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Evaluation of Annual Energy Loss Reduction Based on Reconfiguration Scheduling

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***Abstract*—In distribution network management, switch reconfiguration is an important tool for reducing energy loss. Recently, a variety of annual reconfiguration planning methods considering energy loss have been studied. However, no conventional methods address the reconfiguration periods in fine granularity. Practically, switch durability does not support high-frequency switching. Therefore, this paper proposes a new optimization method for annual reconfiguration scheduling. This method determines switch configurations and their reconfiguration periods with a constraint on the permissible reconfiguration times. In addition, this paper reveals the annual energy loss reduction effect of this optimization. Our method is based on partial network optimization with exhaustive enumeration of all feasible configurations. Experiments were conducted using a standard Japanese distribution network model with 468 switches. The results show that optimizing the reconfiguration periods reduces energy loss by up to 2.1 times, relative to that in a simulated conventional operation, which considers reconfiguration at equal intervals. We believe that this is the first quantitative report to address the difference between optimal reconfiguration scheduling and conventional reconfiguration.**

***Index Terms*—Distribution network, energy loss, network reconfiguration, zero-suppressed binary decision diagram (ZDD).**

NOMENCLATURE

m	Number of unit periods.
n	Number of switches.
$\overline{k}$	Number of reconfigurations permitted in one year.
T	Number of load profile snapshots in one year.
J	Set of unit periods.
S	$\subseteq J - \{1\}$. Set of reconfiguration periods.
J_k	$\subseteq J$. Consecutive periods between k-th and $k+1$-th reconfigurations given by reconfiguration periods S.
$\mathcal{J}$	Set of possible operation periods.
C	Set of component numbers.
M	Set of switches.
M_c	$\subseteq M$. Set of switches in component c.
X_k	$\subseteq M$. Configuration (set of closed switches) of k-th operation period.
$\mathcal{X}$	Set of feasible configurations.
$\mathcal{X}^{\mathrm{topol}}$	Set of topologically-feasible configurations in a whole network.
$\mathcal{X}^{\mathrm{elec}}$	Set of electrically-feasible configurations in a whole network.
$\mathcal{X}_c$	Set of component-wise feasible configurations of component c.
A_c	Energy loss matrix of component c.
P_ℓ	ℓ-th subproblem in branch-and-bound algorithm.
S_ℓ	Set of reconfiguration periods fixed through branching operations for subproblem P_ℓ.
U_ℓ	Set of unfixed periods for subproblem P_ℓ.
$\mathcal{S}_\ell$	Family of sets of possible reconfiguration periods for subproblem P_ℓ.
$\mathcal{U}_\ell$	Family of sets of unfixed periods for subproblem P_ℓ.
$\hat{\bullet}$	Output variable of algorithms.

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I. INTRODUCTION

DISTRIBUTION networks consist of feeders and switches connected to each other. The topology of distribution, which can be represented as a set of on/off states of the switches, is configured to satisfy system constraints including radial structure and permissible ranges of voltage and current. Changing the network topology will change the line current, and thereby resistive line loss will also change.

Many studies have focused on minimizing *power* loss [1]–[13], which is defined at a specific moment in the load profile. Many related works on power loss minimization [2]–[7], [9], [11] relied on methods that did not provide any guaranteed solutions, such as heuristics or metaheuristics. However, Inoue *et al.* [13] recently proposed a method based on exhaustive enumerating of all feasible configurations with a highly compressed data structure, called the zero-suppressed binary decision diagram (ZDD). Using this method, they successfully obtained configurations in which the errors associated with loss optimization relative to the global optimal lie within a guaranteed range. However, because of the time-dependent nature of the load, the optimal configuration also changes with time. Thus, the optimal configuration derived from a snapshot of the load profile does not guarantee the optimality in another period of time.

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Therefore, we have to consider the *energy* loss, which is defined as the integrated value of power loss. Ingeniously, if switch states can be configured according to demand, optimality may be guaranteed by using conventional snapshot-based minimization methods. In fact, recent penetration of the smart grid technology allows instant change of configurations. However, we cannot select this approach, because such numerous switching operations would incur excessive cost. Actually, many power companies conventionally adopt naive planning; they periodically select a configuration from a fixed set of configuration candidates for each season [14], [15]. From this perspective, annual reconfiguration planning that minimizes annual energy loss has previously been studied [14], [16], [17]. To the best of our knowledge, Chen *et al.* first proposed the idea of operation planning to minimize annual energy loss [14]. Their methods assume seasonal basis reconfiguration and select the optimal configuration for each season. However, they did not consider the reconfiguration periods, when the network reconfigures. Shinh-An Yin *et al.* [16] and Shariatkhah *et al.* [17] proposed a scheduling method to specify the reconfiguration periods in addition to optimizing the configurations. The objective function is the total cost of annual energy loss, customer interruption, and switching costs.

Besides the high operational cost for reconfiguration described above, practically, we have to deal with the physical constraints of the number of reconfigurations. For example, the operating lifetimes of air and vacuum switches, which are used as sectionalizing switches, are approximately two hundred times operations [18]. It has also been reported that frequent reconfigurations such as those performed hourly [19], [20] may generate overvoltage transients [21]. Given these conditions, it would be reasonable to allow only a few reconfigurations within one year. Since conventional methods do not explicitly treat the reconfiguration periods as variables in the optimization problem, the solutions obtained by these methods may lead to extremely frequent reconfigurations. Of course, we avoid such a situation by making the switching cost high. However, doing so may produce an optimal solution with much fewer reconfigurations, such as operation planning without reconfiguration throughout the year. Moreover, there are no quantitative reports in the literature regarding the energy loss reduction through optimization of the reconfiguration periods. Thus, we have to limit the number of reconfigurations permitted in one year. By considering the above conditions, we can assume that the number of reconfigurations permitted in one year would be up to a few times.

Therefore, in this paper, we treat the annual energy loss minimization according to the permissible number of reconfigurations, and report on the energy loss reduction by optimizing the reconfiguration periods. More specifically, we propose a method for optimizing the reconfiguration scheduling to follow the state-of-the-art snapshot optimization method that exploits the ZDD [13]. Although the method derives a near global optimum solution for the power loss minimization problem, we cannot apply it naively to the energy loss minimization problem, because the optimization problem consists of two types of computationally difficult problems: (1) The possible

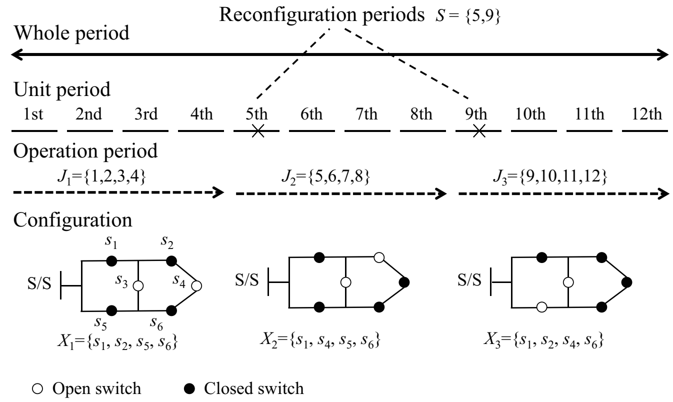

Fig. 1. Example of a reconfiguration scheduling on $n = 12$. The whole period consists of 12 unit periods. The reconfiguration periods S determine the operation periods $\{J_k\}$. Each reconfiguration period j of the set S partitions consecutive periods $\{\ldots, j-1, j, \ldots\}$ into two subsets $\{\ldots, j-1\}, \{j, \ldots\}$. The configurations are assigned to each operation period.

solution space for finding the loss-minimum configuration increases exponentially with the number of switches. (2) The optimization problem involves the problem of determining the reconfiguration period, the complexity of which grows exponentially with the number of annual periods (e.g., 53 weeks or 365 days) and the permissible number of reconfigurations within the year.

Our method overcomes the above difficulties as follows: As for (1), we consider dividing the network into small components with their mutual dependences being theoretically bounded, which is introduced in [13] and the similar idea is introduce in [22]. We focus on the fact that if a joint of optimal configurations inside each component is feasible, it is also optimal for the whole network. Only when it is not feasible, our method falls back to the conventional method. As for (2), we introduced a branch-and-bound (B&B) style algorithm that can reduce the computational cost. This employs a bounding criterion that estimates the lower bound of annual energy loss using the estimated maximal improvement of energy loss according to reconfiguration periods.

The rest of this paper is organized as follows. Section II formulates the problem to minimize annual energy loss. Section III introduces a feature of ZDD. Section IV describes outlines of proposed method. Section V introduces the method to calculate optimal configurations for all operation periods. Section VI describes the optimization process of reconfiguration periods using the B&B algorithm. Section VII discusses our experiments and results. Finally, Section VIII summarizes this paper.

II. Annual Energy Loss Minimization Problem

A typical distribution network contains several line sections, which are surrounded by switches, junctions, or feeding points. For each section, we assume that a load is assigned according to an hourly load curve, which provides sufficient time for an accurate energy loss analysis [23]. Each section load is uniformly distributed on the line section as a constant current load [6]. We also assume that the permissible reconfiguration time $\overline{k}$ in a year is given.

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Let S be a set of reconfiguration periods that is a subset of given annual set of unit periods (daily or weekly n periods) $J = \{1, \ldots, n\}$. Periods in S partition a year J into consecutive periods $\{J_k\}$ where $k \in \{1, \ldots, |S|+1\}$, each of which is called an operation period. Given all switches in a distribution network $M = \{s_1, \ldots, s_m\}$, the configuration of the k-th operation period is expressed as a set of closed switches $X_k \subseteq M$. Fig. 1 shows a diagrammatic representation of the symbols for clarification.

In distribution networks, the configuration of each operation period must satisfy the topological and electrical constraints. Regarding the topological constraint, the configuration forms a radial structure without any loops in any feeders, and each section is connected to only one feeding point. There are two electrical constraints: First, the line current of each section must lie within a permissible range. Second, the voltage drop of the section must lie within the voltage range. This paper defines an operational constraint to satisfy the topological and electrical constraints for hourly loads in a year.

The annual energy loss minimization problem is defined as follows:

$$\min_{S,\{X_k\}} f(S, \{X_k\} : J) = \sum_{k=1}^{|S|+1} \sum_{j \in J_k} Loss_j(X_k), \quad (1)$$

subject to

$$S \in \{S \subseteq J - \{1\} : |S| \leq \overline{k}\}, \quad (2)$$

$$X_k \in \mathcal{X}, \mathcal{X} = \{X \subseteq M : IsFeasible(X)\}, \quad (3)$$

where $Loss_j(X_k)$ is the energy loss in the configuration X_k over the period j. It is calculated as the total power loss in each hour t over the period j. The constraints (2) and (3) indicate the reconfiguration time constraint and operational constraint, respectively.

III. Zero-suppressed binary decision diagram

This section briefly describes the ZDD. The ZDD is a data structure that stores a set of combinations compactly [24]. Conceptually, a ZDD is represented as a form of a directed acyclic graph (DAG). It consists of one root node, internal nodes, and sink nodes. Each internal node is associated with a binary variable and has two out edges, a 0-edge and a 1-edge, which corresponds to off and on states of the switch, respectively. Each path from the root node to the top sink represents a set of combination. For example, the ZDD depicted in Fig 2 (a) represents a set of combinations $\{\{s_1, s_2\}, \{s_2, s_3\}, \{s_3, s_4\}, \{s_2, s_3, s_4\}\}$. A remarkable features of the ZDD is that certain types of set operations can be calculated over two ZDDs without decompressing the holding combinations. In this paper, the ZDD is used for the following three objectives:

(1) The enumeration of feasible configurations as whole network (Section V-B).
(2) The enumeration of feasible configurations as partial area of the network (Section V-B).
(3) The feasibility check of the joint configuration (Section V-D).

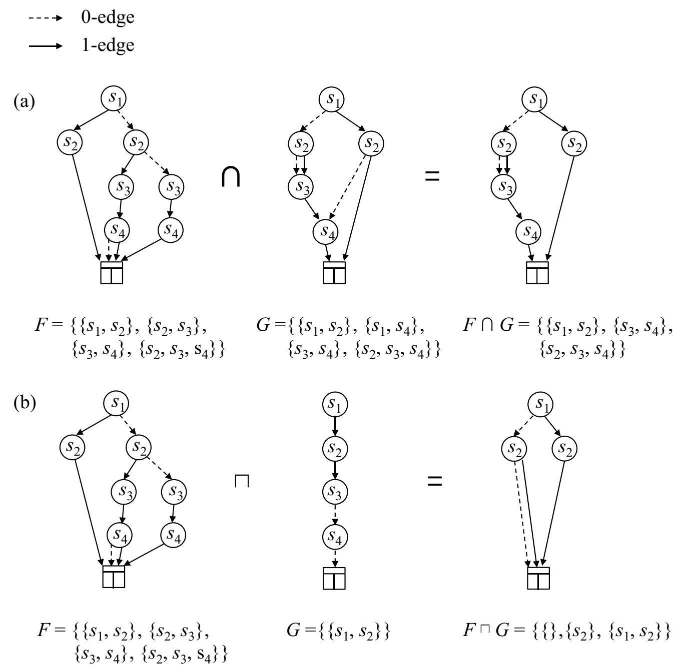

Fig. 2. Example of (a) intersection operation and (b) meet operation on ZDD. Each diagram shows a ZDD, and $\top$ indicates the top sink node. Each ZDD represents the set of combinations below the ZDD.

As for the first and second objectives, two binary operations of the ZDD are used; *intersection* operation [24] and *meet* operation [25]. Given sets of combinations F and G, the intersection operation returns $F \cap G$ (Fig. 2 (a)). The meet operation returns the following set of combinations (Fig. 2 (b)):

$$F \sqcap G = \{\alpha \cap \beta \ : \ \alpha \in F, \beta \in G\}. \quad (4)$$

As for the third objective, membership query [24] is used for confirming whether the ZDD contains a given set of switches.

IV. Outline of the Proposed Method

In this section, we show the outline of the proposed method. Before we outline our method, we briefly describe the snapshot optimization method we followed [13]. Its goal is finding the loss minimum configuration for a given snapshot of the load profile and they successfully obtained configurations in which the errors associated with obtained value relative to the global optimal lie within a guaranteed range. They introduced a technique that divides the network into small components with their mutual dependences being theoretically bounded. More formally, they represent a distribution network as an undirected graph where vertices are feeding points, switches or junctions and their edges are sections. By using this graph, a component is defined as one of the maximal connected subgraphs when feeding points, root sections and first junctions are removed from a distribution network (Fig. 4).

The proposed method consists of two steps. Fig. 3 shows a flowchart of the whole proposed method.

The first step obtains optimal configurations for all possible operation periods. The goal of this step is calculating the results of conventional snapshot optimization method for

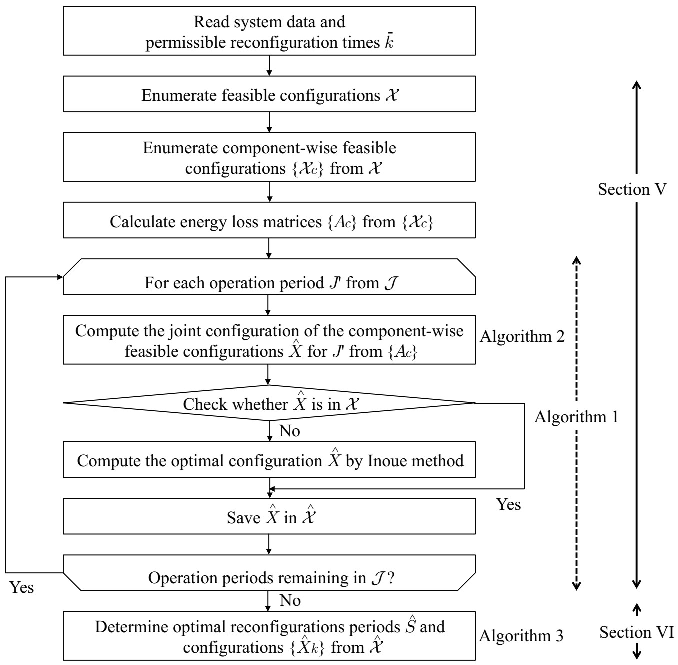

Fig. 3. Flowchart of proposed method.

every time period. This step first enumerates all network-wise feasible configurations and component-wise feasible configurations. Then, it calculates energy losses for each component-wise feasible configuration for each time period and stores it as a form of matrix called energy loss matrix. By using this energy loss matrix, we get optimal configurations for all possible operation periods. We describe this step in detail in Section V.

In the second step, our method determines the optimal reconfiguration periods and their configurations by combining the optimal configurations for all possible operation periods obtained in the above step. Here we also have a computational challenge because the solution space grows exponentially with the number of periods and the permissible number of reconfigurations. Thus, we introduce a branch and bound style algorithm. We describe this step in detail in Section VI.

V. Computation of Optimal Configurations for All Possible Operation Periods

A. Overview

The goal of this section is obtaining the equivalent results of the conventional snapshot base optimization for every time period. However, for n unit periods, the number of periods becomes n^2; thus, calculating for all possible periods using the method is difficult. To reduce the computational cost, we also divide the calculation into components as well as conventional methods. In addition, we further exploit the characteristic of the component. Specifically, we focus on the fact that if a joint of optimal configurations inside each component is feasible, it is also optimal for the whole network.

We define a component-wise configuration as a set of on states of switches in a component. If a component-wise configuration satisfies the operational constraint, i.e., electrical constraints and radiality within the component, it is regarded as a component-wise feasible configuration. A component has two important features:

(1) Since each component usually has a small number of switches, the number of component-wise feasible configurations is significantly smaller than the number of feasible configurations in the whole network.
(2) The whole-network optimization problem can be regarded as a component-wise optimization if the loss generated by the root sections is neglected. Furthermore, the minimum loss generated by the root sections can be estimated, and the error for the whole-network optimization can be bounded.

By exploiting these features, our method obtains the optimal configuration for a fixed time period by the following procedure. First, our method obtains component-wise optimal configurations, each of which is a configuration that minimizes energy loss that evolved inside the component; it is selected among the component-wise feasible configurations. Second, it generates a joint configuration of the component-wise optimal configurations. If the joint configuration satisfies the operational constraint, it can be regarded as the optimal configuration of the whole network. However, since the joint configuration will not always satisfy the operational constraint, our method checks the feasibility of the joint configuration. In the infeasible case, the conventional method [13] is restored to obtain the optimal configuration of the whole network. Thus, if many joint configurations are infeasible, more computation time may be required. However, since the joint configuration has a remarkable feature that it always satisfies the topological constraint (Section V), the possibility of infeasibility can be expected to be small. In fact, we never encountered infeasible joint configurations in the experiments described in Section VII-B. The feasibility of the joint configuration can be quickly checked by exploiting the feature ZDD, which contains all the feasible configurations and provides a linear time membership query (Section V-B).

B. Enumeration of All Feasible Configurations Within a Year

$\mathcal{X}$ denotes the set of feasible configurations and $\mathcal{X}_c$ represents the set of component-wise feasible configurations for a component c. First the set of feasible configurations $\mathcal{X}$ is prepared, which is subsequently used to obtain $\mathcal{X}_c$.

Because the total number of possible combinations of on/off states can be very high depending on the number of switches, naive enumeration and processing requiring a linear combination of the number of configurations should be avoided. Therefore, we used a ZDD for indexing purpose. For network-wise configurations, we referred to the technique reported in [13], which independently constructs two ZDDs: one for all configurations that satisfy the topological constraints $\mathcal{X}^{\mathrm{topol}}$ and the other for those satisfying the electrical constraints $\mathcal{X}^{\mathrm{elec}}$. Since there are multiple snapshots for each time slot t of the load curve duration (24 h $\times$ 365 days) T, a ZDD is prepared for each electrical constraint. As mentioned in

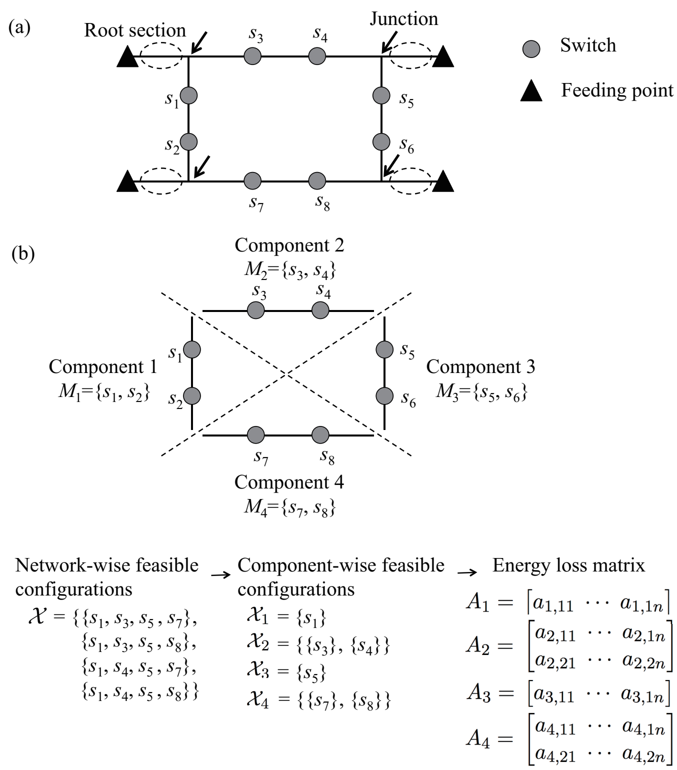

Fig. 4. Schematic of a distribution network and procedure for constructing the energy loss matrix from network-wise feasible configurations. (a) An example of distribution network. The sections surrounded by dotted circle and the points indicated by arrows shows root sections and junctions respectively. (b) An example of components. The network is divided to components by removing root sections, first junctions and feeding points. Each symbol of $M_1, \ldots, M_4$ indicates a set of switches of each component. For a component c, the set $\mathcal{X}_c$ is constructed from the meet operation as $\{M_c\} \sqcap \mathcal{X}$. Each element of the matrix A_c is calculated from the configuration $X \in \mathcal{X}_c$ and loads for the given period j.

Section III, ZDD has some operations. $\mathcal{X}$ can be obtained by taking the intersection of $\mathcal{X}^{\text{topol}}$ and $\mathcal{X}_t^{\text{elec}}$:

$$\mathcal{X} = \mathcal{X}^{\text{topol}} \bigcap_{t=1}^{T} \mathcal{X}_t^{\text{elec}}. \tag{5}$$

The component-wise feasible configurations are derived from $\mathcal{X}$. M_c denotes a set of switches contained in a component c; the component-wise feasible configurations can be obtained by the meet operation as follows:

$$\mathcal{X}_c = \mathcal{X} \sqcap \{M_c\}. \tag{6}$$

C. Computation of Energy Loss Matrix

Our method pre-computes energy losses for each component-wise feasible configuration for each unit period and stores it as a form of matrix, which is called energy loss matrix, to avoid the repetition of the loss calculation for given time step. The energy loss of a specific component-configuration for a load of a specific duration can be computed using conventional methods. Since the component size is usually small, a matrix can be constructed using energy loss as elements, in which the row and column correspond to feasible configurations and unit period, respectively. The precomputed energy loss for the space $\mathcal{X}_c$ is stored in a matrix A_c, which is termed the energy loss matrix. The definition is as follows:

$$A_c = (a_{c,ij})_{\substack{1 \le i \le |\mathcal{X}_c| \\ 1 \le j \le n}}, \tag{7}$$

where i denotes the number of component-wise feasible configurations, and $a_{c,ij}$ denotes the energy loss of the configuration i in the period j.

Algorithm 1 $OptimizeConfigs$

Input: $\mathcal{X}, \{\mathcal{X}_c\}, \{A_c\}$
Output: $\hat{\mathcal{X}}$ // optimal configurations for all operation periods
Set $\hat{\mathcal{X}} \leftarrow \emptyset$.
Let $\mathcal{J}$ be a set of all operation periods.
for $J' \in \mathcal{J}$ **do**
  Compute $\hat{X} \leftarrow OptimizeCompConfigs(J', \{A_c\}, \{\mathcal{X}_c\})$.
  if $\hat{X}$ not in $\mathcal{X}$ **then**
    Compute $\hat{X} \leftarrow SnapshotOptimizationMethod(J', \{A_c\}, \mathcal{X})$.
  end if
  Set $\hat{\mathcal{X}} \leftarrow \hat{\mathcal{X}} \cup \{\hat{X}\}$.
end for

Algorithm 2 $OptimizeCompConfigs$

Input: $J', \{A_c\}, \{\mathcal{X}_c\}$
Output: $\hat{X}$
Set $\hat{X} \leftarrow \emptyset$.
for $c \in C$ **do**
  Compute $X' \leftarrow \operatorname*{argmin}_{X \in \mathcal{X}_c} \sum_{j \in J'} CompLoss_j(A_c, X)$.
  Set $\hat{X} \leftarrow \hat{X} \cup X'$.
end for

D. Algorithm for Obtaining Optimal Configurations for All Operation Periods

This subsections describes how obtain optimal configurations can be obtained for all possible operation periods efficiently. The inputs of this process are a ZDD $\mathcal{X}$ representing feasible configurations, a set of ZDDs $\mathcal{X}_c$ where $c \in C$ represents component-wise feasible configurations, and the energy loss matrix A_c. The output is optimal configurations for all possible operation periods $\hat{\mathcal{X}}$. The pseudocode of this process is represented as $OptimizeConfigs$ in Algorithm 1.

For a given operation period J', the method first obtains component-wise optimal configurations for all components ($OptimizeCompConfigs$ in Algorithm 2). In the algorithm $OptimizeCompConfigs$, for a given component c, the method first calculates the loss for every component-wise configuration in $\mathcal{X}_c$ for the given period J' using the energy loss matrix A_c and obtains the component-wise optimal configuration X'. By repeating this process for every component c of C, the joint configuration $\hat{X}$ of these component-wise optimal configurations is obtained. The method checks if $\hat{X}$ is contained in the ZDD $\mathcal{X}$, which represents a set of feasible configurations. If the joint configuration $\hat{X}$ is contained in $\mathcal{X}$, the algorithm outputs $\hat{X}$ as an optimal configuration. If not, the conventional method is restored [13]. The method repeats the above procedure for all possible operation periods J'.

When reverting to the conventional method the optimal configuration can be computed. However, this involves computational difficulty. The method requires transforming a ZDD, which is a DAG with nodes representing switches, into a DAG in which the nodes represent components. Then, it computes the shortest path, which represents the minimum configuration. Since the number of paths in the transformed DAG is considerably larger than the number of feasible configurations in the component, the computation time will be large.

Although the joint configuration may not always be a feasible configuration, it has a desirable property. It always satisfies topological constraints because of the graphical feature; a connected graph of the root sections of one or more rooted trees (i.e., component-wise feasible configuration) is always a tree. Thus we only need to care about electrical constraint violation. There are two cases that joint configuration of component-wise feasible configurations violate the electrical constraint: 1) the current in root section causes overload or 2) their voltage drop cause voltage deviation inside the component (especially, end of feeder). However, we can expect that the possibility of violation is reduced by at least following two factors. First, since we calculate every time period in a year, we can expect that time periods whose load demand is near-peak is limited; the large part of the periods have some room of capacity. Constraint violations may not occur if we have enough capacity margins, even when the joint of component-optimal configurations brings larger power flow in root sections than the normally operated configuration. Second, we consider the degree of symmetry. This consists of three factors: distribution of the line impedance, distribution of the load, and the network topology. Regarding the line impedance and load, as they become more uniformly distributed across the entire network, we say that the network is symmetrical. Regarding the network topology, we say that the network is symmetrical if each topology is the same when viewed from each substation. If we suppose that the network has a perfectly symmetrical structure, any configurations that maintain this symmetry will be feasible both in terms of the current and the voltage drop. Regarding the current, in such cases, all of the currents in the root sections will have an equal value. Since we assume that all the root sections have the same capacity, the configuration should be feasible. Regarding the voltage drop, their current provide same amount of voltage drop for each root section. Besides, minimizing the energy loss in a component brings load balancing configurations. As a result, the joint configuration of a component-wise optimal configuration becomes electrically feasible. Of course, real networks are not perfectly symmetric. However, many networks have a symmetric structure into some extent. For example, in the networks shown in [2], [4], [26]–[28], the root sections are connected to the same number of components. In addition, the network used in our experiment has a kind of symmetrical structure; the number of components connected to root sections are always 2. In the experiment, we never encountered an infeasible joint configuration. This corroborates the effect of the symmetry.

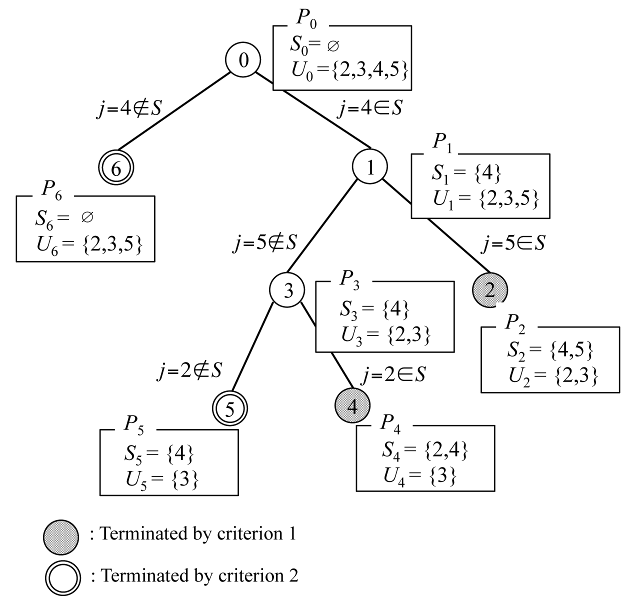

Fig. 5. Example of search tree on $n = 5$. The root node indicates the original problem P_0, and other nodes indicate generated subproblems P_ℓ. The problem number ℓ is assigned according to the bounding operation order.

VI. Optimization of Reconfiguration Periods

The optimization is based on a B&B style algorithm, which is an enumerative scheme for solving the optimization problem. Using this algorithm, a comprehensive search of the solution is realized in an efficient manner, as the bounds are the clue to prune the search. For the efficient search of solutions, the bounds on the B&B must be designed tightly. We propose a concept of a improvement value and establish a critical lower bound. The B&B method is composed of a branching operation and a bounding operation.

A. Branching Operation

By defining the search space of reconfiguration periods as $\mathcal{S} = \mathcal{P}(J - \{1\})$, the branching operation can be specified to partition a particular search space $\mathcal{S}_\ell$ into two subsets:

$$\begin{cases} \mathcal{S}_{\ell_1} = \{S \in \mathcal{S}_\ell : j \in S\}, \\ \mathcal{S}_{\ell_2} = \{S \in \mathcal{S}_\ell : j \notin S\}. \end{cases} \tag{8}$$

In this paper, the subproblem P_{ℓ_1}, P_{ℓ_2} is used to denote problems corresponding to the partitioned search spaces $\mathcal{S}_{\ell_1}, \mathcal{S}_{\ell_2}$. The branching operation partitions a search space into smaller subsets repeatedly from the original problem. The generated subproblems are expressed in the form of a search tree, as shown in Fig. 5.

B. Bounding Operation

The goal of this section is to calculate a lower bound for a subproblem. We designed the lower bound to exploit the two aspects of this annual reconfiguration problem. The first aspect is the variation in the loads between seasons. If the input data varies considerably, the improved values obtained by the reconfiguration will be highly dependent on when the reconfiguration is performed. To this end, the lower bound is calculated as the maximum improvement value among all the possible operation periods that contain the target unit period assuming that a reconfiguration is performed in the target period. The second aspect is that the problem is an optimization over a range of successive time periods; in a subproblem in which one or more branching variables are fixed, we only have to address the operation periods between the fixed periods. By exploiting this characteristic, we can further narrow down a range of operation periods to be handled by each subproblem, in addition to the usual effect of reducing the solution space through branching operations.

Let P_ℓ be a subproblem performed by the ℓ-th bounding operation. For each P_ℓ, there are two sets of periods. The first set S_ℓ is a set of reconfiguration periods, fixed through the branching operations. The second set U_ℓ is a set of unfixed reconfiguration periods. Since we limit the number of reconfiguration times $\overline{k}$ in a year, P_ℓ can only reconfigure a maximum of $k - |S_\ell|$ periods, which is selected from U_ℓ. Let $\mathcal{U}_\ell$ be a family of sets of the available unfixed periods for P_ℓ: $\mathcal{U}_\ell = \{U \subseteq U_\ell : |U| \le \overline{k} - |S_\ell|\}$. For each $U \in \mathcal{U}_\ell$, we calculate the sum of the maximum improvement values assuming that the network is reconfigured in each period contained in U. The lower bound $b(P_\ell)$ of P_ℓ is defined using the maximum of the sum:

$$b(P_\ell) = f(S_\ell, \{\hat{X}_k\} : J) - \max_{U \in \mathcal{U}_\ell} \sum_{j \in U} Imp(j, S_\ell), \tag{9}$$

where $Imp(j, S_\ell)$ is a maximum improvement value obtained by fixing the reconfiguration at j, which we define below.

Given a target period j and fixed periods S_ℓ, $Imp(j, S_\ell)$ is calculated as:

$$\begin{aligned} Imp(j, S_\ell) = \max_{p,q} \{ & f(\varnothing, \{\hat{X}_k\} : J^{(p:q)}) \\ & - f(\{j\}, \{\hat{X}_k\} : J^{(p:q)})\}, \end{aligned} \tag{10}$$

subject to

$$\begin{cases} \max\{j' \in S_\ell + \{1\} : j' < j\} \le p < j, \\ j \le q < \min\{j' \in S_\ell + \{n\} : j' > j\}, \end{cases} \tag{11}$$

where $J^{(p,q)}$ is the operation period, ranging from p to q: $\{p, p+1, \ldots, q\}$. In Equation (10), the first term on the right side is the minimum energy loss of the period $J^{(p:q)}$ with the optimal configuration $\hat{X}_k$. The second term is the minimum energy loss after reconfiguration in period j. Equation (11) indicates that the possible range of the operation period $J^{(p:q)}$ is given by periods S_ℓ. For example, when $S_\ell = \{126, 182, 278, 300\}$ and $j = 200$ for 365 daily periods are given, the range of p and q becomes $182 \le p < 200$, $200 \le q < 278$. Equation (11) indicates that, provided the periods are fixed through branching operations, the possible range of the period $J^{(p:q)}$ becomes narrower. Eventually, we can expect that Imp to become tighter. Since the Imp is the upper bound of the improvement value obtained by the reconfiguration, the lower bound $b(P_\ell)$ does not exceed the optimal value.

C. Search for Reconfiguration Periods Using B&B Algorithm

The B&B algorithm is implemented through a recursive operation of the branching operation and bounding operation.

Algorithm 3 $OptimizeReconfigurationPeriods$

Input: $\hat{\mathcal{X}}$
Output: $\hat{S}$ // optimal reconfiguration periods

1: Set $\hat{S} \leftarrow \varnothing, z \leftarrow \infty, \Omega \leftarrow \{P_0\}$.
2: **while** $\Omega \neq \varnothing$ **do**
3: Let P_ℓ be a right-most problem in the deepest problems of Ω.
4: **if** ($|S_\ell| \le \overline{k}$ **and** $f(S_\ell, \{\hat{X}_k\} : J) < z$) **or** ($|S_\ell| < |\hat{S}|$ **and** $f(S_\ell, \{\hat{X}_k\} : J) = z$) **then**
5: Set $z \leftarrow f(S_\ell, \{\hat{X}_k\} : J)$, $\hat{S} \leftarrow S_\ell$.
6: **end if**
7: **if** $|S_\ell| = \overline{k}$ **or** $b(P_\ell) > z$ **then**
8: **go to** 11.
9: **end if**
10: Let P_{ℓ_1}, P_{ℓ_2} be subproblems of P_ℓ by branching operation and set $\Omega \leftarrow \Omega \cup \{P_{\ell_1}, P_{\ell_2}\} - \{P_\ell\}$, then **go to** 3.
11: Set $\Omega \leftarrow \Omega - \{P_\ell\}$, then **go to** 3.
12: **end while**

The search strategy is important to the design of an efficient B&B algorithm. That is, we should define a proper order of branching variables. Since the value Imp is determined as the potential of the energy loss reduction effect of the reconfiguration in period j, we can expect that a period with a large Imp will be included in the optimal reconfiguration periods. Therefore, we arranged the variables in ascending order of Imp.

The branching operation is conducted by employing a depth-first search. In this operation, search is pruned by using two criteria: (1) The search space does not satisfy the permissible reconfiguration time. (2) The lower bound of the subproblem P_ℓ is larger than the incumbent value. The B&B algorithm is described in Algorithm 3.

VII. EXPERIMENT

This section discusses the evaluation of annual energy loss for reconfiguration periods at optimal intervals and equal intervals (e.g., seasonal reconfigurations [14]). These periods are termed as $\hat{S},\ S^{\text{equal}}$. The evaluations were performed for daily and weekly unit periods, called the daily-base and weekly-base reconfigurations, respectively. With the equal interval d calculated as the quotient of division $|J|/n$ (the remainder is distributed to the intervals), the period S^{equal} is expressed as:

$$S^{\text{equal}} = \{d+1, 2d+1, \ldots, \overline{k}d+1\}. \tag{12}$$

In these experiments, our proposed method was applied to two power system models. While the experiments require the annual loads as a constant current model, these models do not feature such long-term loads. Therefore, datasets of annual loads at hourly intervals were created for each model based on three types of load profiles: (a) [1] residential-type load profile of demonstrative research on the grid-interconnection of clustered photovoltaic power generation systems by New Energy Industrial Technology Development Organization, (b)

[1]http://www.nedo.go.jp/activities/ZZ_00229.html

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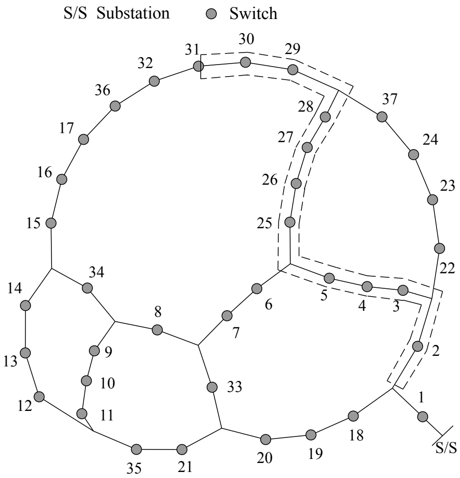

Fig. 6. 32-bus network. The line sections surrounded by the dotted line have industrial-type load (b). These line sections belong to the main feeder specified by the optimal open switches reported by [13]. The other line sections have residential-type load (a).

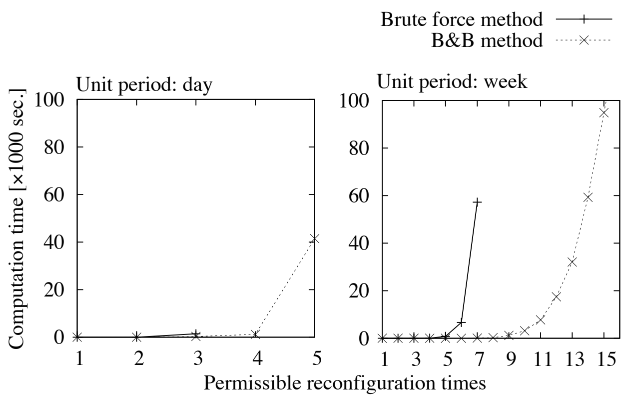

Fig. 7. Computation time of determining reconfiguration periods for 32-bus network between brute force and B&B method in the daily-base (left) and weekly-base (right) reconfigurations.

industrial-type load profile of an actual industrial institution, (c) [2] multiple-type load profile of the total load in the district of Tokyo Electric Power Company (TEPCO). The experiments were conducted using a computer with a dual-socket Xeon E5-2690 (8 core, 2.9 GHz).

A. 32-bus Network

The first model that was verified is a 32-bus network introduced by Baran and Wu [4] (Fig. 6). The model has one substation, in which the sending voltage is 12.66 kV and there are 37 switches. It provides a single-phase load for one snapshot as a constant power load for each line section. Regarding the electrical constraint, the permissible range of voltage drop is within 10% of the sending voltage, but the line capacity is not indicated. Hence, the line capacity was excluded from the operational constraint. A dataset of annual loads at hourly intervals for all sections was created through the following steps. First, each constant power load

[2]http://www.tepco.co.jp/forecast/index-j.html

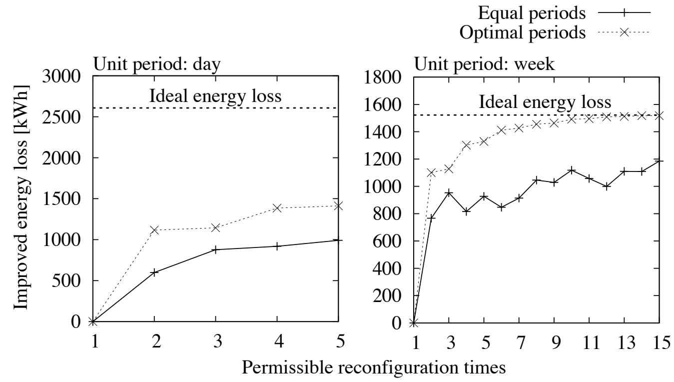

Fig. 8. Energy loss reduction using both reconfiguration periods S^{equal} and $\hat{S}$ in daily-base (left) and weekly-base (right) reconfigurations for a 32-bus network.

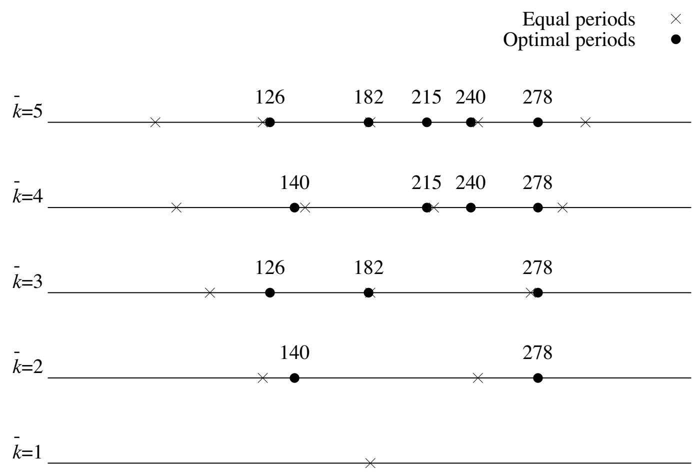

Fig. 9. Reconfiguration periods $\hat{S}$, S^{equal} for a 32-bus network. The numbered lines indicate the year, and the numbers represent the number of $\hat{S}$.

was divided by the sending voltage. The values were regarded as the rated current load of the line sections. Second, load profiles (a) and (b) were assigned for each rated current load.

The number of all feasible-configurations satisfying the operational constraint was 22 237. Since a 32-bus network has only one component, joining component-wise configurations described in Section V is not necessary. In this case, a component-wise optimal configuration is considered as the network-wise global optimal configuration. Moreover, the B&B algorithm described in Section VI gives the global optimal reconfiguration periods for a given energy loss in the operation periods. Therefore, for this test system, our proposed method can derive optimal solutions for the annual energy loss minimization problem.

Fig. 7 shows the computation time between B&B algorithm and brute force method within 100,000 s. For the range of $\overline{k}$ that B&B algorithm determined, Fig. 8 shows the energy loss reduction by reconfiguration at periods $\hat{S}$ and S^{equal} when the base value is the annual energy loss with one optimal configuration (181,471 kWh). Compared to that for equal periods, the amount of energy loss significantly decreased for all conditions of $\overline{k}$. Interestingly, in the weekly case,

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TABLE I
SPECIFICATIONS OF THE FUKUI-TEPCO NETWORK

Number of substations	4
Number of banks per substation	3
Number of feeders per bank	6
Number of buses	432
Number of switches	468
Line capacity	350 A
Sending line voltage	6.6 kV
Maximum voltage drop	0.3 kV

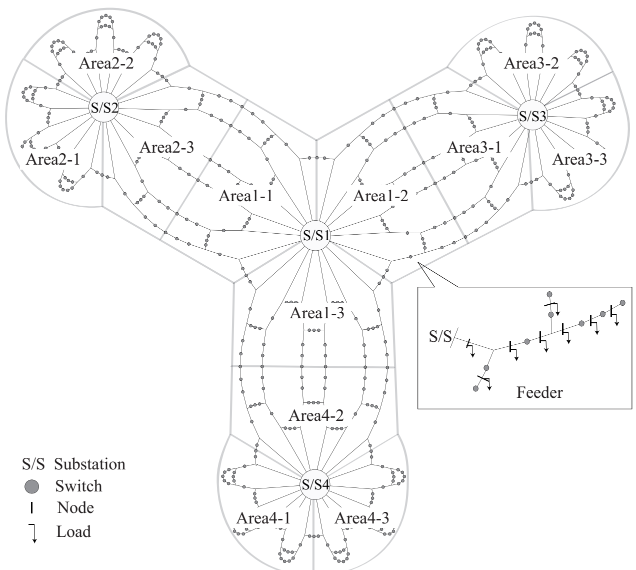

Fig. 10. Fukui-TEPCO network. Different areas of the network have different types of load. The second digit in the area number indicates the assigned load profile: the numbers 1-3 indicate the residential-type (a), multiple-type (c), and industrial-type loads, respectively.

the growth rate gradually decreases with $\overline{k}$. The label "Ideal energy loss" indicates the reduction of energy loss with optimal configurations at every unit period. In the weekly-base reconfiguration, an energy loss almost equal to the ideal value around $\overline{k} = 10$ was achieved.

Fig. 9 shows the reconfiguration periods $\hat{S}$, S^{equal}. In the case of $\overline{k} = 1$, there was no reduction of energy loss by reconfigurations.

B. Fukui-TEPCO Network

The second model that was verified is a three-phase alternating current system developed by Fukui University and TEPCO in 2006 [28]. It simulates standard overhead distribution lines and network topologies in TEPCO area based on measured data. Table I shows the specifications of this model.

A dataset of the annual load profile at hourly intervals for each section was created as per the method described in [28]. Specifically, the maximum sending line current was set to 300 A, which corresponded to an average feeder's peak-load of 4,175 kW (371.5 A), as per the in-service usage data in TEPCO. The sending line current was distributed uniformly among 8 line sections belonging to one feeder. The distributed values were treated as the related load current, and then three types of load profiles were assigned for the section current

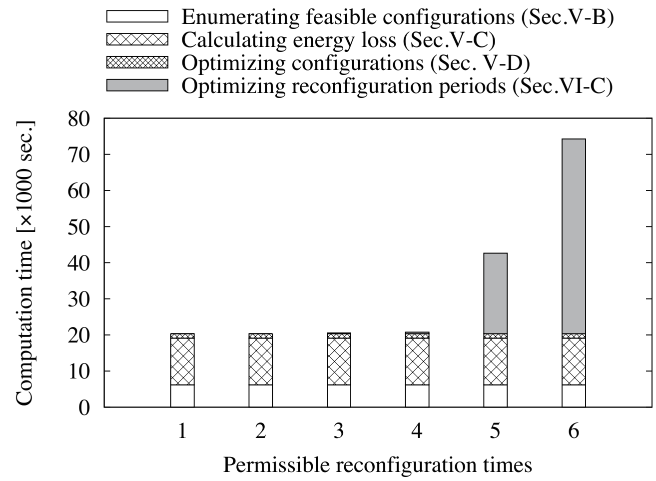

Fig. 11. Computation time for each computation process in the case of daily-base reconfiguration of the Fukui-TEPCO network.

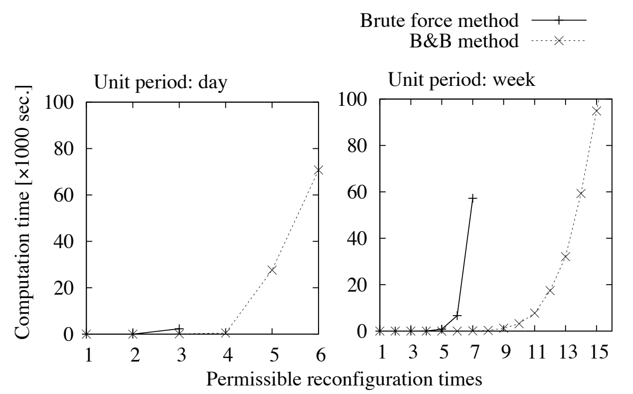

Fig. 12. Computation time of determining reconfiguration periods for Fukui-TEPCO network between brute force and B&B method in the daily-base (left) and weekly-base (right) reconfigurations.

shown in Fig. 10. The annual total load calculated as the product of the sending voltage and total current load was 976,966,183 kWh.

The number of configurations satisfying the operational constraint was approximately 3.879×10^{50}. Fig. 11 shows the computation time for each computation process in the daily-base reconfiguration. We can see that the computation time for the step of optimizing configurations for all operation periods, if $\overline{k}$ is larger than four, is negligibly small compared to the whole process. Note that in this process, a recourse to the conventional method never occurred. If the recourse is occurred for every operation period, that is, if we only use conventional snapshot optimization method, the time is estimated as approximately 6393.9×10^3 s. As for the step of optimizing reconfiguration periods, the B&B algorithm obtained optimal periods up to $\overline{k} = 6$ (in the weekly case, $\overline{k} = 15$) with a time limit of 100,000 s. The computation time of the B&B algorithm is compared to brute force method in Fig. 12.

We evaluated the energy loss reduction by optimizing reconfiguration periods in Fig. 13 (the base energy loss was

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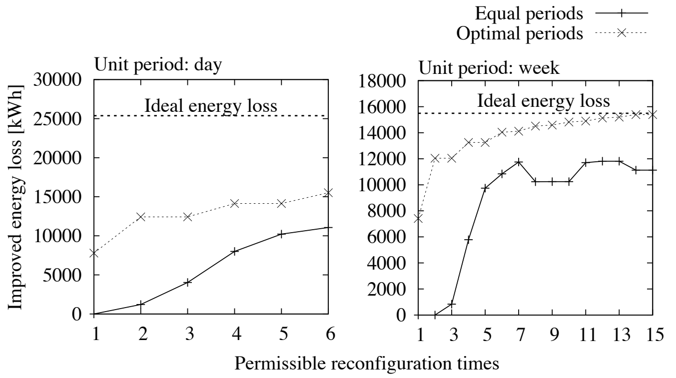

Fig. 13. Energy loss reduction for both the reconfiguration periods S^{equal} and $\hat{S}$ in the daily-base (left) and weekly-base (right) reconfigurations for the Fukui-TEPCO network.

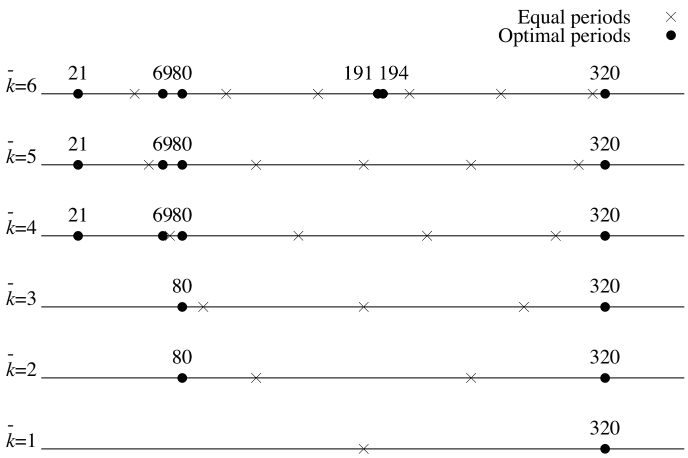

Fig. 14. Reconfiguration periods derived by the proposed method for the Fukui-TEPCO network. The numbered lines indicate the year, and the number represents the number of $\hat{S}$.

11,126,455 kWh). Consequently, we observed that the reduction effect at $\hat{S}$ was larger than that at periods S^{equal}. In particular, when $\overline{k} = 3$ (simulated seasonal base operation), the energy loss at periods $\hat{S}$ drastically decreased by 2.1 and 13.3 times compared to that at periods S^{equal} for daily and weekly-base reconfigurations. The reconfiguration periods are shown in Fig. 14.

VIII. Conclusion

This paper has presented a new optimization method for determining reconfiguration scheduling to minimize annual energy loss. Our method considers the permissible number of reconfigurations to reflect the switch durability. In the experiments, we evaluated the energy loss reduction resulting from optimal scheduling by applying our method to a large-scale Japanese distribution network. The results indicate that the optimal scheduling significantly reduced the energy loss up to 2.1 times relative to simulated conventional scheduling, which is a season-based reconfiguration. To the best of our knowledge, this is the first quantitative report addressing the difference in the energy loss reduction achieved with optimal scheduling and the conventional reconfiguration for the practical-scale distribution networks. If we apply our method to existing distribution networks, we can also evaluate the network efficiency from the energy loss.

A low carbon society requires more efficient network operation than is possible with conventional networks. In addition, given that a barrier to introducing smart grid technology is the associated high cost, it may be selectively or preferentially implemented to evaluate the introduction effects. We believe that our work would provide directions toward more efficient network operations and the realization of automation guidelines.

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