that of agent 10. This trend needs to be confirmed for larger networks with more agents. Simulations were performed on one core of an Intel Core i7-9850H 2.60GHz. Results presented in table 1 are for a 250 time steps simulation, which represents 250min simulated.

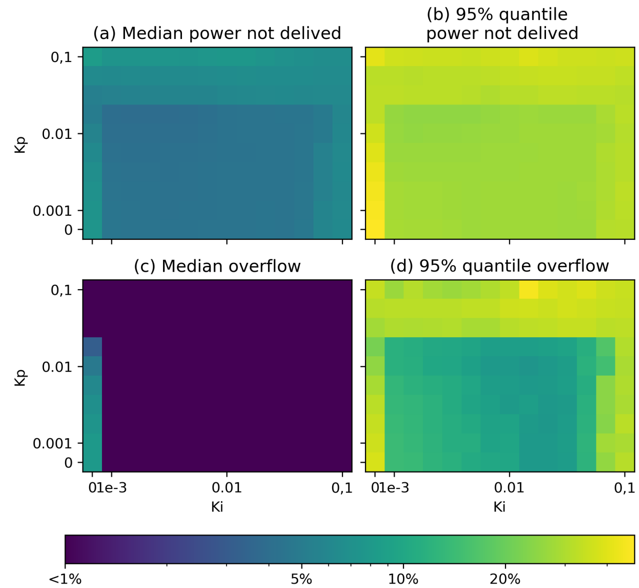

Fig. 5. Sensitivity analysis for the PI controler. Fig. (a) and (b) represent the quantile of power deference between the exogenous algorithm and the OPF with line limits expressed in %. Fig. (c) and (d) represent the quantile of maximum loading expressed in %. Each value is taken for a specific K_i and K_p pair.

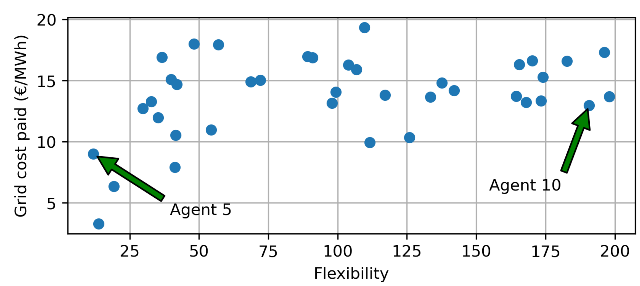

Fig. 6. Influence of the flexibility (arbitrary range) on network charges paid. Agents 5 and 10 whose time series are given in Fig. 2 respectively very flexible and inflexible pay different prices for the same amount of energy.

4 Conclusion

In this paper, we proposed a new algorithm to manage congestion in a distribution network in real time by broadcasting, through smart meters, a variable representing the cost of network usage. At each time step t, the agents retrieve the network charges γ^t. Then, they compute the optimum of their cost function f^t_n and propose trades p^t_{nm} to the other agents. They directly apply the result of their minimization to the network (i.e., consume the power p^t_n) without worrying about the convergence of the algorithm or the possible congestion this could create. The DSO then estimates the state of the network, in particular the maximum line congestion. It infers a price $\gamma^{t+\Delta t}$ with the goal

TABLE 1
Computation time

Algorithm	*Exogenous*	*OPF*	*OPF without constrains*
time (s)	23	263	258

of resolving congestions. The algorithm being peer to peer, it is scalable and able to manage a large number of agents without increasing the computation time – minimizations are performed locally by agents.

The proposed algorithm was tested on a modified version of the CIGRE low voltage 44-bus test system. We used a simple, yet effective, PI controler to set the network charges. The algorithm not only reduces the number of overloaded lines but also the amplitude of the overload. Moreover, in our case study, less than 5% of prosumers had a significant drop in their consumption.

This exogenous approach is a good candidate for future implementation of peer-to-peer markets with low involvement of the system operator, but it needs to be tested on a more representative test case that takes into account the realistic constraints of distribution networks – hundreds of agents and buses. Designing a more complex pricing system anticipating the agents' response should improve the algorithm's performance. Other types of pricing can be considered: for example, to maintain voltage in their operating limits, to manage unbalanced three-phase networks or to encourage producers and consumers in a different way. Other questions require additional investigation, in particular : is the grid costs universal for the whole grid or it only applies for the congested area ? If it is universal, agents in the network areas without congestion are unnecessarily penalized. If it is locational, it is not fair for those agents in the weaker network areas because they always lose money due to the imposed grid cost. In conclusion, this approach should not be seen as a way to generate revenue for the DSO in order to strengthen the network. It is a new emergency way of managing the network. The matter of redistributing the profit between agents equally remains an open question.

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