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Lifetime Estimation for Electrical Components in Distribution Systems Using Their Inspection and Maintenance Records

Hirotaka Takano[1]*, Kan Nakae[1], Ryuto Shigenobu[2], Masakazu Ito[2], Yuusuke Kokubo[3], Shoichi Higashiyama[3]

[1]*Gifu University*
[2]*University of Fukui*
[3]*Kansai Transmission and Distribution Inc.*
Corresponding author E-mail: takano@gifu-u.ac.jp

Abstract

Distribution system operators inspect electrical components in the distribution systems to maintain the reliability of power supply. Results of the inspection and necessary actions for them have been accumulating in databases as the inspection and the maintenance records. The authors propose an estimation method of operating lifetime of newly constructed electrical components as an application of these records. The aim of this study is to utilize the inspection and the maintenance records to decision making in expansion planning of the distribution systems. In the proposed method, decision tree learning is applied to analyze relationships between initial information of the electrical components (sets of specifications and weather conditions) and their operating lifetime. The resulting tree-like model uses initial information of the target component as input and estimates its operating lifetime. Numerical simulations are carried out for verifying the validity of the authors' proposal using actual inspection and maintenance records accumulated in a Japanese electric power company. In addition, influential factors on the operating lifetime are specified through the numerical simulations and discussions on their results.

Keywords: *decision tree learning, distribution equipment, inspection record, lifetime estimation, maintenance record*

1. Introduction

Electrical power distribution systems consist of distribution feeders, electric poles, pole transformers and switchgears, and have extremely important roles in delivering electrical power to the customers. Historically, the distribution feeders have been expanded radially from the distribution substations to supply power to spreading power consuming area [1]. If a trouble occurs in the distribution systems, the resulting power failure brings significant impacts on activities of our society. Therefore, to maintain the stable power supply, distribution systems' operators (DSOs) make inspection for electrical components in the distribution systems sequentially and decide necessary actions correlating with results of the inspection [2]. Conditions of the components and necessary actions for them have been accumulated in databases of the DSOs through the inspection and its resulting maintenance.

Since the gathered information often includes useful rules, knowledge and judgement criteria [3], we can expect to improve the reliability, the quality and the efficiency in operations and planning of the distribution systems by its appropriate applications [4,5]. However, records of the inspection and the maintenance have been only referred in the decision-making process that the components require to be taken measures or not for keeping their functions [6]. This is because the total numbers of the distribution components are extremely large [1,7], and therefore, it is difficult to analyze and utilize these records relying on knowledge and experiences of the DSOs. Under the circumstances, there is still plenty of room for discussion on how to utilize the massive records and what kinds of techniques are suitable for analyzing and utilizing them [8,9].

This paper presents a way to utilize the inspection and the maintenance records in estimation of operating lifetime of newly constructed electrical components in the distribution systems. Here, the authors define the operating lifetime as the duration from the operation starting date to the date when the DSOs require 'replacement', that is available period of the target component. A decision tree learning is selected as the basis of the estimation method. During the learning process, relationships between initially available information (sets of attributes of the electrical components and weather conditions) and operating lifetime are analyzed. In this process, the operating lifetime of the target component is calculated by referring both of the inspection and the maintenance records. As a result of analysis, a tree-like estimation model is constructed. The constructed model can visually provide influential factors on the operating lifetime, and this is the strongest reason why the authors emphasize the decision tree learning algorithms. By input the initial information to the constructed model, we can estimate the operating lifetime of newly constructed electrical components. The aim of the proposed estimation method is to support decision making process of expansion or planning of the distribution systems.

Through numerical simulations and discussions on their results, the validity of the authors' proposal is verified. In the

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numerical simulations, the inspection and the maintenance records accumulated in a Japanese electric power company are used. Influential factors on the operating lifetime are also specified as a result of the estimation model construction. Furthermore, as an improvement strategy of the proposed method, a random forest is applied as same as the decision tree learning and examined its performance.

2. Estimation conditions

In general, the DSOs make several decisions on the distribution system planning with the limited information. This is the reason why the authors focus on sets of the attributes of electrical components and the weather conditions, that are readily available information. The attributes of electrical components are roughly classified into specifications and locational conditions. For instance, in the concrete electric poles, “type” and “length” are included in the specification attributes, while “salt damage level” and “soil quality” are in the locational attributes. This section introduces overview of the initial information (input of the estimation process) and sets the average operating lifetime in the estimation target.

2.1. Overview of initially available information (input data)

Table 1 shows available electrical components and total numbers of each component. Although the authors applied the proposed method to these components individually, the concrete electric poles, which have the largest share in the available records as shown in Table 1, are emphasized in this paper. Table 2 summarizes breakdown of the concrete poles.

Table 1: Total Numbers of Available Components.

Concrete pole	Pole transformer	Switchgear
1,382,067	1,056,191	95,776

Table 2: Breakdown of Target Components (Concrete Electric Poles).

Total number of all concrete poles	1,382,067
Total number of concrete poles including missing data (removed from discussions)	28,143
Total number of concrete poles finishing their lifetime (available for model construction)	4,951
Total number of concrete poles having lifetime under 20 years (removed from discussions of this paper)	266

In the learning process, relationships between the attributes, the weather conditions and the actions for the inspection results, “follow-up observation”, “repair” or “replacement”, are analyzed. The attributes and the weather conditions are also used as the input in the estimation process.

As summarized in Table 3, nine attributes and five weather conditions are used in this paper. The specification attributes consist of “type”, “length”, “with or without pole transformer”, “with or without switchgear” and “facility type” (SP 1-5), while the locational attributes include “salt damage level”, “surrounding condition”, “geological condition” and “soil quality” (LC 1-4). The weather conditions are composed by “yearly precipitation”, “mean daily temperature”, “mean daily maximum temperature”, “mean daily minimum temperatures” and “mean wind speed” (WC 1-5). In the inspection record, scores or actual values corresponding with each attribute are included. Since the proposed method is aiming to apply in the planning phases of distribution systems, the inspection results, that represent conditions of the target components, are removed from discussions in this paper. These results will be useful in the residual lifetime estimation or the anomaly diagnosis.

Table 3: Available Attributes and Weather Conditions.

Input attributes	Ellipsis	Contents
Type	SP 1	Symbol A to Z
Length	SP 2	8 to 30 (m)
Transformer (w or w/o)	SP 3	1 (w) or 0 (w/o)
Switchgear (w or w/o)	SP 4	1 (w) or 0 (w/o)
Facility type	SP 5	Score of 1 to 4
Salt damage level	LC 1	Score of 1 to 3
Surrounding condition	LC 2	Score of 1 to 7
Geological condition	LC 3	Score of 1 to 3
Soil quality	LC 4	Score of 1 to 5
Yearly precipitation	WC 1	599.5 to 2,146.9 (mm)
Mean daily temperature	WC 2	13.3 to 17.7 (°C)
Mean daily maximum temperature	WC 3	17.5 to 21.9 (°C)
Mean daily minimum temperature	WC 4	8.7 to 14.1 (°C)
Mean wind speed	WC 5	1.3 to 4.3 (m/s)

If we change the estimation target, five specification attributes (SP 1-5) are replaced with those of the other components.

2.2. Calculation of average lifetime

With the aim of setting the standard of discussions, the average lifetime of concrete electric poles was calculated using the available records. As defined in Section 1, the operating lifetime in this paper is the available period of concrete poles, and therefore, it can be calculated by associating the operation starting date and the date when the DSOs described ‘replacement’. Although 4,951 concrete poles were available for the calculation, the authors regarded 266 concrete poles having too short operating lifetime (under 20 years) as the samples of irregular replacement, e.g. disaster-originated replacement.

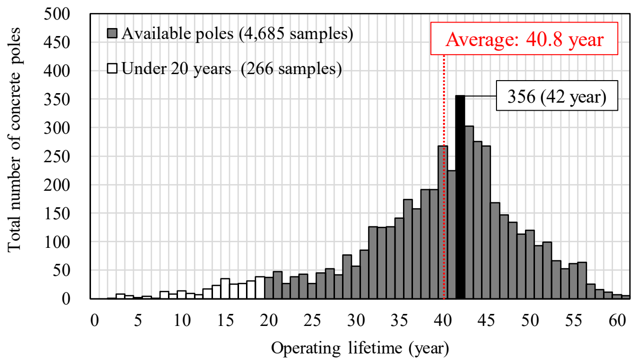

Figure 1: Distribution of Operating Lifetime of Concrete Electric Poles.

Figure 1 displays the distribution of operating lifetime of the concrete poles and their average lifetime. In this figure, the average lifetime of the concrete poles was 40.8 years. In Japan, the average lifetime of concrete poles has been generally estimated in the range of 30 to 40 years by knowledge and experience of the DSOs. On the other hand, it is also well known to change the actual lifetime depending on various factors [10,11]. From Fig. 1, we can confirm that the target concrete poles have slightly longer lifetime as compared to the general average.

3. Operating lifetime estimation

There are various estimation models in machine learning techniques including multiple regression models, artificial neural networks and decision tree models [12-16]. In this paper, a decision tree model is selected as the basis of the operating lifetime estimation. Decision tree learning constructs a tree-like model representing its decisions and decision-making process visually and explicitly, and thus we can easily understand judgement criteria in the estimation as compared to the others. This section presents details of the decision tree-based estimation method.

3.1. Overview of lifetime estimation

The decision tree learning is a knowledge representation that ultimately makes decisions by accumulating questions about the attributes of objects. The decision tree is classified into the classification and the regression models. In this paper, the regression model is used for estimating the operating lifetime (available period) of the target components.

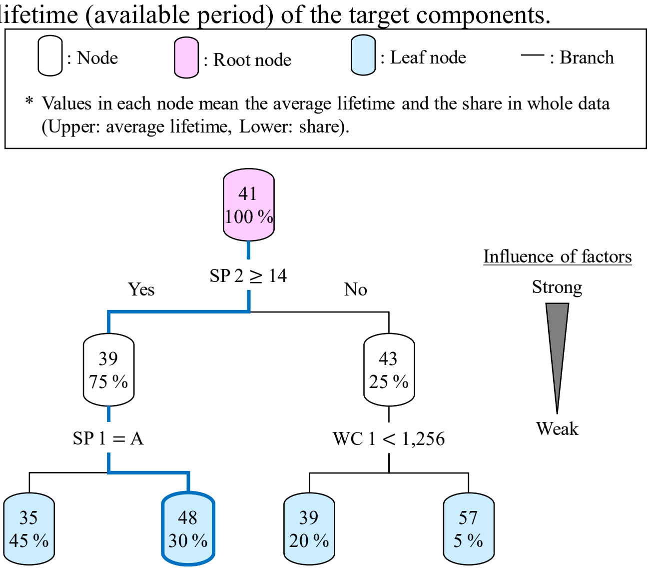

Figure 2: Sample of Constructed Estimation Model.

As shown in Fig. 2, the decision tree model is normally composed by nodes and branches. One node expresses a question on an attribute, and one leaf node represents a class. A set of paths from the root node to the leaf node shows one classification rule. In Fig. 2, the constructed tree judges that the operating lifetime of the target component is 48 years through the answers for questions, "Length (SP 2) is longer than or equal to 14 meters" and "Type (SP 1) is not A". It also means that 30 % of all data included in the model construction step had the same characteristics.

3.2. Estimation model construction

Typical approaches for creating the decision tree are Classification and Regression Tree (CART), Iterative Dichotomiser 3 (ID3) and C 4.5 [17,18]. The authors select a CART algorithm, which is one of the most popular approaches for non-parametric decision tree learning.

The CART algorithm involves selecting input variables and splitting points on those variables until satisfying the convergence criterion. This process is 'growth' of the tree. In this paper, the residual sum of squares (RSS) is used as the splitting criterion. The RSS is used to measure the amount of variance in a dataset and expressed as

$$RSS_n = \sum_{i=1}^{S_n} (x_i - \mu[n])^2, \quad (1)$$

where n is the node number; N is the total number of nodes; i is the number assigned to concrete poles; S_n is the total number of concrete poles included in the node n; x_i is the actual lifetime of the concrete pole i; $\mu[n]$ is the average lifetime for concrete poles included in the node n.

Since the resulting maximum tree model has a possibility of overfitting exists, verbose paths are integrated until the complexity cost F becomes sufficiently small. This is 'pruning' of the tree.

$$F = \sum_{n \in L} \left(\frac{|S_n|}{S} \cdot RSS_n \right) + \alpha \cdot N, \quad (2)$$

where L is the set of leaf nodes; S is the total number of concrete poles; α is the control parameter.

Through process of the growth and the pruning, a tree-like estimation model for the target components is constructed.

4. Numerical simulations

By using the records of actual inspection and maintenance, numerical simulations were carried out to verify the validity of the authors' proposal. As summarized in Table 2, there are 4,685 available concrete poles, of which 4,451 (95 %) poles were used in steps of the data analysis and the model construction (learning process). The remaining 234 (5 %) poles were used in the estimation step (verification process) regarded as the data of newly constructed concrete poles. While interchanging the verification dataset with the learning dataset, the estimation models were repeatedly constructed 20 times. Table 4 summarizes datasets for the learning and the verification.

Table 4: Breakdown of Dataset for Training and Verification.

	Below average	Above average	Total
Learning dataset	1,969	2,482	4,451
Verification dataset	106	128	234

4.1. Estimation results

Numerical simulation results of the lifetime estimation are summarized in Table 5, and error distribution of the numerical simulations is displayed in Fig. 3. As for reference, results only using the attributes of concrete electric poles (without the weather conditions) are shown in Table 6 [19]. Figure 4 illustrates the best regression tree in 20 cases, and Fig. 5 displays analysis results of the judgement criterion.

In the numerical simulations, the root mean square error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE) were respectively calculated as

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}(z_k^* - z_k)^2}, \tag{3}$$

$$MAE = \frac{1}{K}\sum_{k=1}^{K}|z_k^* - z_k|, \tag{4}$$

$$MAPE = \frac{1}{K}\sum_{k=1}^{K}\left|\frac{z_k^* - z_k}{z_k^*}\right| * 100, \tag{5}$$

where k is the number assigned to concrete poles; K is the total number of estimation targets; z_k^* is the actual operating lifetime of the concrete pole k; z_k is the estimated lifetime of the concrete pole k.

Table 5: Estimation Results of Decision Tree

Estimation target		RMSE	MAE	MAPE	Maximum absolute error
Learning dataset	Best	2.0 years	1.2 years	3.0 %	21.0 years
	Average	2.2 years	1.3 years	3.3 %	25.2 years
	Worst	2.4 years	1.4 years	3.6 %	31.4 years
Verification dataset	Best	1.9 years	1.2 years	3.2 %	11.8 years
	Average	2.8 years	1.5 years	4.0 %	20.9 years
	Worst	3.6 years	1.8 years	4.7 %	38.4 years

In Table 5, the RMSE values in all cases were lower than 4 years (Best: 1.9 years; Worst: 3.6 years). As compared to Table 6 (Best: 6.0 years; Worst: 7.3 years), it can be understood that all values of the evaluation indexes were dramatically improved in Table 5. Since the average lifetime in the available dataset was 40.8 years as described in Section 2, we can expect that the estimation accuracy was sufficiently high in practical use of the distribution system planning. Although results in the verification dataset were slightly worse than those in the learning dataset, there was no significant difference between them. From these results, the authors concluded that the proposed estimation method functioned very well.

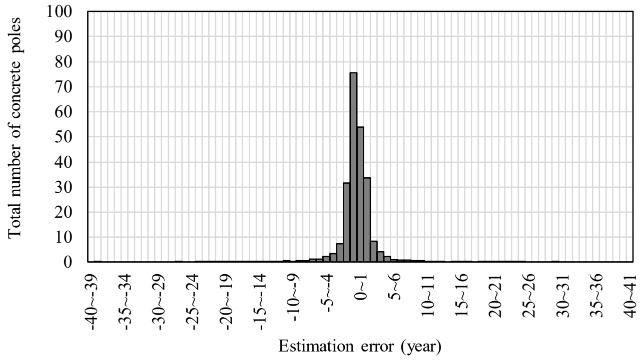

Figure 3: Error Distribution in Decision Tree (Average).

Table 6: Estimation Results of Decision Tree (Without Weather Conditions).

Estimation target		RMSE	MAE	MAPE	Maximum absolute error
Training dataset	Best	6.5 years	4.9 years	13.5 %	24.7 years
	Average	6.6 years	5.0 years	13.7 %	26.1 years
	Worst	6.7 years	5.1 years	14.0 %	28.8 years
Verification dataset	Best	6.0 years	4.7 years	12.5 %	18.6 years
	Average	6.8 years	5.2 years	14.3 %	23.0 years
	Worst	7.3 years	5.7 years	15.6 %	30.8 years

In Fig. 4, all of the weather conditions (WC 1-5) frequently appeared as the judgement criteria. With reference to Fig. 5, we can confirm that "type" (SP 1) and "length" (SP 2) in addition to the weather conditions were selected as the influential factors in the lifetime estimation.

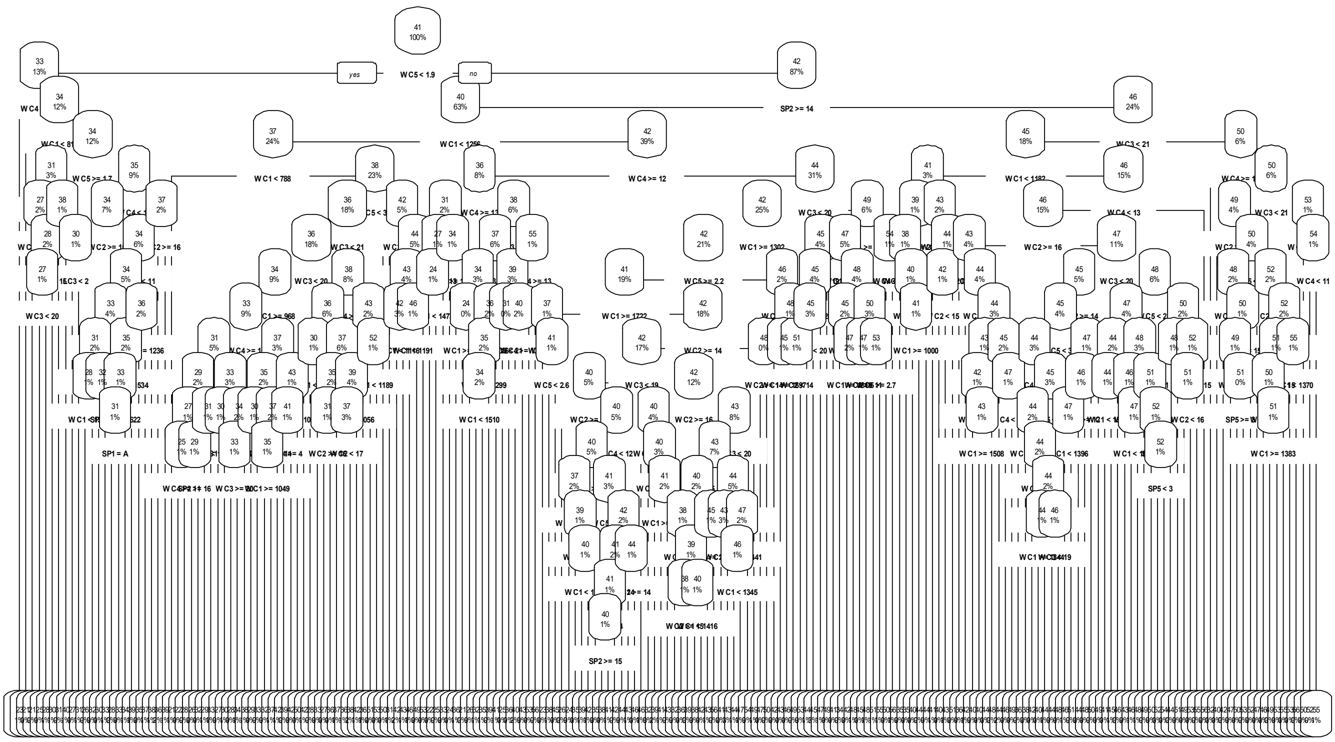

Figure 4: Constructed Tree Model (Best Result in 20 trials).

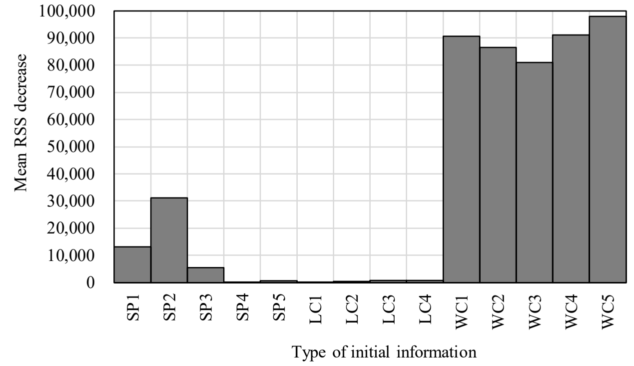

Figure 5: Influential Factors in Results of Decision Tree.

4.2. Discussions

In the constructed tree models, all weather conditions (WC 1-5) and the type and the length of concrete poles (SP 1 and 2) were selected as the influential factors in estimation of the operating lifetime of concrete poles. Here, the above results are verified with focusing on the length of concrete poles in more details. Figure 6 shows the length distribution of concrete poles in the available dataset, and Fig. 7 summarizes the relationship between the pole length and the actual operating lifetime.

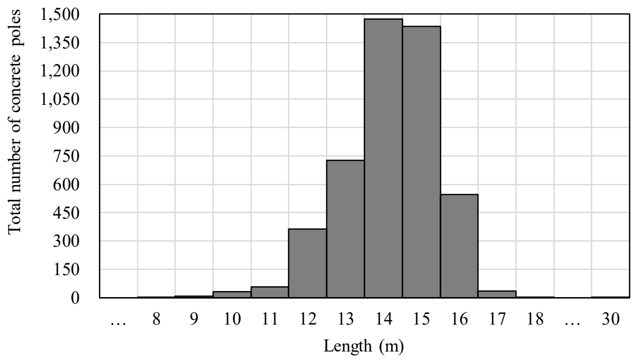

Figure 6: Length Distribution in Available Data.

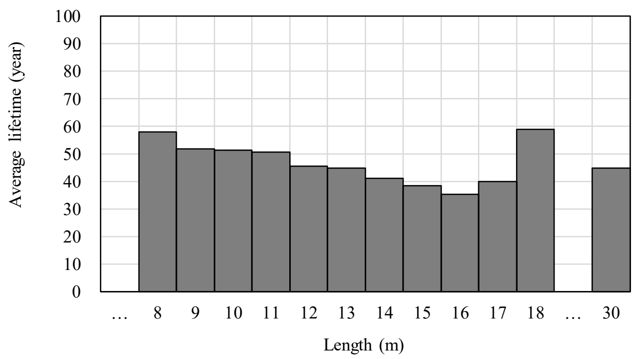

Figure 7: Average Lifetime of Concrete Poles on Each Length.

In Fig. 6, most of the concrete poles have length of 12-16 meters, especially 14 or 15 meters, in the available record. As shown in Fig. 7, the operating lifetime decreased gradually in contrast to the length of concrete poles until the length reached 17 meters. These figures show that the length had actually influences on the operating lifetime of concrete poles.

5. Application of random forest

Although values in the RMSE, the MAE and the MAPE were sufficiently high in the results of Section 4, the decision tree, as is well known, has issues in accuracy and stability in its application. In fact, values of the maximum absolute errors described in Table 5 became large. As an improvement strategy of the operating lifetime estimation, the authors applied a random forest instead of the decision tree learning.

Random forest is an ensemble learning method using bagging as the ensemble method and decision tree as the individual model. With the aim of reducing the variance, random forests average multiple decision trees trained on different parts in the same dataset [21]. Estimation accuracy of the random forests generally is higher than that of decision trees; however, data characteristics can affect their performance.

Under the same conditions as Section 4, the operating lifetime of concrete poles was estimated. Table 7 summarizes the results of random forest application. Error distribution of the random forest is illustrated in Fig. 8.

Table 7: Estimation Results of Random Forest.

Estimation target		RMSE	MAE	MAPE	Maximum absolute error
Training dataset	Best	0.8 years	0.5 years	1.32 %	8.1 years
	Average	0.8 years	0.5 years	1.35 %	8.6 years
	Worst	0.8 years	0.5 years	1.37 %	10.9 years
Verification dataset	Best	1.3 years	0.9 years	2.33 %	7.7 years
	Average	1.7 years	1.0 years	2.64 %	13.3 years
	Worst	2.1 years	1.2 years	2.96 %	22.1 years

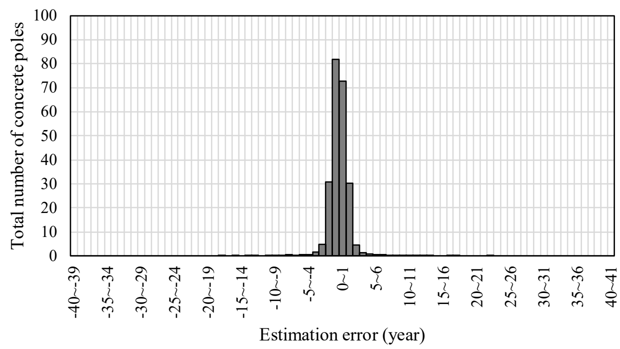

Figure 8: Error Distribution in Random Forest (Average).

In Table 7, values of all evaluation indexes became lower than those in Table 5. In particular, the maximum absolute errors were reduced significantly, and it also means that the estimation stability was actually improved by the random forest. Since the RMSE values were almost under 2 years in the verification dataset (Best: 1.3 years; Worst: 2.1 years), we can conclude that the random forest was more practical in the records used for this study than the decision tree learning.

Figure 9 shows influential factors in the random forest, and Fig. 10 summarizes comparison with those in decision tree learning. From Figs. 9 and 10, it can be understood that priority of each factor was changed. In the results of random forest, influences of the weather conditions (WC 1-5), especially for the mean daily temperature (WC 2), were reduced. Moreover, influence of the type of concrete poles (SP 1) became very weak. As a result, influence of the length (SP 2) was emphasized in the random forest.

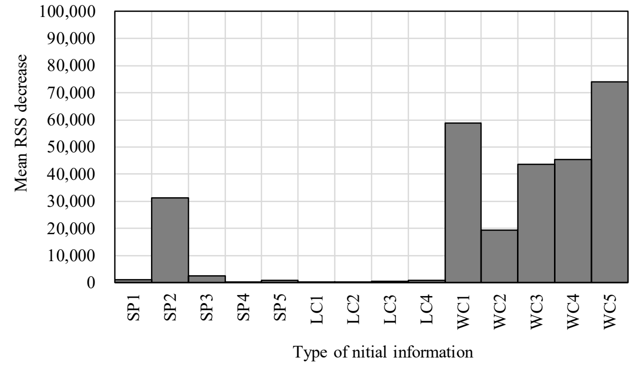

Figure 9: Influential Factors in Results of Random Forest.

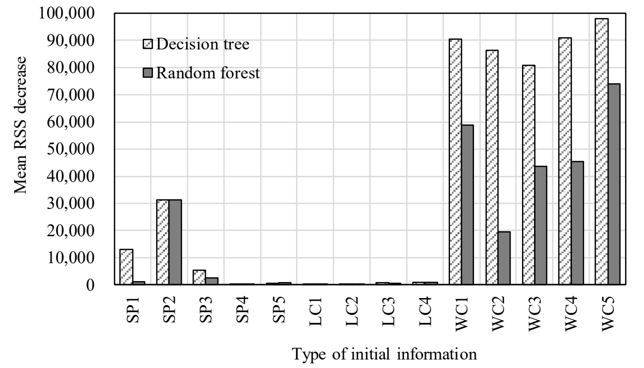

Figure 10: Comparison of influential factors in simple decision tree and random forest

6. Conclusions

The authors proposed a decision tree-based estimation method for operating lifetime of newly constructed electrical components. In estimation of the operating lifetime, the inspection and the maintenance records were utilized for analyzing relationships between initially available information (sets of the attributes of target component and the weather conditions) and the operating lifetime. The resulting tree-like model achieved the operating lifetime estimation by using only the initial information of newly constructed electrical components. From the results of numerical simulations, we could confirm that the proposed estimation method had sufficiently high accuracy in practical use of the distribution system planning. In addition, the weather conditions and type and length of the concrete poles were specified as the influential factors on the operating lifetime.

In future work, the authors will analyze the relationship between the influential factors and the operating lifetime in more detail. Improvement of the estimation stability, as shown in Section 5, also become an important issue of this study.

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