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Planning a flexible distribution network with energy storage systems considering the uncertainty of renewable sources and demand

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Abstract: This study proposes a stochastic model for multi-stage distribution system expansion planning to enhance the network flexibility via the optimal installation of energy storage systems. In this model, installation of new substations and feeder sections, as well as reinforcement of the existing ones alongside investing in energy storage systems are considered as various alternatives for the network expansion. Uncertainty of customer-owned renewable generation and electricity demand is captured through considering several scenarios for daily patterns of nodal demand and generation. The model is then cast as a mixed-integer linear optimisation problem. Implementation of the proposed model on an 18-node distribution grid reveals the significant impact of energy storage systems on network flexibility. The obtained results show that incorporating flexibility requirements into the planning problem improves the grid performance in presence of uncertain renewable generations through reducing power curtailment of renewable sources, decreasing operational costs, and lowering necessities for network capacity enhancement.

1 Introduction

Recently, the widespread deployment of renewable energy sources (RESs) in distribution networks has resulted in several challenges for energy distribution system planners and operators. On one hand, the natural nature of renewable sources has introduced new uncertainties in planning and operation studies [1], and on the other hand, their intermittent generation has increased the ramp-rate requirements for power systems [2]. As an example, studies conducted by the California ISO estimated that a ramp-up of 13,000 MW is required in three hours to satisfy customers’ demand owing to the high-renewable penetration [2]. This has been also reported in the reports of the Council of European Energy Regulators emphasising the importance of flexibility needs for future distribution networks with high penetration of intermittent power generation from renewable sources [3].

Based upon these facts, flexibility is going to play an important role in planning and operation studies of future distribution networks. In this respect, a market structure is proposed in [4] to provide distribution system operators with the flexibility from prosumers through competing aggregators. Authors in [5] have thoroughly investigated the potential capabilities of electric vehicles (EVs) as a source of flexibility for distribution grids, and proposed market design requirements for harnessing such resources. Aiming at enhancing the flexibility of a high RES-penetrated distribution system, a novel EV charging management strategy has been introduced in the work of Rajaei et al. [6]. Direct load control of residential heating, ventilation, and air conditioning units as well as optimal management of energy storage systems to enhance the flexibility of distribution systems have been investigated in the work of Taackraaoglu et al. [7].

Although operational flexibility of distribution systems has been widely studied in the existing literature, a few works have been dedicated to the flexibility provision in network expansion planning [8]. Considering the monopolistic nature of the electricity distribution sector, several regulatory policies have been proposed in the work of Karimi-Arpanahi et al. [8] to persuade distribution companies to enhance the flexibility while planning their networks to meet the growing demand and RES generation. In the work of Karimi-Arpanahi et al. [9], a model for multi-stage distribution system expansion planning is presented in which the installation of dispatchable distributed generation units is leveraged to provide flexibility. Nonetheless, the stochastic nature of RES generation and electricity demand and the potential benefits of energy storage systems have been neglected in such studies.

Motivated by these points, we aim to propose an innovative stochastic model for the expansion planning of distribution networks considering flexibility requirements to accommodate ever-increasing RES generation. In the proposed model, optimal installation of energy storage systems at various nodes of the network is considered as an option to enhance network flexibility. Moreover, installation and reinforcement of major network assets, namely substations and feeder sections, are considered as the other network expansion options.

2 Methodology

The general structure of the proposed framework is depicted in Fig. 1. As per this figure, required input data including technical (e.g. capacity limitations, impedances, as well as wind and solar radiation patterns) and financial (e.g. investment and operational costs of various network equipment, customer interruption cost, and energy price) information affecting the network planning and operation are collected first. Then, the mathematical model of the problem is developed in which distribution network assets, namely feeders, substations, and energy storage systems are planned in anticipation of the growing demands and customer-owned RES. As shown in Fig. 1, prosumers are characterised by their electricity demand and power production. Due to the intrinsic uncertainties
associated with the prediction of renewable generation and electricity demand, stochastic programming is employed in which several scenarios are considered for solar radiation and wind speed patterns, as well as daily load curves. Then, considering the installed capacity of photovoltaic panels and wind turbines at various nodes of the distribution grid, the RES generation scenarios at each load node are attained based on the considered solar radiation and wind speed patterns.

In order to meet the requirements of the prosumers, distribution companies need to invest in the network to not only enhance the grid capacity but also its flexibility. Thus, besides traditional expansion alternatives including construction and reinforcement of feeders and substations, installation of energy storage systems is also considered in the proposed model for the sake of improving the flexibility of the network to host the increasing penetration of RES.

The resulting expansion-planning model is inherently a mixed-integer nonlinear programming optimisation problem. Thus, in order to guarantee the attainment of a global optimal solution, the model is recast as a mixed-integer linear programming (MILP) problem using sufficiently accurate linear approximations. Such a MILP model can be efficiently solved using off-the-shelf optimisation software guaranteeing a finite convergence to the global optimal solution [10, 11].

In the next section, the mathematical modelling of the problem is explained in detail.

3 Problem formulation

As expressed in (1), the objective of the proposed multi-stage expansion planning model is to minimise the present value of the network costs over the planning horizon $T$. The network costs are comprised of investment costs $Inv$, operational costs $Op$, as well as costs of RES generation curtailment $y^g$ and customer demand interruption $y^D$. In addition, $\delta^I$ and $\delta^O$ denote present value factors for investment and operational costs, which are calculated based on the infinite perpetuity approach explained in the work of Jooshaki et al. [12].

$$\text{Minimize } OF = \sum_{t=1}^{T} \left( \delta^I \cdot Inv_t + \delta^O \cdot (Op_t + y^g_t + y^D_t) \right)$$

Network investment cost in each time stage $t$ includes costs associated with various investment alternatives for feeder sections, substations, and energy storage systems as expressed below:

$$Inv_t = \sum_{k \in K} \sum_{h \in S} \rho_{k,t} \cdot x_{k,t}^S + \sum_{\ell \in \Omega} \sum_{h \in S} \rho_{\ell,h} \cdot x_{\ell,h}^{ESS} \sum_{\ell \in \Psi} \sum_{h \in S} \rho_{\ell,h} \cdot y_{\ell,h}^{ESS}$$

where $\Lambda$, $\Omega^S$, and $\Omega^F$ are sets of feeder sections, substation nodes, and candidate nodes for installation of energy storage systems, respectively. $\Psi_h$, $\Psi_n$, and $\Psi_s$ represent sets of candidate investment plans for feeder section $\ell$, substation located at node $s$, and energy storage system connected to node $n$. The capital recovery rate for each asset, signified by $\rho_{\ell,h}$, are calculated based on the useful lifetime of the asset using the approach employed in the work of Jooshaki et al. [12]. Investment cost for alternative $k$ of each network asset, namely, feeder section, substation, and energy storage system, are represented by $I_{\ell,k}$, $I_{h,s}$, and $I_{n,h}$, respectively. Finally, $\lambda_{\ell,h}$ and $\lambda_{h}$ are binary decision variables for feeder sections, substations, and energy storage systems, which become equal to 1 if their investment alternative $k$ is selected at stage $t$, being 0 otherwise.

Moreover, network operational cost at stage $t$ is comprised of the operation and maintenance costs of feeder sections $OMC^F_t$, substations $OMC^S$, and storage systems $OMC^{ESS}_t$, as formulated below:

$$Op_t = OMC^F_t + OMC^S_t + OMC^{ESS}_t$$

where $OMC^F$ and $OMC^S$ are functions of the selected investment alternatives for feeder sections and substations, i.e. $\lambda_{\ell,h}$ and $\lambda_{h}$, as well as operational conditions of the network, e.g. nodal demand and RES generation scenarios. $OMC^{ESS}$ is also modelled as below:

$$OMC^{ESS}_t = \sum_{d \in D} \sum_{h \in H} \sum_{k \in S} \left( \sum_{t=t_{rep}}^{T} \left( ESS_{t,\ell,h} \cdot MCESS_{t,\ell,h} \right) \right) + \sum_{d \in D} \sum_{h \in H} \sum_{k \in S} \sum_{t=t_{rep}}^{T} \left( \sum_{h \in H} \left( p^C_{k,t_{rep}} \cdot \psi_{k,t_{rep}} \right) \right)$$

where $MCESS_{t,\ell,h}$ is maintenance cost; $D$, $F$, and $H$ are set of representative days in each planning stage $t$, set of scenarios for nodal demand, and RES generation patterns in each representative day, respectively, and set of time steps in each representative day; $\phi_{k,t_{rep}}$ is frequency of occurrence for representative day $d$ in a planning stage $t$ (days per year); $\pi$ is the occurrence probability of scenario $z$; $\phi_s$ is duration of time step $h$ (hours per day); $p^C_{k,t_{rep}}$, $p^C_{h}$ are charging and discharging power of the storage systems; and $\lambda_{h}$ is the electricity price.

It is worth noting that each scenario $z$ includes daily patterns for nodal demands and RES (wind and solar) generations, as well as electricity retail price.

The optimisation model is also subject to numerous technical and logical constraints comprising capacity limitation of equipment (i.e. feeder sections, substations, and energy storage units), network power flow constraints, operational constraints of storage systems (e.g. charging, discharging, energy storage limit, and efficiency), and logical utilisation and investment constraints. In order to reach a MILP model, mixed-integer linear approximation explained in [13, 14] is utilised to linearise the power flow equations. Energy storage model was developed based on the work of Karimi-Arpahan et al. [8], and the capacity limitation of network assets as well as the logical investment and utilisation constraints are devised based on the technique employed in the work of Jooshaki et al. [12].

4 Numerical results

The proposed multi-stage expansion planning model is implemented on the 18-node test network depicted in Fig. 2. As per this figure, the test system has 16 load points, 2 substations, and 24 feeder sections.
of which 8 feeder sections are initially existing and the rest are candidates for construction. Customer-owned solar- and wind-generating units are also scattered throughout the network while wind units are merely connected to three nodes, i.e. nodes 4, 10, and 15, solar panels are at 12 out of 16 load nodes. As shown in Fig. 2, five load nodes are considered as candidates for the installation of storage systems.

In the simulations, three planning stages are modelled, and two representative days are considered for each planning stage. Then, in order to take the uncertainty of daily patterns of nodal RES generation and demand into account, 12 scenarios are considered in each representative day. Each scenario is a set of daily patterns for nodal demand and RES generation. The data for these scenarios are taken from Jooshaki et al. [15].

For the network expansion, two investment alternatives are considered for each grid asset, i.e. feeder section, substation, and storage system. As for the existing assets, these alternatives include reinforcing actions, whereas, for the new candidate assets, they are different construction alternatives. The data associated with these investment alternatives are based on the work in Jooshaki et al. [15].

The optimisation model is implemented in GAMS 24.9 and solved by CPLEX 12.6. In order to investigate the effects of energy storage systems on network flexibility, two cases are considered. In Case I, investment in energy storage systems are included in the model, whereas, in Case II, energy storage systems are disregarded.

The obtained results for both cases are presented in Table 1. As per this table, the objective function for Case II is an order of magnitude higher than that of Case I. This is due to the significant amount of cost incurred by the curtailment of the customer-owned RES generation as well as load interruption, i.e. 51.389 M$ in Case II compared to merely 0.397 M$ for Case I.

Another interesting deduction is that investment in storage systems (Case I) has resulted in the reduction of the total investment cost of feeders and substations. In this respect, although the investment cost of feeders is higher for Case I, it is dominated by the decrease in the substation investment cost.

Optimal network topology at the last stage of the planning horizon for Case I is also depicted in Fig. 3. As illustrated, four feeder section, namely, branches 2–3, 10–11, 12–16, and 14–15 are switched off to satisfy the radial operation of the distribution network. Moreover, the optimal investment alternatives for feeder sections are determined in the figure. For instance, A2T1 for feeder section 5–17 implies that investment alternative 2 (as mentioned before two investment alternatives are considered for each feeder section) must be performed at planning stage 1.

As for the substations, capacities of both are increased by 10 MW. Nonetheless, the substations located at node 17 are expanded at stage 2, whereas the investment in substation 18 is carried out at stage 3.

As per Fig. 3, electrical energy storage systems are also installed at two load nodes, namely nodes 4 and 7. Storage capacity at each of these nodes is 1 MWh. As depicted in Fig. 2, node 4 is a node with wind generation. Moreover, node 7 is connected to substation node 18, which serves wind nodes 4 and 15. Thus, considering also the solar generation units, it can be concluded that the storage system installed at node 7 can provide storage services for the nodes with high RES generation capacities supplied through substation node 18.

### 5 Conclusion

A stochastic multi-stage model for the expansion planning of electricity distribution networks has been presented in this paper. The aim is to enhance the network flexibility using energy storage systems while planning the network to meet the growing uncertain demand and customer-owned renewable generation. Accordingly, various investment alternatives for major network assets, namely, substations, feeder sections, and storage systems, were considered in the model. Uncertainty of nodal demand and RES generation was also captured via several scenarios. Formulated as an instance of MILP problem, the model was then applied to an 18-node test network and the results were thoroughly discussed.

### 6 References

3. Council of European Energy Regulators (CEER): ‘European energy regulators (ACER-CEER) white paper #3, facilitating flexibility, relevant to European Commission’s clean energy proposals’, May 2017

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**Table 1 Numerical results**

<table>
<thead>
<tr>
<th>Objective function, OF (M$)</th>
<th>Case I</th>
<th>Case II</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.074</td>
<td>54.161</td>
<td></td>
</tr>
<tr>
<td>Total RES curtailment and demand interruption cost (M$)</td>
<td>0.397</td>
<td>51.389</td>
</tr>
<tr>
<td>Investment cost of substations (M$)</td>
<td>2.130</td>
<td>2.231</td>
</tr>
<tr>
<td>Investment cost of feeders (M$)</td>
<td>0.467</td>
<td>0.420</td>
</tr>
<tr>
<td>Total investment in feeders and substations (M$)</td>
<td>2.597</td>
<td>2.651</td>
</tr>
<tr>
<td>Investment cost of storage systems (M$)</td>
<td>1.941</td>
<td>0</td>
</tr>
<tr>
<td>Energy storage capacity (MWh)</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

