APPLICATIONS OF DATA MINING TECHNOLOGY TO ENHANCE O&M: AUTOMATIC PLANNING OF ELECTRICAL ISOLATION WITH DEEP LEARNING

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ABSTRACT

Data mining technology is now readily available, thanks to high powered, low cost computing resource and useful coding tools. We study several applications of data mining to enhance operation and maintenance (O&M), such as abnormality prediction, efficiency diagnosis, document traceability, image recognition, etc. In field support, we try automatic planning of electrical isolation with deep learning. Currently, a skilled engineer plans electrical isolation procedure with hundreds of the circuit diagrams and the related documents, taking man-hours. If this task becomes automatic, it is very efficient. The automatic planning has two issues. One is much calculation time of electrical circuit simulator, searching billions of electrical conducting paths. The other is interpretation of human fuzzy information, such as ease of work. Deep learning is helpful to resolve them. We performed a model case study of the electrical isolation. We applied a deep neural network (DNN) for dropping in the calculation time. We trained the circuit diagrams and the responses of the circuit simulator to the DNN, constructing an efficient path search algorithm in the DNN. The calculation time of the DNN was shorter by a factor of 32 for the model case, compared with that of the electrical circuit simulator. We applied a deep Q-network (DQN) for the interpretation of fuzzy information. The DQN optimized isolation procedure from the viewpoint of the work load with the equipment layout, related doses, and values of wet bulb globe temperature (WBGT) to prevent heatstroke.

Key Words: data mining, deep learning, deep Q-network, artificial intelligence

1 INTRODUCTION

Data mining technology is now readily available, thanks to high powered, low cost computing resource and useful coding tools. We study several applications of data mining to enhance operation and maintenance (O&M), such as abnormality prediction, efficiency diagnosis, document traceability, image recognition, etc. In field support, we try automatic planning of electrical isolation with deep learning. Currently, a skilled engineer plans electrical isolation procedure with hundreds of the circuit diagrams and the related documents, taking man-hours. If this task becomes automatic, it is very efficient.

The automatic planning has two issues. One is much calculation time of electrical circuit simulator, searching billions of electrical conducting paths. The other is interpretation of human fuzzy information, such as ease of work. Deep learning is helpful to resolve them. We performed a model case study of the electrical isolation. We applied a deep neural network (DNN) for dropping in the calculation time. We trained the circuit diagrams and the responses of the circuit simulator to the DNN, constructing an efficient path search algorithm in the DNN. We applied a deep Q-network (DQN) for the interpretation of fuzzy information. The DQN optimized the isolation procedure from the viewpoint of the work load with the equipment layout, related doses, and values of wet bulb globe temperature (WBGT) to prevent heatstroke. The details are described in the following sections.

2 METHODOLOGY AND MODEL CASE STUDY

2.1 Overview

Figs.1 and 2 show and a model case diagram and automatic planning procedure, respectively. The model case diagram is a single wire circuit diagram consisting of 76 equipments including three power sources, 27 breakers, and two alarms. A metal-clad switchgear is the inspection target and must be isolated before the inspection with no alarm. Sections of A to S indicating the equipment location are added in Fig.1. The automatic planning procedure is described as follows. First, breaker-on/off patterns isolating the metal-clad switchgear with keeping no alarm are derived from the diagram. Second, the patterns are screened from the viewpoint of the work load. The best pattern and its procedure are derived from the equipment layout, related doses, and WBGTs. We used TensorFlow™[1] for deep learning computation.

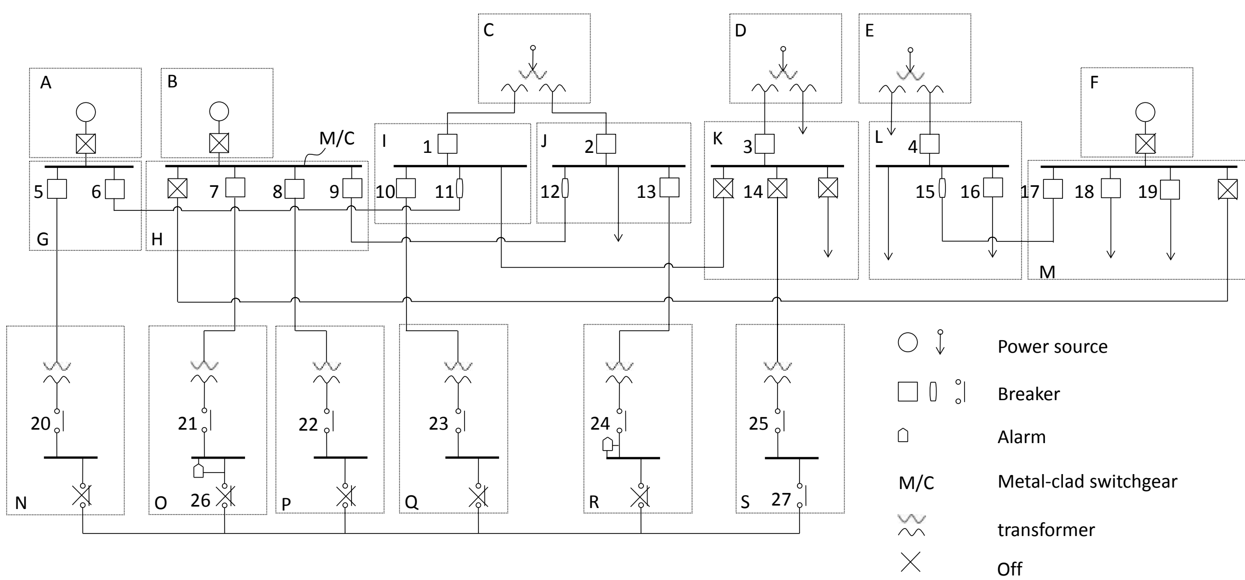

Figure 1. Model case diagram.

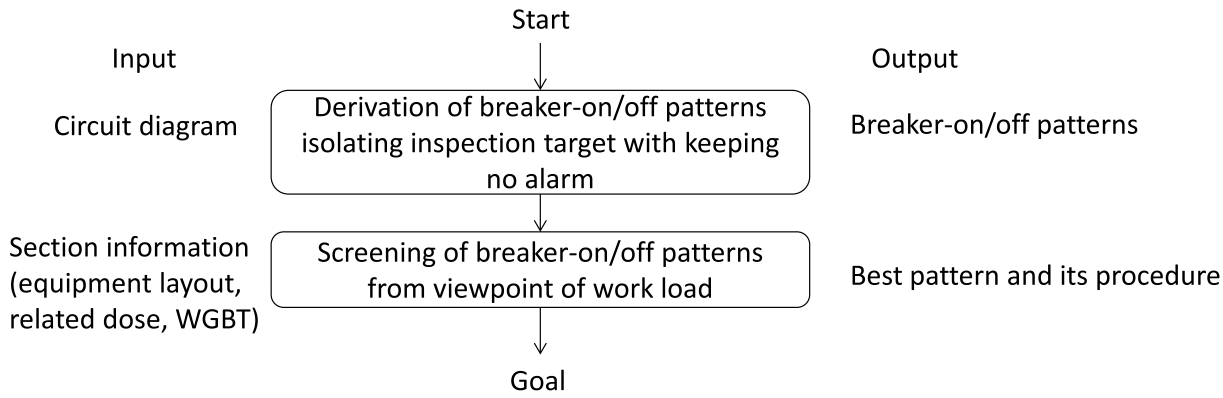

Figure 2. Automatic planning procedure.

2.2 Derivation of Breaker-on/off Patterns Isolating Inspection Target with No Alarm

The breaker-on/off patterns isolating the inspection target with keeping no alarm can be derived with a conventional electrical circuit simulator. But, it takes much calculation time. An enormous number of breaker-on/off patterns exists. For the case study, the 27 breakers generate on/off patterns of 2^{27}. We need to calculate them and find the patterns isolating the target. High-speed calculation is needed. However, the electrical circuit simulator is slow. Unlike checking the electrical continuity, checking the electrical isolation needs to search all of the electrically conducting paths between the inspection target and the power sources. A fast path search algorithm is needed. We speeded up the algorithm with deep learning.

Deep learning has an ability to automatically construct a logic algorithm from the train data. We trained the responses of the circuit simulator to a deep neural network (DNN). Fig.3 shows the DNN diagram. We used the DNN of multi-layer perceptron with 6 layers and 300 units. In the train data and the test data, the input was the breaker-on/off pattern of the 27 breakers (x1, x2, x3, ……x27) , where xi =0/1 when the breaker *i* is on/off. The output was the electrical conducting status pattern of the inspection target and the two alarms (y1, y2, y3), where yi=0/1 when the inspection target y1 or the alarm y2/y3 is conductive/ not conductive. We made the train data and the test data by inputting the random breaker-on/off pattern into the circuit simulator. We used 12,000 of the train data and 413,000 of the test data for training the DNN.

Fig.4 shows the training time vs. the correct answer rate of the DNN for 413,000 of the test data. The correct answer rate rapidly rose up and went to over 99% after 1 minute of the training start. The computing time of the path search algorithm was measured for 413,000 of the test data. The average computing time of the electrical conducting status pattern (y1, y2, y3) for one breaker-on/off pattern (x1, x2, x3, ……x27) was 0.0013 seconds with the trained DNN, and 0.042 seconds with the circuit simulator under the same computer environment. The trained DNN was faster by a factor of 32.

For the case study, automatic search with the trained DNN found over 10,000 of the breaker-on/off patterns isolating the inspection target with keeping no alarm.

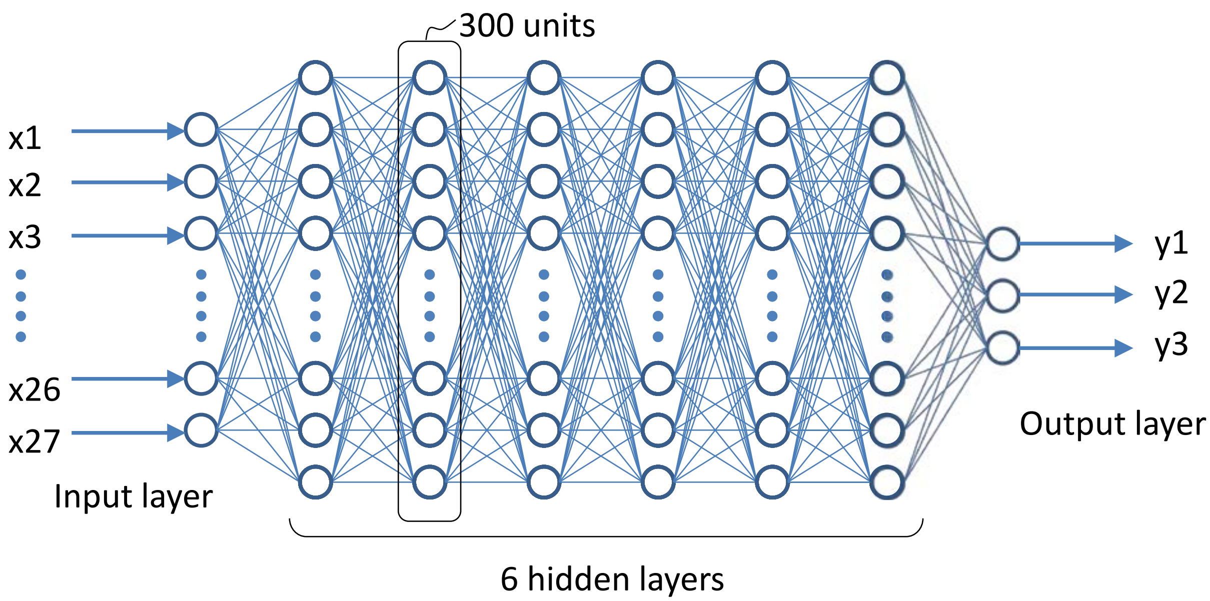

Figure 3. Diagram of deep neural network (DNN).

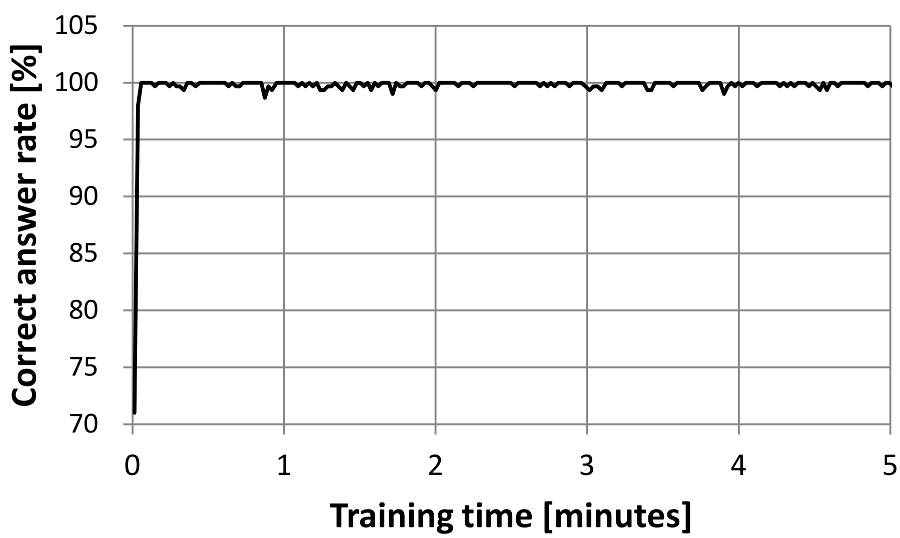

Figure 4. Training time vs. correct answer rate.

2.3 Screening of Breaker-on/off Patterns from Viewpoint of Work Load

Table I shows each section information in Fig. 1 of location, related dose, and WBGT. A worker turns on/off one breaker in one section, and moves to another section, and turns on/off another breaker, and move to …… This procedure should be optimized from the viewpoint of the work load. However, it is difficult to quantify contribution of each parameters of information to the work load. Methodology of interpreting the information and making a decision is needed. We paid attention to deep Q-network [2,3].

Deep Q-network (DQN) is Q-learning using Q-function made with DNN. Q-learning is one of reinforcement learning methods. The Q-learning user sets reward *r* when one in current state *s* performs action *a* and moves to new state *s'*. Q-function is given by the repeat calculation:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha(r + \gamma\ \max_{a'} Q(s',a')), \tag{1}$$

where α and γ are learning rate and discount rate, respectively. The best action in the state *s* is given as the action *a* when Q(*s*,*a*) becomes the maximum value. We gave the reward *r* by:

$$r = -100r_1 - 0.1r_2 - r_3, \tag{2}$$

where r_1, r_2, and r_3 are the related dose, the WGBT, and the moving distance of a worker between the two sections, respectively. The coefficients of r_1, r_2, and r_3 were temporary values. The r_3 was given by:

$$r_3 = \sqrt{(x_1-x_2)^2 + (y_1-y_2)^2 + (z_1-z_2)^2}, \tag{3}$$

where (x_1,y_1,z_1) and (x_2,y_2,z_2) are locations of sections when a worker is in status *s* and *s'*, respectively. We used a DNN of multi-layer perceptron with 4 layers and 100 units as the Q-function.

Table II shows the Q function values derived where γ was 0.9. The isolation procedure is automatically derived by selecting the action of the maximum value of the Q-function. Fig. 5 shows the isolation procedure result when evaluating one of the breaker-on/off patterns (the breaker number of 7, 8, 9, 12, 14, 21, 22, 26) where the sum of the maximum Qs was -583. All of the breaker-on/off patterns are evaluated with the Q-function and screened according to the ranking of the sums of the maximum Qs. This gives the best pattern and its procedure.

Table I. Section information

Section	Dose r_1 (a.u.)	WGBT r_2 (a.u.)	Location r_3 (a.u.)		
			x	y	z
A	0.1	23	0	0	0
B	0.15	24	1	0	0
C	0.5	28	2	0	0
D	0.01	35	3	0	4
E	0.1	31	4	0	0
F	0.15	25	5	0	0
G	0.05	24	0	1	0
H	0.1	20	1	1	0
I	0.2	23	2	1	0
J	0.1	21	3	1	0
K	0.05	26	4	1	0
L	0.3	24	5	1	0
M	0.06	20	6	1	0
N	0.3	19	1	2	0
O	0.05	22	2	2	0
P	0.04	19	3	2	0
Q	0.07	24	4	2	0
R	0.01	17	5	2	0
S	0.08	25	6	2	0

Table II. Q-function.

Current state (currently located secton)	Action (destination section)																		
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
A	−77	−78	−79	−82	−81	−82	−78	−78	−79	−80	−81	−82	−83	−79	−80	−81	−81	−82	−83
B	−82	−81	−82	−86	−84	−85	−83	−82	−83	−83	−84	−85	−86	−83	−83	−85	−85	−86	−87
C	−118	−117	−116	−120	−118	−119	−118	−118	−117	−118	−118	−119	−120	−118	−118	−119	−119	−120	−121
D	−74	−74	−73	−69	−73	−74	−74	−74	−73	−73	−73	−74	−74	−74	−74	−74	−74	−75	−75
E	−79	−78	−77	−79	−75	−76	−79	−79	−78	−77	−76	−77	−78	−79	−78	−78	−77	−78	−78
F	−85	−84	−83	−84	−81	−80	−85	−84	−83	−82	−81	−81	−81	−84	−83	−82	−82	−83	−82
G	−73	−73	−74	−77	−76	−77	−72	−73	−74	−75	−76	−77	−78	−73	−74	−75	−76	−77	−78
H	−77	−76	−77	−80	−78	−79	−76	−75	−76	−77	−78	−79	−80	−76	−77	−78	−78	−79	−80
I	−87	−86	−86	−89	−87	−88	−87	−86	−85	−86	−87	−88	−89	−86	−86	−87	−87	−88	−89
J	−77	−77	−76	−78	−76	−77	−77	−76	−75	−74	−75	−76	−77	−77	−76	−75	−76	−77	−77
K	−73	−72	−71	−73	−70	−71	−73	−72	−71	−70	−69	−70	−71	−72	−71	−71	−70	−72	−71
L	−99	−98	−97	−98	−95	−95	−99	−98	−97	−96	−95	−94	−95	−98	−97	−96	−95	−97	−95
M	−76	−75	−74	−75	−72	−71	−76	−75	−74	−73	−72	−71	−70	−75	−74	−73	−72	−73	−71
N	−97	−97	−97	−100	−99	−99	−96	−96	−96	−97	−98	−99	−100	−95	−96	−97	−98	−99	−100
O	−72	−72	−71	−74	−72	−73	−72	−71	−70	−71	−72	−73	−74	−70	−69	−71	−71	−72	−73
P	−72	−71	−70	−73	−70	−71	−71	−70	−70	−69	−70	−70	−71	−70	−69	−68	−69	−71	−71
Q	−75	−74	−73	−75	−73	−73	−75	−74	−73	−72	−72	−72	−73	−74	−73	−72	−71	−73	−73
R	−72	−71	−71	−72	−69	−69	−72	−71	−70	−69	−68	−68	−68	−71	−70	−69	−68	−67	−68
S	−78	−77	−76	−77	−74	−74	−78	−77	−76	−75	−74	−73	−73	−77	−76	−75	−74	−75	−72

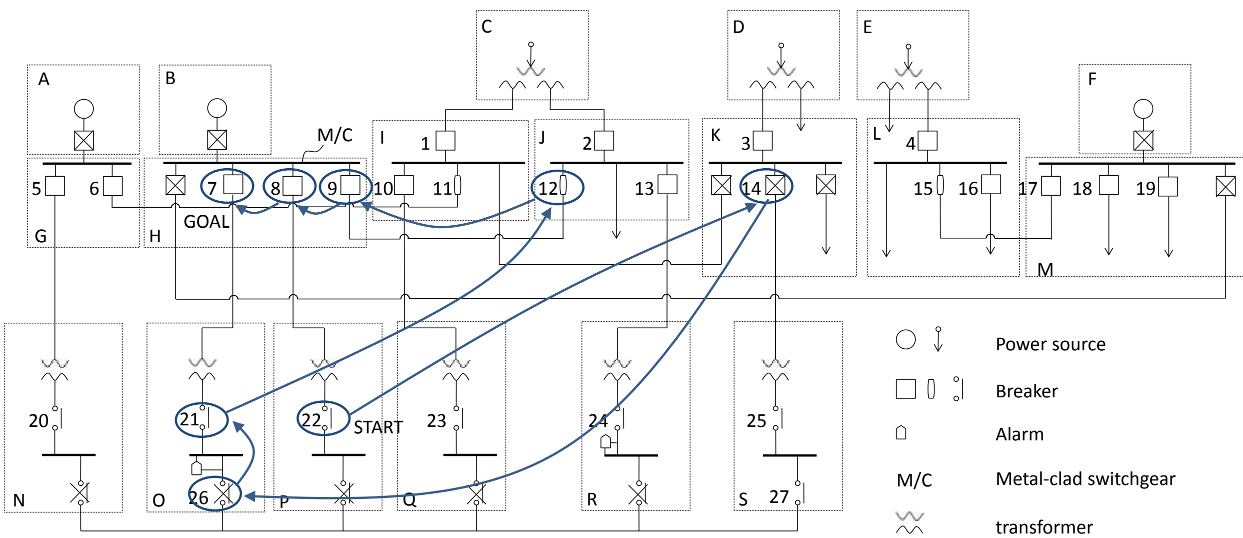

Figure 5. Example of isolation procedure derived with DQN. Circles and arrows indicate breaker-on/off pattern and breaker-on/off procedure (22 off → 14 on → 26 on → 21 off → 12 off → 7 off → 8 off → 9 off) , respectively.

3 DISCUSSIONS AND CONCLUSIONS

We performed the model case study of the automatic planning of the electrical isolation with deep learning. We trained the responses of the circuit simulator to a deep neural network (DNN), constructing the efficient path search algorithm in the DNN. The calculation time of the DNN was shorter by a factor of 32 for the model case, compared with that of the electrical circuit simulator. We applied a deep Q-network (DQN) for interpreting fuzzy information and making a decision. Q-function considering the equipment layout, related doses, and WBGTs was derived. We confirmed that the best isolation procedure could be derived with DQN.

In Sec.2.2, the difference in computing speed between the trained DNN and the circuit simulator increases with an increase in the circuit scale, such as the number of the breakers. This is because the path search time of the circuit simulator increases exponentially with the circuit scale, while the calculation time of the DNN is the same regardless of the circuit scale when using the same DNN. Empirically, the DNN used did not change regardless of the scale although there should be a limit. We consider that the advantage of using the DNN increases as the scale increases. On the other hand, the DNN rarely makes a mistake. The correct answer rate of the DNN was over 99% for the case study, but could not be 100%. Manual confirmation of the results is needed. However, unlike checking an enormous number of the on/off patterns, checking the final results, i.e., one or several isolation procedures will not be difficult.

In the case study, it is not necessary to use DQN. The DQN is the methodology dealing with the large number of parameters in Q-learning. We used DQN to correspond to increasing information, such as the past incompatible cases, etc. The reward r used in the case study was temporary value. In practice, it is necessary to comprehensively decide the reward by interviews with workers, the past data, etc.

We presented the automatic planning of the electrical isolation with deep learning, one of applications of data mining to enhance O&M. This technology is aimed at improving the efficiency of field engineering work, and can also be developed as an advanced goal into application of circuit analysis of probabilistic risk assessment (PRA), etc. From a larger perspective, we aim for enhancement of plant life cycle management (PLCM). To advance the enhancement of O&M, we will continue to study and develop various applications of data mining technology.

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