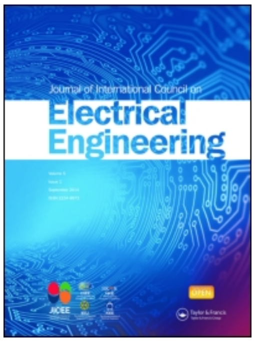

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A study on maintenance decision support for power grid components using their inspection and maintenance records

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ABSTRACT

Electric power companies are storing massive records such as results of inspection and maintenance through their daily operations. Although the massive records have been expecting to utilize for efficiency improvement of the power grid operations and planning, applications of the massive records have been limited in a small portion until now. The authors analyse 3.0 million sets of inspection scores and 0.9 million cases of their measures (need follow-up observation, or need repair or replacement) that have been actually stored in an electric power company. Moreover, based on the analysis results, a decision support model is constructed for judging maintenance necessity (need repair or replacement) in response to the inspection scores. A decision tree analysis, which represents its decisions and decision-making process visually and explicitly, is applied in the process. Usefulness of the authors' proposal is verified through numerical simulations and discussions on their results.

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Big data; data utilization; decision support; decision tree analysis; inspection record; maintenance record

1. Introduction

Owing to the rapid growth in technologies of measurement, monitoring and communication, quantities of information, which have been gathered by several measurement systems, are increasing dramatically in various fields. If the massive data is utilized effectively, we can expect several benefits by the resulting improvement of our social efficiency [1,2]. It also can be applied to the electric power field [3–5]. For example, power grid operators have been making inspection and maintenance for electrical components to sustain the stable operations of power grids. The sets of inspection scores have been stored in databases as the inspection record, and also utilized during the decision-making process whether the electrical components require to be taken measures or not to keep their functions appropriately. Meanwhile, the judgement results (measures for the inspection), such as Need follow-up observation or Need repair or replacement, described and stored as the maintenance record. These records are not only referred in expansion planning of the power grid equipment but also expected to apply for improving operational efficiency and saving operators' labour. However, since quantities of the inspection and the maintenance records are indeed large, it has been extremely difficult to apply them for the power grid operations and planning effectively relying on knowledge and experience of the operators only. Actually, applications of the massive records are limited in a small portion of the electric power fields yet [6,7]. That is, there is still plenty room for discussion on how to utilize the massive records, and what kinds of techniques are suitable for analysing and/or utilizing them.

The authors focus on a decision tree analysis, and propose a support method of maintenance decision for electrical components in response to their inspection scores. The decision tree analysis, which is well known as one of machine learning techniques, represents its decisions and decision-making process visually and explicitly [8], and this is the strongest reason why the authors apply it to the maintenance decision support. By using the decision tree analysis, historical datasets of the inspection scores and their measures are analysed in the learning process. Subsequently, a tree-like decision model is constructed as result of the learning process. In accordance with description of the maintenance record, the constructed tree model automatically judges maintenance necessity of the target component (need follow-up observation, or need repair or replacement) when a set of inspection scores are newly input. Moreover, with referring to the constructed decision tree, we can comprehend factors

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that have influence on the judgement. Numerical simulation results for 3.0 million sets of the inspection scores and 0.9 million cases of their measures, which were actually stored in the database of an electric power company, are introduced. Here, the target electrical components are specified into electric poles, pole transformers and switchgears in power distribution networks. This is because these components have larger shares in the electrical components of Japanese power grids than those of the others.

2. Maintenance decision support

2.1 Overview of proposed decision support method

In a machine learning community, prediction methods are normally referred to supervised learning techniques [9,10]. The supervised learning technique attempts to discover the relationship between input and output datasets, and the discovered relationship is represented in a structure. Representative techniques include artificial neural networks (ANNs), support vector machines (SVMs) and decision trees [11,12]. The NN and the SVM are often regarded as complicated techniques since the constructed models are difficult to understand without knowledge of their algorithm. On the other hand, the decision tree has distinctive feature that represents its learning result visually, and therefore their judgement criteria are easily understandable. For these reasons, the authors apply the decision tree to treat the target massive records in this paper.

There are several decision tree analysis. Iterative Dichotomiser 3 (ID3), C4.5, and Classification and Regression Tree (CART) are their typical examples [13]. In this paper, the CART algorithm, which is one of the most popular tools for non-parametric decision tree learning, is selected in the learning process. The CART algorithm makes decision trees to minimize entropy, which expresses randomness in the information, or Gini coefficient. Now, the Gini coefficients is emphasized as the criterion in the CART algorithm. The Gini coefficient evaluates the inequality among values of a frequency distribution. If the Gini coefficient becomes zero, all values are perfectly equal. In contrast, a Gini coefficient of 1 (or 100%) expresses maximal inequality among the values. General definition of the Gini coefficient is defined as

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

where t is the node number;C is the number of classes; and $p(j/t)$ is the probability density function.

By using the Gini coefficients, the CART algorithm constructs a decision tree to split one node into two child nodes repeatedly. Its constructing process can be classified into the following two steps: one is the tree growth and another is the branch pruning. In the former, a creating tree model involves selected input data and split points on each score (growth) until satisfying the convergence criteria. In contrast, the latter integrates verbose paths (pruning) until the Gini coefficient becomes sufficiently small.

2.2 Decision tree-based method

The proposed decision support method judges maintenance necessity of the target electrical component (need repair or replacement, or not) automatically in response to the inspection scores. The following shows its procedure.

- Step 1 Correlate the inspection and the maintenance records in each component.
- Step 2 Learn relationship between the historical inspection scores and its maintenance necessity.
- Step 3 Construct a decision tree in accordance with the tree growth and the branch pruning steps.
- Step 4 Judge the maintenance necessity in response to input data (a set of unknown inspection scores).

Step 1 is pre-processing for the learning process of the decision tree analysis. By using the ID codes for target electrical component, the sets of inspection scores are correlated with the measures for the inspection as input datasets for the learning process. In Step 2 and 3, the CART algorithm analyses the relationship between the input datasets. Specifically, useful information such as rules, knowledge or judgement criteria on the maintenance decision are extracted from the relationship of input datasets, and the CART algorithm constructs the decision tree in Step 3 relying on the extracted information. Finally, the maintenance necessity is judged by the constructed decision tree when the set of inspection score of target component are newly input. Figure 1 shows a conceptual illustration of decision tree construction.

3. Numerical conditions

3.1 Targeted inspection and maintenance records

The power grid operators have been checking and scoring conditions of the electrical components, and

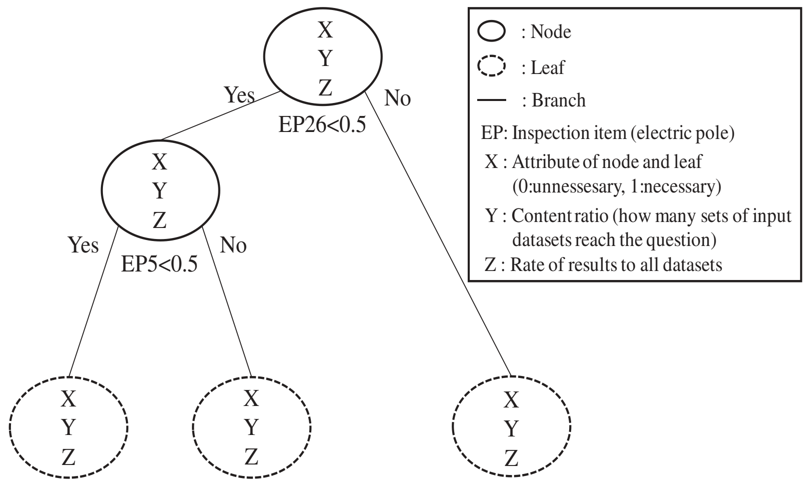

Figure 1. An example of a part of decision tree model.

deciding measures for the components with referring to the inspection scores. These results have been stored in the database as inspection record and the maintenance one, respectively. The target inspection record of this paper has the following information: (1) Inspection date, (2) ID code of the target component, (3) Specifications, and (4) Set of inspection scores (each component has 40 inspection indexes, however how many indexes are available is depending on type of the target component). In the inspection scores, the lower value means the better condition. If all scores are zero, the target component does not have any trouble on its condition. On the other hand, the measures for inspection described in the maintenance record can be roughly classified into three types: 'Need follow-up observation', 'Need repair' and 'Need replacement'. Here, the authors aggregate the types of 'Need repair' and 'Need replacement' as the type of 'Need maintenance'.

Table 1 summarizes the inspection and the maintenance records. The inspection data is the result of 2 years inspection, and the maintenance data is the result of 10 years operations. In Table 1, a portion of the records including any missing or overlapping were already removed. As the result of data processing, 1,835,485 sets of the inspection scores (electric pole: 1,374,587; pole transformer: 386,533; switchgear: 74,365) and 8,079 samples of the maintenance requirement (electric pole: 3,209; pole transformer: 2,464; switchgear: 2,406) are available in the numerical simulations.

3.2 Outline of numerical simulations

The authors use the records of inspection and maintenance summarized in Table 1, which were actually stored in an electric power company. In Table 1, 95% datasets are used as the learning data, and the remaining 5% datasets are used for evaluating performance of the decision tree. In this paper, the authors construct two types of decision tree: one is individual decision tree using the learning datasets in each area, and another is the decision tree for whole area. Under these conditions, the authors examine the following three prediction accuracy.

Table 1. Available inspection and maintenance records in each area.

	Electric pole			Pole transformer			Switchgear		
Area code	No need maintenance	Need maintenance	Total	No need maintenance	Need maintenance	Total	No need maintenance	Need maintenance	Total
1	164,886	342	**165,228**	55,720	131	**55,851**	13,242	679	**13,921**
2	189,427	753	**190,180**	76,335	256	**76,591**	13,581	200	**13,781**
3	205,263	817	**206,080**	54,435	1079	**55,514**	9,477	431	**9,908**
4	185,491	482	**185,973**	44,285	675	**44,960**	10,309	155	**10,464**
5	110,320	226	**110,546**	34,348	121	**34,469**	4,472	159	**4,631**
6	150,931	52	**150,983**	33,393	46	**33,439**	5,991	73	**6,064**
7	144,747	82	**144,829**	32,831	57	**32,898**	5,833	407	**6,240**
8	220,313	455	**220,768**	52,712	99	**52,811**	9,054	302	**9,356**
Total	**1,371,378**	**3,209**	**1,374,587**	**384,069**	**2,464**	**386,533**	**71,959**	**2,406**	**74,365**

Case 1: Inspection scores for the learning process, which were used to construct the decision tree.

Case 2: Individual inspection scores for evaluating performance of the decision tree in each area (Area 1–8).

Case 3: Whole inspection scores for evaluating the performance of the decision tree.

Parameters for the CART algorithm are set by trial and error.

4. Results and discussions

4.1 Results of electric pole

In case of the electric poles, 33 inspection indexes (defined as EP 1–33) are available. Table 2 summarizes the learning and the evaluation datasets. In Table 2, 1,302,801 sets of inspection scores and 3,057 samples of the maintenance requirement were used for the learning datasets. On the other hand, 68,577 sets of inspection scores and 152 samples of the maintenance requirement were regarded as unknown data, and used for evaluating performance of the decision tree. The decision tree for electric pole using the whole datasets (Areas 1–8) is illustrated in Figure 2, and Table 3 shows its numerical results.

As shown in Figure 2, the decision tree selected conditions, 'EP 2 < 0.5', 'EP 8 < 0.5', 'EP 18 < 0.5', 'EP 14 < 0.5' and 'EP 24 < 0.5', as the judgment criteria. If the inspection results satisfied these conditions, the proposed method judged that the target electrical component was requiring its repair or replacement. This trend was almost same in every cases. In Table 3, we can confirm differences in the accuracy of each area, however all values of overall accuracy exceeded 80% (minimum accuracy: 80.9% in Area 2 of Case 1; Maximum accuracy: 99.2% in Area 7 of Cases 1 and 2), and therefore the authors concluded that the proposed method functioned very well.

Table 2. Learning data and evaluation data for electric pole.

	Learning data		Evaluation data	
Area code	No need maintenance	Need maintenance	No need maintenance	Need maintenance
1	156,640	327	8,246	15
2	179,953	718	9,474	35
3	194,999	777	10,264	40
4	176,213	461	9,278	21
5	104,804	215	5,516	11
6	143,387	47	7,544	5
7	137,507	81	7,240	1
8	209,298	431	11,015	24
Total	**1,302,801**	**3,057**	**68,577**	**152**

4.2 Results of pole transformer

In case of the pole transformer, 9 inspection indexes (defined as PT 1–9) are available. Table 4 summarizes the learning and the evaluation datasets. In Table 4, 364,843 sets of inspection scores and 2,345 samples of the maintenance requirement were used for the learning datasets. Meanwhile hand, 19,206 sets of inspection scores and 119 samples of the maintenance requirement were regarded as unknown data, and used for evaluating performance of the decision tree. The decision tree for pole transformer using the whole datasets (Areas 1–8) is illustrated in Figure 3, and Table 4 shows its numerical results.

As shown in Figure 3, the decision tree selected conditions, 'PT 4 < 0.5', 'PT 3 < 1.5', 'PT 9 < 0.5', 'PT 2 < 0.5',

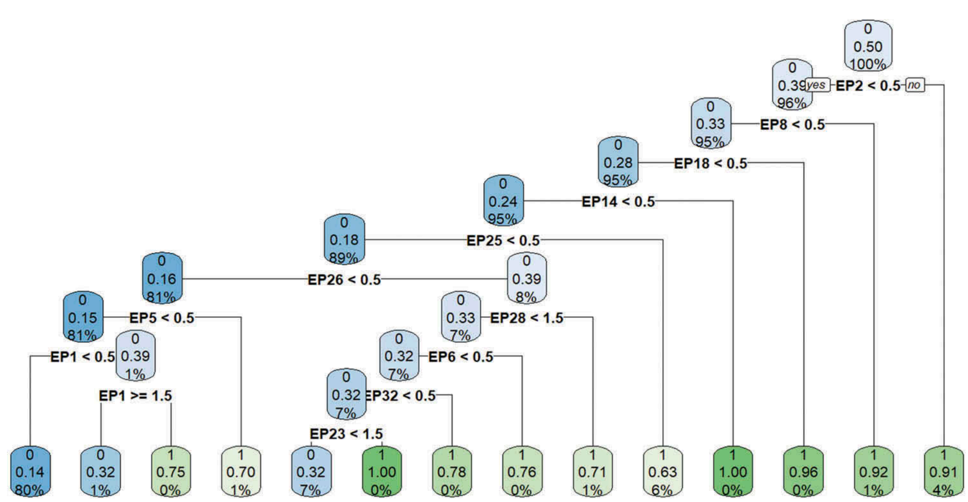

Figure 2. Decision tree (electric pole, all area).

Table 3. Results of electric pole.

Area code	Accuracy for Case 1: No need maintenance	Need maintenance	Overall	Accuracy for Case 2: No need maintenance	Need maintenance	Overall	Accuracy for Case 3: No need maintenance	Need maintenance	Overall
1	89.7	79.8	**89.7**	89.2	73.3	**89.1**	92.5	57.2	**92.4**
2	80.9	80.1	**80.9**	81.5	71.4	**81.5**	88.5	52.0	**88.4**
3	95.8	82.2	**95.8**	95.8	85.0	**95.7**	88.2	81.0	**88.2**
4	94.7	83.5	**94.7**	94.5	85.7	**94.5**	94.0	73.0	**93.9**
5	96.5	91.6	**96.5**	96.5	81.8	**96.4**	95.9	52.6	**95.8**
6	99.1	80.9	**99.0**	98.9	80.0	**98.8**	97.5	44.1	**97.4**
7	99.2	75.3	**99.2**	99.2	0.0	**99.2**	97.5	52.0	**97.4**
8	95.8	85.6	**95.8**	95.8	70.8	**95.7**	94.4	57.9	**94.3**
Whole	**87.8**	**83.0**	87.8				**87.7**	**81.6**	**87.7**

Table 4. Learning data and evaluation data for pole transformer.

Area code	Learning data: No need maintenance	Need maintenance	Evaluation data: No need maintenance	Need maintenance
1	52,936	123	2,784	8
2	72,518	243	3,817	13
3	51,710	1,029	2,725	50
4	42,081	631	2,204	44
5	32,626	120	1,722	1
6	31,721	46	1,672	0
7	31,197	56	1,644	1
8	50,074	97	2,638	2
Total	**364,863**	**2,345**	**19,206**	**119**

'PT 5 < 0.5' and 'PT 8 < 0.5', as the judgment criteria. If the inspection results satisfied these conditions, the proposed method judged that the target electrical component was requiring its repair or replacement. In addition, it was confirmed that every cases had similar tendency. From Table 5, there are differences in the accuracy of each area, however all values of overall accuracy were 85% or higher (Minimum accuracy: 86.5% in Area 3 of Case 3; Maximum accuracy: 98.2% in Area 5 of Case 2) like the results of electric pole.

4.3 Result of switchgear

In case of the switchgear, 9 inspection indexes (defined as SW 1–SW 9) are available. Table 6 summarizes the learning and the evaluation datasets. In Table 6, 68,357 sets of inspection scores and 2,290 samples of the maintenance requirement were used for the learning datasets. On the other hand, 3,602 sets of inspection scores and 116 samples of the maintenance requirement were regarded as unknown data, and used for evaluating performance of the decision tree. The decision tree for switchgear using the whole datasets (Areas 1–8) is illustrated in Figure 4, and Table 7 shows its numerical results.

As shown in Figure 4, the decision tree is a little more complicated as compared to those of the electric pole and the pole transformer. Actually, in Table 7, accuracy of the maintenance necessity totally became lower. There are several possibilities in the result, such as insufficiency of inspection indexes. However, these will be discussed in future works since accuracy in the unnecessary cases and values of overall accuracy were sufficiently high

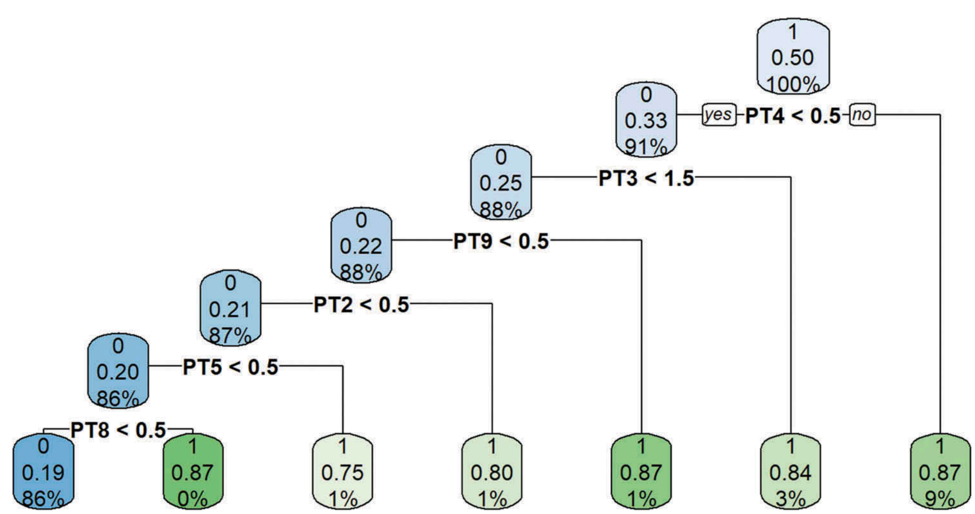

Figure 3. Decision tree (pole transformer, all area).

Table 5. Results for pole transformer.

	Accuracy for Case 1			Accuracy for Case 2			Accuracy for Case 3		
Area code	No need maintenance	Need maintenance	Overall	No need maintenance	Need maintenance	Overall	No need maintenance	Need maintenance	Overall
1	89.7	79.8	**89.7**	89.2	73.3	**89.1**	92.5	57.2	**92.4**
2	80.9	80.1	**80.9**	81.5	71.4	**81.5**	88.5	52.0	**88.4**
3	95.8	82.2	**95.8**	95.8	85.0	**95.7**	88.2	81.0	**88.2**
4	94.7	83.5	**94.7**	94.5	85.7	**94.5**	94.0	73.0	**93.9**
5	96.5	91.6	**96.5**	96.5	81.8	**96.4**	95.9	52.6	**95.8**
6	99.1	80.9	**99.0**	98.9	80.0	**98.8**	97.5	44.1	**97.4**
7	99.2	75.3	**99.2**	99.2	0.0	**99.2**	97.5	52.0	**97.4**
8	95.8	85.6	**95.8**	95.8	70.8	**95.7**	94.4	57.9	**94.3**
Whole	**87.8**	**83.0**	87.8				**87.7**	**81.6**	87.7

Table 6. Learning data and evaluation data for switchgear.

	Learning data		Evaluation data	
Area code	No need maintenance	Need maintenance	No need maintenance	Need maintenance
1	12,578	647	664	32
2	12,900	192	681	8
3	9,000	413	477	18
4	9,795	146	514	9
5	4,251	148	221	11
6	5,691	70	300	3
7	5,538	390	295	17
8	8,604	284	450	18
Total	**68,357**	**2,290**	**3,602**	**116**

(minimum accuracy: 77.1% in Area 8 of Case 2; Maximum accuracy: 96.2% in Areas 2 and 6 of Case 1).

5. Conclusions

This paper presented a decision support method for judging maintenance necessity of power grid components in response to the inspection scores, as an application of the massive records for the electric power fields. Since decision tree analysis, which is well known as one of the machine learning techniques, can be used to visually and explicitly represent decisions and decision-making, the author selected this learning methods.

The proposed method was evaluated using 1,835,485 sets of the inspection scores (electric pole: 1,374,587; pole transformer: 386,533; switchgear: 74,365) and 8,079 samples of the maintenance requirement (electric pole: 3,209; pole transformer: 2,464; switchgear: 2,406). In the learning process, 95% datasets are used as the learning data, and the remaining 5% datasets are used for evaluating performance of the decision tree. As the results of numerical simulations, the proposed method has approximately 80% or higher accuracy in the electric poles and the pole transformers. However, in the case of switchgear, accuracy in the necessary cases became lower than those of the electric poles and the pole transformers. In future works, the authors will analyse its causes in more detail.

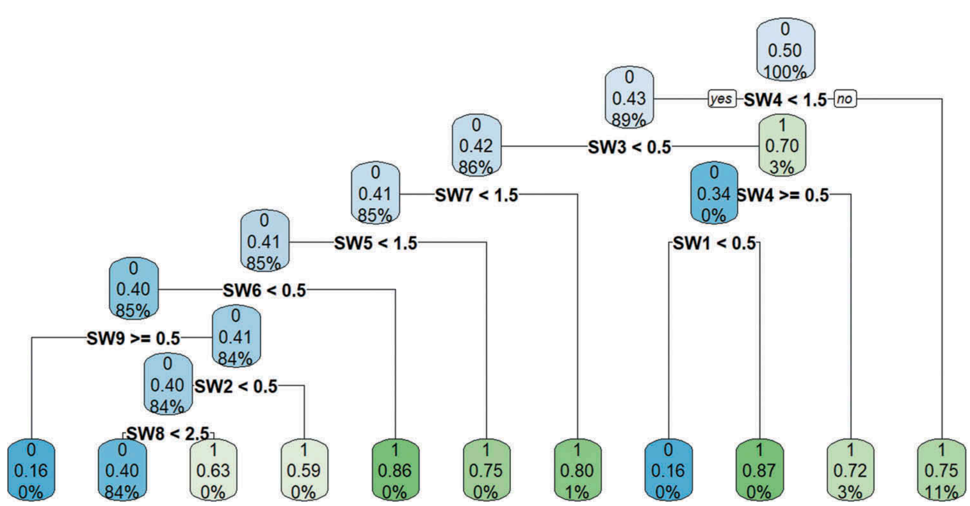

Figure 4. Decision tree (switchgear, all area).

Table 7. Results for switchgear.

Area code	Accuracy for Case 1			Accuracy for Case 2			Accuracy for Case 3		
	No need maintenance	Need maintenance	Overall	No need maintenance	Need maintenance	Overall	No need maintenance	Need maintenance	Overall
1	93.9	16.8	**90.1**	94.7	9.4	**90.8**	92.4	21.6	**90.2**
2	94.1	59.4	**96.2**	93.2	37.5	**92.6**	96.2	21.6	**93.9**
3	89.7	54.4	**88.2**	90.8	27.8	**88.5**	85.0	39.7	**83.6**
4	88.0	67.1	**87.6**	89.3	44.4	**88.5**	86.6	34.5	**84.9**
5	95.3	26.4	**93.0**	95.0	27.3	**91.8**	92.3	17.2	**89.9**
6	97.1	20.0	**96.2**	96.0	33.3	**95.4**	90.7	24.1	**88.6**
7	85.5	37.4	**82.4**	85.4	41.2	**83.0**	89.0	31.9	**87.2**
8	77.7	70.8	**77.5**	77.1	77.8	**77.1**	85.6	40.5	**84.2**
Whole	**85.3**	**42.4**	**83.9**				**85.5**	**40.5**	**84.0**

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Disclosure statement

No potential conflict of interest was reported by the authors.

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