Day-Ahead Optimal Power Flow for Smart-Community Microgrid with Centralized Electrical Storage and Wind Turbine

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***Abstract*— This research presents the innovate method of Day-Ahead Optimal Power Flow (DA-OPF) management of Smart Community Microgrid (SCM) with a wind turbine generation and Centralized Energy Storage System (CESS). The developed DA–OPF is based on the Deep Learning (DL) Long Short-Term Memory (LSTM) network for the wind generation and community consumption data forecast. The Optimal Power Flow (OPF) problem is formulated to reduce Locational Average Marginal Price (LAMP) and is solved by Mixed-Integer Nonlinear Programming (MINLP) model. To take into account the forecast error of forecast system, also as its influence on the SCM system stability, this method includes the evaluation system based on the Monte-Carlo Simulation (MCS). This allows developing DA-OPF strategy assure not only the optimal operation, but also the resilience and stability of the SCM. The evaluation of the proposed method was realized on the case of conversion of real conventional community into SCM. This was made by the integration of CESS, a wind turbine and developed DA-OPF management. The practical evaluation and subsequent economic analysis show the efficiency of the proposed DA-OPF method and its good effect on reducing community energy price and to respect the energy transition process.**

Keywords*— *microgrid; deep learning; optimal power flow; mixed-integer nonlinear programming; long short-term memory; monte carlo simulation

I. Introduction

The goal of the European Union for the coming decades is to increase the share of Renewable Energy (RE) sources in the total energy balance to 45% and reduce carbon dioxide emissions by 55% by 2030 according to Climate Target Plan for the energy transition for green growth [1]. From one side, this process provides for an increase in RE sources to respect these goals [2] and large capacities of RE sources will be installed [3]. On the other hand, the intermittent generation of these sources will lead to perturbations in the conventional Distribution Grid (DG) and it will no longer be able to assure the reliable energy supply [4]. DG will need more flexibility to compensate for this impact and the issue of flexibility will become very important, especially local flexibility that can help to stabilize the power grid locally closer to the place where it is necessary [5].

Small towns, villages and even districts can become not only consumers of electricity and energy, but sources of electricity for the DG as well as sources of flexibility for the grid (compensate the intermittence of RE sources or support DG reliability locally) [6]. They can form a Smart Community Microgrids (SCM), and that electricity or flexibility can be traded for financial gain in markets specifically designed for that purpose, but this requires the preliminary negotiations [7]. Therefore, the management of SCN requires a predicted and generally day-ahead management forms [8].

Therefore the purpose of this study is to show an innovative method of SCM microgrid management through the innovate Day-Ahead Optimal Power Flow (DA-OPF) management system. The forecast part of this algorithm is assured by the Deep Learning (DL) Long Short-Term Memory (LSTM) neural network, which has proven it efficiency in predicting of long data sequences [9], [10]. The optimization problem is solved with Mixed Integer Nonlinear Programming (MINLP) which allows taking into account the non-linearity of some components of which there are a lot in the DG [11], [12]. The another innovativeness of this method is that this algorithm takes into account the forecast error and its associated impact on SCM operation. This is realized with an evaluation block that uses Monte Carlo Simulation (MCS) to generate possible moves from the initial data. Ultimately, a practical application of this DA-OPF to a real community will be presented to show the efficiency and effectiveness of this method.

II. Day-Ahead Optimal Power Flow Operation

Fig. 1 shows the graphical representation of the proposed DA-OPF SCM management algorithm. This algorithm is dedicated to effective management of the community with a wind turbine and considers uncertainties caused by this intermittent energy source.

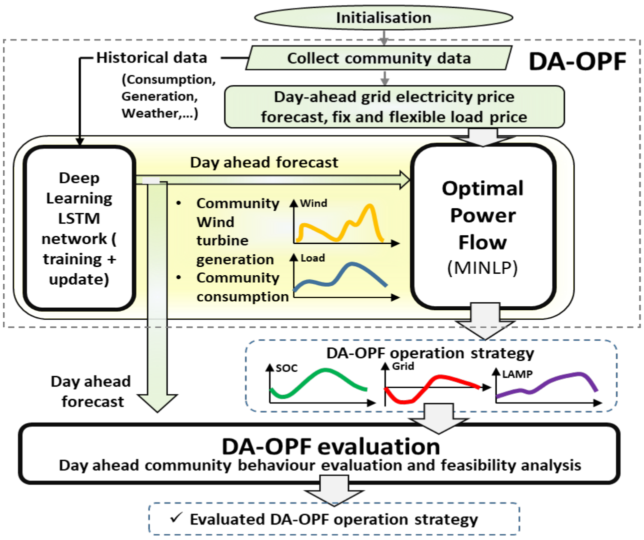

Fig. 1. Graphical representation of the developed DA-OPF SCM management algorithm.

This control method starts with a collection of existing SCM data. Then this data along with historical data such as history of energy consumption, wind generation, weather and others enter in the block of "Deep Learning LSTM" data forecast to generate the day ahead community wind turbine generation and the community energy consumption forecasts, respectively. More precise the LSTM neural network dedicated to SCM forecast is presented in [10], [13], [14].

After that, the system collects the electricity price forecast for the day-ahead from the power grid manager, also the cost of load shedding of fixed and flexible load from the SCM and all this data goes into the system of "OPF" resolved by MINLP which will be presented below. The OPF system finds an optimization function and finds a global optimal solution to a complex optimization problem. Then it generates the DA-OPF SCM operation strategy which, under all given circumstances, minimizes the operational function more than all other solutions. This method aimed to minimize the Locational Average Marginal Price (LAMP) as a very characteristic parameter for SCMs [10]. Since we cannot influence the production of the wind turbine and partially affect SCM energy consumption (flexible load), the obtained optimal DA-OPF strategy is to controlling the of charging and discharging reference of the CESS, it is possible to control the power flows from/to the distribution grid [12].

Before applying obtained DA-OPF strategy of SCM operation, it is necessary to take into account the forecast error of "Deep Learning LSTM" block, since these errors can lead to deviations of the real parameters compared to the predicted ones, and as a consequence to exceed of the system limits and to bring it to SCM collapse and blackout. For this, the "DA-OPF evaluation" system is proposed and shown in Fig. 2.

This system uses Monte Carlo Simulation (MCS) to generate a day-ahead wind turbine generation profile and SCM energy consumption profile taking into account possible evaluation due to forecast uncertainties. In more detail, this method is presented in [15], [16]. Then these profiles enter in the "OPF" that will be described above. Solving the optimization problem, the "OPF" generates optimal control strategy for this case, which will be stored in the "collection of results" block. The cycle will repeat until the stopping criterion presented in (1) riches the minimum limit:

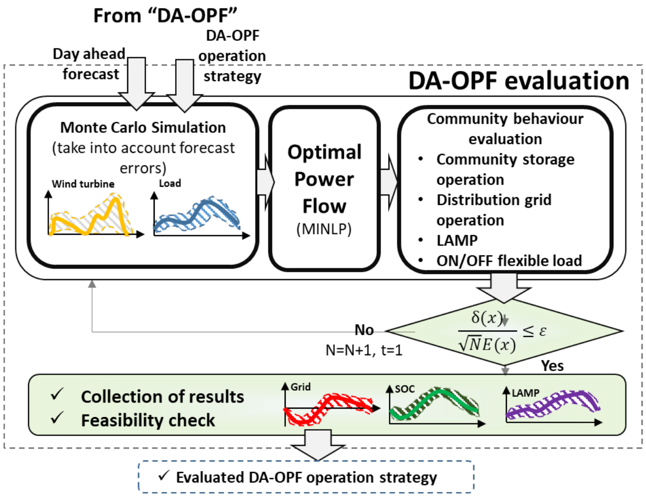

Fig. 2. Graphical representation of the "DA-OPF evaluation" system of the developed DA-OPF SCM management algorithm.

$$\frac{\sigma(X)}{\sqrt{N}E(X)} \leq \varepsilon \tag{1}$$

where $E(X)$ is the mean value of LAMP for considered simulated case and $\sigma(X)$ its standard deviation, N represent the number of simulation samplings, ε represents the chosen maximum simulation error.

As soon as the stop criteria is met, the system analyzes all received profiles to identify possible critical moments at which the operating parameters may exceed the operating limits and lead to the collapse of the SCM supply system.

In the case that the "DA-OPF evaluation" system did not show exceeding the limits of all components of SCM, this strategy is considered feasible and will be applied to the SCM management during the day-ahead. Otherwise, this strategy will be considered dangerous and possible to lead to the collapse of the energy system. In this case, reconfiguration of the system composition is required and the whole process of this algorithm should start again.

Next chapter will present more precisely the OPF optimization method used in this DA-OPF algorithm.

III. Mixed Integer Nonlinear Optimization Method for OPF

The objective function of developed DA-OPF provided to be resolved through MINLP method presented in [17]–[19]. It is dedicated to minimize the operation cost of SCM and is presented in (1)

$$f(x) = f_g(g_+, g_-) + f_s(s_0, p_c, p_d) \tag{1}$$

The first part of (1) represent the cost of electricity originating from or going to the grid with corresponding costs and is shown in (2)

$$f_g(g_+, g_-) = \sum_t \sum_i \left[C_{g+}^{ti}(g_{g+}^{ti}) + C_{g-}^{ti}(g_{g-}^{ti}) \right] \tag{2}$$

where t represents a time period, i is the unit index (index of fixed or flexible load, index of supply power lines, etc.), g_{g+}^{ti} and g_{g-}^{ti} are the energy injected to or absorbed from the grid at time t, for unit i respectively, C_{g+}^{ti} and C_{g-}^{ti} are the cost functions for the injected or absorbed active power to or from the power grid at time t and unit i respectively.

The second part of (1) take in consideration the stored energy cost at the beginning and at the end of each considered period and is shown in (3)

$$f_s(s_0, p_c, p_d) = C_{s0} Se_0 - (C_{s0}^t Se_0 + C_c p_c + C_d p_d) \tag{3}$$

where Se_0 represents the initial stored energy in the storage unit i, p_c and p_d are the charged or discharged power of storage unit i at the moment t respectively, C_{s0} and C_{s0}^t are the price vectors linked to reaching the stored energy Se_0 in the storage unit i in the $t = 0$ or in the terminal end-of-horizon base state respectively, C_c and C_d are the vector prices for terminal charging or discharging contributions, respectively, of storage unit i at the end-of-horizon terminal base states.

Considering constraints, the general OPF equality constraints q^t and inequality $t^t$are presented in (4) and (5) respectively:

$$q^t(\theta^t, V^t, p^t) = 0 \tag{4}$$

$$t^t(\theta^t, V^t, p^t) \leq 0 \tag{5}$$

Where θ^t, V^t and p^t represent voltage angels, magnitudes and active power injections at time t.

$$o^{ti} p_{min}^{ti} \leq p^{ti} \leq o^{ti} p_{max}^{ti} \quad (5)$$

Where o^{ti} represents a commitment state in a binary form for the unit I at the time t (1 for on-line unit, 0 for off-line), p_{max}^{ti} and p_{min}^{ti} represent the active injection limits for unit i at the time t.

The storage operation and level limits, respectively, are presented in (6)-(8):

$$p^t \leq p_c^t + p_d^t \quad (6)$$

$$p_c^t \leq 0 \quad (7)$$

$$p_d^t \geq 0 \quad (8)$$

$$Se_-^{ti} \geq S_{min} \quad (9)$$

$$Se_+^{ti} \geq S_{max} \quad (10)$$

Where Se_+^{ti} and Se_-^{ti} represent the stored energy upper or lower limits, respectively, in the storage unit I at the end of period t which is calculated endogenously. More precisely the optimization function and other constraints are presented in [11].

Below will be presented the practical application of the proposed management system on the real data community case.

IV. Practical Evaluation

To evaluate efficiency of developed original DA-OPF method dedicated to SCM with wind turbines, it was chosen by the conventional rural community in Eymoutiers, France. This commune has around 1200 inhabitants and around 200 households, with maximum actual consumption 1500 kW. This research study the case of conversion of this conventional rural community to SCM through installation of centralized energy storage and a wind turbine. The existing infrastructure of the community consisted of power line BUS1-BUS3 which links the community to the main distribution grid as shown in Fig. 3. It is assumed that due to the constant growth of the community (up to 1800 kW of installed power), the existing infrastructure will no longer be able to assure the reliable supply of community related to the saturation of the main power line.

There are two solutions to get out of this situation. The first one is a conventional solution: to build a second power line to increase the alimentation capacity from the main power grid. The second solution is to create an SCM through

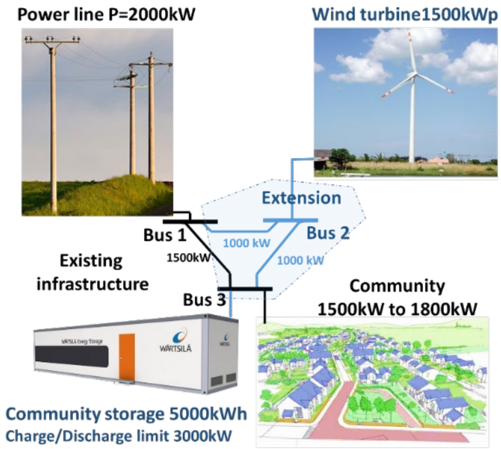

Fig. 3. The general structure of the studied SCM : existing and expanded infrastructure.

the installation of a wind turbine as a source of renewable energy and a centralized energy storage system to manage local energy flows. For actual evaluation, the second case will be selected as the most appropriate for energy transition. Fig. 3 will show these transformations in detail. The installation of an additional two power lines to connect a wind turbine will bring the system to the shape of a triangle, but their length can be neglected compared to the length of the main power line. A CESS will be connected to BUS3 and wind turbine to BUS2. Thus, the resulting description on obtained SCM is presented in TABLE I.

TABLE I. General Data of Obtained SCM

Topology	3-bus triangle network
Power supply line	2000 kVA limit, power line at bus 1
Load (Consumption)	1800 kW total load at bus 3 the fixed load is curtailable at €1/kWh the flexible load is curtailable at 35c€/kWh
Branches	1500 kVA limit, line 1–3 1000 kVA limit, line 1–2 1000 kVA limit, line 2–3
Wind turbine	unit at bus 2 with 1500 kW output in the nominal case
Storage	Capacity: 5000 kWh unit at bus 3 Max Charging/Discharging Rate: 3000 kW/hour Charged/discharged electricity price is 35 c€/kWh

The next step of practical evaluation is to apply the developed DA-OPF management methodology to this SCM. For actual study, March 21, 2022, is selected as the day of the strategy creation and March 22 is selected as the day-ahead. As described earlier, the first step is to get the wind turbine generation forecast and the community energy consumption forecast for the day-ahead. For this is used DL LSTM neural network. Fig. 4 shows the example of wind generation forecast compared to real values. It can be seen that the input data are the historical data of wind generation also as the historical and actual data of wind speed forecast. For community energy consumption was taken the historical data of consumption. It forecast value can be seen in Fig. 6 in the main blue line.

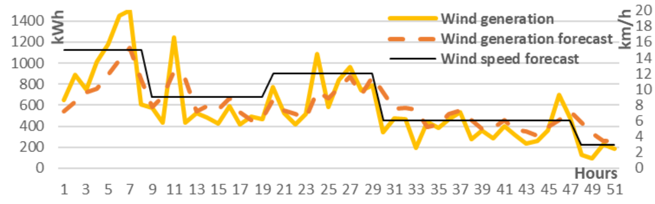

Fig. 4. Example of wind generation data forecast by DL LSTM network.

To evaluate the efficiency of data forecast the Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) was chosen and its values are presented in TABLE II [14]. It can be seen that the forecast errors for wind generation are much larger than for energy consumption, which is related to the difficulty of forecasting and with the large discontinuity of wind turbine generation.

TABLE II. MAE AND MAPE OF DATA FORECAST

	Wind generation	Community consumption
MAE	381.4 kWh	78 kWh
MPAE (%)	23.87 %	7.3 %

The input of the "OPF" system are obtained forecasts for day-ahead presented in Fig. 5 and Fig. 6 main lines, the grid electricity price profile presented in Fig. 9, the dotted line and all other SCM system data. Then, the "OPF" system resolves the optimization problem and create the DA-OPF optimal SCM operation strategy. Obtained strategy for day-ahead can be seen in the Fig. 7 and Fig. 8, main lines. Fig. 9 in main line show obtained LAMP for given DA-OPF strategy.

The next step is to evaluate the obtained strategy to check that it does not exceed the unit limits of SCM units and that its use will not lead to the energy collapse of this community in day-ahead. Fig. 5 - Fig. 9 shows the evaluation results of the proposed DA-OPF strategy.

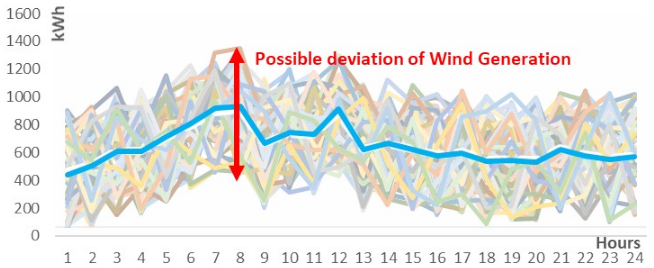

Fig. 5. DA-OPF input data: cyan line - the wind generation forecast, other lines – possible evaluation of wind generation profile due to forecast error (from MCS simulation).

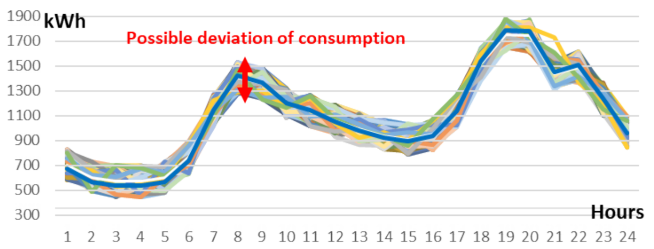

Fig. 6. DA-OPF input data: blue line - the community consumption forecast, other lines – possible evaluation of community consumption profile due to forecast error (from MCS simulation).

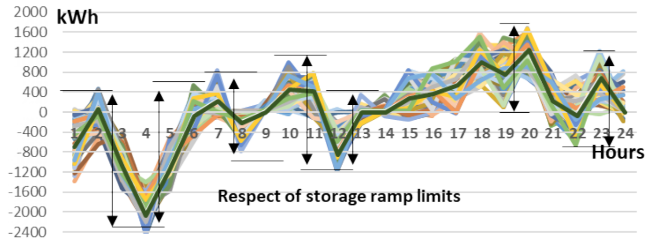

Fig. 7. DA-OPF output data: green line – the profile of OPF community storage management strategy for day-ahead, other lines – possible deviation of OPF community storage management strategy due to forecast error (from OPF).

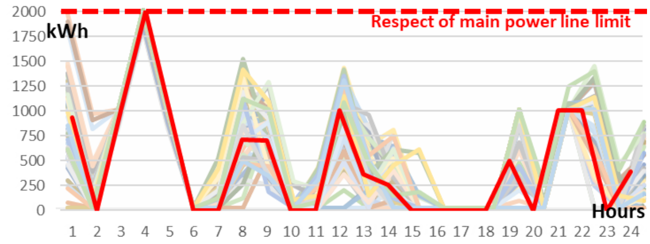

Fig. 8. DA-OPF output data: red line – expected grid operation due to the application of OPF community storage management strategy for day-ahead (from Fig. 8), other lines – possible deviation of grid operation due to forecast error (from OPF).

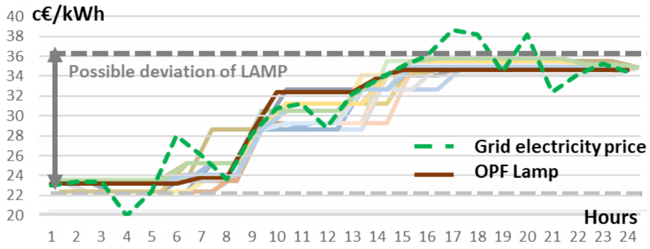

Fig. 9. DA-OPF: grin dotted line – grid electricity dynamic price for day-ahead (DA-OPF input), the brown line – LAMP profile for DA-OPF strategy for day-ahead (from OPF), other lines – possible deviation of LAMP due to forecast error (from OPF).

It can be seen that the "DA-OPF evaluation" system, for each combination of each parameter, verify not exceeding functional limits (power lines limits, unit limits, charge/discharge ramp limits, etc.). In this case, after 61 evaluations, the "DA-OPF evaluation" system did not find an excess of any operational parameters and this strategy, and thus the proposed DA-OPF strategy is confirmed for day-ahead SCM operation. TABLE III shows operational values of this strategy.

TABLE III. MAE AND MAPE OF DATA FORECAST

	Operation value
Wind generation	15615 kWh
Community consumption	26061 kW
CESS operation	6226/-6226kWh
Grid operation	10845 kWh
Grid price (average)	30.5 c€/kWh
LAMP (average)	29.91 c€/kWh

How it can be seen, for this day, the wind generation represents 15615 kWh, the community consumption is 26061kWh, and due to DA-OPF the energy charged from the grid represents only 10845 kWh. This table with Fig. 9 show that the LAMP for this day is generally lower or equal than the grid electricity price due to developed DA-OPF.

For the conventional case, the community must pay 8245 € to DG for supplied electricity. In the case of SCM deployment but without proposed DA-OPF strategy, the community bill is 3626 euro, what represents 56% of reduction of community electricity price. Application of developed innovated DA-OPF brings the SCM electricity price to 2898 euro, what represents 20% of reduction compared to SCM without DA-OPF and a 65% of reduction compared to conventional community, without changing the system parameters and for the same operating conditions. That is, in other words, only due to the intelligence of this method. Thus, the proposed DA-OPF management system shows its effectiveness and profitability for use in future SCM communities with wind turbines and for the continuation of the process of energy transition also as to feed flexibility to the DG locally (response to dynamic pricing).

V. Conclusion

This research presents the innovate method of Day-Ahead Optimal Power Flow management of Smart Community Microgrid with a wind turbine generation and Centralized Energy Storage System. The developed DA–OPF is based on the Deep Learning Long Short-Term Memory network and the Optimal Power Flow problem is formulated by Mixed-Integer Nonlinear Programming model. The Monte-Carlo Simulation takes into account the forecast error and its influence on the SCM system stability. The evaluation of the proposed innovated DA-OPF management method was realized in the case of conversion of real conventional community into SCM. This was made by the integration of CESS, a wind turbine and developed DA-OPF management. The practical evaluation and subsequent economic analysis show that the proposed innovated DA-OPF method allows reducing the SCM electricity cost by 20% compared of SCM with classical management method, and by 65% compared to conventional community before SCM conversion. It's all without changing the system parameters and for the same operating conditions. That is, in other words, only due to the intelligence and efficiency of the developed operation method.

Acknowledgment

This work has been partially supported by the Centre for Studies and Thermal, Environment and Systems Research, IUT of Creteil-Vitry, University Paris-Est, the ENEDIS, distribution grid manager in France and the city council of Alfortville, Ile-de-France region, France.

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