Optimal Distribution Feeder Reconfiguration for Integration of Electric Vehicles

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***Abstract*—Penetration levels of electric vehicles (EVs) and distributed energy resources (DER) increase as the power distribution grid continues to change. This leads to a significant variation in the distribution system load profile, reduce the voltage quality and create congestion in some nodes of the network. Distribution network reconfiguration (DNR) presents an alternative to reduce the impact of EVs and DER while avoiding requirements of network reinforcement. This work proposes a day-ahead optimal network reconfiguration to mitigate the negative impact caused by the presence of EVs in the distribution system. The distribution network is optimized using genetic algorithm (GA). A sequence of hourly network configuration is proposed to minimize the operating cost resulting from both power losses and switching operation. The cost of power losses is calculated based on the National Electricity Market of Singapore (NEMS)'s electricity hourly price. Simulations results are provided to validate the proposed method.**

***Index Terms*—Distribution System Operation, Electric Vehicles, Network Reconfiguration**

I. Introduction

Transition to smarter power grids involves an increment of DERs and EVs connected at the distribution level. Main issues resulting from the high penetration of these resources include changes in daily load profiles, congestion, voltage and line overloading problems. Installation of distributed solar photovoltaic (PV) generation may improve the overall system voltage profile and reduce power losses [1]. At the same time, increased PV penetration could cause reverse power flow, resulting in overvoltages and power quality deterioration. Adding EVs at different buses of the distribution grid will require additional capacity to charge the batteries. Uncontrolled charging may lead to increase in peak load, higher power losses, voltage issues and decrease in system load factor [2], [3]. As penetration of EVs grows network reinforcement may be necessary.

The distribution system operators (DSOs) are responsible for operating the system in an optimal way and plan the required network upgrades. One of the smart grid's targets is to improve the energy efficiency by an optimal utilization of the existing network. According to [4], there are two methods that DSOs can use for improving the system operation. Market methods use price signals or contracts to influence the behavior of flexible loads. On the other hand, direct control methods include changing the network topology using DNR and demand response (DR) programs which involve fixed contracts that allow operators to control the active and reactive power set-points based on the user constraints.

Different optimization techniques have been used to solve DNR. In [5], GA was applied to find the configuration that minimizes the total system losses. In [6], particle swarm optimization was used to consider load variations and distributed generation for power loss reduction and voltage profile improvement. An optimal reconfiguration based dynamic tariff method for congestion management and loss reduction was presented in [7]. The objective of DNR is to find a optimal radial structure by changing the state of sectionalizing and tie switches. In [8], authors derived a formula to estimate the loss reduction resulting from network reconfiguration. The algorithm proposed in [9] considers meshed networks instead of the radial topology. Although there are several authors proposing methods to solve the DNR using linear or convex approximations of the power flow equations [7], [10], [11], these methods are usually computational intensive and solving them becomes harder as the network size increases. The authors in [12] propose a DC approximation of the power flow equations, this could result in violation of the voltage limits for long distribution feeders. The authors in [10], [11] use convex relaxation of the AC optimal power flow problem, they require special conditions for the power flow relaxation to be exact.

Some literature exists regarding distribution systems in the presence of EVs. Authors focus either in reducing the total losses [2] or in reduction of feeder overload [13]. In [14], network reconfiguration was proposed to mitigate possible problems of feeder overload, low voltage and power loss increase due to EV charging. But it should be noted that the aforementioned authors did not take into account the system operating cost while performing the DNR. Deregulation of markets results in variable daily prices. In this variable price structure, minimization of total system losses may result in sub-optimal total daily operative costs.

In this work, GA is used to obtain an optimal day-ahead sequence of network configurations that minimizes the total daily operating cost. The optimization takes into consideration

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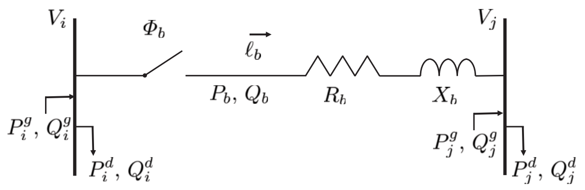

Fig. 1. Distribution network notation

the cost for the DSO resulting from the system losses and the switching costs. This is done while maintaining stability and security of the distribution grid. The proposed method ensures that cost is minimized while reducing the number of switching operation. This results in lower maintenance and extended lifetime for the switchgear.

The paper is organized as follows. Section II first explains concepts related to DNR for loss reduction, GA and power flow for distribution systems and then presents the proposed methodology. Section III explains the simulation setup and the results are presented in Section IV. Finally, Section V shows the conclusion and an outlook for future research areas.

II. Distribution Network Reconfiguration

Distribution networks are the most extensive part of the electrical power system. They are normally built as mesh networks, but many are operated radially [15]. This means that there is only one path for power to flow from the distribution substation to the consumer. Power losses are considerably high because of the low voltage level. Shifting from centralized to decentralized market structures allows DSOs to serve as load aggregators, their responsibility includes managing and coordinate the operation of some part of the distribution network. Line losses result in higher operative costs and it is therefore of their interest to minimize the cost resulting from losses in the distribution grid. DNR modifies the radial structure of the distribution feeders by opening and closing tie and sectionalizing switches, thus transferring loads from one feeder to another [8]. Topological constraints need to be taken into account to ensure the structural feasibility and radiality of the system. Feasibility indicates that all nodes in the system must be connected to some branches and radiality ensures there are no loops in the network.

A. Distribution System Model

This work assumes a balanced distribution network connected to the medium voltage through a distribution transformer. The system is modeled using a single phase equivalent. An overview of the notation used is shown in Fig. 1.

Power balance equations are introduced to account for provision of both active and reactive power

$$\sum_{n\in\Omega^N} P^g_{n,h} = \sum_{n\in\Omega^N} P^d_{n,h} + \sum_{b\in\Omega^b}\left[R_b \cdot \ell^2_{b,h}\right] \tag{1}$$

$$\sum_{n\in\Omega^N} Q^g_{n,h} = \sum_{n\in\Omega^N} Q^d_{n,h} + \sum_{b\in\Omega^b}\left[X_b \cdot \ell^2_{b,h}\right] \tag{2}$$

where $\ell_{b,h}$ depicts the line current and $P^g_{i,h}$ and $Q^g_{i,h}$ are the active and reactive power generated at bus i. Similarly, $P^d_{i,h}$ and $Q^d_{i,h}$ depict the demand at bus i. Sets Ω^N and Ω^B represent the set of all buses and lines in the distribution grid respectively.

The total cost for losses during period h is then defined by

$$\chi^L_{b,h} = R_b \cdot \ell^2_{b,h} \cdot \Delta t \cdot \lambda_h \tag{3}$$

where Δt is the period duration and λ_h depicts the energy price during period h. Similarly, the cost for operating the switches is defined by

$$\chi^S_h = \sum_{b\in\Omega^b}\left[\mid \Phi_{b,h-1} - \Phi_{b,h} \mid \cdot \mu\right] \tag{4}$$

where $\Phi_{b,h}$ represents the status of the switch, $\Phi_{b,h} = 1$ if the switch is closed and $\Phi_{b,h} = 0$ if open. The term μ represents the switching cost and is defined using the total cost for the switchgear and the estimated number of switching operations before the device reaches the end of life.

The following constraints are added to ensure radial operation of the distribution feeders

$$\sum_{b\in\Omega^b} \Phi_{b,h} = \left|\Omega^N\right| - n^s \qquad \forall h \in \Omega^H \tag{5}$$

where n^s is the number of substations in the distribution network.

B. EV carpark model

The carpark model is derived from [16]. The arrival-departure data for each carpark was derived using a probabilistic model based on driver profiles for Singapore. Let $\Omega^{ev}_n \in \mathbb{R}^M$ denote the set of all EVs connected at bus n of the distribution grid. Each carpark is modeled as a virtual battery connected at the distribution grid. The state space representation for the aggregated carpark model is given by

$$\boldsymbol{x}_{n,h+1} = \boldsymbol{A}_n \cdot \boldsymbol{x}_{n,h} + \boldsymbol{B}_n \cdot \boldsymbol{u}_{n,h} \tag{6}$$

where $\boldsymbol{x}_{n,h} \in \mathbb{R}^M$ depicts the battery state of charge (SOC) of all cars connected at bus n during time period h. Variable $\boldsymbol{u}_{n,h} \in \mathbb{R}^M$ represents the power drawn from bus n at the distribution grid. Coefficients $\boldsymbol{A}_n \in \mathbb{R}^{M\times M}$ and $\boldsymbol{B}_n \in \mathbb{R}^{M\times M}$ depict the relationship between the inputs and the state of the vehicles at the next market period.

The following constraints are added to prevent discharge of the vehicle battery to the grid and ensure the SOC is within the safe operating limits for all vehicles in the carpark:

$$\boldsymbol{x}^{min}_{n,h} \leq \boldsymbol{x}_{n,h} \leq \boldsymbol{x}^{max}_{n,h} \tag{7}$$

$$\boldsymbol{0} \leq \boldsymbol{u}_{n,h} \leq \boldsymbol{u}^{max}_{n,h} \tag{8}$$

where variables $\boldsymbol{x}^{min}_{n,h}$ and $\boldsymbol{x}^{max}_{n,h}$ depict the minimum and maximum battery SOC for the EVs connected at bus n at time step h. Similarly, the term $\boldsymbol{u}^{max}_{n,h}$ restricts the maximum charging rate based on the EV limits.

The total cost for the aggregated virtual battery connected at bus n for each period h is given by:

$$\chi_{n,h}^{V} = ||\boldsymbol{u}_{n,h}|| \cdot \Delta t \cdot \lambda_h \tag{9}$$

C. Power Flow in Distribution Systems

Traditional methods to solve the power flow problem like Gauss-Seidel or Newton-Raphson are well established for transmission networks but may not be suited for distributions systems. This is due to the high number of branches and nodes, larger R/X ratio and radial operating structure. Alternative power flow methods are required for distribution networks. The approach proposed in [17] is implemented in this paper. A direct solution is obtained by using the topological characteristics of the distribution network.

D. Feeder reconfiguration algorithm

The proposed method determines the optimal hourly network configuration considering the availability of the EV, the energy requirements and the optimal switching sequence. The total operating cost for the system is obtained by minimization of the following cost function

$$min \sum_{h\in\Omega^H} \sum_{n\in\Omega^N} \sum_{b\in\Omega^B} \left[\chi_{n,h}^{V} + \chi_{b,h}^{L} + \chi_{b,h}^{S}\right] \tag{10}$$

subject to

Equations (1), (2) and (5) to (8)

$$\mid \ell_{b,h} \mid \leq \ell_b^{+} \qquad \forall\, b \in \Omega^B \text{ , } h \in \Omega^H \tag{11}$$

$$V^{-} \leq V_{n,h} \leq V^{+} \qquad \forall\, n \in \Omega^N \text{ , } h \in \Omega^H \tag{12}$$

The term $V_{n,h}$ depicts the voltage at bus n during period h and $\ell_{b,h}$ represents the current flowing through branch b during period h. Equations (11) and (12) represent the current and voltage constraints, respectively. The term ℓ_b^{+} is the maximum current limit for branch b. Similarly, V^{+} and V^{-} are the system maximum and minimum voltage allowed by the DSO.

Two indexes are developed in this paper to measure the effectiveness of the proposed method. The voltage deviation index (ϑ) is based on the power load in each bus. This index measures the aggregated voltage deviation from the nominal value for all buses based on the bus load and the total system load.

$$\vartheta_h = \sum_{n\in\Omega^N} \frac{\sqrt{\left(V_{n,h} - V'\right)^2} \cdot P_{n,h}}{\sum_{i\in\Omega^N} P_{i,h}} \tag{13}$$

The branch capacity index (ζ) measures the deviation from the maximum allowable current based on the ration between losses at each distribution system branch and the total losses for the system. Although (11) ensures the current at all branches are within the safe limits, a lower value represents lower congestion in the system.

$$\zeta_h = \sum_{b\in B} \frac{\left[\ell_b^{+} - \ell_{b,h}\right] \cdot R_b \cdot \ell_{b,h}^2}{\sum_{y\in\Omega^B} R_y \cdot \ell_{y,h}^2} \tag{14}$$

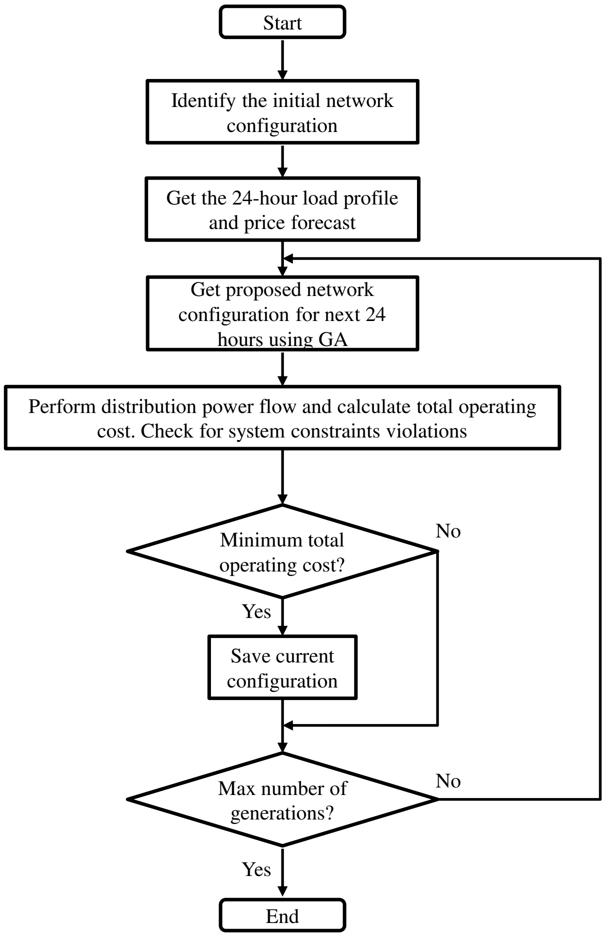

Fig. 2. Proposed algorithm

An overview of the proposed solution method is shown in Fig. 2. The main purpose of the algorithm is to define a operational schedule for the distribution network that considers both the base load and cost optimal scheduling for the different EV aggregators. This algorithm also considers the operating cost for the DSO and defines the optimal distribution network topology based on minimization of system losses and the switchgear lifetime.

In this work, the optimal switching sequence for both sectionalizing and tie switches are found by making use of GA. The GA algorithm was implemented using a modified version of the global optimization toolbox from MATLAB©. This optimization technique is used to solve nonlinear problems by implementing evolutionary biology concepts to search for the global minimum. Characteristics like working with coding of parameters and using probabilistic transition rules, make GA a more robust option than other nonlinear optimization techniques [18]. Another advantage of GA is that since the objective function is computed independently, power flow equations can be modeled using the full AC model. This allows GA to be able to solve not only single phase equivalent circuits, but also solve the problem for three-phase unbalanced distribution networks while ensuring the voltage and line

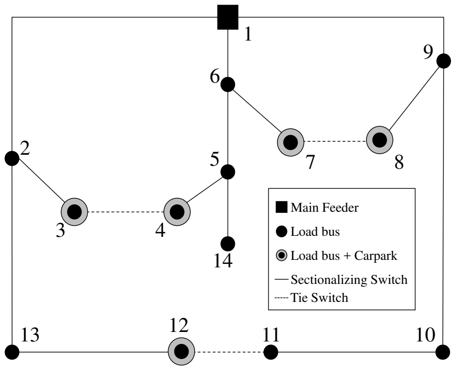

Fig. 3. 14-bus IEEE test system

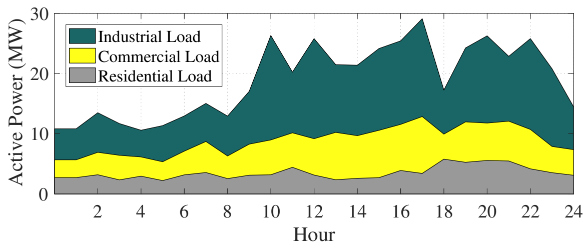

Fig. 4. Active power demand by customer type

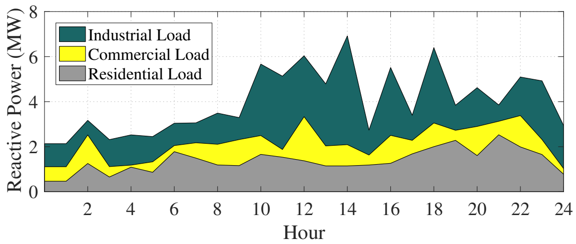

Fig. 5. Reactive power demand by customer type

constraints are not violated.

III. System Description

The algorithm is tested using a modified version of the IEEE 14-bus distribution system Fig. 3. It consists of thirteen sectionalizing switches and three tie switches. There is a main feeder and 13 load buses including residential, commercial and industrial customers. The system initial load profile is depicted in Fig. 4, where the daily demand for each customer type is illustrated in hourly periods. The peak demand occurs at hour 17, reaching 29.12 MW of consumption. This papers assumes EVs are integrated to the system through five aggregators connected to buses 3, 4, 7, 8 and 12.

IV. Simulation Results

As the demand in the system increases, a considerable increase in the daily total cost of power loss is produced. The total power loss of the system grows from 6.46 MW to 10.11 MW after the integration of the car parks.

The implementation of DNR is an effective method to reduce power losses. Consideration of the switching cost and the cost resulting from these losses may result in a different switching sequence in order to minimize the operating cost

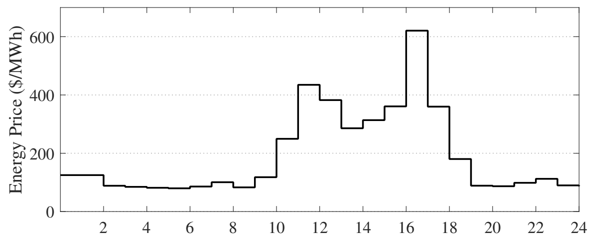

Fig. 6. NEMS's energy price forecast

of the system. The switching cost is assumed to be 0.35 Singapore dollars ($) per commutation. This number is derived based on the switchgear cost and the maximum number of switching operations possible during the entire mechanical life of the switchgear. Energy price for the NEMS is used for the simulation. The energy price forecast for a 24-hour interval is shown in Fig. 6. The base case assumes that no DNR is allowed and considering both the 24-hour base load shown in Fig. 4 and the increase in load required by the EV load aggregators in Fig. 7. Three different scenarios are evaluated in order to analyze the DSO's operating cost.

A. *Case 1: Day ahead fixed configuration*

In this case, the objective is to find a fixed configuration that minimizes the total system losses for the entire 24 hours. This configuration is maintained throughout the day. The main advantage of this method is that the power loss reduction is achieved without any intra hour switching commutation. This method results in extended switchgear lifetime due to the smaller number of switching operations.

B. *Case 2: Hourly distribution network reconfiguration*

DNR is performed hourly and 24 optimal switching sequences are obtained in order to find the network topology resulting in minimum power losses. Power losses are reduced in comparison to the results in Case 1. However, the drawback of this method is that due to the limited number of switching operations the switchgear can sustain through its lifetime. Excessive switching may result in higher maintenance costs and will require the switchgear to be replaced more frequently.

C. *Case 3: Proposed method*

For the proposed method, the cost of losses and switching operations are considered. Minimization of the objective function proposed in (10) is carried out. The objective is to find the optimal 24-hour switching sequences that minimize the total operating cost. Consideration of switching costs allows changes in the topology of the system to be made only when the savings resulting from this new configuration lead to lower operational costs for the DSO, i.e. a topology with higher losses may be preferred if less switching is required.

Results fo hourly and total system losses under different scenarios are shown in Table I. Reductions in power losses are achieved by all cases when compared to those of the base case. A 10.45% loss reduction from 10.11 MW to 9.05 MW when

Table I
SYSTEM LOSSES UNDER DIFFERENT SCENARIOS

Hour	Base Case	Case 1	Case 2	Case 3
1	0.0740	0.0685	0.0685	0.0685
2	0.1032	0.0974	0.0974	0.0974
3	0.0720	0.0666	0.0666	0.0666
4	0.0618	0.0587	0.0587	0.0587
5	0.0736	0.0669	0.0669	0.0669
6	0.0919	0.0878	0.0878	0.0878
7	0.1160	0.1110	0.1110	0.1110
8	0.1526	0.1401	0.1401	0.1401
9	0.5208	0.5191	0.5096	0.5191
10	1.0959	0.9620	0.9620	0.9620
11	0.2973	0.2738	0.2738	0.2738
12	0.7899	0.6396	0.6396	0.6396
13	0.6238	0.5736	0.5670	0.5684
14	0.4166	0.3632	0.3619	0.3619
15	0.4031	0.3561	0.3551	0.3551
16	0.4757	0.4137	0.4137	0.4137
17	0.7371	0.6437	0.6433	0.6437
18	0.6271	0.6730	0.6271	0.6345
19	0.9256	0.8805	0.8805	0.8805
20	0.8839	0.7409	0.7409	0.7409
21	0.4881	0.4038	0.4038	0.4038
22	0.5494	0.4804	0.4804	0.4804
23	0.3664	0.2919	0.2919	0.2919
24	0.1662	0.1426	0.1426	0.1426
Total Power Loss (MW)	10.1120	9.0550	8.9902	9.0090

Table II
DAILY OPERATING COST FOR DSO

Case	Number of Switching Operations	Switching Cost ($)	Power Loss Cost ($)	Total Cost ($)
Base	0	0	2277.6	2277.6
1	0	0	2018.9	2018.9
2	24	8.4	2006.7	2015.1
3	8	2.8	2009.7	2012.5

comparing the base case and the fixed configuration (Case 1 in Table I). Hourly reconfiguration (Case 2 in Table I) results in a reduction of 11.09% (from 10.1121 MW to 8.9902 MW). As expected, the hourly reconfiguration produces the maximum total loss reduction. Lastly, 10.90% reduction in losses is achieved using the proposed method (Case 3 in Table I, from 10.1121 MW to 9.0090 MW).

Table II details the number of switching commutations and the total daily operating cost, i.e. switching cost, power loss cost and operating cost, for each scenario. It should be

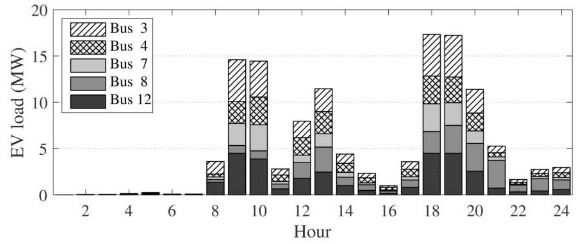

Fig. 7. Car parks load schedule

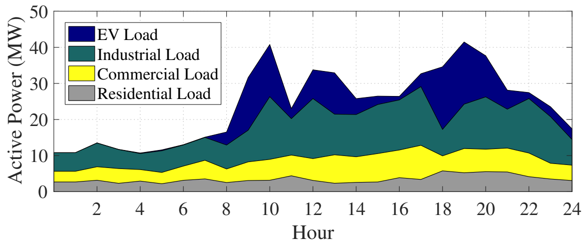

Fig. 8. Total load demand considering EVs

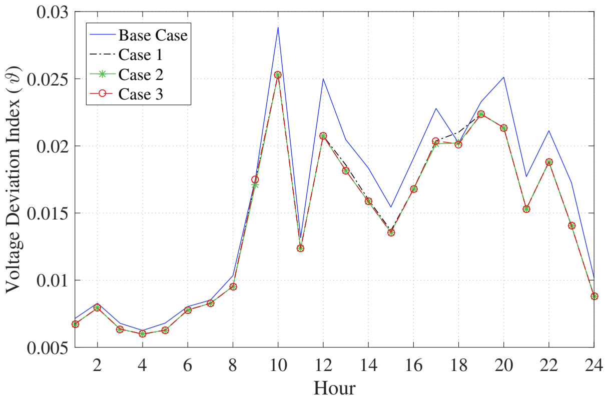

Fig. 9. Voltage deviation index

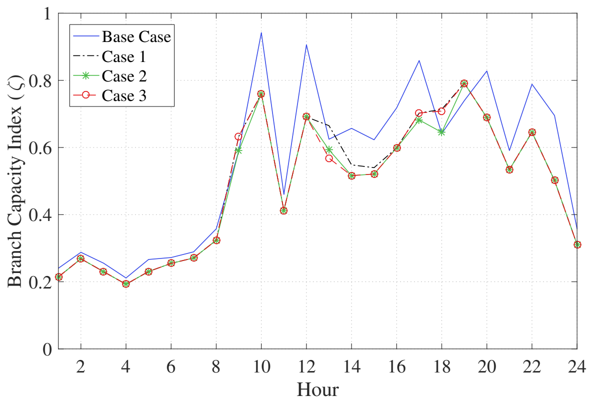

Fig. 10. Branch capacity index

noted that keeping a fixed configuration is not so effective for cost reduction comparing to the others cases. In Case 2, the maximum power loss cost reduction is reached, however, a higher number of switching operations makes this approach less attractive. The minimum total operating cost is obtained when both loss and switching cost are minimized. A noticeable reduction in the number of switching operations is observed.

Each carpark aggregator schedules the individual EV charging operations independently. The aim of each aggregator is to minimize their operating costs. This schedule is passed to the DSO and is added to the system loads. The car parks' hourly schedule results for the proposed method are shown in Fig. 7. An overview of the total system load is shown in Fig. 8. Addition of EVs results in an increase in total system demand, at the same time, the system peak is shifted to hour 19, with a new value of 41.48 MW.

Figure 9 shows a comparison of the voltage deviation index for each case. A lower value of this index indicates less voltage deviation meaning better overall voltage profile. Results show that voltage profile is generally improved when DNR is considered. Similarly, Fig. 10 show improvements in the branch capacity index, which is used as a measure of congestion for the system. Case 2 and 3 show similar improvements in the voltage and current indexes, on the other hand, the fixed configuration proposed in case 1 results in deterioration of the voltage profile, specially during hours 17 to 19. From Fig. 10 it can also be seen that during hours 13 to 16 the system is more congested for Case 1 than it is for Cases 2 and 3.

V. Conclusion

This paper presents an optimal day-ahead hourly configuration in order to minimize the total system operating cost. Time-varying load and EVs are integrated in the distribution network. An objective function is proposed and a GA technique is used for solving the optimization problem. The proposed method analyzes both switching and power loss costs in order to find the optimal configuration for each hour and reduce the total operating cost.

Results show that improvements in both the voltage and current profiles could be obtained when compared to those of the base case. Reductions of about 12% in the total system operating costs are obtained. At the same time, the lifetime of the switchgear is increased by reducing the number of switching operations.

Since uncertainties on the load and EV parameters could have a big effect on the performance of the proposed algorithm, uncertainties could be modeled using robust formulation or introducing concepts like interval optimization. Another interesting area for future research is the evaluation of the proposed algorithm using an unbalanced distribution network model. Effects of integration of DER, i.e PV and wind turbines, in the distribution system and effect of these resources in the network losses could also be evaluated.

Acknowledgments

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