Dispatch Optimization of Energy Communities for Collective Provision of Network Congestion Management

Artem Vanin[1], Shchurovskaya Ellina[2]
[1, 2] Electrical Power Systems Department
[1, 2] Faculty of Electrical Engineering
[1, 2] National Research University "MPEI"
[1, 2] Moscow, Russian Federation
[1]artem.vanin@gmail.com, [2]ellinashurovsk@gmail.com

Pedro Juliano Nardelli[3], Aleksei Mashlakov[4]
[3] Control Engineering and Digital Systems Department
[4] Electricity Market and Power Systems Department
[3, 4] Faculty of Electrical Engineering
[3, 4] LUT
[3, 4] Lappeenranta, Finland
[3]Pedro.Nardelli@lut.fi, [4]Aleksei.Mashlakov@lut.fi

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Abstract*—Nowadays the installation of distributed energy resources (DERs) is very popular all over the world. DERs bring partial independence from the external grid, fewer interruptions in the electric supply, economic benefits, improvement of the electrical energy quality and the green energy to the systems of the prosumers. However, they also bring network congestions and increase the complexity of the energy management especially when the renewable DERs with their inconstant generation profiles are used. One of the possible solutions for these problems for the prosumers is to organize and join an energy community. Energy community members can both exchange electrical energy to maintain energy balance and sell excess energy to the operator. There are two basic energy management strategies for the community members: collective and individual. This paper focuses on determining the most beneficial one by simulating an energy community with different levels of cooperation and assessing multiple parameters.

Keywords—DER, energy community, optimization, Pandapower, Python.

I. INTRODUCTION

As the technology of distributed energy resources (DERs) become more and more widespread, more and more consumers transform into prosumers [1]. As the name implies, prosumers are not just passive electricity receivers, they participate in all activities related to electrical energy - not only consumption, but also generation and storage [2]. This transformation leads to flexibility in grid management for both supply and demand sides. Yet it requires addressing the possible challenges and rethinking of distribution and transmission system operators' management approaches and concepts of accompanying governance models.

Prosumers operate via microgrids, aggregators, virtual power plants, and local electricity markets [3]-[5] based on various location and control levels. Another concept that is relatively new and develops rapidly is energy communities or local cooperatives. It is not required for energy community members to be connected directly as it is done in the microgrids; energy communities might be distributed both geographically and topologically. The concept of local cooperatives is based on the community governance design [6]. The cooperation of the prosumers is the key reason for the optimal energy distribution, yet every prosumer is individually in charge of his equipment. In this way, the surplus or shortage of electrical energy of the communities may be neutralized by exchanging electrical energy with other prosumers, system operator or the markets.

The main objective of the research is to conduct simulations for individual and collective energy management strategies in an energy community. The individual strategy is based on the peak-shaving control method or, in other words, this strategy minimizes the net imported energy of each prosumer. The collective strategy, on the other hand, treats the whole community as a single entity and minimizes the net imports from the grid.

This paper is organized in the following way. Firstly, a Pandapower network model is described. Secondly, the grid is simulated with prosumers using the individual energy management strategy. Then the collective strategy is tested. Finally, both strategies are analyzed by means of the network performance indicators.

II. A PANDAPOWER NETWORK MODEL

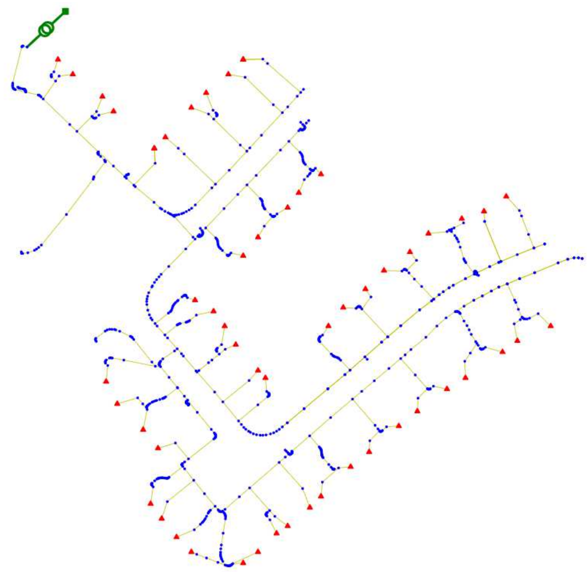

Fig. 1. The test grid.

The strategies will be tested in Pandapower. The standardized IEEE grid "European Low Voltage Test Feeder" is selected as the test grid as it satisfies the requirements of having a relatively high amount of load nodes with different load profiles and two voltage levels, which allows us to evaluate the network parameters at different voltages.

The test grid is connected to the main grid via the 11 kV-0.4 kV transformer [7]. Fig. 1 presents the lay-out of the grid. All in all, there are 55 consumers with individual load profiles. The profiles are stored in excel files with 1-minute resolution. Additional electrical equipment will later be

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added to the consumer nodes to transform the consumers into prosumers.

To turn consumers into prosumers, the photovoltaic (PV) generation unit, the storage element and the electrical vehicle (EV) will be installed in every consumer node. The PV unit is typical for the low voltage prosumer. The installed generation power is $3\ kW$ $(P_{PV} = 3\ kW)$. The generation parameters during a day are set according to [8]. The storage parameters: rated energy capacity $E_{bat} = 7.7$ kWh, rated power $P_{bat} = 3$ kW , charge and discharge efficiencies $\eta_{ch} = \eta_{disch} = 92\ \%$ are set according to the study in [9].

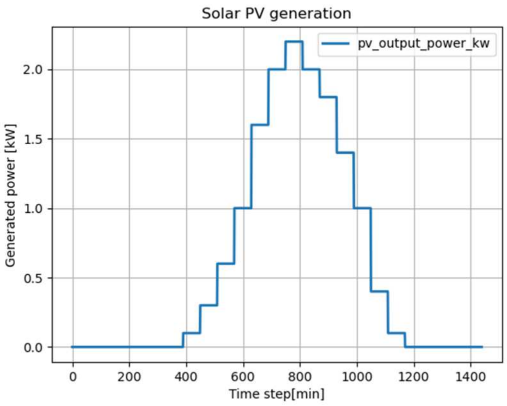

Fig. 2. Solar PV generation $P_{PV} = 3\ kW$ [8].

Unlike the aforementioned PV units, that share the same generation profile, the EV units use individual load profiles. These profiles contribute to the combined load profile of each consumer. The EV profile data is stored in CSV-file with 10-minute resolution [10]. In order to simplify the simulation and optimizations, the data is decimated so that each profile has a 10-minute resolution.

III. INDIVIDUAL OPTIMIZATION. "MINIMIZE POWER" APPROACH

The "Minimize Power" approach will be used for this strategy. The assumptions of this method include the perfect foresight of the PV generation and load during a day. The storage element can be charged by PVs or by the external grid. The optimization function aims to minimize the sum of the squares of the power demand from the grid during 24 hours. Fig. 3 is showing the optimization problem of "Minimize power" approach.

The objective function is formulated in *(1)*, it tends to minimize the sum of the squares of the power flow in the node of the prosumer over the day. The power flow contains the data of the load $P_{load}(t)$, the EV charging $P_{EV}(t)$, PV generation $P_{PV}(t)$ and the storage $P_{str}(t)$. The equations *(2)-(10)* that follow next present the physical constraints of the storage element. The parameters of the storage are restricted in the range of the rated power and rated energy capacity. It is assumed that the storage is half-charged at the beginning of the day. Also, there is a limit to how fast the storage can charge or discharge [11].

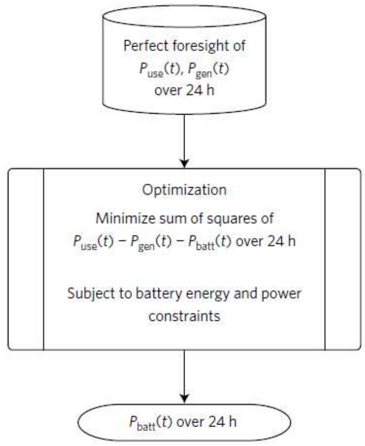

Fig. 3. Optimization algorithm. Adapted from [11].

$$f_{obj} = min \sum_{t=1}^{144} (P_{load}(t) + P_{EV}(t) - P_{PV}(t) - P_{str}(t))^2 \quad (1)$$

$$P_{str}(t) = P_{ch}(t) + P_{disch}(t) \quad (2)$$

$$P_{str}^{i}(t) = P_{ch}(t) \cdot \eta_{ch} + P_{disch}(t) / \eta_{disch} \quad (3)$$

$$E_{str}(t) = E_{str\ init} + \sum_{n=1}^{t} \Delta E_{str}\ (n) \quad (4)$$

$$E_{str\ init} = \frac{E_{rated}}{2} \quad (5)$$

$$\Delta E_{str}(t) = -P_{str}^{i}(t) \cdot \Delta t \quad (6)$$

$$(z(t) - 1) \cdot P_{rated} \leq P_{ch}(t) \leq 0 \quad (7)$$

$$0 \leq P_{disch}(t) \leq\ z(t) \cdot P_{rated} \quad (8)$$

$$E_{min} \leq E_{str}(t) \leq E_{max} \quad (9)$$

$$z(t) = \{0{,}1\} \quad (10)$$

The next step is the introduction of the optimization algorithm in the Python language. Since the objective function is convex in nature and Pandapower can't work with convex functions out of the box, it is necessary to use the third-party module. The CVXPY module is designed as the environment for dealing with convex functions [12]. Firstly, the parameters are assigned as the part of the CVXPY module with the time argument T. All physical constraints (2)-(10) are taken into consideration and created later. Then the objective function is declared. To implement the last step of the program and to solve the optimization problem in the Pandapower software the ECOS_BB is used. The reason this solver is used for the optimization is due to its mixed-integer nature: the z(t) is essentially a boolean variable.

```
p = cvxpy.Variable(T)
E = cvxpy.Variable(T)
pChg = cvxpy.Variable(T)
pDischg = cvxpy.Variable(T)
z = cvxpy.Variable(T, boolean=True)

constraints = [
    E >= 0.0,
    E <= battery_energy_max,
    p == pChg + pDischg,
    cvxpy.diff(E.T) == -(pChg[1:]*charge_efficiency +
        pDischg[1:]/discharge_efficiency) *
        interval_length,
    E[0] - 3.85 + (pChg[0]*charge_efficiency +
        pDischg[0]/discharge_efficiency)
        * interval_length == 0.0,
    (z - 1.0) * rated_p <= pChg,
    pChg <= 0.0,
    0.0 <= pDischg,
    pDischg <= z * rated_p,
    E[0] == E[T-1]]

for t in range(0, T):
    power += cvxpy.square(loadProfile[t] +
        evProfile[t] - pvProfile[t] - p[t])
obj = cvxpy.Minimize(power)

prob = cvxpy.Problem(obj, constraints)
prob.solve(solver=cvxpy.ECOS_BB)
```

Fig. 4 presents a graphical result of the “Minimize power” approach tested on the “European Low Voltage Test Feeder” for the prosumer connected to the bus № 34; one can see the values of the load (the blue line), PV generated power (the orange line), charging/discharging of the storage (the green line) and the storage energy capacity (the light green line with the of y-axis label in the right) for 24 hours. The results confirm that the approach perfectly matches the idea of peak shaving. Keeping the storage charged to the optimal level during the day allows for the neutralization of consumption spikes and helps utilize energy in the most efficient way. Although this approach requires the load prediction and the PV generated power which is difficult to achieve in real life, “Minimize power” meets the needs of the research questions.

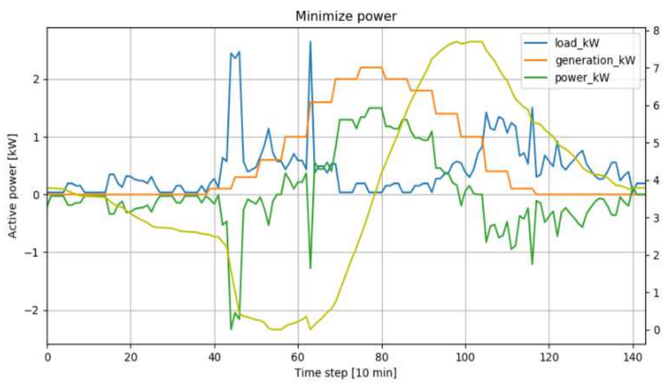

Fig. 4. “Minimize power” approach.

IV. Collective Optimization

As it was stated earlier, the electrical energy is most efficiently utilized when every member of the energy community is involved in the energy management process. However, the community member might be satisfied with the results of the individual energy management strategy, abstaining from the participation in collective energy management.

The same “Minimize power” approach is used to simulate the community with collective strategy, but the target function is transformed according to *(11)*. In this case, the sum depends not only on the timesteps but also on the members who are cooperating in the energy management processes.

$$f_{obj} = min \sum_{t=1}^{144} \Big(\sum_{i=1}^{55} (P_{load\ i}(t) + P_{EV\ i}(t) - P_{PV\ i}(t) - P_{str\ i}(t)) \Big)^2 \qquad (11)$$

The program in Pandapower of collective optimization is similar to an individual one. Firstly, the variables are set. However, now they depend not only on the timesteps T, but also on the prosumer N. Then the constraints and optimization function are set. The entire code of the program can be found in [13].

```
N = 55
p = cvxpy.Variable((N, T))
E = cvxpy.Variable((N, T))
pChg = cvxpy.Variable((N, T))
pDischg = cvxpy.Variable((N, T))
z = cvxpy.Variable((N, T), boolean=True)

for t in range(0, T - 1):
    power_tmp = 0
    for n in range(0, N):
        power_tmp += (
loadProfiles[n][t] - pvProfiles[n][t] - p[n][t])
    power += cvxpy.square(power_tmp)
obj = cvxpy.Minimize(power)
prob = cvxpy.Problem(obj, constraints)
```

V. Results

The Net Load Factor (NLF) and Voltage Factor (VF) are introduced to evaluate grid performance. Both indicators are calculated as the ratio of the mean value to the maximum one for 24 hours. The NLF presents the power flow ratio, while the VF - the voltage ratio. The NLF is used since the power flow in the node can go in two ways: in the traditional one electrical energy goes in the direction to the load, and another case is when the value of PV generated power is higher than the demand, so the power is fed into the grid.

$$NLF = \frac{P_{net\ mean}}{P_{net\ max}} \qquad (12)$$

$$VF = \frac{V_{net\ mean}}{V_{net\ max}} \qquad (13)$$

In order to evaluate the impact of the different kind of DERs on the grid performance separately, the system will be tested in 3 different scenarios: EV plus the storage, PV plus the storage and EV, PV plus the storage. Additionally, the grid performance indicators will be considered in a prosumer node and in the LV transformer node. The range of NLF and VF values with different DERs are shown in Table 1. The division according to the number of DERs and further division according to the number of the prosumers participants in the collective optimization is done for the result graph plotting. The number of installed DERs gradually increases in increments of 10%. Then the number of consumers with DERs is divided into two groups, those who participate in collective optimization and the number of participants is constantly growing and those who are not. The increment is 25%. Fig. 5 is showing the results of the simulation.

TABLE I RESULTS OF DIFFERENT SIMULATION SCENARIOS

Simulation scenario:		EV-storage	PV-storage	EV-PV-storage
NLF	Consumer node	[0,0293; 0,0452]	[0,0246; 0,0532]	[0,0244; 0,0507]
	Transformer node	[0,4711; 0,7117]	[0,3213; 0,7762]	[0,3178; 0,6416]
VF	Consumer node	[0,9960; 0,9966]	[0,9759; 0,9980]	[0,9996; 0,9977]
	Transformer node	[0,9999; 1,0000]	[0,9999; 1,0000]	[0,9999; 1,0000]

According to the result graph the values of the VF fluctuate in the small interval. However, the VF in both nodes goes up steadily. The highest point of the VF values is characterized by the maximum possible DER penetration and collaboration levels.

One might note that the VF and the NLF follows a remarkably similar trend. As the number of prosumers with DERs increases, the values of the NLF rises gradually to the highest point. Nevertheless, in the scenarios with PV generation there is a slight drop in the middle that is under the start level with no DER, that can be explained with the fact of bidirectional power flow which occurs with the PV penetration; this effect is no longer observed after the point with 50% DER penetration. One can find almost all NLF values with 100% collective optimization higher than the other values within the framework of one DER penetration level and it is another thing that should be highlighted. It is especially noticeable in the cases with the PV generation in the consumer node and connected with the fact of electrical energy lack and excess sharing among the community members.

The VF and NLF are selected as the key performance indicators to estimate the distribution grid efficiency. Their high values mean the balance between the supply and demand, load profile flattening and the optimum of the transformer and cables feeding. According to the graph result, the DER level expansion contributes to the adjustment of almost all the values of the indicators in a positive way. As well as the DER level expansion the collective optimization provides the growth of the indicators but can be considered as insignificant in most cases.

VI. CONCLUSION

The main outcome of the research is the formulation of the optimization problem and its implementation in the program in the Pandapower software suite for the means of the community-based governance design grid with the prosumers that own different DER technologies and have the ability to combine their assets. The program includes the individual and the collective optimizations carried out with two approaches: "Minimize power" and "Target zero". The second one was not mentioned in the article as it was not an accurate way to express the collective optimization, however, it can be still used for the individual one.

The simulation results analysis on the basis of the key performance indicators reveals the positive tendency of the grid to improve the efficiency of electrical energy utilization with DERs growth.

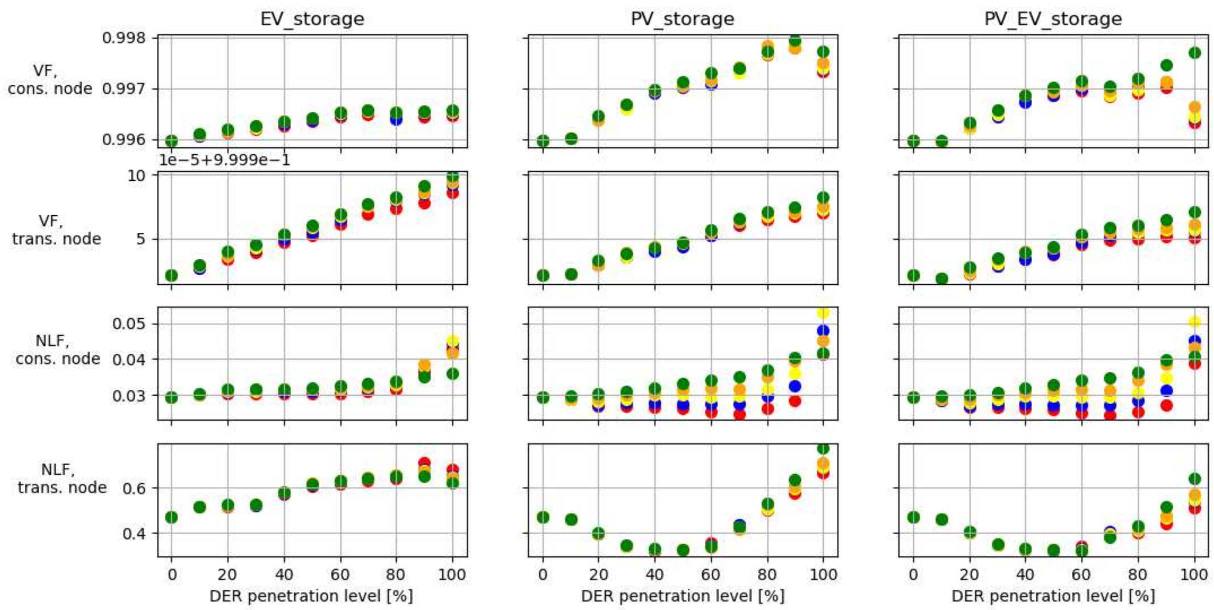

Fig. 5. Results of the simulation. 0% of the cooperation share is marked with a red point, 25% with a blue point, 50% - yellow, 75% - orange and 100% with a green one.

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