A Short-Term Preventive Maintenance Scheduling Method for Distribution Networks With Distributed Generators and Batteries

Jianfeng Fu, Alfredo Núñez, *Senior Member, IEEE*, and Bart De Schutter, *Fellow, IEEE*

***Abstract*—Preventive maintenance is applied in distribution networks to prevent failures by performing maintenance actions on components that are at risk. Distributed generators (DGs) and batteries can be used to support power to nearby loads when they are isolated due to maintenance. In this paper, a novel short-term preventive maintenance method is proposed that explicitly considers the support potential of DGs and batteries as well as uncertainties in the power generated by the DGs. Two major issues are addressed. To deal with the large-scale complexity of the network, a depth-first-search clustering method is used to divide the network into zones. Moreover, a method is proposed to capture the influence of maintenance decisions in the model of the served load from DGs and batteries via generation of topological constraints. Then a stochastic scenario-based mixed-integer non-linear programming problem is formulated to determine the short-term maintenance schedule. We show the effectiveness and efficiency of the proposed approach via a case study based on a modified IEEE-34 bus distribution network, where we also compare a branch-and-bound and a particle swarm optimization solver. The results also show that the supporting potential of DGs and batteries in preventive maintenance scheduling allows a significant reduction of load losses.**

***Index Terms*—Distributed generators and batteries, preventive maintenance, short-term maintenance scheduling.**

NOMENCLATURE

Sets and Indices

b	Battery index
g	Iteration index in PSO
h	Particle index in PSO
j	Candidate maintenance action index
k	Generating or consuming component index
p, q, q'	Zone index
t	Time slot index
$\mathcal{T}^{\mathrm{D}}$	Set of day time slots
$\mathcal{T}^{\mathrm{N}}$	Set of night time slots
Ω_p	Set of neighbor zones of zone p
Ω_p^{c}	Set of non-neighbor zones of zone p
$\Theta_{p,q}$	Set of candidate maintenance actions on the path between zone p and its neighbor zone q
Φ	Set of scenarios

Parameters

A	Sweep area of wind turbine blades
$c_{1\mathrm{p}}, c_{2\mathrm{p}}$	Acceleration constants of PSO
C_{p}	Tip speed ratio of wind turbines
$C_{\mathrm{pril},p}(t)$	Electricity price for zone p in time slot t
$C_{j,p,q}^{\mathrm{N}}, C_{j,p,q}^{\mathrm{N}}$	Day-time and night-time maintenance cost for action j between zone p and its neighbor zone q
$\mathrm{C}_{\mathrm{set}}^{\mathrm{day}}(t)$	Budget for performing day-time maintenance in time slot t
$\mathrm{C}_{\mathrm{set}}^{\mathrm{night}}(t)$	Budget for performing night-time maintenance in time slot t
$d_{j,p,q}$	Deterioration stage of the component where maintenance action j has to be performed on the path between zone p and zone q
n_{Z}	Total number of non-PCC zones after clustering
N_{b}	Number of batteries
$P_{\mathrm{pred},p,s}(t)$	Predicted load of zone p in time slot t when no maintenance actions are performed in time slot t for scenario s
S_{PV}	Area of PV panel
$S_{\mathrm{bat},b}^{\mathrm{min}}$	Minimal battery capacity of battery b
$S_{\mathrm{bat},b}^{\mathrm{max}}$	Maximal battery capacity of battery b
$S_{\mathrm{bat},b}^{\mathrm{cap}}$	Capacity of battery b
t_{d}	Number of time slots in this maintenance scheduling period
T_{em}	Temperature of PV panel
$T_{\mathrm{em}}^{\mathrm{ref}}$	Reference temperature of PV panel
v_{out}	Cut-off wind speed
v_{start}	Start-up wind speed
v_{wmax}	Maximum wind speed
w_{p}	Inertia weight factor of PSO
W_p	Total number of generating, consuming and energy storage components in zone p
α	Weight coefficient of the deterioration cost
α_{PV}	Temperature coefficient
β	Weight coefficient to assure that SOC stays around the level σ
η_{PV}	PV panel conversion efficiency

Manuscript received May 23, 2020; revised October 11, 2020; accepted November 8, 2020. Date of publication November 16, 2020; date of current version April 19, 2021. This work was supported by CSC (China Scholarship Council) with funding number: 201806280023. Paper no. TPWRS-00851-2020. *(Corresponding author: Jianfeng Fu.)*

Jianfeng Fu and Bart De Schutter are with the Delft Center for Systems and Control, Delft University of Technology, 2626CN Delft, Netherlands (e-mail: 1543580611@qq.com; b.deschutter@tudelft.nl).

Alfredo Núñez is with the Section of Railway Engineering, Department of Engineering Structures, Delft University of Technology, 2626CN Delft, Netherlands (e-mail: a.a.nunezvicencio@tudelft.nl).

Color versions of one or more of the figures in this article are available online at https://doi.org/10.1109/TPWRS.2020.3037558.

Digital Object Identifier 10.1109/TPWRS.2020.3037558

ρ	Air density
σ	SOC penalty level
$\tau_{j,p,q}$	Duration of action j between zone p and its neighbor zone q
ϖ	Equality penalty weight in PSO
ζ_{leak}	Battery leakage coefficient
ζ_{char}	Battery charging efficiency

Variables

$C_{\text{loss},s}$	Total cost of load losses for scenario s
C_{main}	Total cost of performing maintenance actions
C_{deg}	Cost related to the degradation of the components
$C_{\text{soc},s}$	Penalty term for the SOC utilization of the batteries for scenario s
I_{PV}	Solar radiations
$P_{p,k,s}(t)$	Power generated or consumed by the kth generating, consuming, or energy storage component in zone p in time slot t for scenario s
$P_{\text{bat},b,s}(t)$	Power generated/consumed by battery b in time slot t for scenario s
$P_{\text{loss},p,s}(t)$	Load loss of the zone p in time slot t for scenario s
$P_{p,s}(t)$	Served load for zone p when maintenance actions are being performed in time slot t for scenario s
$S_{\text{bat},b,s}(t)$	SOC level of battery b at the end of time slot t for scenario s
v_w	Wind speed
$\delta_{p,q}(t)$	Connectivity between zone p and any other zone q in the distribution network in time slot t
$\Delta_{j,p,q}(t)$	Indicates whether the jth maintenance action on the path between the zone p and its neighbor zone q is performed in time slot t

I. Introduction

In 2016, 12% of the installed wind turbine capacity in Europe was older than 15 years, and this share will increase to 28% by 2020 [1]. These old wind turbines will soon reach the end of their designed service life, which is typically 20 years [2]. In addition, in today's power systems, commonly used XLPE cables are suffering from degradation, especially the water tree [3], [4]. Transformers, one of the critical assets in a power grid, are also suffering from degradation [5], [6]. Due to the deterioration of the components in the power system, the efficiency of generation and the reliability of the power system will be decreased, as the power system may suffer from faults or breakdowns. Thus, adequately scheduled maintenance actions are necessary to ensure the quality of the components and the efficiency and reliability of power generation and delivery.

Maintenance scheduling of power systems is mostly corrective or preventive [7]. Corrective maintenance is performed after failure of components [8], [9]. Preventive maintenance is performed before the failure of components [10]–[12]. It can result in significant budget savings compared to the corrective maintenance. For example, in [13]–[16], the preventive maintenance actions are performed to avoid failures of generation units. Besides, in [17]–[20] a new preventive maintenance concept "smart maintenance" has been proposed. Smart maintenance utilizes smart inspections based on big data analysis technologies, smart devices to collect the data, smart services, asset management, and other techniques to make preventive maintenance decisions. In particular, in [20], a review of the possible applications of big data on failure diagnosis, the internet of things on data collecting, and other technologies on smart maintenance can be found.

In preventive maintenance, the degradation conditions of the components can be evaluated based on different standards. For example, [21] analyzed the influence of factors such as power fluctuation, states of charge, and the charging/discharging rates on the life spans of the electric vehicle batteries. According to the factors, a charging plan was proposed to enlarge the life spans of electric vehicle batteries. In [22], the bathtub curve is used to measure the probability that a component will survive beyond an established time. A mathematical quantification model is presented to evaluate the degradation condition of the components by representing the bathtub curve as a Markov process. Then the degradation condition is used in the preventive maintenance of generation units. In [23], a reliability modeling method for systems composed by multiple components is proposed. The reliability indices of each component were used to derive the reliability of the whole system. In the standards such as the "Guide for condition evaluation of distribution network equipment," as shown in Chapter 7 of [24], a procedure to evaluate the condition scores of the components is described by evaluating the condition score of each sub-component individually and then summing them up with different weights.

Then, a cost-effective strategy [10] or a reliability-based strategy [25]–[27] can be used to determine a maintenance schedule. In the literature, different methods for preventive maintenance scheduling have been proposed [28], [29]. In [28], preventive maintenance is derived by considering the impact of increased short-circuit current flows on the failure rate. In [29], a cost-effective maintenance scheduling method with reliability constraints for overhead lines is proposed. Cost-based reliability indices are used for modeling. The methods in the literature for preventive maintenance scheduling in power systems minimize maintenance costs, maximize reliability, and also consider other factors, e.g., the influence of short-circuit currents on the failure rate [28] and the reliability [29]. In these *preventive* maintenance scheduling methods, the supporting power potential of DGs and batteries to reduce load loss cost was not explicitly considered. In [30], a preventive maintenance strategy considering the distributed generation in distribution networks is proposed. However, the islanding mode of the microgrids is not considered in the problem formulation. Thus, the supporting power potential of the DGs and batteries when microgrids are being islanded was not evaluated.

In literature, *corrective* maintenance and system restoration methods have been proposed considering the supporting power potential of DGs, batteries and the reconfiguration [8], [31]–[33]. Although one of the objectives of these methods is to serve more loads using DGs and batteries, these methods are designed for scheduling the maintenance actions after the failures and damages have emerged, e.g., a flood or a hurricane. However, preventive maintenance methods are designed for scheduling the maintenance actions so as to prevent the failures by considering the trade-off between the degradation status of the components and the total maintenance cost including cost of load shedding and the cost of performing maintenance actions. Thus, corrective maintenance methods differ from preventive maintenance methods and they cannot be used for the short-term preventive maintenance scheduling directly.

When the number of nodes of the distribution network increases, the number of the variables increases and the computation burden is enlarged. In this paper, a state-of-art depth-first-search (DFS) clustering method is proposed to simplify the topology of the network into a smaller-scale but still equivalent topology. Different zones in the distribution network are constructed according to the locations of the candidate maintenance actions. Grouping by zones results in a significant decrease of the number of nodes. In this way, the formulated preventive maintenance scheduling problem is simplified, and the computational burden is reduced.

Further, a scenario-based approach is proposed to allow the inclusion of stochasticities in the optimization problem while avoiding expensive computational efforts resulting from traditional robust approaches that require complete realizations of the stochasticities. Still, the scenario-based approach is more complicated than a deterministic solution (where no stochasticities are included), but it can be kept tractable according to the selected scenario generation method and scenario reduction method.

After that, two solvers are analyzed, branch-and-bound (BB) and particle swarm optimization (PSO). The BB solver can obtain the optimal solution but takes more computation time. While the PSO solver cannot obtain the optimal solution but can take less computation time. Interesting results using the PSO solver have been reported in the literature. For example, a PSO algorithm is used in [34] to minimize the overall cost, including investment, replacement, operation, and maintenance costs during the 20 years of a hybrid wind/photovoltaic generation system lifetime. A novel multi-objective PSO optimization algorithm is proposed in [35] to minimize three objective functions, namely the annualized cost of the system, loss of load expected, and loss of energy expected, when designing hybrid wind-solar generating microgrid systems. A multi-objective PSO algorithm is proposed in [36] to solve the optimal allocation problem for flexible alternating current transmission system devices. Besides, a new multi-objective optimization problem for the coordination of overcurrent relays in interconnected networks is presented in [37]. The problem is then solved by using multi-objective PSO and a fuzzy decision-making tool.

The main contributions of this paper are:

- We propose a short-term condition-based preventive maintenance scheduling method that considers the supporting potential of DGs and batteries.
- Aspects faced in practice are included, such as the uncertainties in decision making, different electricity prices in different locations, and different durations of maintenance actions. The problem is formulated as a stochastic mixed-integer non-linear programming problem and solved using a scenario-based approach.
- A DFS clustering method is proposed to simplify the topology into a smaller-scale but equivalent topology, resulting in a large reduction of the complexity of the distribution network topology and the computational burden.
- Two optimization algorithms are considered: BB and a modified PSO algorithm. The BB approach uses an exact reformulation of the mixed-integer non-linear programming problem into a linear programming one. The BB solver always finds the optimal global solution; however, recasting the problem increases the number of optimization variables. The modified PSO algorithm directly solves the mixed-integer non-linear programming problem and allows managing the computational burden at the expense of performance.

The remainder of this paper is organized as follows. Section II describes the issues of the preventive maintenance problem and the framework of the proposed method. Section III introduces the method to simplify the topology of the distribution network. Section IV proposes a method to generate topological connectivity constraints so as to obtain explicit relationships between served loads by DGs and batteries and maintenance decision making variables. Section V formulates the maintenance scheduling problem, proposes a method to generate and reduce the number of scenarios, and then introduces the BB solver and proposes a specific PSO solver for this problem. Section VI presents the results and analysis of a case study. Section VII discusses the contributions and possible applications of the proposed method. Finally, in Section VIII conclusions and topics for future research are included.

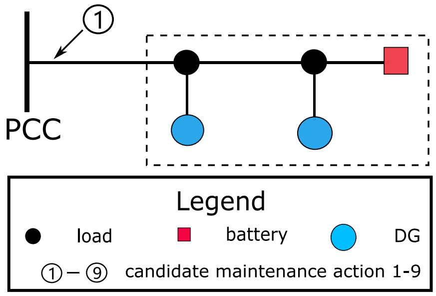
II. Problem Description and Proposed Framework

In this section, we will first describe the problems we face and intend to tackle. After that, we propose a framework for scheduling short-term preventive maintenance actions and give a brief introduction.

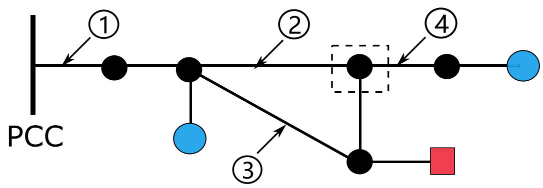
A. Problem Description

Mid-term preventive maintenance scheduling is a basic component in asset management of distribution networks. It is a maintenance scheduling strategy with a larger time scale and a longer period than the short-term preventive maintenance scheduling. Thus, it is a rougher preventive maintenance decision-making strategy. In the mid-term preventive maintenance scheduling, the maintenance actions are determined based on the operation cost, load loss, and degradation of the components in a medium time scale, e.g., one month or several months. In this paper, we assume that a mid-term maintenance scheduling method determines which maintenance actions should be performed one week in advance [7]. Then we propose a method to allocate these candidate maintenance actions within the days of a week. Now, we discuss two major problems for the design of preventive short-term maintenance scheduling considering the supporting energy from DGs and batteries.

1) Problem 1: In the case of large-scale distribution networks, the number of variables to characterize the possible



(a) Maintenance in one spot



(b) Maintenance in four spots

Fig. 1. Distribution networks for illustrating Problem 2.(a)Maintenance in one spot.(b)Maintenance in four spots.

dynamics during maintenance in the maintenance scheduling problem can be huge. As such, a method to reduce redundant variables and to simplify the distribution network without losing crucial information is required. In this paper, a clustering method is proposed to simply the network so as to reduce the number of variables in the maintenance scheduling problem.

2) Problem 2: Fig. 1 shows two networks to discuss another problem addressed in this paper. The numbers in circles with an arrow indicate the locations where preventive maintenance actions are to be conducted and the numbers represent labels of maintenance actions. The blue circles represent DGs, while the red boxes represent batteries.

In Fig. 1(a), ① should be maintained when the DGs and the battery can support the loads as much as possible to reduce the load loss. The load loss is given by the power required by the loads minus the power provided by the DGs and the battery. Thus, the time slots to maintain ① when the minimum load loss happens can be estimated. However, when there are several maintenance actions and the network is more complex as shown in Fig. 1b, the load loss cannot be calculated easily because of the connectivities between loads, DGs and the battery determined by where and when maintenance actions are performed. Where and when maintenance actions are performed are decision making variables in the maintenance scheduling problem. For example, the served load in the dashed box of Fig. 1b is determined by the sum of all the other connecting loads, DGs and the battery. Further, the connectivities are different for different combinations of maintenance actions, e.g., when maintenance is performed at ② or when ② and ③ are maintained simultaneously. Thus, another problem is to establish the relationships between load loss at each time step and maintenance action decision making variables for complex distribution networks.

B. Proposed Framework

A framework for scheduling short-term preventive maintenance is proposed as shown in Fig. 2.

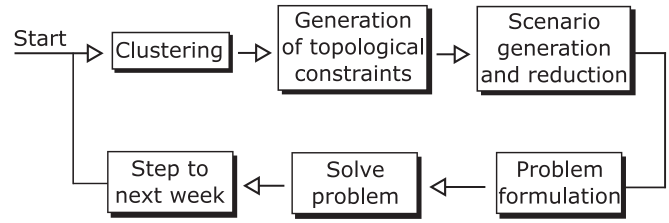


Fig. 2. Flowchart of proposed method.

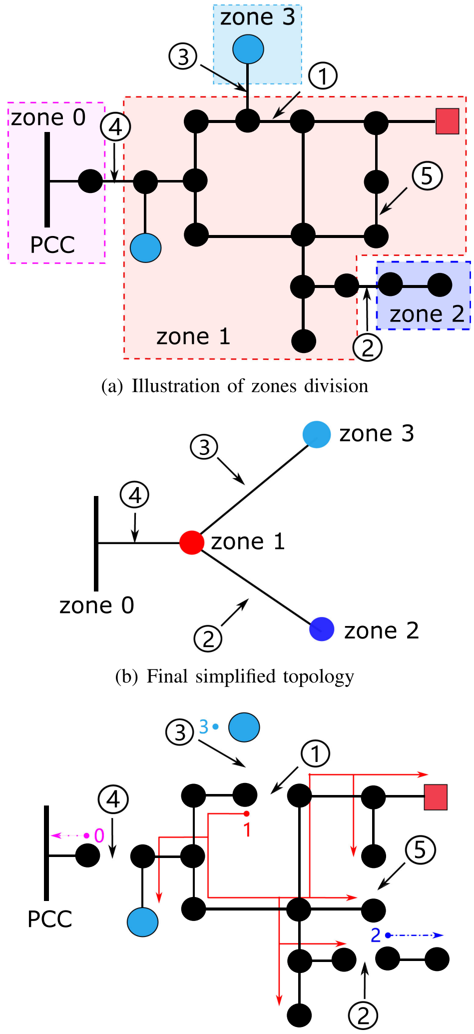
In this framework, after obtaining the candidate maintenance actions from the mid-term maintenance scheduling method, a clustering method is applied to divide the network into zones according to the week-ahead candidate maintenance operations. Then, a sum of products method is proposed to represent the connectivity of the topology by maintenance decision making variables. The explicit expression of the relationship between maintenance decision making variables and load loss cost is then derived. After that, the scenarios used to describe the uncertainties in the programming problem will be generated by scenario generation and reduction methods. Then a stochastic MINLP problem is formulated and solved to determine the daily preventive maintenance schedule. The method determines the maintenance schedule by minimizing the maintenance cost including the performance cost, load loss cost, and the cost related to the degradation of the components based on a score index. We next introduce the three main parts of the proposed method including: clustering method, generation of topological connectivity constraints, and problem formulation associated with the scenario generation and reduction methods as well as two possible solvers.

III. Clustering Method

Distribution networks consist of many components, e.g., paths, DGs, and batteries. Each of these components can be modeled to understand the dynamics of the network. However, when considering maintenance operations, usually not all the components have to be maintained. Thus, the detailed dynamics of each component might not be required for maintenance scheduling purposes, and methods can be used to reduce the complexity of the network. In this paper, we define a zone as the maximal set of connected components such that no matter when and which candidate maintenance actions are performed, the connectivity in one zone will not change.

For illustration purposes, Fig. 3 shows a distribution network with a coupled loop topology. There are five candidate maintenance actions, marked from ① to ⑤. In Fig. 3a, zone 1 contains one DG, one battery, and loads, while zone 2 contains loads; zone 3 contains one DG and zone 0 is a point of common coupling (PCC) zone that connects the outside system. From Fig. 3a, it can be seen that the connectivity between components within the five zones will not change when any of the candidate maintenance actions are being performed. The simplified representation of the distribution network in Fig. 3a is shown in Fig. 3b.

In Fig. 3b, ① and ⑤ are inner maintenance actions of zone 1 whose scheduled execution time will not influence the connectivities of the components. From Fig. 3a and Fig. 3b, it can



(a) Illustration of zones division

(b) Final simplified topology

(c) Illustration of searching trees generations

Fig. 3. Illustrations of the proposed clustering mechanism.

be seen that components in Fig. 3a are clustered into four zones in Fig. 3b. A zone can be seen as an integrated component, so the scale of the maintenance scheduling problem can be largely simplified.

As for a method to search the zones to simplify the network, the depth first search (DFS) method [38]–[40] is considered to find the largest connecting areas. To fit the DFS method in the maintenance clustering problem, each component is seen as a node, and the paths that do not need to be maintained are seen as connecting path, while the paths that need to be maintained are seen as break-points, as shown in Fig. 3c. Here we define a tree as a set of connected paths and nodes. The details of the steps of the DFS method are as follows:

1) Select as starting node one of the nodes that has not been visited by other trees. Start a new tree from this starting node.
2) Visit paths that come out of the most recently visited node p_0. Consider only paths going to un-visited nodes.
3) When all of p_0's paths have been visited, the search backtracks until it reaches an un-visited adjacent node. This process continues until all of the nodes that are reachable from the starting node have been visited. Then a largest connecting tree has been generated and the components on the tree originated from the starting point can be included in one zone.
4) If there are any un-visited nodes, select one of them as a new starting point and repeat the search from that node.
5) The algorithm repeats this entire process until it has visited every node. In this paper, we define the zone that includes the PCC point as zone 0.

Different starting points selection sequences do not influence the simplified topology, because if from a node p_u there is a path that can reach another node p_v, this means that from p_v there must be a path can reach p_u. In Fig. 3c, the zone generation process is shown. The search trees for the cluster generations are marked with a purple line, red lines, a blue line, and a green line to represent zone 0 to zone 3 respectively. In addition, the starting nodes of these searching trees are marked as filled circles in respective colors.

IV. Generation of Topological Connectivity Constraints

The load loss cost mentioned in Section II is related to the gap between the power served to loads and the power required by the loads, such that for zone p:

$$P_{\text{loss},p}(t) = P_{\text{pred},p}(t) - P_p(t) \tag{1}$$

where $P_p(t)$ is determined by the connectivity between the loads and other loads, DGs, batteries, and the PCC based on power balance equation, such that:

$$\sum_{q=0}^{n_{\text{Z}}} \delta_{p,q}(t) P_p(t) = 0,\ \forall t \in \{1,\ldots,t_{\text{d}}\} \tag{2}$$

where the zone containing the PCC is zone 0. In (2), the binary variable $\delta_{p,q}(t)$ is introduced to describe the connectivity between zones. Define $\delta_{p,q}(t)$ equals 1 if zone p and zone q are connected in time slot t. The connectivity variables $\delta_{p,q}(t)$ are determined by the maintenance actions because these will generate break-points dynamically in the network. Next, we propose a method to express the connectivity between zones by the maintenance decision making variables.

We introduce the binary maintenance decision making variable $\Delta_{j,p,q}(t)$ to indicate whether the maintenance actions are performed or not. If the jth maintenance action is assigned to be performed on the path between zone p and zone q in time slot t, then $\Delta_{j,p,q}(t) = 1$; else $\Delta_{j,p,q}(t) = 0$.

Two points need to be clarified: Firstly, for the maintenance actions on DGs (or batteries), e.g. the DG in zone 3 of Fig. 3a, the DG in zone 3 will be shut down and disconnected from zone 1. Furthermore, performing maintenance actions on the connecting path between the DG in zone 3 and zone 1 will also cause the DG in zone 3 to be disconnected from zone 1. Thus, maintenance actions on DGs or batteries can be seen as maintenance actions on the connecting paths between these DGs or batteries and the other parts of the network. Secondly, if a maintenance action takes several hours, e.g. 4 hours, then the

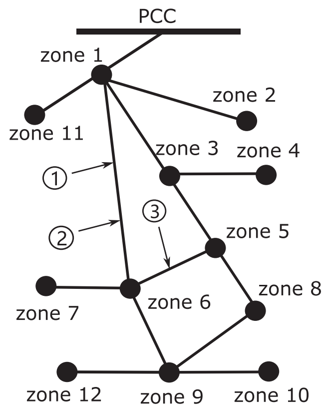


Fig. 4. An example of a distribution network.

corresponding connectivity variable $\Delta_{j,p,q}(t)$ equals 1 for each of the 4 hours when the maintenance action is performed.

After defining maintenance decision making variable $\Delta_{j,p,q}(t)$, firstly the connectivity status of zone p and its neighbor zone q can be derived as:

$$\delta_{p,q}(t) = \prod_{j=1}^{N_z}(1-\Delta_{j,p,q}(t)),$$
$$\forall t \in \{1,\ldots,t_{\rm d}\}, \forall p \in \{0,\ldots,n_{\rm Z}\}, q \in \Omega_p, j \in \Theta_{p,q} \quad (3)$$

Equation (3) represents that when maintenance actions are performed on the path between zone p and its neighbor zone q in time slot t, zone p and zone q will be disconnected. Secondly, by defining $\Omega_p^{\rm c}$ as the set of the non-neighbor zones of p, for each pair of zones p and q' (with $p \neq q'$ and $q' \in \Omega_p^{\rm c}$), we determine all possible elementary (i.e. without circuits) paths $p \mapsto p_1 \mapsto p_2 \mapsto \ldots \mapsto p_{h-1} \mapsto q'$ from zone p to zone q', possibly including the PCC (with index 0) by using the paths searching approaches mentioned in, e.g. [41]. Let $(p, p_1, p_2, \ldots, p_{h-1}, q')$ represent an elementary path from p to q' and let $\mathcal{H}_{p,q'}$ be the set of all such paths, then we have:

$$\delta_{p,q'}(t) = \begin{cases} 0 & \sum_{(p,\ldots,q')\in\mathcal{H}_{p,q'}} \delta_{p,p}(t)\delta_{p,p_1}(t)\ldots\delta_{p_{h-1},q'}(t) = 0 \\ 1 & \text{otherwise} \end{cases} \quad (4)$$

In this way, the relationship between the maintenance decision variables Δ and the connectivity variables δ can be derived. Apart from that, the connectivity status from zone p to its neighbor zone q or non-neighbor zone q' is the same as that from zone q' or zone q to zone p. In addition, the value for any $\delta_{p,p}$ is equal to 1 at any time because the status between a zone and itself is always connected. Thus, we have:

$$\delta_{p,q}(t) = \delta_{q,p}(t),\ \delta_{p,q'}(t) = \delta_{q,'p}(t),\ \delta_{p,p}(t) = 1,$$
$$\forall t \in \{1,\ldots,t_{\rm d}\}, \forall p \in \{0,\ldots,n_{\rm Z}\}, \forall q \in \Omega_p, \forall q' \in \Omega_p^{\rm c} \quad (5)$$

Fig. 4 shows an example for illustration purposes. In Fig. 4, we will derive $\delta_{1,8}(t)$ by using (3) to build the relationship between the connectivity status variable of zone 1 and zone 8 and the maintenance decision making variables. There are 3 paths from zone 1 to zone 8, so $\mathcal{H}_{1,8} = \{(1,3,5,8),(1,6,5,8),(1,6,9,8)\}$. Thus, we can derive that:

$$\delta_{1,8}(t) = \begin{cases} 0 & \text{if} \sum_{(p,\ldots,q')\in\mathcal{H}_{1,8}} \delta_{p,p}(t)\delta_{p,p_1}(t)\ldots\delta_{p_{h-1},q'}(t) = 0 \\ 1 & \text{otherwise} \end{cases} \quad (6)$$

as well as:

$$\delta_{1,6}(t) = (1-\Delta_{1,1,6}(t))(1-\Delta_{2,1,6}(t)),$$
$$\delta_{5,6}(t) = 1-\Delta_{1,5,6}(t),\ \forall t \in \{1,\ldots,t_{\rm d}\}, \quad (7)$$

where $\Delta_{1,1,6}(t)$, $\Delta_{2,1,6}(t)$ and $\Delta_{1,5,6}(t)$ represent whether to perform maintenance actions ①, ② and ③ respectively in time slot t. Thus, in this way, the relationship between all the connectivity variables and maintenance decision-making variables can be built. The relationships can be used to generate the power balance functions. The generated power balance functions can dynamically represent the served powers to the zones using the maintenance decision variables (see Section V-A).

V. Scheduling Problem and Possible Solvers

In this section, firstly the stochastic MINLP problem of the proposed short-term preventive maintenance method will be formulated. Secondly, the scenario generation and reduction methods will be illustrated. Thirdly, two possible solvers will be introduced.

A. Problem Formulation

This subsection formulates the optimization problem for the proposed method. We search for a vector Δ that contains all the variables $\Delta_{j,p,q}(t)$, and that minimizes the following objective function:

$$\min_{\Delta} J = \mathbb{E}_\Phi[C_{{\rm loss},s} + C_{\rm main} - C_{\rm deg} + C_{{\rm soc},s}] \quad (8)$$

where $\mathbb{E}_\Phi$ represents the expected value for scenario set Φ. More specifically,

$$C_{{\rm loss},s} = \sum_{t=1}^{t_{\rm d}}\left(\sum_{p=1}^{n_{\rm Z}}(P_{{\rm pred},p,s}(t) - P_{p,s}(t))\,C_{{\rm pril},p}(t)\right) \quad (9)$$

$$C_{\rm main} = \sum_{p=1}^{n_{\rm Z}}\sum_{q=p+1}^{n_{\rm Z}}\sum_{j\in\Theta_{p,q}}\frac{1}{\tau_{j,p,q}}\left(\sum_{t\in\mathcal{T}^{\rm D}}(1-\Delta_{j,p,q}(t))C_{j,p,q}^{\rm D} + \sum_{t\in\mathcal{T}^{\rm N}}(1-\Delta_{j,p,q}(t))C_{j,p,q}^{\rm N}\right) \quad (10)$$

In this paper we assume that the working crews of day-time and night-time are different; so we do not consider maintenance actions that are partially performed during the day-time and partially during the night-time. Note that the result of summing the $(1-\Delta_{j,p,q}(t))$ values is $\tau_{j,p,q}$, so the result should be divided $\tau_{j,p,q}$ in order to avoid the maintenance cost $C_{j,p,q}$ being added multiple times. In addition,

$$C_{\text{deg}} = \alpha \sum_{p=1}^{n_{\text{Z}}} \sum_{q=p+1}^{n_{\text{Z}}} \sum_{j\in\Theta_{p,q}} \frac{d_{j,p,q}}{\tau_{j,p,q}} \left(t_{\text{d}} - \sum_{t=1}^{t_{\text{d}}} (1-\Delta_{j,p,q}(t)) \right) \tag{11}$$

In (11), the deterioration stage $d_{j,p,q}$ can be identified by technicians based on standards (further discussed in Section VI-A).

It should be noticed that in the short-term preventive maintenance, the degradation condition of the components should also be included in the scheduling problem. That is because, if there are too many candidate maintenance actions to be performed in the current week, due to various uncertainties, limitations, and conditions, only a few time slots can be used for performing them. As not all candidate maintenance actions can be performed this week, the components more likely to become defective associated with a heavy degradation status should be maintained with a higher priority. Thus, the degradation status can help define a sort of priority to perform the maintenance actions in the short-term preventive maintenance when not all the maintenance actions can be performed. In our formulation, not only degradation but also other objectives such as costs are considered. Additionally, mid-term degradation evaluation is usually rougher, more uncertain, and dependent on a good degradation model. In the case of the degradation in the short-term, this can be more refined, for instance, if it relies on measurements conducted recently on the component. The short-term degradation factor will thus include the spatial behavior with the fact that at some locations, the degradation condition is different than in other locations. Regarding the temporal dimension, as the prediction is short-term, it is assumed that no huge changes in the dynamics of degradation are expected. If this is not the case for an application, reactive maintenance methodologies are to be considered. Furthermore,

$$C_{\text{soc},s} = \beta \sum_{b=1}^{N_{\text{b}}} \sum_{t=1}^{t_{\text{d}}} \mid S_{\text{bat},b,s}(t) - \sigma S_{\text{bat},b}^{\text{cap}} \mid \tag{12}$$

where $C_{\text{Soc},s}$ is defined to keep the SOC of all batteries of scenario s around a certain level σ, by adding penalties when the SOC is below or above this level, and the weight to assure the SOC to stay around the level σ is β.

Using the topological connectivity variables between two zones introduced in Section IV, now the power balance constraints can be derived:

$$\sum_{q=0}^{n_{\text{Z}}} \delta_{p,q}(t) P_{p,s}(t) = 0,\ \forall t \in \{1,\ldots,t_{\text{d}}\}, \quad \forall p \in \{0,\ldots,n_{\text{Z}}\},\ \forall s \in \Phi \tag{13}$$

The output power of one zone is the sum of all the output powers of all the loads, DGs, and batteries in this zone:

$$P_{p,s}(t) = \sum_{k=1}^{W_p} P_{p,k,s}(t),\ \forall t \in \{1,\ldots,t_{\text{d}}\}, \quad \forall p \in \{1,\ldots,n_{\text{Z}}\},\ \forall s \in \Phi \tag{14}$$

The power constraints of the components in the zones can be described as:

$$P_{p,k}^{\min}(t) \le P_{p,k,s}(t) \le P_{p,k}^{\max}(t),\ \forall t \in \{1,\ldots,t_{\text{d}}\}, \quad \forall p \in \{1,\ldots,n_{\text{Z}}\},\ \forall k \in \{1,\ldots,W_m\},\ \forall s \in \Phi \tag{15}$$

The constraints on the maintenance costs are as follows:

$$\frac{1}{\tau_{j,p,q}} \sum_{p=1}^{n_{\text{Z}}} \sum_{q=p+1}^{n_{\text{Z}}} \sum_{j\in\Theta_{p,q}} \Delta_{j,p,q}(t) C_{j,p,q}^{\text{D}} \le \text{C}_{\text{set}}^{\text{day}}(t),\ \forall t \in \mathcal{T}^{\text{D}},$$
$$\frac{1}{\tau_{j,p,q}} \sum_{p=1}^{n_{\text{Z}}} \sum_{q=p+1}^{n_{\text{Z}}} \sum_{j\in\Theta_{p,q}} \Delta_{j,p,q}(t) C_{j,p,q}^{\text{N}} \le \text{C}_{\text{set}}^{\text{night}}(t),\ \forall t \in \mathcal{T}^{\text{N}} \tag{16}$$

To avoid that maintenance actions are performed more than once, the total maintenance duration for each maintenance action must be zero (i.e. maintenance will not be performed at all) or it should be equal to the duration $\tau_{j,p,q}$ (i.e. maintenance will be performed, but only once). So, the following constraint is added:

$$\sum_{t=1}^{t_{\text{d}}} \Delta_{j,p,q}(t) = \tau_{j,p,q} \vee \sum_{t=1}^{t_{\text{d}}} \Delta_{j,p,q}(t) = 0 \quad \forall p,q \in \{1,\ldots,n_{\text{Z}}\},\ \forall j \in \Theta_{p,q} \tag{17}$$

In order to keep the process of performing maintenance action continuous, we have the following constraint by assuming $\Delta_{j,p,q}(0) = 0$:

$$\sum_{t=1}^{t_{\text{d}}} \mid \Delta_{j,p,q}(t) - \Delta_{j,p,q}(t-1) \mid \le 2, \quad \forall p,q \in \{1,\ldots,n_{\text{Z}}\},\ \forall j \in \Theta_{p,q} \tag{18}$$

which means that if a certain maintenance action will be performed, we can only start once (i.e. $\Delta_{j,p,q}(t-1) = 0$, $\Delta_{j,p,q}(t) = 1$) and only stop once (i.e. $\Delta_{j,p,q}(t-1) = 1$, $\Delta_{j,p,q}(t) = 0$). Furthermore, the SOC dynamic equations are:

$$S_{\text{bat},b,s}(t) = \zeta_{\text{leak}} S_{\text{bat},b,s}(t-1) + \zeta_{\text{char}} P_{\text{bat},b,s}(t), \quad \forall t \in \{1,\ldots,t_{\text{d}}\},\ \forall b \in \{1,\ldots,N_{\text{b}}\},\ \forall s \in \Phi \tag{19}$$

The remaining capacity constraints are:

$$S_{\text{bat},b}^{\min} \le S_{\text{bat},b,s}(t) \le S_{\text{bat},b}^{\max},\ \forall t \in \{1,\ldots,t_{\text{d}}\}, \quad \forall b \in \{1,\ldots,N_{\text{b}}\},\ \forall s \in \Phi \tag{20}$$

B. Scenario Generation Method and Reduction Method

In the short-term preventive maintenance problem, the uncertainties in the prediction of DG generated powers and load demands will affect the scheduling solutions. In this paper, we include the uncertainties of the DG generations and load demands in the optimization problem as scenarios related to stochastic distributions [42]. The autoregressive moving average (ARMA) model is applied to generate a scenario tree [43]. However, the number of generated scenarios will increase with the number of prediction steps, and the computational efforts might become time-prohibitive. Thus, to reduce the computational burden, a fast forward selection scenario reduction method is applied.

A classic scenario tree is shown in Fig. 5. In the figure, stages represent the prediction periods. For example, in this paper, the weekly prediction horizon is 120 hours (24 hours per day and five workdays in one week), and each stage represents 4 hours. Then, there are 30 stages in the weekly prediction horizon. Stage 0 is the current time, so the value of the variables in stage 0 is known (deterministic). Then, to predict the value of stage 1,

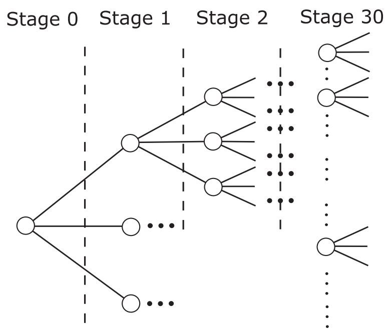


Fig. 5. Scenario generation process and scenario tree.

different scenarios are predicted and branched based on the value of stage 0. Iteratively, scenarios of each stage can be generated by the values of its related previous stage.

To generate the scenario tree of the wind speeds, solar radiations, and load demands, an ARMA model is used [44]. We define $X(k) = [X_{\mathrm{L}}(k), X_{\mathrm{W}}(k), X_{\mathrm{P}}(k)]^{\mathrm{T}}$ as the prediction error where $X_{\mathrm{L}}(k)$, $X_{\mathrm{D}}(k)$, and $X_{\mathrm{P}}(k)$ are prediction errors of the load demand, the wind speeds, and solar radiations at stage k, respectively. Then, the vector $Y(k) = [Y_{\mathrm{L}}(k), Y_{\mathrm{W}}(k), Y_{\mathrm{P}}(k)]^{\mathrm{T}}$ includes the random Gaussian variables, where $Y_{\mathrm{L}}(k)$, $Y_{\mathrm{W}}(k)$, and $Y_{\mathrm{P}}(k)$ are random Gaussian variables of the load demands, the wind speeds and solar radiations at stage k with standard deviations σ_{L}, σ_{W} and σ_{P} respectively. The general ARMA$(\mathrm{p_g}, \mathrm{q_g})$ model whose numbers of autoregressive terms and moving-average terms are $\mathrm{p_g}$ and $\mathrm{q_g}$ respectively, can be expressed as:

$$X(k) = \rho_0 + \sum_{m=1}^{\mathrm{p_g}} \rho_m X(k-m) + Y(k) + \sum_{n=1}^{\mathrm{q_g}} \varrho_n Y(k-n) \tag{21}$$

where parameters $\rho, \sigma_{\mathrm{L}}, \sigma_{\mathrm{W}}$ and σ_{P} of the Gaussian distributions can be obtained based on the historical data of the wind speeds, solar radiations, and load demands [45]. In order to branch the scenarios randomly, $Y(k)$ is sampled using the Monte-Carlo method. Then, each $X(k)$ obtained by each sampled $Y(k)$ is considered as one possible scenario at stage k.

The predictions of wind speeds, solar radiations, and demand loads are obtained by adding their averaged predicted profiles with their corresponding errors $X(k)$. The original prediction curves can be derived by data methods, e.g., regression analysis [45]. Then, the generation power of the wind turbines can be obtained by the equation below based on the wind speeds [46]:

$$p_{\mathrm{WT}} = \begin{cases} 0, & v_{\mathrm{w}} < v_{\mathrm{start}} \\ \frac{1}{2}\rho A C_{\mathrm{p}} v_{\mathrm{w}}^3, & v_{\mathrm{start}} \leq v_{\mathrm{w}} \leq v_{\mathrm{wmax}} \\ \frac{1}{2}\rho A C_{\mathrm{p}} v_{\mathrm{wmax}}^3, & v_{\mathrm{wmax}} < v_{\mathrm{w}} \leq v_{\mathrm{out}} \\ 0, & v_{\mathrm{w}} > v_{\mathrm{out}} \end{cases} \tag{22}$$

As for the PV panels, the generated powers can be obtained by [47]:

$$p_{\mathrm{PV}} = I_{\mathrm{PV}} S_{\mathrm{PV}} \eta_{\mathrm{PV}} \left(1 - \alpha_{\mathrm{PV}}(T_{\mathrm{em}} - T_{\mathrm{em}}^{\mathrm{ref}})\right) \tag{23}$$

A fixed number of scenarios per stage leads to many possible scenarios for the whole prediction horizon. For example, if ten scenarios are considered, at the 30 th stage of the scenario tree, there will be 10^{30} possible cases, which makes the scheduling problem unsolvable. Thus, we apply a fast forward selection method in [48] to reduce the number of generated scenarios. The goal is to reduce the original scenario set into a smaller one that still preserves characteristics of the original scenario set. In the fast forward selection method, at one particular stage, the preserved scenario set is generated based on minimizing the Kantorovich distances between the original scenario set distribution and the preserved scenario set distribution. The preserved scenarios are selected one by one until a maximum number of scenarios has been reached. Furthermore, the probability of one preserved scenario will be recomputed by summing its original probability and the probabilities of the deleted scenarios that are closest to this preserved scenario.

C. Two Possible Solvers

In this paper, we consider two solution strategies to solve the formulated MINLP problem. The BB solver can obtain the optimal solution, and the modified PSO solver may obtain a solution near the optimal solution but much faster than the BB solver [34]–[37], [49].

1) BB Solver: The problem formulated in Section V-A can be transformed into an MILP problem. The 'or' logic in (17), the absolute value in (12) and (18), the products between binary variables in (3) and (4), can all be exactly recast into mixed-integer linear constraints as described in [50]. Thus, the optimization problem with objective function (8) and constraints (3)–(5), (9)–(20) can be categorized as an MILP problem. In the literature, various solvers are very useful for MILP problems. For instance, the BB solver can be used to obtain the optimal solution of the MILP problem.

2) PSO Solver: Using the PSO algorithm [34]–[37], the optimization problem can be solved directly from its MINLP form. It is possible to directly handle non-linear constraints, e.g., the 'or' logic, the absolute values, or products between binary variables. That is because we just have to evaluate them when computing the objective function value and/or the constraint violations. Additionally, constraints can be converted into soft constraints via a penalty function. The PSO solver considers a population of candidate solutions (particles) and defines the dynamics of how these particles will move in the search space by updating their position and velocity. In the maintenance problem formulated in this paper, it is difficult for randomly generated particles to satisfy the many included constraints. Thus, we propose a modified PSO algorithm such that the number of constraints is substantially reduced, making it more likely to obtain feasible solutions. The scheme of the modified PSO algorithm is shown in Fig. 6.

Four main modifications are considered in the proposed PSO-based solution. The first one is to deal with (17) and (18). These two constraints are hard to be satisfied when the binary decision-making variables $\Delta_{j,p,q}(t)$ are generated randomly. That is because for $\Delta_{j,p,q}(t)$ where $t \in \{1,\ldots,t_d\}$ we have 2^{t_d} combinations of $\Delta_{j,p,q}$, but only very a little number of them satisfy (17) and (18). Thus, instead of $\Delta_{j,p,q}(t)$, we consider the variable $\widetilde{\Delta}_{j,p,q}(t), t \in \{0,\ldots,t_d\}$, which represents the starting

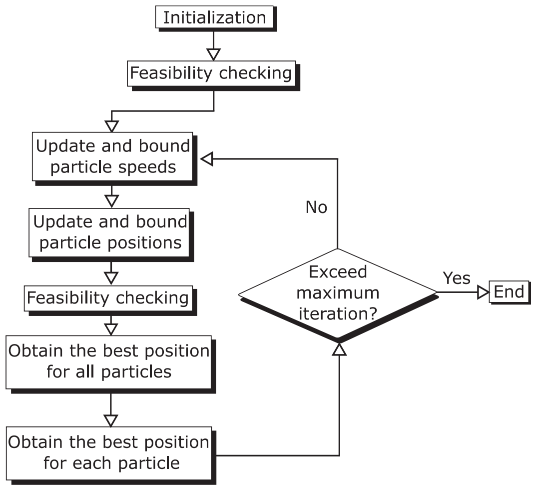


Fig. 6. Modified PSO algorithm.

time of the maintenance action. Only one component in $\widetilde{\Delta}_{j,p,q}(t)$ where $t \in \{1,\ldots,t_d\}$ will be equal to 1, and the others are set to 0. When we do not perform the maintenance action at any time slot, $\widetilde{\Delta}_{j,p,q}(0)$ will be set to 1, and other components are set to 0. For example, $\widetilde{\Delta}_{j,p,q}(5)=1$ and $\widetilde{\Delta}_{j,p,q}(t)=0$ for $t \in \{0,\ldots,t_d\}\setminus\{5\}$ represents a solution where the maintenance action $\Delta_{j,p,q}$ is performed starting at time slot 5. With $\widetilde{\Delta}_{j,p,q}$ and maintenance action durations $\tau_{j,p,q}$ is possible to calculate $\Delta_{j,p,q}$. For example, if $\widetilde{\Delta}_{j,p,q}(2)=1$ and $\tau_{j,p,q}=2$, then $\Delta_{j,p,q}$ is equal to 1 at $t=2$, $\Delta_{j,p,q}(2)=1$. As the duration is 2, then $\Delta_{j,p,q}$ is equal to 1 at $t=3$, $\Delta_{j,p,q}(3)=1$. Finally, $\Delta_{j,p,q}=0$ for all other values of t. By using this transformation strategy, the number of combinations of $\Delta_{j,p,q}$ can be reduced from 2^{t_d} to $(t_d+2-\tau_{j,p,q})$, and constraints (17) and (18) can be easily satisfied by randomly generated variables.

The second modification is to obtain intermediate variables. For example, $\delta_{p,q}(t)$ can be obtained from $\Delta_{j,p,q}(t)$ using (3), (4), and (5). Variable $P_{p,s}(t)$ can be obtained from $P_{p,k,s}(t)$ via (14). Variable $S_{\mathrm{bat},b,s}(t)$ can be obtained from $P_{\mathrm{bat},b,s}(t)$. Then, constraints (3)–(5), (14), and (19) will be satisfied automatically, and the number of variables is further reduced.

The third modification is to set the boundaries of the particles by using some of the constraints. For instance, when generating the particle position of $P_{p,k,s}(t)$, (15) can limit the particle position of $P_{p,k,s}$ within its boundary. Then (15) can be removed from the feasibility checking process.

The fourth modification is that some of the equality constraints can be included in the objective function via a penalty term weighted with considerable high value. Then these constraints can be removed from the feasibility checking process. Including the constraints (8)–(13) in the objective function results in the following:

$$J = \mathbb{E}_{\Phi}\Bigg[C_{\mathrm{loss},s} + C_{\mathrm{main}} - C_{\mathrm{deg}} + C_{\mathrm{soc},s} + \varpi \cdot \sum_{p=0}^{n_Z} \Big|\sum_{q=0}^{n_Z} \delta_{p,q}(t) P_{p,s}(t)\Big|\Bigg] \tag{24}$$

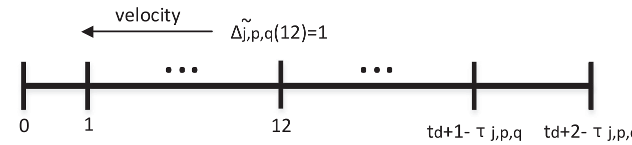


Fig. 7. Update the 1-value index.

where $\varpi \gg 1$ is a very high positive number. Finally, only the inequality constraints (16) and (20) can be violated with the randomly generated particles, resulting in a reduced number of constraints in the feasibility checking process compared to the original problem.

As for updating the particle velocity and location iteration by iteration, the variables expressed by the particles are $\widetilde{\Delta}_{j,p,q}$ and $P_{p,k,s}$. First, feasibility check is conducted for each particle. For particles that do not lead to constraint violations, the velocities and positions of $P_{p,k,s}$ can be updated according to the basic PSO algorithm such that:

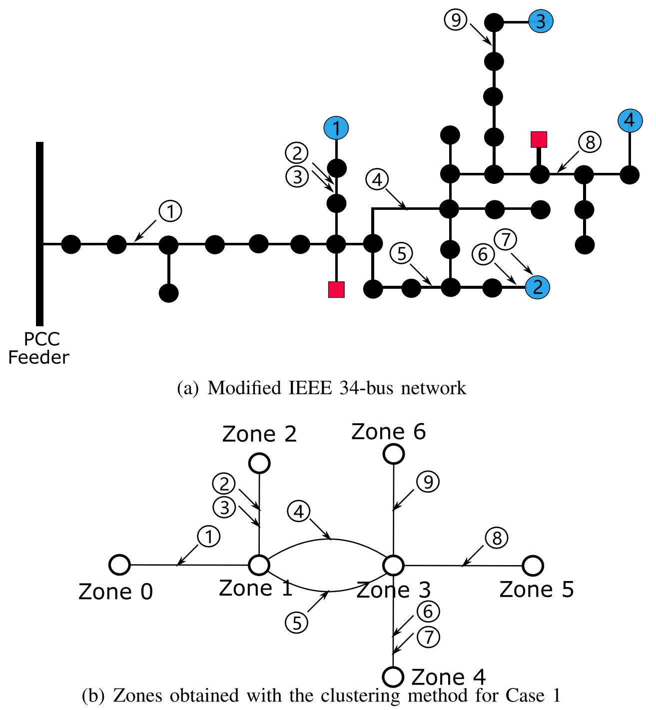
$$\begin{aligned} vP_{p,k,s}(h,g+1) &= w_{\mathrm{p}} \cdot vP_{p,k,s}(h,g) + c_{1\mathrm{p}} \cdot rand() \\ &\quad \cdot (P^{\mathrm{lbest}}_{p,k,s}(h) - P_{p,k,s}(h,g)) + c_{2\mathrm{p}} \\ &\quad \cdot Rand() \cdot (P^{\mathrm{gbest}}_{p,k,s} - P_{p,k,s}(h,g)) \end{aligned} \tag{25}$$

$$P_{p,k,s}(h,g+1) = P_{p,k,s}(h,g) + vP_{p,k,s}(h,g+1) \tag{26}$$

where $rand()$ and $Rand()$ are independent random variables, uniformly distributed between 0 and 1. Unfeasible particles are not updated, but they are also not removed from the population. In the next iteration, all particles are updated based on the feasible particles in the previous iteration. For the binary variable $\widetilde{\Delta}_{j,p,q}$, (25) and (26) cannot be applied as these are the equations of PSO for continuous variables. Thus, we use an integer/discrete strategy to update the velocity and position of $\widetilde{\Delta}_{j,p,q}$ in the next iteration directly, by introducing the 1-value index of $\widetilde{\Delta}_{j,p,q}$. By definition, among $\widetilde{\Delta}_{j,p,q}(t)$, $t \in \{0,\ldots,t_d\}$, there is only one value of t for which $\widetilde{\Delta}_{j,p,q}(t)=1$, and we define t as the 1-value index. Then the updating steps of the 1-value index of $\widetilde{\Delta}_{j,p,q}$ for the next iteration are:

1) Firstly, the 1-value index of $\widetilde{\Delta}_{j,p,q}$ is a one dimensional representation of the particle position. Then we can obtain the velocity and position of the 1-value index in the next iteration using (25) and (26). The updated variables can then be real values.
2) Secondly, we separate the interval $[0, t_d+2-\tau_{j,p,q})$ into $t_d+1-\tau_{j,p,q}$ intervals $[k_1,k_2)$ where $k_1 \in \{0,\ldots,t_d+1-\tau_{j,p,q}\}$ and $k_2=k_1+1$. If the position in the dimension of the 1-value index falls in interval $[k_1,k_2)$, then we assume the integer solution will be at the 1-value index k_1.

An example of the updating mechanism is shown in Fig. 7. In Fig. 7, at the current iteration, the 1-value index of $\widetilde{\Delta}_{j,p,q}(t)$ is 12, which represents that the particle position in the dimension of the 1-value index is 12. Just as an example, we assume that the current best 1-value index is 1, while the global best 1-value index is 3. Then the particle is updated according to (25)–(26). At the next iteration, this 1-value index moves to 7.83. So the position of the particle in the dimension of the 1-value index



(a) Modified IEEE 34-bus network

(b) Zones obtained with the clustering method for Case 1

Fig. 8. Distribution network of the case study and its simplification for Case 1.

is 7. Until now, the 1-value index moves from $t = 12$ to $t = 7$. By doing this, we can update the 1-value index of $\widetilde{\Delta}_{j,p,q}$ and equivalently update $\Delta_{j,p,q}(t)$.

VI. Case Study

The test case considers a modified version of the IEEE 34-bus distribution network [51] as shown in Fig. 8a. Compared to the IEEE 34-bus network in [51], a path is added to generate a loop topology. Furthermore, two batteries and four DGs are added into the distribution network.

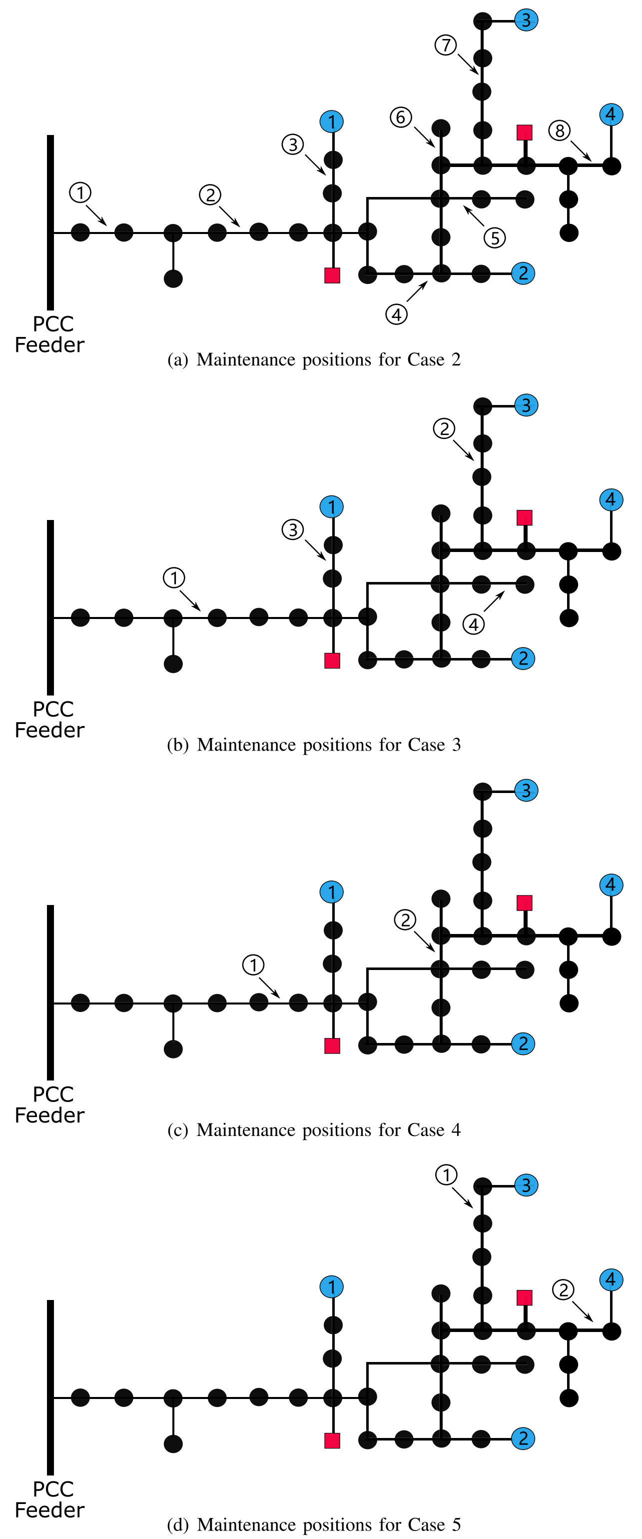
As for the candidate maintenance actions, five sets of candidate maintenance actions that have already been determined by the mid-term preventive maintenance scheduling are considered as five cases. In addition, in each case we consider scenarios with different generated powers of the DGs and different load demands that are generated by the scenario tree method and the scenario reduction method.

A comparison method that does not consider the the supporting ability of DGs and batteries in the preventive maintenance is designed to quantify the effectiveness of the proposed method. Both the proposed method and the comparison method will use the results from the clustering method, the topological constraints generation, and the scenarios generation and reduction.

Furthermore, after the comparison between the methods, the BB solver and PSO solver will be compared. Both solvers are implemented on Matlab R2020a.

A. Set-Up of the Cases

The case study networks marked with candidate maintenance actions of Case 1–5 are shown in Fig. 8a and Fig. 9, and the



(a) Maintenance positions for Case 2

(b) Maintenance positions for Case 3

(c) Maintenance positions for Case 4

(d) Maintenance positions for Case 5

Fig. 9. Distribution networks of Case 2 to Case 5.

maintenance actions are indicated with an arrow pointing to the location where they are to be performed. The numbers surrounded by circles are the labels of the maintenance actions. Here we assume that the maintenance personnel only works from Monday to Friday, which means that t_d equals to 24×5.

TABLE I
PARAMETERS OF THE CANDIDATE MAINTENANCE ACTIONS

Case	Candidate maintenance action	Performance duration (Hours)	Day-time cost ($/10 k)	Night-time cost ($/10 k)	Deterioration stage
1	①	1	1.82	2.22	34
	②	2	1.59	1.99	35
	③	3	2.76	3.36	41
	④	1	2.75	2.95	59
	⑤	1	1.91	2.11	81
	⑥	2	2.06	2.46	76
	⑦	1	2.71	2.91	62
	⑧	2	1.18	1.58	52
	⑨	3	1.46	2.06	52
2	①	2	1.11	2.02	45
	②	2	2.59	4.99	65
	③	3	1000	2.36	24
	④	3	2	3.95	81
	⑤	3	2.01	3.11	79
	⑥	2	1.76	2.54	63
	⑦	2	1.13	2.45	52
	⑧	2	1.38	2.76	48
3	①	1	1.11	4.02	36
	②	2	2	6.86	75
	③	3	1.4	1.76	64
	④	2	1.78	3.82	43
4	①	2	1.76	5.9	40
	②	2	1.89	8.2	73
5	①	2	1.76	5.9	40
	②	2	1.89	8.2	73

Because different sets of candidate maintenance actions cause different simplified network, here we only show the simplified networks of Case 1 after using the clustering method in Fig. 8b.

We assume that from the mid-term maintenance scheduling step we have obtained candidate maintenance actions as shown in Table I, where "Performance duration" is the number of time slots (hours) required to perform these maintenance actions, the column of "Day-time cost" is the cost for performing the candidate maintenance action during the day-time (8:00-18:00) while the night-time (19:00-7:00) cost is shown in the "Night-time cost" column. In Case 2, we consider a restriction that maintenance action 3 must be performed at night-time by giving the action a large day-time costs (1000 $/10 k). Other parameters, e.g. DGs and batteries parameters are the same as for Case 1. In addition, in all cases, we assume that after performing maintenance, the deterioration stage of the component will be zero (as good as new).

In Table I, "Deterioration stage" is a score from 0 to 100 to represent the deterioration level of a component that this candidate maintenance action has to be performed on. The score at a deterioration stage can be evaluated based on standards, for example, the ones of the State Grids for Chinese distribution network (Q/GDW 643-2011, Q/GDW 644-2011, and Q/GDW 645-2011). To evaluate the degradation status of a transmission line unit, the degradation statuses of the sub-components, e.g., conductors and tower structure, will be evaluated first by checking the temperature, broken strands, rustiness, etc., for conductors as well as toppling, and cracks, etc., for the tower structure. Then, the degradation status of each sub-component is multiplied by their weights and then be summed up as the degradation status of the whole transmission line unit [52].

In addition, the rated generated powers of DG1, DG2, DG3, and DG4 are 100 kW, 150 kW, 200 kW, and 150 kW respectively; their composition details are shown in Table II. We assume that these wind turbines and PV panels can operate in islanding mode. This can be realized by planning controllable DGs, e.g., small hydro generators, which can support reference voltage and frequency when in islanding mode, and by installing small capacity batteries on the DC links of the wind turbines and PV panels as indicated in [53]. Furthermore, the parameters of the batteries are listed in Table III and the initial SOCs of the batteries are all 50%.

TABLE II
COMPOSITION OF THE DGS

DG	Wind turbine (kW)	PV panel (kW)	Controllable DGs (kW)
DG1	10	20	70
DG2	30	20	100
DG3	40	40	120
DG4	10	40	100

TABLE III
PARAMETERS OF THE BATTERIES

Label	Capacity (kW.h)	Minimal/Maximal Capacity (kW.h)	Minimal/Minimal Power (kW)
1	300	45/270	-30/30
2	800	120/720	-80/80

The load demand curves for the 10 scenarios are shown in Fig. 10a. The wind turbine generated power curves are shown in Fig. 10b. The PV panel generation curves are shown in Fig. 10c and the load prices of the 34 buses are shown in Fig. 10d. In Fig. 10c, the power generated by the PV panels at night is 0 and during the day the generated power of the PV panels can slightly exceed their rated power [54]. In Fig. 10d, we adopt the electricity price data in the USA such that the industrial electricity, commercial electricity and residential electricity prices are 0.07 $, 0.1 $ and 0.13 $ per kW.h individually. Then the electricity prices of the 34 buses are the mixtures of these three different electricity prices.

The parameter α in (11) is set to be large enough to assume that all the maintenance actions obtained from the mid-term scheduling step are actually performed, e.g. $\alpha = 1$. Moreover, β and σ in (12) is set to 0.0001 and 0.5 individually to assure that the batteries can provide supporting energy to the shed loads as well as recover the SOC to the level σ when the SOC deviates from this level.

B. Comparison of Methods

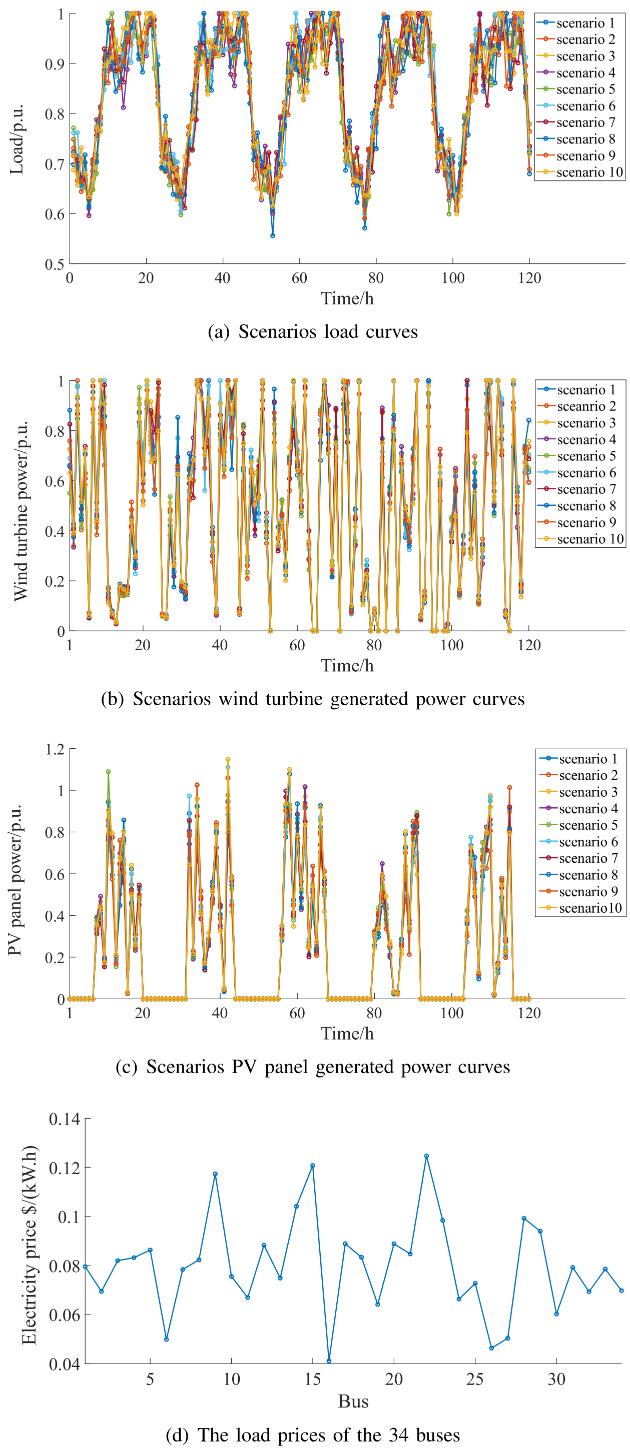
The method used for comparison does not consider the supporting energy ability of the DGs and batteries. Thus, the corresponding optimization problem can be presented as:

$$\min_{\Delta'} J' = \mathbb{E}_{\Phi}[C'_{\mathrm{loss},s} + C'_{\mathrm{cost}} + C'_{\mathrm{deg}}] \tag{27}$$

where the expressions of the terms are the same as (8)–(10). In constraints (13) and (14), the computation of the total output power of the zones omits the generation powers of the DGs and batteries in the zones, such that (14) we have:

$$P'_{p,s}(t) = \sum_{k=1}^{W'_m} P_{p,k,s}(t),$$
$$\forall t \in \{1, \ldots, t_{\mathrm{d}}\},\ \forall p \in \{0, \ldots, n_{\mathrm{Z}}\},\ \forall s \in \Phi \tag{28}$$

where W'_m is the total number of consuming components in zone p regardless of the powers of the DGs and the batteries,



(a) Scenarios load curves

(b) Scenarios wind turbine generated power curves

(c) Scenarios PV panel generated power curves

(d) The load prices of the 34 buses

Fig. 10. Scenarios curves and load price curves.

and $P'_{p,k,s}(t)$ is the power generated or consumed by the kth consuming component in zone p in time slot t of scenario s. In addition in (15), the power limitations on the components in the zones can be described as:

$$P^{\min}_{p,k}(t) \le P'_{p,k,s}(t) \le P^{\max}_{p,k}(t),\ \forall t \in \{1,\dots,t_{\mathrm{d}}\},$$
$$\forall p \in \{1,\dots,n_{\mathrm{Z}}\},\ \forall k \in \{1,\dots,W'_m\}\ \forall s \in \Phi \quad (29)$$

TABLE IV
MODIFICATIONS PROGRAMMING PROBLEM FOR COMPARISON

Constraints or objective function	Modification
(3)-(5), (9)-(11), (13), (16)-(18)	No modification
(8), (14)-(15)	Delete terms related to DGs and batteries
(12), (19)-(20)	Not included

TABLE V
MAINTENANCE ACTIONS DETAILS OF METHODS COMPARISON

Case	Candidate maintenance action	Performance time slots of the proposed method	Performance time slots of the comparison method
1	①	72	74
	②	73 - 74	73 - 74
	③	33 - 35	105 - 107
	④	9	60
	⑤	18	87
	⑥	62 - 63	83 - 84
	⑦	13	81
	⑧	108 - 109	71 - 72
	⑨	72 - 74	71 - 73
2	①	105 - 106	57 - 58
	②	105 - 106	57 - 58
	③	72 - 74	72 - 74
	④	11 - 13	107 - 109
	⑤	84 - 86	36 - 38
	⑥	81 - 82	9 - 10
	⑦	83 - 84	12 - 13
	⑧	62 - 63	36 - 37
3	①	109	57
	②	107 - 108	58 - 59
	③	107 - 109	57 - 59
	④	73 - 74	73 - 74
4	①	108 - 109	57 - 58
	②	108 - 109	57 - 58
5	①	105 - 106	9-10
	②	105 - 106	57-58

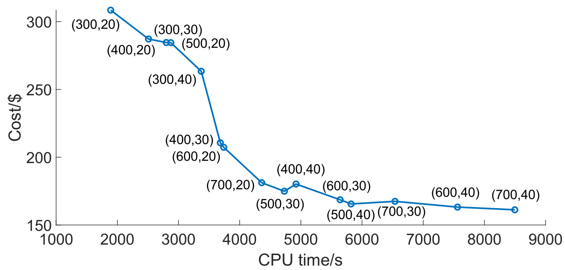
TABLE VI
LOAD LOSS COSTS OF METHOD COMPARISON

Case	Load loss costs for the proposed method ($)	Load loss costs for the comparison method ($)
1	124.8	167.87
2	454.18	533.65
3	200.49	215.13
4	227.98	247.14
5	0	0

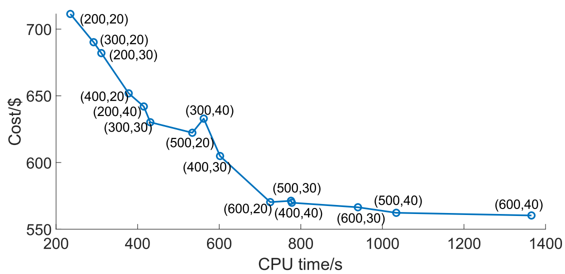
As for (19)–(20), they are not included in the comparison model. The modifications of the programming problem for comparison are shown in Table IV.

In order to find the optimal solution, the BB solver is used for the proposed method and the comparison method. The simulation results are shown in Table V and Table VI. In Table V, the details of the maintenance action performances are listed. In Table VI, the "Load loss costs for the proposed method" was calculated from the expectation of $C_{\mathrm{loss},s}$ in (8). The "Load loss costs for the comparison method" is the sum of the load loss costs in each zone while maintenance actions are performed.

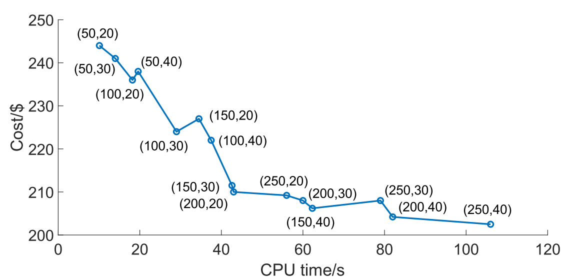
When comparing between Case 4 and Case 5, although the durations of the maintenance actions are the same, the load loss costs are different. That is because in Case 4 maintenance actions are in the main paths, and performing these maintenance actions will cause a large amount of load loss. However in Case 5, performing maintenance actions will cause no load loss because DG3 and DG4 are sufficient to support the loads isolated from the PCC while maintenance actions are performed. So the more



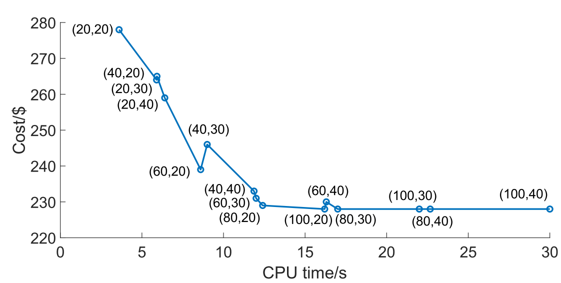
(a) PSO simulation results of Case 1



(b) PSO simulation results of Case 2



(c) PSO simulation results of Case 3



(d) PSO simulation results of Case 4

Fig. 11. PSO simulation results.

maintenance actions are on the main paths, the more load will be shed.

Furthermore, among the cases, the load loss costs of the proposed method are much lower than those obtained by the comparison method, with 35%, 17.5%, 7.3%, 8.4% load loss costs reductions in Case 1 to Case 4 individually. Thus, the proposed method can reduce the load loss costs effectively.

C. Comparison of the Solvers

In this subsection, the results of the comparison between the BB solver and the modified PSO solver will be presented and analyzed. After sensitivity analysis, we find the parameters associated with good performance are $\varpi = 500000$, $w_{\mathrm{p}} = 0.9$,

TABLE VII
COMPARISON BETWEEN THE PSO SOLVER AND THE BB SOLVER

Case	PSO solver					BB solver	
	Worst	Best	STD	AVR	Time	Cost	Time
1	248.85	130.79	33.4	174.89	4743	124.8	7563
2	646.99	489.89	66.89	570.31	725	454.18	1398
3	230.78	204.04	12.2	211.5	42.6	200.49	96
4	241.32	227.98	3.71	229	12.4	227.98	36
5	0	0	0	0	3	0	30

$c_{1\mathrm{p}} = c_{2\mathrm{p}} = 0.9$, and the velocity boundaries are ± 100. We study the influence of the number of particles and the number of iterations on the performance of the modified PSO solver, including the load loss costs and the CPU time. For each selected combination of the number of particles and the number of iterations, we run the PSO solver 10 times to obtain the average values of the load loss costs and the CPU time. The results are presented in Fig. 11. Results of Case 5 are not included in Fig. 11 because when the number of particles is 20 and the number of iterations is 20, the PSO can obtain the optimal solution in 3 s.

In Fig. 11, in the parentheses are the number of iterations and the number of particles used to obtain the data point. From Fig. 11, we can observe that when the combinations of the number of iterations and the number of particles are (500, 30), (600, 20), (200, 20), (80, 20), for Case 1 to 4 respectively, the increase of the number of iterations influences little on reducing the costs, but it results in a large increment of CPU time. We will use the combinations (500, 30), (600, 20), (200, 20), (80, 20), (20, 20) for Case 1 to 5 respectively, to compare with the BB solver. The results of the comparison are in Table VII.

In Table VII, "Worst" and "Best" are the best and worst costs among ten runs separately. "STD" represents the standard deviation, and "AVR" the average of the costs. "Time" of the PSO solver is the average CPU time of the ten runs. It can be seen from Table VIII that the modified PSO solver obtains sub-optimal solutions that deviate from the optimal solution obtained by the BB solver with 40.14%, 25.57%, 5.49%, and 0.45%, and 0% for Cases 1 to 5, respectively. However, the modified PSO solver can largely reduce the computation time with 37.29%, 48.14%, 55.63%, 65.56%, and 90% for Cases 1 to 5, respectively. Besides, the relative standard deviations of the load loss costs with respect to 19.1%, 11.73%, 5.77%, 1.62%, and 0% for Cases 1 to 5, respectively.

According to the results, when the scale of the problem becomes larger, the sub-optimal solutions obtained by the PSO solver are characterized by larger differences from the optimal solution, but the computation time reduction is significant for all the cases. Also, the standard deviations for the PSO solver are not very large, except for Case 1. However, regarding the IEEE 34-bus distribution network associated with a small number of candidate maintenance actions, e.g., below 10, the computation time for BB solver is acceptable. That is because, for weekly preventive maintenance scheduling, the decision-making time is sufficient. In this case study, the longest computing time is 7563 seconds. At the beginning of every week, the system operator can use 2-3 hours to solve the proposed short-term preventive maintenance scheduling problem using the BB solver. In this case, the BB solver is better than the PSO solver. In settings where less time is available for decision making, larger networks, and more maintenance activities, PSO will provide a sub-optimal solution within the time limitations.

VII. Discussions

The proposed short-term preventive maintenance scheduling method is evaluated in five cases to schedule the maintenance actions to their optimal time slots. In these cases, different numbers of candidate maintenance actions with different locations, different durations, and different costs are considered. In all the cases, load losses can be caused when performing maintenance actions. The proposed method can reduce the load loss costs from 7.3% to 35% when the supporting power potential of the DGs and batteries is considered. The proposed short-term preventive maintenance method can be used by the power system operator to reduce the influence of the load shedding when performing maintenance actions.

Furthermore, a comparison between two different solvers is performed and the results are analyzed. The BB solver can obtain the optimal global solution, but the computation time is higher due to the number of equations and variables included when the exact reformulation of the original problem is constructed. With the modified PSO solver, sub-optimal solutions are obtained, but the computation time can be reduced. In addition, the evaluation of the cost function for each particle in PSO can be performed in a fully parallel way. That would make the computation time of PSO even more competitive. The power system operator should define the right trade-off between accuracy and computation time when selecting the right solver for the application. When the problem is solved for small-scale or medium-scale networks, e.g., the IEEE 34-bus network used in the case study, the computation time of the BB solver can be acceptable. However, when the topology of the distribution network is much more complex, and when there are many candidate maintenance actions, e.g., above ten candidate maintenance actions for the IEEE 34-bus network, the modified PSO might become a better choice.

In this study, the DGs can support energy to the loads, particularly when they are part of a dynamically formed microgrid functioning in islanding mode. An interesting further study would be to consider how to reduce the influence of the switching between the islanding mode and the connected mode on the power system stability. When the DGs are connected to the power systems by inverters, this will require to include aspects of power electronics, and for instance, to improve the performance of the controllers. This can be done by installing communication devices in the network, so that a synchronized or coordinated control can be realized. Other control frameworks proposed in the literature can be tested, such as the hierarchical droop-based control of [55].

In the case study settings of this paper, we have assumed that there are controllable DGs and enough capacity batteries on the DC links of the wind turbines and PV panels. However, in some networks, this assumption might not hold. Then, additional constraints have to be included in the optimization problem. For instance, consider a distribution network containing any number of loads, one DG whose zone label is d, one PCC whose zone label is 0, and one battery whose zone label is b. The actual generated power of the DG is $P_d(t)$, and the rated generated power of the DG is $P_{\mathrm{DG}}(t)$. Then if we consider that the DGs can only operate when they are connected to the battery or PCC or both of them, the following additional constraint is required:

$$P_d(t) = P_{\mathrm{DG}}(t)\,(1 - (1 - \delta_{d,0}(t))(1 - \delta_{d,b}(t)))$$

where $\delta_{d,0}(t)$ and $\delta_{d,b}(t)$ are the connecting statuses from the distributed generator to the PCC and to the battery at time step t. Then, if the distributed generator is neither connected to the PCC nor the battery, the value of $P_d(t)$ will be zero which means that no power is generated by the distributed generator.

In addition, the proposed approach is not limited to the use of the topological connectivity constraints to formulate the problem as shown in this paper, but it can also consider constraints based on power balance rules or others.

VIII. Conclusion

This paper has proposed a short-term preventive scheduling method for power systems to reduce the load loss costs when performing maintenance actions. The power supporting potential of DGs and batteries when performing maintenance actions in the distribution network can be systematically optimized with the proposed method. A DFS clustering method has been proposed to reduce the computational complexity of the short-term based scheduling problem. To be able to express the power balance equations in case of maintenance actions being performed, topological connectivity constraints are generated and used to define the corresponding maintenance action connectivity variables, which are then used to write down in the power balance equations. In addition, the scenarios generated by the scenario generation and reduction methods are considered to express the uncertainties of the generation powers of the DGs. The simulation results show the effectiveness and improvement of this method and its capacity to reduce the load loss costs during maintenance. In addition, for the IEEE 34-bus network with a small number of candidate maintenance actions, the BB solver is better than the PSO solver. As for the future work, the control strategy of the DGs, e.g., hierarchical droop-based control, will be considered so that the formed microgrids during maintenance can operate more in a more stable condition. Another topic of further research is the inclusion of transient stages in the formulation, particularly when the system switches from one configuration to another. Moreover, an approach based on Bayes theorem maybe be used for short-term preventive maintenance scheduling.

References

[1] G. Corbetta, A. Mbistrova, A. Ho, I. Pineda, and K. Ruby, “Wind in power: 2015 European statistics,” European Wind Energy Association, Brussels, 2016.

[2] L. Ziegler, E. Gonzalez, T. Rubert, U. Smolka, and J. J. Melero, “Lifetime extension of onshore wind turbines: A review covering Germany, Spain, Denmark, and the UK,” *Renew. Sustain. Energy Rev.*, vol. 82, pp. 1261–1271, 2018.

[3] K. Zhou, Q. Xiong, W. Zhao, W. Wen, and W. Tao, "Electrical properties and micro-structures of water-tree aged XLPE cables after siloxane fluid injection," *High Voltage Eng.*, vol. 41, no. 8, pp. 2657–2664, 2015.

[4] Y. Zhang, D. Liu, J. Wu, and Y. Yin, "A modified algorithm for the simulation of charge behavior in water tree aged cross-linked polyethylene cable," *IEEE Access*, vol. 6, pp. 23 929–23 938, 2018.

[5] J. I. Aizpurua, S. D. McArthur, B. G. Stewart, B. Lambert, J. G. Cross, and V. M. Catterson, "Adaptive power transformer lifetime predictions through machine learning and uncertainty modeling in nuclear power plants," *IEEE Trans. Ind. Electron.*, vol. 66, no. 6, pp. 4726–4737, Jun. 2019.

[6] N. Hashemnia, A. Abu-Siada, and S. Islam, "Detection of power transformer bushing faults and oil degradation using frequency response analysis," *IEEE Trans. Dielect. Elect. Insul.*, vol. 23, no. 1, pp. 222–229, Feb. 2016.

[7] O. Tor and M. Shahidehpour, "Power distribution asset management," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jun. 2006, pp. 1–6.

[8] A. Arif, Z. Wang, J. Wang, and C. Chen, "Power distribution system outage management with co-optimization of repairs, reconfiguration, and DG dispatch," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4109–4118, Sep. 2018.

[9] M. Mahdavi, H. Monsef, and R. Romero, "Reliability effects of maintenance on TNEP considering preventive and corrective repairs," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3768–3781, Sep. 2017.

[10] A. Abiri-Jahromi, M. Fotuhi-Firuzabad, and M. Parvania, "Optimized midterm preventive maintenance outage scheduling of thermal generating units," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1354–1365, Aug. 2012.

[11] B. Wang, X. Wang, Z. Bie, P. D. Judge, X. Wang, and T. C. Green, "Reliability model of MMC considering periodic preventive maintenance," *IEEE Trans. Power Del.*, vol. 32, no. 3, pp. 1535–1544, Jun. 2017.

[12] P. Bangalore and L. B. Tjernberg, "An artificial neural network approach for early fault detection of gearbox bearings," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 980–987, 2015.

[13] A. Petcu and B. Faltings, "Distributed generator maintenance scheduling," in *Proc. First Int. ICSC Symp. Artif. Intell. Energy Syst. Power: AIESP'06*, 2006, pp. 647–652.

[14] I. Kuzle, H. Pandžić, and M. Brezovec, "Hydro generating units maintenance scheduling using benders decomposition," *Tehnički Vjesnik*, vol. 17, no. 2, pp. 145–152, 2010.

[15] H. Pandzic, A. J. Conejo, and I. Kuzle, "An EPEC approach to the yearly maintenance scheduling of generating units," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 922–930, May 2013.

[16] O. Sadeghian, A. M. Shotorbani, and B. Mohammadi-Ivatloo, "Generation maintenance scheduling in virtual power plants," *IET Gener. Transmiss., Distrib.*, vol. 13, no. 12, pp. 2584–2596, 2019.

[17] M. S. Alvarez-Alvarado and D. Jayaweera, "Reliability-based smart-maintenance model for power system generators," *IET Gener. Transmiss., Distrib.*, vol. 14, no. 9, pp. 1770–1780, 2020.

[18] J. Hu and P. Chen, "Predictive maintenance of systems subject to hard failure based on proportional hazards model," *Reliab. Eng. Syst. Saf.*, vol. 196, 2020, Art. no. 106707.

[19] M. S. Alvarez-Alvarado and D. Jayaweera, "Operational risk assessment with smart maintenance of power generators," *Int. J. Electr. Power Energy Syst.*, vol. 117, 2020, Art. no. 105671.

[20] D. Bumblauskas, D. Gemmill, A. Igou, and J. Anzengruber, "Smart maintenance decision support systems (SMDSS) based on corporate big data analytics," *Expert Syst. Appl.*, vol. 90, pp. 303–317, 2017.

[21] A. Ali, D. Raisz, and K. Mahmoud, "Voltage fluctuation smoothing in distribution systems with RES considering degradation and charging plan of EV batteries," *Electr. Power Syst. Res.*, vol. 176, 2019, Art. no. 105933.

[22] M. S. Alvarez-Alvarado and D. Jayaweera, "Bathtub curve as a Markovian process to describe the reliability of repairable components," *IET Gener. Transmiss., Distrib.*, vol. 12, no. 21, pp. 5683–5689, 2018.

[23] J. Zhao, S. Si, and Z. Cai, "A multi-objective reliability optimization for reconfigurable systems considering components degradation," *Reliab. Eng. Syst. Saf.*, vol. 183, pp. 104–115, 2019.

[24] Production technology department of State Grid Corporation of China, *The Guide of Condition-Based Maintenance for Distribution Network Equipment*. China Electric Power Press, 2011.

[25] A. Abiri-Jahromi, M. Fotuhi-Firuzabad, and E. Abbasi, "An efficient mixed-integer linear formulation for long-term overhead lines maintenance scheduling in power distribution systems," *IEEE Trans. Power Del.*, vol. 24, no. 4, pp. 2043–2053, Oct. 2009.

[26] P. Dehghanian, M. Fotuhi-Firuzabad, F. Aminifar, and R. Billinton, "A comprehensive scheme for reliability centered maintenance in power distribution systems—Part i: Methodology," *IEEE Trans. Power Del.*, vol. 28, no. 2, pp. 761–770, Apr. 2013.

[27] D. Zhang, W. Li, and X. Xiong, "Overhead line preventive maintenance strategy based on condition monitoring and system reliability assessment," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1839–1846, Jul. 2014.

[28] S. Behzadirafi and H. Salehfar, "Preventive maintenance scheduling based on short circuit and overload currents," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1740–1747, Jul. 2015.

[29] H. Mirsaeedi, A. Fereidunian, S. M. Mohammadi-Hosseininejad, P. Dehghanian, and H. Lesani, "Long-term maintenance scheduling and budgeting in electricity distribution systems equipped with automatic switches," *IEEE Trans. Ind. Inform.*, vol. 14, no. 5, pp. 1909–1919, May 2018.

[30] S. Pei-feng *et al.*, "Research on maintenance schedule optimization of distribution network including distributed generation," in *Proc. China Int. Conf. Electr. Distrib.*, 2016, pp. 1–5.

[31] A. Arif, S. Ma, Z. Wang, J. Wang, S. M. Ryan, and C. Chen, "Optimizing service restoration in distribution systems with uncertain repair time and demand," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6828–6838, Nov. 2018.

[32] K. Chen, W. Wu, B. Zhang, and H. Sun, "Robust restoration decision-making model for distribution networks based on information gap decision theory," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 587–597, Mar. 2015.

[33] D. Bernardon, A. Mello, and L. Pfitscher, *Real-Time Reconfiguration of Distribution Network With Distributed Generation*, 2016. [Online]. Available: https://www.intechopen.com/citation-pdf-url/50636

[34] A. K. Kaviani, H. R. Baghaee, and G. H. Riahy, "Optimal sizing of a stand-alone wind/photovoltaic generation unit using particle swarm optimization," *Simulation*, vol. 85, no. 2, pp. 89–99, 2009.

[35] H. Baghaee, M. Mirsalim, G. Gharehpetian, and H. Talebi, "Reliability/cost-based multi-objective pareto optimal design of stand-alone wind/PV/FC generation microgrid system," *Energy*, vol. 115, pp. 1022–1041, 2016.

[36] H. R. Baghaee, M. Mirsalim, G. B. Gharehpetian, and A. K. Kaviani, "Security/cost-based optimal allocation of multi-type facts devices using multi-objective particle swarm optimization," *Simulation*, vol. 88, no. 8, pp. 999–1010, 2012.

[37] H. R. Baghaee, M. Mirsalim, G. B. Gharehpetian, and H. A. Talebi, "MOPSO/FDMT-based pareto-optimal solution for coordination of overcurrent relays in interconnected networks and multi-DER microgrids," *IET Gener. Transmiss., Distrib.*, vol. 12, no. 12, pp. 2871–2886, 2018.

[38] B. Awerbuch, "A new distributed depth-first-search algorithm," *Inf. Process. Lett.*, vol. 20, no. 3, pp. 147–150.

[39] R. Van Katwijk, B. De Schutter, and J. Hellendoorn, "Traffic adaptive control of a single intersection: A taxonomy of approaches," in *Proc. 11th IFAC Symp. Control Transp. Syst.* Citeseer, 2006, pp. 227–232.

[40] R. Tarjan, "Depth-first search and linear graph algorithms," *SIAM J. Comput.*, vol. 1, no. 2, pp. 146–160, 1972.

[41] M. Migliore, V. Martorana, and F. Sciortino, "An algorithm to find all paths between two nodes in a graph," *J. Comput. Phys.*, vol. 87, no. 1, pp. 231–236, 1990.

[42] J. Fu, G. Song, and B. De Schutter, "Influence of measurement uncertainty on parameter estimation and fault location for transmission lines," *IEEE Trans. Autom. Sci. Eng.*, vol. 18, no. 1, pp. 337–345, Jan. 2021.

[43] R. Barth, P. Meibom, and C. Weber, "Simulation of short-term forecasts of wind and load for a stochastic scheduling model," in *Proc. IEEE Power Energy Soc. Gen. Meeting*., 2011, pp. 1–8.

[44] J. Zhang and C. Wang, "Application of arma model in ultra-short term prediction of wind power," in *Proc. Int. Conf. Comput. Sci. Appl.*, 2013, pp. 361–364.

[45] M. Jacob, C. Neves, and D. Vukadinović Greetham, *Short Term Load Forecasting*. Cham: Springer International Publishing, 2020, pp. 15–37. [Online]. Available: https://doi.org/10.1007/978-3-030-28669-9_2

[46] J. Fu, G. Song, and Y. Gong, "Exploration of a DC wind farm integrated by variable-speed squirrel cage induction generator (SCIGs)," *J. Eng.*, vol. 2017, no. 13, pp. 1488–1493, 2017.

[47] D. Song, "Research on generating power forecasting of grid-connected PV power plant," Master's Thesis, Liaoning Univ. Technol., 2016.

[48] S. Park, Q. Xu, and B. F. Hobbs, "Comparing scenario reduction methods for stochastic transmission planning," *IET Gener. Transmiss., Distrib.*, vol. 13, no. 7, pp. 1005–1013, Apr. 2019.

[49] A. Parizad and K. Hatziadoniu, "Security/stability-based pareto optimal solution for distribution networks planning implementing NSGAII/FDMT," *Energy*, vol. 192, 2020, Art. no. 116644.
[50] A. Bemporad and M. Morari, "Control of systems integrating logic, dynamics, and constraints," *Automatica*, vol. 35, no. 3, pp. 407–427, 1999.
[51] IEEE PES Power System Analysis, Computing, and Economics Committee, "IEEE 34 node test feeder," Sep. 2010, [Online]. Available: http://ewh.ieee.org/soc/pes/dsacom/testfeeders/feeder34.zip
[52] Y. Tang, "Research on condition maintenance decision of distribution network," Master's Thesis, North China Electric Power Univ., 2014.
[53] J. P. Lopes, C. Moreira, and A. Madureira, "Defining control strategies for microgrids islanded operation," *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 916–924, May 2006.
[54] G. Wang, M. Ciobotaru, and V. G. Agelidis, "Power smoothing of large solar PV plant using hybrid energy storage," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 834–842, Jul. 2014.
[55] H. R. Baghaee, M. Mirsalim, and G. B. Gharehpetian, "Performance improvement of multi-der microgrid for small- and large-signal disturbances and nonlinear loads: Novel complementary control loop and fuzzy controller in a hierarchical droop-based control scheme," *IEEE Syst. J.*, vol. 12, no. 1, pp. 444–451, 2018.

Jianfeng Fu received the B.Sc. degree from Northeast Electric Power University and the M.Sc. degree from Xi'an Jiaotong University. He is currently the Ph.D. Candidate with the Delft University of Technology. His research field is operations research in power system.

Alfredo Núñez (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from the University of Chile, Santiago, Chile, in 2010. He is an Assistant Professor in the field of data-based maintenance for railway infrastructure with the Section of Railway Engineering, Department of Engineering Structures, Delft University of Technology in The Netherlands. He was a Postdoctoral Researcher with the Delft Center for Systems and Control. He has authored or coauthored more than a hundred international journal and international conference papers. He is in the Editorial Board of the journals IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS AND APPLIED SOFT COMPUTING. His current research interests include railway infrastructures, intelligent conditioning monitoring and maintenance of engineering structures, computational intelligence, big data, risk analysis, and optimization.

Bart De Schutter (Fellow, IEEE) is a Full Professor with the Delft Center for Systems and Control, Delft University of Technology, Delft, The Netherlands. He is a Senior Editor of the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS. His current research interests include intelligent transportation, infrastructure and power systems, hybrid systems, and multi-level control.