Low Voltage Grid Operation Scheduling Considering Forecast Uncertainty

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Abstract. A model for day-ahead scheduling of batteries and branch switches in the low voltage grid, considering forecasts uncertainties, is proposed. The objective is to reduce the energy losses of the distribution lines and avoid critical events such as congestions or over and under-voltages in the local network. Simulations of different day-ahead situations are performed with a modified particle swarm optimisation algorithm. The results show that critical events are avoided and energy self-consumption within the local network is increased.

Keywords: Robust optimisation - Smart grids - Particle swarm optimisation - Network reconfiguration - Energy storage management

1 Introduction

The quantity of distributed generation (DG) connected to low voltage (LV) grids is rapidly increasing due to the technological advances in DG and policies promoting them. However, LV grids have been designed to be passive elements of the electricity network only used to provide the required energy to costumers. Thus, distribution system operators (DSOs) managed the network under their responsibility at medium voltage (MV) since it was not necessary to actively manage the LV grid. The increase of DG raises the problem of a lack of observability of the LV grid and an absence of systems to actively operate it.

Despite the deficiency of grid operability at LV, there are LV grid actuators such as controllable distributed generators (CGs), battery energy storage systems (BESSs) and branch switches (BSs) that permit to act on the LV grid [1–10]. When these grid assets are available, the DSO can tackle the problem of scheduling them to optimise objectives such as the quality of service and power losses.

This paper formalises the problem of scheduling BESSs and BSs in a grid with renewable energy generation. The scheduling of these grid actuators is performed considering the energy demand and supply forecast with its corresponding uncertainty, in order to prevent or mitigate critical events in the grid and minimise the power losses associated with the transmission.

Previous studies of BESSs and other storage units have shown that they can reduce power losses, perform peak shaving and solve over-voltages situations [1, 2]. Distribution network reconfiguration (DNR) with BSs approaches have also been used to reduce losses, prevent congestions or balance loads [3–5]. The aim of this paper is to use these actuators together to improve their efficiency and reduce their individual costs.

The intrinsic randomness of DGs, such as photovoltaic power generation (PV) or wind power plants, and the uncertainty of load demand are important factors for the decision-making process in the optimisation of the operation scheduling [6, 7]. We consider the uncertainty of load demand and renewable generation with a chance constraint formulation [8–10] and we approximate it to robust optimisation.

2 Problem Formulation

Optimisation problems under uncertainties are usually modelled with chance constrained formulations, which consists of setting a confidence level of the conditions of the problem given a set of uncertainties [9, 10]. The general expression is as follows,

$$\min\{\mathrm{E}\,[f(\boldsymbol{x},\boldsymbol{\xi})]\} \quad \text{s.t.} \quad \Pr\{g_i(\boldsymbol{x},\boldsymbol{\xi}) \leq 0\} \geq \alpha_i \quad i = 1, 2, ..., m \ , \tag{1}$$

where f is the objective function and g_i are the constraints of the problem, $\boldsymbol{x}$ is a vector with the deterministic variables and $\boldsymbol{\xi}$ the stochastic variables, α_i determines the probability or confidence level of the constraints. $\Pr\{\}$ denotes the probability of the events, considering the probability density function (PDF) of all the random variables. Because the objective function depends on random variables, the trend is to optimize the expected value, but some interesting works also consider the deviations [11].

Although the chance constrained formulation has been proved useful at modelling the optimisation problem with uncertainties, it is known that solving these approaches is very time consuming in computational terms. To reduce the computation time we use a robust optimisation formulation of the problem. The robust optimisation only considers the worst possible case instead of the probability to fulfil the constraints. This is the limit of Eq.(1) when $\alpha_i = 1$,

$$\min\{\mathrm{E}\,[f(\boldsymbol{x},\boldsymbol{\xi})]\} \quad \text{s.t.} \quad g_i(\boldsymbol{x},\boldsymbol{\xi}) \leq 0 \quad i = 1, 2, ..., m \ . \tag{2}$$

With this formulation, we assume that all the conditions of Eq.(1) are fulfilled if the worst situations given $\boldsymbol{\xi}$ meet the conditions in Eq.(2).

The stochastic variables of the study are associated with the energy demand forecast uncertainty and the generation profile of the PVs. The PDFs of both forecast errors are usually modelled as Gaussian distributions [12]. The demand or generation output of each bus in the grid is then the sum of the forecasted value and a random number with a Gaussian distribution $\mathcal{N}(0, \sigma_l^2(t))$ or $\mathcal{N}(0, \sigma_g^2(t))$, being σ_l and σ_g the corresponding standard deviations of energy demand and generation.

2.1 Problem objectives

The tackled problem consists of scheduling the operation of BESSs and BSs in order to avoid or minimise critical events such as congestion and over/under-voltages, minimise the import/export of energy from/to the MV grid so as to minimise transport losses, and finally minimise the operation costs of BESSs and BSs.

Critical events. One purpose is to avoid congestions and over/under voltages on the branches, these are considered as constraints of the optimisation. The congestions are avoided as single constraints that assure the loading of each branch to be below a particular threshold, in this case, 90% of the thermal limit. The voltages are secured to be between plus-minus 5% of the nominal value with a joined constrain. In the chance constrained picture

$$\Pr\{\phi_r(\boldsymbol{x}, \boldsymbol{\xi}) < \phi_{\text{thresh}}\} \geq \alpha \quad \forall r \ , \tag{3}$$

$$\Pr\{V_{\text{min}} < V_r(\boldsymbol{x}, \boldsymbol{\xi}) < V_{\text{max}}\} \geq \beta \quad \forall r \ , \tag{4}$$

where ϕ_r and V_r are the load and voltage of the grid branch r and ϕ_{thresh}, V_{min}, V_{max} are the corresponding limits to fulfil with probabilities α and β given all the stochastic possibilities.

Instead, we can consider a robust optimisation approach and reduce this to only looking if the conditions inside $\Pr\{\}$ are met in the three worst scenarios:

1. maximum load demand and maximum variable generation.
2. maximum load demand and minimum variable generation.
3. minimum load demand and maximum variable generation.

The first case corresponds to the worst scenario for congestion, while the second and third to the under- over- voltages respectively.

If the conditions are violated, the corresponding solution is punished for each hour that does not fulfil at least one of these conditions, the term is formulated as

$$f_{\text{critical}} = \sum_{t=t_0}^{t_f} c(t) \ , \tag{5}$$

where c is a binary variable being 0 if the conditions are met for the three scenarios and 1 if any condition is not satisfied, thus f_{critical} is the number of hours that present possible critical events, t_0 is the initial or present time and t_f is the time horizon or final time of the scheduling and time is discretised in n periods of Δt time steps, being $n\Delta t = 24$ h.

Power losses. On the other hand, we also want the grid to as self-sufficient as possible. To achieve this, we minimise the difference between the total energy given by the variable generators E_{VG} and the BESSs E_{B} with the demanded in the grid E_{L}. Actually, this is the same as minimising the exchange with the external grid E_{EG}, since the energy balance equation between the local and the external grid is

$$E_{\mathrm{EG}}(t) = E_{\mathrm{L}}(t) - E_{\mathrm{B}}(t) - E_{\mathrm{VG}}(t) \ , \tag{6}$$

assuming there are no power losses in the local grid. The self-consumption term for the objective function is formulated as

$$f_{\mathrm{self}} = \sum_{t=t_0}^{t_f} |E_{\mathrm{L}}(t) - E_{\mathrm{B}}(t) - E_{\mathrm{VG}}(t)| \ . \tag{7}$$

Operational costs and restrictions. Critical events and power losses may be avoided or reduced with the scheduling of BESSs, nevertheless its use has associated restrictions and costs. The energy given or stored by a BESS during a time period Δt depends on the change of the state of charge (SoC) as

$$\mathrm{SoC}(t) = \begin{cases} \mathrm{SoC}(t-\Delta t) - \eta_c \frac{E_b(t)}{E_m} \Delta t \ \text{ if } E_b(t) \leq 0 \\ \\ \mathrm{SoC}(t-\Delta t) - \frac{1}{\eta_d} \frac{E_b(t)}{E_m} \Delta t \ \text{if } E_b(t) \geq 0 \end{cases} \tag{8}$$

with $\mathrm{SoC}(t)$ the charge of the battery at time t, η_c and η_d the charging/discharging efficiency of the battery, E_m the energy that the BESS can charge/discharge in an hour, depending on the nominal capacity and the ramping down/up, and $E_b(t)$ the energy exchanged during the period $(t, t+\Delta t)$ between the grid and the BESS b. The BESSs energy exchange depends on the SoC restrictions, which are the initial and final charge and

$$\mathrm{SoC}_{\mathrm{min}} < \mathrm{SoC}(t) < \mathrm{SoC}_{\mathrm{max}} \ , \tag{9}$$

$$\Delta\mathrm{SoC}_{\mathrm{min}} < |\Delta\mathrm{SoC}(t)| < \Delta\mathrm{SoC}_{\mathrm{max}} \ , \tag{10}$$

where $\Delta\mathrm{SoC}(t) = \mathrm{SoC}(t) - \mathrm{SoC}(t-\Delta t)$.

In order to maximise the life of the batteries we consider a term to model the use of the battery. Since the wear and tear of the BESS depend on many technicalities of the kind of BESS used, we simply add a term with the total exchanged energy during the time horizon. In this way, the use of all the batteries in the grid is described via

$$f_{\mathrm{batt}} = \sum_{\forall b} \sum_{t=t_0}^{t_f} |E_b(t)| \quad . \tag{11}$$

The presence of BSs can also be very helpful preventing grid critical events, nevertheless changing the state of one switch presents a hard operational cost we want to avoid and it is preferred to keep the BSs inactive. For these reasons we want to reduce the number of BSs changes and the number of time slots the BSs are active. The function associated with these costs is formulated as

$$f_{\text{switches}} = \sum_{\forall s} \left\{ \sum_{t=t_0}^{t_f} a_s(t) + \sum_{t=t_0+\Delta t}^{t_f} |a_s(t) - a_s(t-\Delta t)| \right\} \ , \tag{12}$$

where $a_s(t)$ is the state of the branch switch s during the period $(t,\ t+\Delta t)$, with 1 as active and 0 inactive. The first part of Eq.(12) is the number of hours active and the second are the amount of changes.

3 Solution Approach

3.1 Objective Function

The formulation presented in the previous section is a multi-objective optimisation problem of Eq.(5),(7),(11) and (12). The solution approach proposed for the multiple-criteria decision-making is a hybrid between a hierarchical method and a weighted sum. Through scalarization, the multi-objective problem is converted into a single objective with the following hierarchical preferences.

The first objective to accomplish is to reduce the critical events of the grid Eq.(5), with an assigned coefficient $M_1 >> 1$. Secondly, minimise the operational cost of the BSs Eq.(12), with a coefficient $M_2 << M_1$. Finally, a weighted combination of the self-consumption Eq.(7) and the BESSs use Eq.(11) is also minimised, with a relation weight ν. Altogether, the objective function

$$f = M_1 f_{\text{critical}} + M_2 f_{\text{switches}} + \nu f_{\text{self}} + (1-\nu) f_{\text{batt}} \ . \tag{13}$$

3.2 Simulation Algorithm

This paper adopts a particle swarm optimisation (PSO) to solve the model proposed because of its efficiency of computation and adaptable implementation [13–17]. Each particle of the algorithm, represents a solution with all the scheduled BESSs and BSs, these particles move according to simple rules converging to the optimal schedule. All the particles adjust their positions through iterations according to their experience and to the entire community's. The status of the particles is described by its position x_p and velocity v_p which are updated as

$$v_p = \omega v_p + c_1 ran_1 (p_p - x_p) + c_2 ran_2 (g - x_p) \ , \tag{14}$$

$$x_p = x_p + v_p \ , \tag{15}$$

where ω is the inertia weight, c_1 and c_2 are the learning factors, ran are random numbers in $(0, 1)$, p_p is the best position of the particle and g the best position of all the particles [14].

If a new velocity moves the particle out of the search space it is changed by the maximum velocity such the particle keeps inside v_{max}.

Each BESS in the grid is a dimension of the particle, while all the BSs act together as one single dimension. At the same time each dimension in the particle consists of an array with a number of values equal to the number of time-series slots we want to schedule. Therefore, we have a position and velocity for every time-slot, for each dimension and for all particles.

We have adopted a dissipative-PSO (DPSO) with a linear time varying (LTV) inertia descending from ω_{max} to ω_{min} to avoid local minima. With the LTV weight we reduce the movements in the search-space progressively, starting with large movements through all the space and increasing the convergence speed when reducing the weight [15].

The dissipative part is introduced changing the positions and velocities randomly after the updates with a given probability d_v for the velocity and d_x for the position. Therefore, we create an open system out from equilibrium and improve the efficiency [16].

To move the BSs in the PSO, the set of binary states of the switches is ordered and converted into a decimal number. After moving the decimal number with the updated velocity it is rounded up and the state of the switches is changed to the corresponding binary state. Other more sophisticated approaches can also be used for the network reconfiguration [17].

After moving the particles, the fitness of each one is evaluated and the best individual and global solution are determined. With the robust approach, we only need to run the three power flow solvers (PFSs) corresponding to the worst possible scenarios described in section 2.1, in order to compute the fitness. Otherwise, if we apply chance constrained optimisation we would have to evaluate the probabilities by sampling, thus, run many PFSs (what takes a lot of computer time). Notice that, the only term with stochastic variables is f_{self}, thus we have to average only this part to compute the mean.

The algorithm parameters used are $\omega_{max} = 0.9$, $\omega_{min} = 0.4$, $c_1 = c_2 = 2$, $d_x = d_v = 0.01$. We have used GridCal as the PFS in our simulations.

4 Experimentation

4.1 Set Up

The proposed formulation is simulated with a network topology and historical data of a real LV grid. The pilot grid consists of two radial networks connected to the MV grid. One radial part, network-I, has 9 loads and 2 PVs, while the other, network-II has 7 loads and also 2 PVs. To the grid we add two BESSs, one on each network, and two BSs between buses of the networks. We can see a schematic representation of the grid in figure 1.

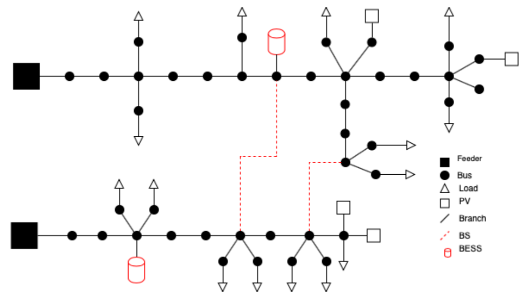

Fig. 1. Pilot grid representation. Network-I in the top and network-II in the bottom.

To determine the constant terms in the objective function, Eq.(13), several simulations were performed, first without critical events and BSs, to get a non-dominated solution of the pareto front depending on ν. Because f_{self} decreases when increasing ν from 0 to 1 but stabilizes around $\nu = 0.65$ and f_{batt} keeps increasing, this weight have been set a priori. To maintain the hierarchy of the other terms described in section 2.1 we have set $M_1 = 10^{10}$ and $M_2 = 10^8$ in the objective function.

The restriction values for the BESSs used in the study are $\text{SoC}_{\text{min}} = 0.2$, $\text{SoC}_{\text{max}} = 0.8$, $\Delta\text{SoC}_{\text{min}} = 0.05$, $\Delta\text{SoC}_{\text{max}} = 0.15$, $\text{SoC}_{\text{ini}} = \text{SoC}_{\text{final}} = 0.5$, $E_m = 100\text{kWh}$, $\eta_c = \eta_d = 0.95$.

The standard deviation σ_l determining the error distribution of the energy demand at each bus is set to a corresponding mean absolute percentage error (MAPE) of 10% and a confidence level of 95%. For the deviation σ_g of the PVs generation uncertainty we take the same confidence level but a MAPE of 5%.

The scheduling has been done with a time step $\Delta t = 1\text{h}$ (from 00h to 23h), since this is the resolution of the data used. The algorithm parameters used are $N = 60$ particles and 300 iterations.

4.2 Results

Based on the robust optimisation model and the solution approach described above, a day-ahead scheduling of the BESSs and BSs of the grid has been performed. The numerical calculation results of several cases are presented in table 1. Each case corresponds to a different day with the generation and consumption values increased in order to be close or have critical events in the grid and be coherent with the sizing of the BESSs.

Case 1 corresponds to the 1st of March with the values increased 4.5 times, case 2 is 6.5 times the values of the 1st of May, case 3 is 7 times the 1st of July, case 4 is 6.5 times the 1st of September and case 5 is 4.5 times the 1st of December.

Cases 1 and 4 do not present any grid issue. Because of the hierarchy of the objective function, the optimal solution of the BSs is to remain off and the BESS scheduling aims to reduce f_{self}.

Table 1. Objective function values for different cases with and without the scheduling.

Case	Scheduling	f_{critical}	f_{switches}	f_{self}	f_{batt}	f
1	✗	0	0	894950	0	581717
	✓	0	0	792361	186089	580166
2	✗	2	0	1314848	0	$2.00008 \cdot 10^{10}$
	✓	0	3	1180532	230854	$3.00848 \cdot 10^{8}$
3	✗	1	0	919180	0	$1.00006 \cdot 10^{10}$
	✓	0	3	806909	196834	$3.00593 \cdot 10^{8}$
4	✗	0	0	815202	0	529881
	✓	0	0	673555	220621	515028
5	✗	0	0	1162551	0	755658
	✓	0	0	1174690	204834	835240

We can notice the effect on the energy self-sufficiency comparing the energy exchanged with the MV grid with and without BESSs, see figure 2. The peaks of energy surplus (when the generation exceeds the demand) are shaved, and the amount of energy given is also reduced almost at every hour.

In case 5 we do not have a exceed of generation at any time of the day. Thus, there is no BESSs scheduling that can improve the energy self-sufficiency and reduce the fitness of the objective value. Therefore, in this case the scheduling should not be applied since it aggravates the problem.

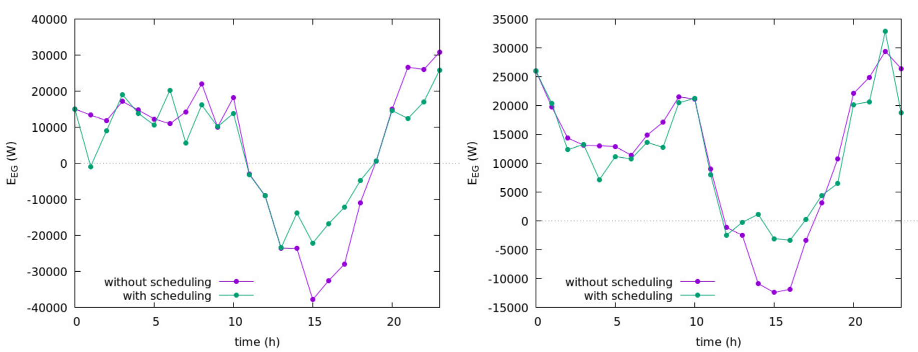

Fig. 2. Energy exchanged with the external grid for the case 1, with and without scheduling. Left for the grid network-I, right for network-II.

Case 2, without scheduling, presents possible congestions at two different hours. One possible critical event is avoided only with the BESSs scheduling, while the other is eliminated by activating one BS during one hour. Similarly, in case 3 one congestion is avoided with the activation of one BS.

Similar results have been found using samplings to evaluate the probabilities of the chance constrained formulation. Since the constraints are less severe, better solutions are possible. Nevertheless, this approach needs much more computer time to find similar results, about 6-7 hours compared with 15-25 min of the robust method. Also, we have to take into account the error associated with the random sampling. All this makes unfeasible the chance constrained formulation, since the aim is to propose the scheduling in a few minutes.

With the scheduling, part of the critical events can be avoided. Nevertheless, because of the complexity of the problem, it is not trivial to determine if an event can be solved or not a priori.

5 Conclusions

This paper has presented a novel formulation integrating the scheduling of battery energy storage systems (BESSs) and branch switches (BSs) considering the uncertainties associated with energy generation and demand forecasts. The model has the purposes to avoid possible grid critical events such as congestions and over/under voltages and reduce power losses by improving the local self-sufficiency, while keeping the operational costs of the BESSs and BSs as low as possible.

Simulations of the proposed approach have been done through a dissipative particle swarm optimisation algorithm on a real grid. Results show to successfully avoid possible critical events with the scheduling of BESSs and BSs. The peaks of energy exchange, associated with power losses on the transmission lines, are reduced with the BESSs if the generation in the local grid is greater than the load in at least a period of the scheduled time.

With the approximation of the robust approach versus the chance constrained optimisation, we lose accuracy on the formulation, but the computational implementation is more efficient and makes it possible to obtain a viable solution in less than half an hour.

In future works we expect to adopt a rolling-horizon scheme in order to permit re-scheduling of the assets using more recent forecast. Moreover, the solution approach algorithm could include state-of-the-art techniques such as opposition based learning or improved selective mechanisms to enhance its performance.

Acknowledgments

This work has been developed under the European project RESOLVD of the Horizon 2020 research and innovation program (topic LCE-01-2016-2017) and grant agreement N773715.

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