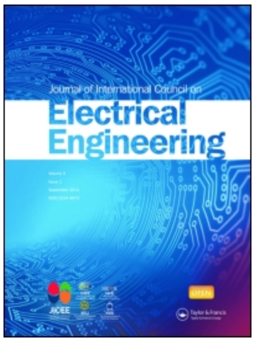

Taylor & Francis
Taylor & Francis Group

Journal of International Council on Electrical Engineering

ISSN: (Print) 2234-8972 (Online) Journal homepage: https://www.tandfonline.com/loi/tjee20

A study on operating lifetime estimation for electrical components in power grids on the basis of analysis of maintenance records

Ryuhei Shiomi, Hironobu Shimasaki, Hirotaka Takano & Hisao Taoka

To cite this article: Ryuhei Shiomi, Hironobu Shimasaki, Hirotaka Takano & Hisao Taoka (2019) A study on operating lifetime estimation for electrical components in power grids on the basis of analysis of maintenance records, Journal of International Council on Electrical Engineering, 9:1, 45-52, DOI: 10.1080/22348972.2019.1612975

To link to this article: https://doi.org/10.1080/22348972.2019.1612975

Published online: 20 May 2019.

JOURNAL OF INTERNATIONAL COUNCIL ON ELECTRICAL ENGINEERING
2019, VOL. 9, NO. 1, 45–52
https://doi.org/10.1080/22348972.2019.1612975

ARTICLE

A study on operating lifetime estimation for electrical components in power grids on the basis of analysis of maintenance records

Ryuhei Shiomi[a], Hironobu Shimasaki[a], Hirotaka Takano[b] and Hisao Taoka[c]

[a]Department of Electrical and Electronics Engineering, Graduate School of Engineering, University of Fukui, Fukui-shi, Japan; [b]Department of Electrical, Electronic and Computer Engineering, Faculty of Engineering, Gifu University, Gifu City, Japan; [c]Department of Electrical and Electronics Engineering, Faculty of Engineering, University of Fukui, Fukui-shi, Japan

ABSTRACT
This paper presents an estimation method of operating lifetime for electric power components, such as electric poles and pole transformers, utilizing massive records on their inspection and maintenance. The proposed method analyzes initial information, which is easily available, and real historical records of the inspection and measures for the inspection (maintenance) storing the database in an electric power company (e.g. 1.4 million and 53.4 thousand cases in the concrete electric poles). Subsequently, lifetime estimation models on each component are constructed using relationship between the initial conditions and the taking measures in the maintenance record. This method is aiming to apply on expansion planning phase of the power grid, and therefore the initial conditions are only used as its input in estimation process. Through numerical simulations, it was confirmed that accuracy of the lifetime estimation exceeds 70% (approximately 7 years). In addition, factors, which have an influence on the operating lifetime of the target component in process of lifetime estimation were clarified.

ARTICLE HISTORY
Received 15 October 2018
Accepted 16 April 2019

KEYWORDS
Big data; decision tree analysis; inspection record; lifetime estimation; maintenance record; operating lifetime of electrical components

1. Introduction

Japan is well known as one of the countries with the fewest power outages and the fast recovery of them. The average annual outage time is a few minutes per household excluding natural disaster-originated outages [1]. In order to achieve the stable operations of electric power grids, power grid operators have been making inspection and maintenance for electric power equipment and its components such as electric poles, pole transformers and switchgears. Records of the inspection and measures for the inspection results (need follow-up observation, repair or replacement) have been gathered, and then stored in databases of each electric power company. If we make good uses of the massive records, efficiency in the power grid operations and planning can be improved. However, there is still plenty room for discussion on how to utilize the massive records, and what kinds of techniques are suitable for analyzing and/or utilizing them. For these reasons, applications of the inspection and the maintenance records are limited yet in a small portion of the actual operations and planning in the power grid [2].

With a view to addressing the circumstances, the authors propose an estimation method for operating lifetime of the electrical components based on a decision tree analysis. The decision tree analysis is a popular technique to make its results easily understandable [3–5], and this is the strongest reason why it is applied in the proposed method. The proposed method requires two processes before the lifetime estimation process. One is to extract useful information (rules, knowledge and/or judgement criteria), and another is to construct tree-like estimation models by using the extracted information. Initial information of the target component, such as type, size and locational conditions, and historical records of the inspection results and the taking measures for the results are used in the former (analysis process). In the latter, the tree-like decision models are constructed to estimate the operating lifetime of the target components. During the process, we can comprehend judgement criteria of the lifetime estimation visually. This method is aiming to apply on expansion planning phase of the power grid and or its equipment, so that it estimates the operating lifetime when the initial conditions are newly input.

Numerical simulations are carried out to verify the validity of the authors' proposal. In the numerical simulations, real historical records of the inspection and the maintenance, which have been stored in databases of a Japanese electric power company, are used (e.g.

CONTACT Hirotaka Takano takano@gifu-u.ac.jp Department of Electrical, Electronic and Computer Engineering, Faculty of Engineering, Gifu University, Gifu City, Japan

1.4 million and 53.4 thousand cases in the concrete electric poles). Although the proposed method was applied to several electrical components, concrete electric poles are emphasized as a typical example of them in this paper. This is because the concrete electric pole has the largest share in the electrical components, and therefore has an impact on the power grid operations and planning. Moreover, there are various causes in the concrete deterioration, and they also become difficult to estimate the operating lifetime relying on only knowledge and experience of the power grid operators [6,7].

2. Estimation conditions

On the expansion planning phase, available information is normally limited. In this paper, two types of the lifetime estimation are examined by using only the initial conditions, such as type, size and locational conditions of the electrical components. First one simply judges whether the operating lifetime of target component (electric poles) is longer than or equal to its average or not. Second one estimates yearly operating lifetime of each electric pole. This section introduces outline of the historical records of inspection and maintenance, and defines the operating lifetime and its average.

2.1 Definition of operating lifetime and its average

The maintenance record includes the measures for inspection results, which can be categorized into several levels such as 'Need follow-up observation', 'Need repair' and 'Need replacement'. In this paper, the operating lifetime is defined as the duration depending on the operators' judgement for necessity of repair or replacement.

These states mean that the target component cannot keep its stable operation. Figure 1 shows distribution of the operating lifetime for the concrete electric poles in the target record. In Figure 1, the authors remove cases that have shorter operating lifetime than 20 years as irregular cases. This is because cases of accidental repair or replacement are included in the maintenance record without any additional information (available in the other record). As shown in Figure 1, the average lifetime of the electric poles is set by 40.8 years, and it uses as the base value of the former estimation. This result almost matches with our knowledge and experience which regards their lifetime as 30–40 years [7].

2.2 Target data

In the analysis process, the initial conditions and the records of inspection and maintenance are used as input datasets, and mainly the relationship between the initial conditions and the taking measures for the inspection results (need follow-up observation or maintenance) are analyzed to extract the useful information. Table 1 summarizes the initial conditions of the target component, which are all easily available, and Table 2 shows outline of usable inspection and maintenance records. As already mentioned, the concrete electric pole, which has the largest share in Japan, is emphasized as the typical example of the electrical components.

As shown in Table 1, 14 attributes are selected as the initial conditions. These conditions can be roughly classified into specifications of the target component (type, length, etc.) and the locational conditions (salt damage level, geological condition, etc.). In Table 2, the inspection record, which is extracted from 1.4 million

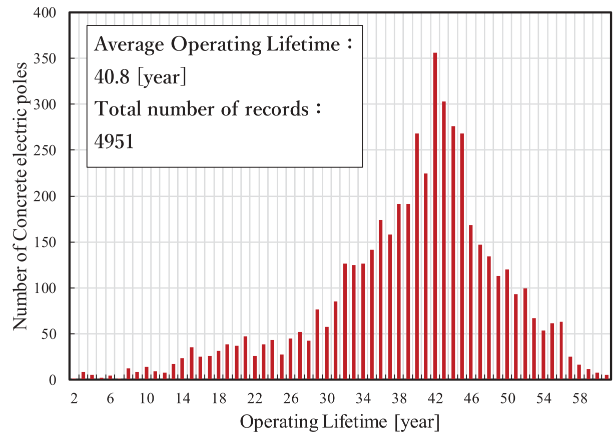

Figure 1. Distribution of operating lifetime of concrete electric poles.

Table 1. Details of initial conditions.

Input attributes	Ellipsis	Contents
Type	TYP	Symbol A – Z
Length	LEN	8–30 [m]
Salt Damage Level	SAL	Score 1–3
Surrounding Condition	SUR	Score 1–7
Geological Condition	GEO	Score 1–3
Soil Quality	SOI	Score 1–5
Facility Type	FAC	Score 1–4
Maximum Precipitation	PRE	86–124 [mm]
Temperature (High)	HIG	35–37 [℃]
Temperature (Low)	LOW	−1 – −4 [℃]
Maximum Wind Speed	WIN	9–18 [m/s]
Number of Electric Poles in Each Area	NUM	10,694–60,172
Transformer	TRN	With or Without
Switch	SWT	With or Without

a Higher score expresses higher influence in Table 1.

Table 2. Outline of inspection and maintenance records.

	Below average	Above average	Total
Training dataset	1,969	2,482	**4,451**
Test dataset	106	128	**234**
Good sample		286,137	**286,137**
Special sample		487	**487**
Total	**2,075**	**289,234**	**291,309**

sets of inspection scores, is classified into cases requiring repair or replacement and the others. The former includes 4,685 sets (picked up from 4,951 sets) that these samples were already finished their operating lifetime. From the viewpoint of the operating lifetime, these samples also can be categorized into longer than or equal to the average lifetime ('Above average') or shorter than it ('Below average'). During the model construction process, 95% of samples are used for training, and the remaining 5 % of samples are used for evaluating performance of the constructed models. On the other hand, 'Good sample' means the electric pole who is operating until now and already exceeding the average lifetime. In addition, 'Special sample' has been operating over 60 years. The good and the special samples are also used in evaluation of the performance of constructed models.

3. Estimation method

There are various estimation models in machine learning techniques including multiple regression models, artificial neural networks and decision tree models [3–5,8,9]. The authors select a decision tree model as the basis of the operating lifetime estimation. The decision tree, as is well known, is a tree-like model representing its decisions and decision-making process visually and explicitly, and therefore we can easily comprehend the judgement criteria without any special knowledge and experience for its algorithm. This section describes details of the proposed estimation method.

3.1 Outline of decision tree model

Decision tree model is a knowledge representation that ultimately makes some kind of decision by accumulating questions about the attributes of objects. The decision tree model normally consists of nodes, branches and leaves. The node represents a question on an attribute (e.g. whether a score is higher than its standard or not), and each leaf node expresses a class label (e.g. operating lifetime). The paths from root to leaf represent classification rules [3–5]. An example of constructed decision tree model is shown in Figure 2. In Figure 2, length of the target components is selected as the most important criterion in the model. If the length is shorter than 14 [m], the decision tree model judges that the operating lifetime of target component becomes 45 or 53 years. Subsequently, the operating lifetime is specified in response to the type (material, etc.) of the target component (type A: 45 years; type B – Z: 53 years).

In this paper, the classification tree is used for the simple classification in whether the lifetime of target component exceeds its average or not. In contrast, the regression tree is used to estimate yearly operating lifetime of the target component (Figure 4 shows an example of this type).

3.2 Classification and regression tree algorithm

Typical approaches for creating the decision tree include Classification and Regression Tree (CART), Iterative Dischotomiser 3 (ID3) and C 4.5 [10]. The

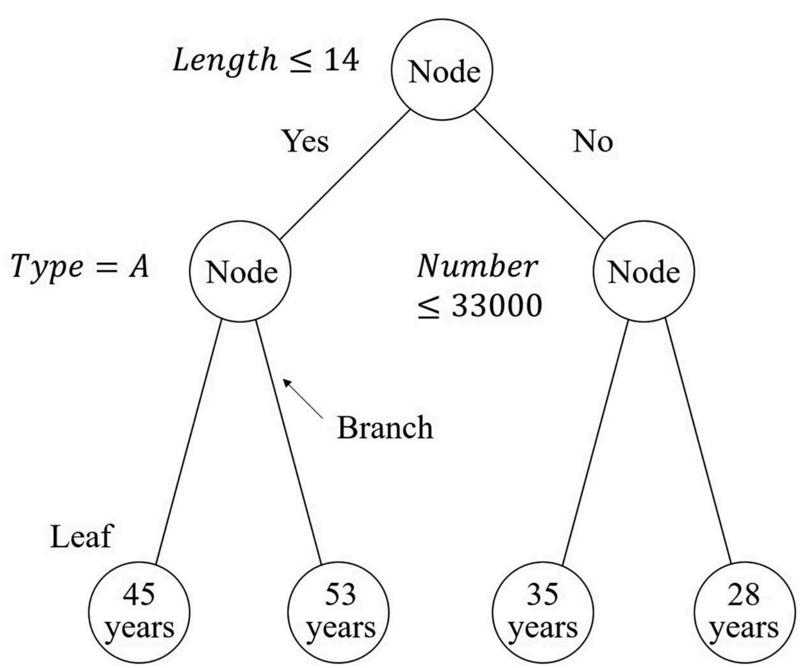

Figure 2. An example of decision tree model.

authors select a CART algorithm, which is one of the most popular approaches for non-parametric decision tree learning. The CART model involves selecting input variables and split points on those variables until satisfying the convergence criterion. In the proposed method, Gini impurity is used as the splitting criterion. When the Gini impurity is taken as the branch criterion, the attribute, which reduces the Gini impurity most after branching, is selected as the question in the node [11,12]. During the process, verbose branches are pruned until the Gini impurity becomes sufficiently small. As shown in (1), if the Gini impurity is zero, all classes are perfectly same. In contrast, a Gini impurity of 1 (or 100%) expresses maximal inequality among the classes.

$$GINI = 1 - \sum_{j}^{C} p(j|t)^2 \tag{1}$$

where t is the node number, C is the number of classes, and $p(j|t)$ is the probability that the case of each class occurs in the whole case.

Now, the case whose datasets have sets of multiple input attributes and a class (output) is focused, and the number of datasets is defined as T . In this case, classes can be represented as $\{C_1, C_2, \cdots, C_j, \cdots, C_n\}$, where n is the number of classes. The procedure is as follows.

Step 1: If all classes in T belongs C_j, the resulting decision tree for T is represented by one leaf, and its class is categorized to C_j .

Step 2: If T includes several classes, the algorithm selects a certain attribute and divides the datasets T by using the attribute value.

Step 3: Steps 1 and 2 are applied to each of the divided the datasets.

On the other hand, in the regression tree, the likelihood separation defined in (2) is taken instead of the Gini impurity as the branch criterion [5]. The attribute which minimizes equation (2) after branching is selected as question of decision tree.

$$D_t = \sum_{j} \left(y_j - \mu[j]\right)^2 \tag{2}$$

where y_j is the measured value of the response variable, and $\mu[j]$ shows the average value in the node t.

3.3 Random forest

Random forest is an ensemble learning method for classification and regression that constructs forests by multiple estimation tree models. The random forest ensemble uses a large number of individual, unpruned decision trees, which are created by randomizing the split at each node of the decision tree. Prediction accuracy of each tree is usually lower than that of the tree created with the exact splits as shown in 3.2. However, by combining several approximated trees in the ensemble, we can achieve more stable accuracy than that of the single tree with exact splits [5]. Figure 3 shows a conceptual illustration of the random forest algorithm.

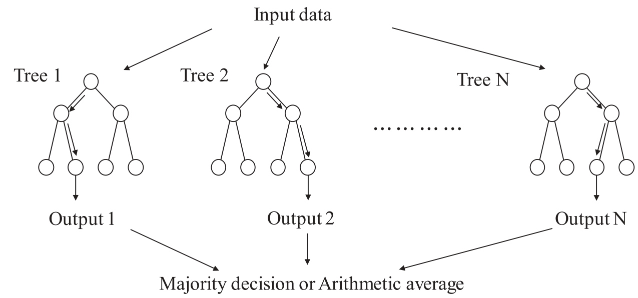

Figure 3. Conceptual illustration of random forest.

As shown in Figure 3, if we input the target data (a set of initial conditions) into each tree model, which is the component of the forest, the tree models individually output their judgement results according to their construction.

Sequentially, the majority decision or the arithmetic average of their results is calculated as the output of the forest. In this approximation, the output of the random forest is the majority decision in the case of the random forest constructed by classification trees and the arithmetic average in the case of the random forest constructed by regression trees [13].

Since it is not easy to understand the structure of tree models in the random forest, this technique is used only for the purpose of improving prediction accuracy of the decision tree.

4. Numerical simulations

4.1 Results of classification tree

The classification tree was constructed to simply judge whether the operating lifetime of target components exceeds their average or not. The resulting decision tree is shown in Figure 4. In Figure 4, '0' in leaves and nodes mean 'less than the average', and '1' means 'higher than or equal to the average'. Specifically, if the answer to question in the leaf is 'Yes', the input dataset moves to the left-side branches. On the other hand, if the answer is 'No', it moves to the right-side. Accuracy of the numerical simulation results are evaluated and discussed from the following viewpoints.

Case 1: Classification accuracy for training data.

Case 2: Classification accuracy for test data.

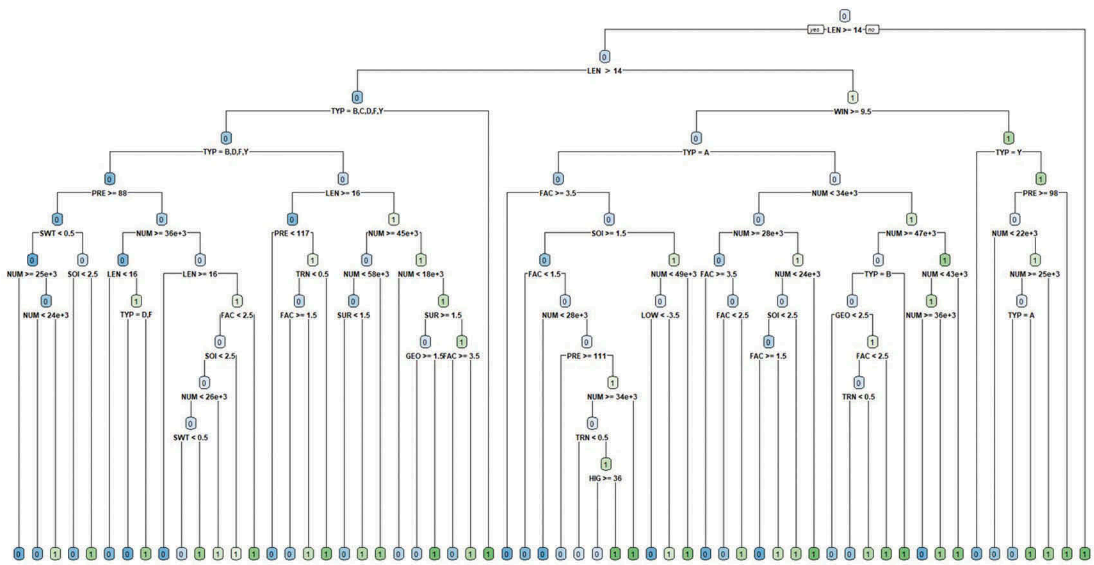

Figure 4. Classification tree.

Table 3. Accuracy in classification tree.

	Below average	Above average	Whole
Training data	75.5 %	74.3 %	74.8 %
Test data	72.6 %	75.0 %	73.9 %
Good samples		74.1 %	
Special samples		76.0 %	

Table 4. Classification results of random forest.

	Below average	Above average	Whole
Training data	79.9 %	85.1 %	82.8 %
Test data	74.5 %	75.8 %	75.2 %
Good samples		75.6 %	
Special samples		76.2 %	

Case 3: Classification accuracy for 'good examples'.

Case 4: Classification accuracy for 'special examples'.

As summarized in Table 3, the minimum classification accuracy was 72.6% for the test data of 'Below average', and the maximum one was 76.0% for the 'Special samples'. Although the single tree model was applied, accuracy in each case exceeded 70%. Furthermore, as shown in Table 4, the random forest shows higher estimation accuracy than the single tree model in every case. The minimum classification accuracy of the random forest was 74.5% for the test data of 'Below average', and the maximum one was 82.8% for the training data of 'Above average'. These results show that the proposed estimation functioned very well in the simple classification.

By utilizing the feature of decision tree, the authors specified the factors, which had an influence on the operating lifetime. Figure 5 shows analysis results of the judgement criteria in the constructed decision trees. From this figure, it is confirmed that LEN (pole length) had remarkable influence on the operating lifetime. Actually, the estimated operating lifetime became shorter than its average if LEN was equal to 14 [m] or longer.

In Figure 5, TYP (type of electric pole), SOI (soil quality), NUM (number of electric poles in each area) and FAC (facility type) were also specified as important criteria on the lifetime estimation. Figure 6 shows the relationship between the length of electric poles and the average lifetime, and the relationship between the length and the average lifetime of Types A and X is illustrated in Figure 7. By these results, we can confirm that the pole length and the operating lifetime are approximated by a negative linear function within 16 m. Here, the longer electric poles are rare cases in the Japanese electrical components. Besides, it is confirmed that Types A and X of the electric poles have generally longer lifetime.

4.2 Result of regression tree

The regression tree was constructed to estimate yearly operating lifetime of the electric poles individually. Accuracy of the numerical simulation results are evaluated and discussed from the following viewpoints.

Case 1: Prediction accuracy for training data.

Case 2: Prediction accuracy for test data.

Case 3: Prediction accuracy for the special samples, which have been operated over 60 years.

Here, the root mean square error (RMSE) is used as the evaluation index of estimation accuracy. Equation (3) shows the definition of RMSE.

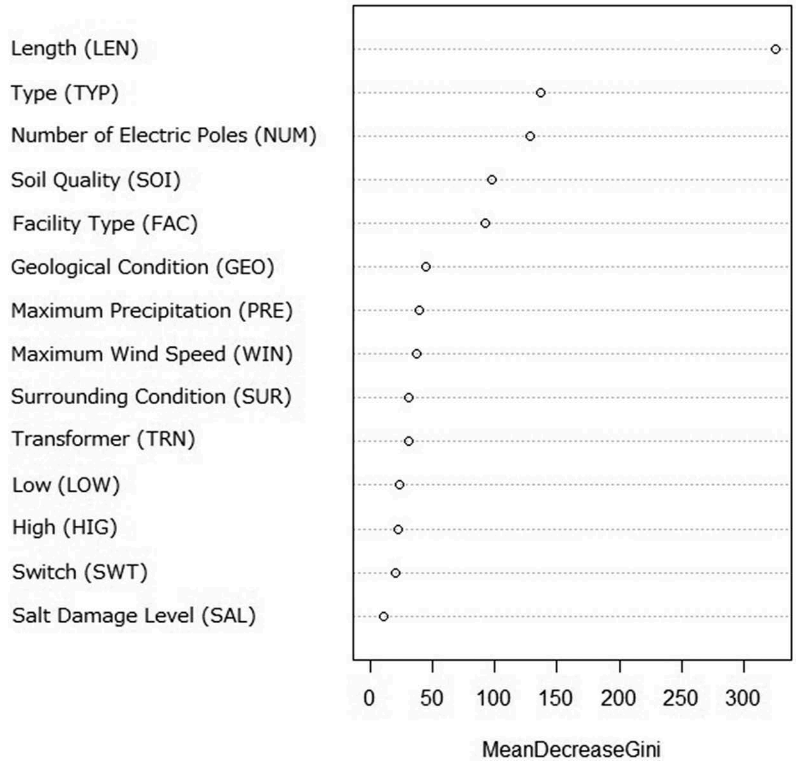

Figure 5. Judgement criterion in decision trees.

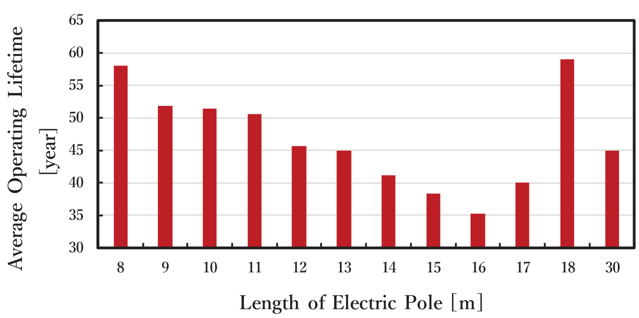

Figure 6. Relationship between pole length and lifetime.

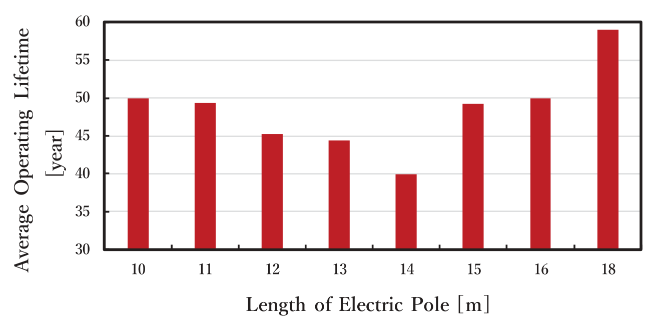

Figure 7. Relationship between pole length and lifetime of Types A and X (Excluding Types B, C, D, F and Y).

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(f_i - y_i)^2} \quad (3)$$

where N is the number of data; f_i is the predicted value; and y_i is the true value.

The lower value of RMSE is better than the higher value. As shown in Table 5, the RMSE for the training and the test data were less than 7 years. However, the RMSE of special samples became 17.7 years. From Figure 1, we can confirm that there are very few electric poles operating over 60 years in the training data. This is a reason why the RMSE became so large. Figure 8 shows estimated lifetime for the special samples. As shown in Figure 8, the proposed method estimated that the special samples have totally longer lifetime

Table 5. Prediction results of regression tree.

	RMSE [years]	Maximum error [years]
Training data	6.3	28.8
Test data	6.8	23.5
Special samples	17.7	30.1

(74.5 %) even though the accuracy was low. Therefore, we can conclude that the decision tree functioned appropriately.

Table 6 summarizes accuracy of each estimation result of the random forest, and Figure 9 illustrates the estimation error for the test data. In the random forest, all estimation results exceeded those of Table 5 excepting for the maximum error in special samples.

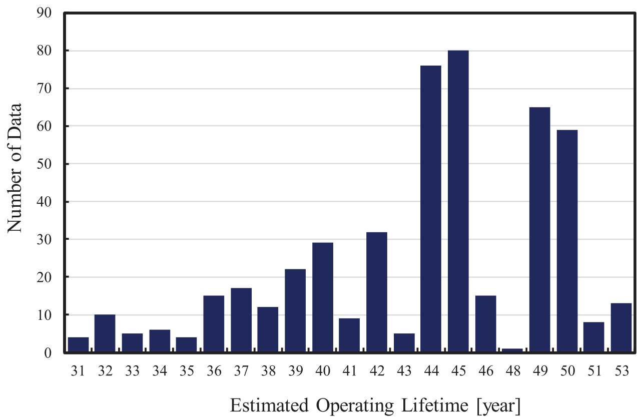

Figure 8. Estimated lifetime for special samples.

Table 6. Prediction results of random forest.

	RMSE [years]	Maximum error [years]
Training data	5.1	24.4
Test data	6.7	19.4
Special samples	17.2	30.4

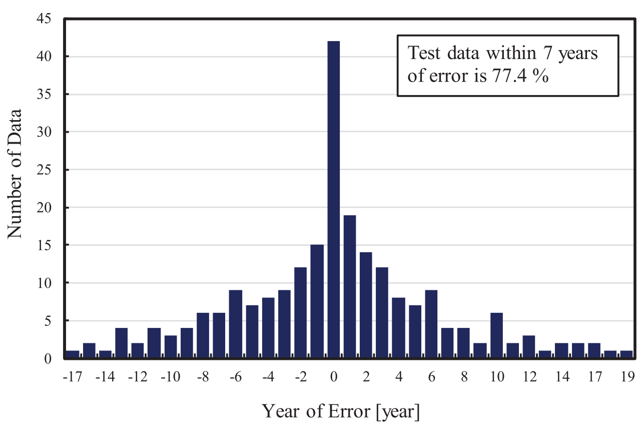

Figure 9. Estimation error of test data in random forest.

Since all electric poles are inspected every five years, the estimation model gained high estimation accuracy. Therefore, the authors concluded that the random forest improved the estimation accuracy in the classification as compared to the individual decision trees as similar to the results of 4.1.

5. Conclusion

In this paper, the authors focused on the decision tree analysis, and proposed an estimation method for operating lifetime of the electrical components. There were two types of operating lifetime estimation were examined, and their results are discussed. First one simply judges whether the operating lifetime of target electric pole is longer than or equal to the average lifetime or not, and second one estimates yearly operating lifetime of each electric pole according to their initial conditions. In the numerical simulations, massive real records of the inspection and the maintenance were used. As a result, all classification accuracy were 70% or higher, and accuracy in the yearly estimation became within 7 years. In addition, with reference to the constructed trees, we comprehended that the length of electric pole had the highest impact on the operating lifetime.

In future works, the authors will analyze importance of each input information on the estimation results and improve the estimation accuracy further.

Acknowledgments

This work was supported by the Kansai Electric Power Co., Inc (KEPCO). The authors are grateful to KEPCO for providing their operational data and suggesting the topic treated in this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Ryuhei Shiomi received B.E degree in Electrical Power from University of Fukui, Japan in 2017. Now he is attending Master Degree Course in University of Fukui, Japan. His research interests are operation planning of power systems and data analysis in power systems.

Hironobu Shimasaki received B.E degree in Electrical Power from National Institute of Technology, Fukui College advanced engineering course Japan in 2017. Now he is attending Master Degree Course in University of Fukui, Japan. His research interest is data analysis in power systems.

Hirotaka Takano received the Master and the Doctor of Engineering degrees from University of Fukui, Japan, in 2003 and 2006, respectively. He then became an assistant Professor at Department of Electrical and Computer Science, National Institute of Technology, Gifu College, Gifu, Japan, until 2011, and an assistant professor at the Faculty of Information Science and Electrical Engineering, Kyushu University, Japan, from 2011 to 2015. From 2015 to 2017, he worked as a senior assistant professor at Faculty of Engineering, University of Fukui. In 2018, he transferred to Gifu University, where he is currently an associate professor at Faculty of Engineering. His research interests are advanced operation and planning of electric power systems, and applications of optimization techniques.

Hisao Taoka graduated from the Graduate School of Engineering at the University of Tokyo in 1979. In 1979, he joined Mitsubishi Electric Corporation, where he has engaged in the research on power system control and analysis using advanced computer technologies. He received a doctoral degree from the University of Tokyo in 1986. After being a professor in Fukui University of Technology for 7 years from 2003, he is now a professor in the Faculty of Engineering, Electrical & Electronics Engineering, University of Fukui.

References

[1] Takano H, Kawamura K, Iizaka T. Industry practice and operational experience of key distribution applications of smart grid technologies. Vol. 2, Smart Grid Handbook, C. Liu ed., S. McArthur ed., S. Lee ed. WILEY; 2016. p. 967–993.

[2] Takano H. Current technologies on energy data utilization. IEEJ Trans Electrics Inf Syst. 2016;136 (6):758–758.

[3] Menzies T, Hu Y. Data mining for very busy people. IEEE. 0018-9162/03/$17.00 © 2003.

[4] Segaran T. Programming Collective Intelligence. O'Reilly Media; 2008.

[5] Rokach L, Maimon O. Data mining with decision trees 2nd ed. World Scientific; 2014.

[6] Yoshikawa H, Oi Y, Marumoto S. Residual compressive strength of concrete under constant cyclic loads and reliability analysis of reinforced concrete column. Jsce. 1995;520/v–28:55–65.

[7] Kakizaki M. Tekkin konkurito zo tatemono no jumyo yosoku (Life prediction of reinforced concrete building). Jsse. 1991;30(6):421–431.

[8] Rawlings J, Pantula S, Dickey D. Applied regression analysis: a research tool, second edition. Springer; 2001.

[9] Haykin S. Neural networks and learning machines third edition. Prentice Hall; 2008.

[10] Singh S, Giri M. Comparative study Id3, cart and C4.5 decision tree algorithm: a survey. Ijaist. 2014;3 (7):47–52.

[11] Loh W. Classification and regression trees. In: WIREs data mining and knowledge discovery. Vol. 1. John Wiley & Sons, Inc; 2011. p. 14–23.

[12] Kaneda S. Ketteiki gakushu: jitsuyoki wo mukaeta nonparametorikku tokei shuho (Decision tree learning: nonparametric statistical method that has reached the practical stage). CICSJ Bull. 1999;17 (4):9–14.

[13] Habe H. Random forests. IPSJ SIG Tech Rep. 2012;2012(31):1–8.