Transactions of the Korean Nuclear Society Spring Meeting
Jeju, Korea, May 9-10, 2024

Interpretability of Unsupervised Anomaly Detection Model: One-Class Support Vector Machine with Rule Extraction

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Keywords: interpretability, unsupervised model, anomaly detection, one-class SVM, rule extraction

1. Introduction

Nuclear Power Plants (NPPs) are safety-critical facilities, and minimizing human errors during operation is essential for maintaining safety. Accordingly, many studies are being conducted to reduce human errors. Among them, Artificial Intelligence (AI)-based decision support systems are being researched to minimize human errors by operators. However, the black-box characteristics of AI need to be addressed before these studies can be applied in the field.

Recently, eXplainable AI (XAI) methods have been developed to address the black-box characteristics of AI systems. The XAI methods can provide users with an explanation of why the AI's output values were derived. These XAI methods are being applied to AI-based decision support systems to reduce human error in NPPs. AI-based decision support systems are categorized into supervised learning-based classification and regression problems, as well as unsupervised learning-based anomaly detection. The application of XAI to supervised learning-based models is an active area of research. On the other hand, the application of XAI to unsupervised learning-based AI models is still limited. Therefore, this study utilizes the One-Class Support Vector Machine (OCSVM) with rule extraction method. It combines OCSVM, an unsupervised learning-based AI method, and rule extraction method, an XAI method. As part of the primary research to evaluate the applicability of the OCSVM with rule extraction, two case studies are conducted as follows:

(1) Anomaly detection using accelerated aging data of Insulated Gate Bipolar Transistor (IGBT)
(2) Anomaly detection using NPP simulation data

The IGBT data are sourced from open-source data provided by the National Aeronautics and Space Administration (NASA), and NPP simulation data are collected using a Compact Nuclear Simulator (CNS). An anomaly detection model is developed and evaluated in the case study using the OCSVM method. Additionally, rule extraction is performed based on the pre-trained anomaly detection model. The extracted rules can identify the logical structure of OCSVM (e.g., the boundary of the normal region can be identified as the rules). Consequently, it is expected to be a useful tool to enhance the interpretability of OCSVM-based anomaly detection models.

2. Methods

This section introduces OCSVM and rule extraction and describes the method that combines them, known as OCSVM with rule extraction.

2.1 OCSVM

The OCSVM method [1] is derived from traditional SVM method. The SVM method is a supervised learning algorithm primarily utilized for classification and regression problems. As a supervised learning algorithm, it necessitates a labeled dataset. Additionally, it employs a kernel function to transform the data into a high-dimensional feature space. This enables it to solve non-linear problems and facilitates the recognition of relationships between the data. The primary goal of the SVM method is to establish a decision boundary between datasets. Fig. 1 illustrates the hyperplane and the line with support vectors separating two datasets (i.e., '+' and '-'). Here, the greater the distance between the hyperplane and the line with support vectors, the higher the confidence level, indicating that training progresses toward enlarging the margin.

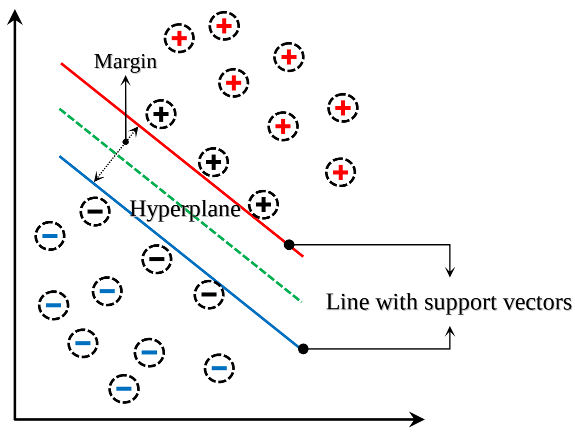

Fig. 1. SVM configuration; hyperplane, line with support vectors, and margin.

The OCSVM method is trained similarly to the SVM method. However, the OCSVM method differs because it is an unsupervised learning algorithm. This means that unlabeled data are used; thus, the margin between the data is not utilized, as depicted in Fig. 1. In the OCSVM method, the margin is the distance between the origin and the hyperplane, as depicted in Fig. 2; similarly to the SVM method, training aims to maximize the margin.

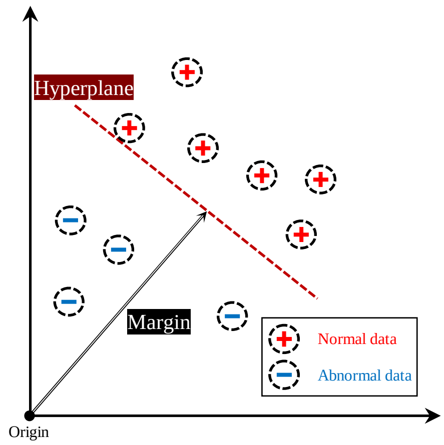

Fig. 2. OCSVM configuration; hyperplane, and margin.

The primary hyper-parameters of the OCSVM method are υ and γ. υ represents the upper bound on the learning error rate and the lower bound on the support vector rate (which primarily determines the anomaly detection boundary). γ is the coefficient for the radial basis function kernel, influencing the curvature of the decision boundary. The complexity of the algorithm increases as both hyper-parameter values increase, so it is crucial to find the parameter values that optimized performance.

2.2 OCSVM with rule extraction

The rule extraction method [2] employs a clustering algorithm to generate a hypercube. The hypercube represents boundary regions in a multi-dimensional feature space. The implementation of this hypercube involves the following steps:

(1) Obtaining clustering results:
  - Clustering algorithms such as k-means and k-prototypes are employed to group the data into clusters, utilizing the outcomes of the OCSVM-based anomaly detection model.

(2) Finding the boundary points of each cluster:
  - To determine the boundaries of each cluster, certain data points belonging to that cluster are selected.
  - The minimum and maximum values of the selected data points define the boundaries, and this process is repeated for each variable.

(3) Constructing a hypercube in a multi-dimensional feature space:
  - Combining the ranges for each variable to create a hypercube.

(4) Verifying the hypercube boundaries:
  - Verify if outliers exist within the hypercube and repeat the hypercube creation process until no outliers are present.

The boundary conditions of these hypercubes serve as rules. In other words, the boundary conditions of the OCSVM-based anomaly detection model can be articulated as rules.

3. Data Preparation

This section describes the datasets used in the case study and discusses data standardization.

3.1 IGBT accelerated aging data

The data on accelerated aging of IGBTs are obtained from open-source data [3]. The IGBT data were subjected to accelerated aging by applying temperature and voltage conditions higher than the design characteristics. As the IGBT ages, it will fail, with the failure symptom being latch-up. Latch-up causes a low output voltage relative to the supply voltage, as shown in Fig. 3. The difference between the supply and output voltage is defined as the degradation characteristic. The failure criterion is the point where the output voltage drops sharply. The IGBT datasets include information for 4 devices, experimental temperature and voltage, and degradation characteristics. For anomaly detection model development, we only use operation time, temperature, and voltage. The other variables, including degradation characteristics, are not available in the field and are therefore excluded from the AI model development. Additionally, we used normal condition data for 3 devices to train the anomaly detection model. The normal condition data for the remaining 1 device and all anomaly data were used for validation.

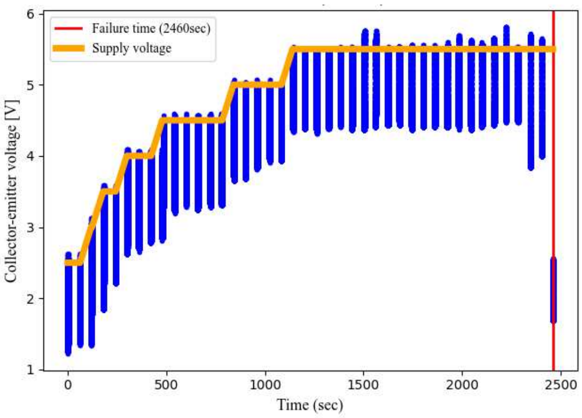

Fig. 3. Degradation characteristic of IGBT data; note the low output voltage (blue line) relative to the supply voltage (orange line).

3.2 NPP simulation data

The NPP simulation data were collected using the CNS. The collected data were divided into normal operating data for training the anomaly detection model and abnormal operating data for validation. Loss of coolant accident and steam generator tube rupture scenarios are utilized for the abnormal operating data. Similar to the IGBT dataset, only the normal operating data are used for training. The validation and test data utilize a subset of the normal operating data and all of the abnormal operating data. 137 variables were selected as input for the AI based on the symptom requirements of each scenario.

3.3 Data standardization

Data standardization is a scaling method that makes the mean 0 and the variance 1 for each variable; that is, the values are transformed to have a Gaussian normal distribution. This is expressed as in Eq. (1).

$$x' = \frac{x - mean(x)}{std(x)} \tag{1}$$

This not only prevents learning from being dependent on the magnitude of the variable values, but also contributes to faster learning.

4. Case Study

This section discusses a series of case studies that utilize the OCSVM method to develop anomaly detection models and then extract rules. The used data are IGBT data and NPP simulation data.

4.1 Development of anomaly detection model and rule extraction using IGBT data

An anomaly detection model is developed and optimized using the IGBT data. Then, based on the pre-trained anomaly detection model, rules are extracted using a rule extraction method. The training data are normal data for 3 devices, as described earlier. The validation and test data consist of normal and anomaly for the remaining 1 device. A grid search algorithm is utilized, and the υ and γ values are optimized. The optimized model is selected based on three metrics calculated using the values (i.e., TP, FP, FN, TN) from Table I.

Table I: Confusion Matrix for Anomaly Detection Model Evaluation

		Expected	
		Normal	Abnormal
Predicted	Normal	TP	FP
	Abnormal	FN	TN

The optimization criteria are based on the following evaluation metrics:

(1) Metric 1: percentage of samples predicted to be normal that are actually normal (for training data; normal data only) (refer to Eq. (2))

$$Metric1 = \frac{TP}{TP+FP} \text{ for training data} \tag{2}$$

(2) Metric 2: percentage of samples predicted to be normal that are actually normal (for validation data; normal data only) (refer to Eq. (3))

$$Metric2 = \frac{TP}{TP+FP} \text{ for validation data} \tag{3}$$

(3) Metric 3: percentage of samples predicted to be abnormal that are actually abnormal (for validation data; abnormal data only) (refer to Eq. (4))

$$Metric3 = \frac{TN}{TN+FN} \text{ for validation data} \tag{4}$$

The highest performance is observed for the hyper-parameter condition with $\upsilon = 0.1$ and $\gamma = 0.4$; the performance percentages for each metric are 90.57% (metric 1), 96.9% (metric 2), and 100% (metric 3). The results obtained through rule extraction based on the optimized model are shown below, with 9 rules were extracted. The rules are divided into the ranges of the input variables, such as time (operation time), temperature, and voltage.

(1) (62 $\leq$ time $\leq$ 784) and (100 $\leq$ temperature $\leq$ 240) and (2.5 $\leq$ voltage $\leq$ 4.5)
(2) (902 $\leq$ time $\leq$ 1504) and (265 $\leq$ temperature $\leq$ 280) and (5 $\leq$ voltage $\leq$ 5.5)
(3) (600 $\leq$ time $\leq$ 1085) and (240 $\leq$ temperature $\leq$ 265) and (voltage = 5)
(4) (2280 $\leq$ time $\leq$ 2281) and (temperature = 100) and (voltage = 5.5)
(5) (1440 $\leq$ time $\leq$ 1805) and (265 $\leq$ temperature $\leq$ 280) and (5 $\leq$ voltage $\leq$ 6)
(6) (1861 $\leq$ time $\leq$ 1924) and (temperature = 280) and (voltage = 6)
(7) (1800 $\leq$ time $\leq$ 1985) and (265 $\leq$ temperature $\leq$ 280) and (voltage = 5.5)
(8) 2041 $\leq$ time $\leq$ 2223) and (temperature = 265) and (voltage = 5.5)
(9) (2042 $\leq$ time $\leq$ 2105) and (temperature = 280) and (voltage = 5.5)

4.2 Development of anomaly detection model and rule extraction using CNS data

An anomaly detection model is developed and optimized using CNS data. Similarly to the IGBT data, rules are extracted based on a pre-trained model. The data were split into normal and abnormal data, as described in subsection 3.2, to serve as training, validation, and test data. The performance of the anomaly detection model using CNS data is as follows: 95.12% (metric 1), 97.35% (metric 2), and 99.6% (metric 3). The hyper-parameters are $\upsilon = 0.1$ and $\gamma = 0.6$. The extracted rules based on the optimized model are shown in Fig. 4. All 137 variables are used as building blocks for the rules. As a result, 86 rules were extracted.

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Combination of categorical variables N° 1
----- Subgroup 1 ------
Rule N° 1: IF BPV145 <= 0.6496325731277466 AND ZCNDTK <= 9.477904319763184 AND CIODMPC <= 99.29454803466795 AND UCHGUT <=
282.28057861328125 AND BLV614 <= 0.015038669109344448 AND QPRZH <= 0.940539002418518 AND ZREAC <= 6.4624671936035165 AND ZINST63
<= 55.140037536621094 AND UNRHXUT <= 54.37397003173828 AND ZINST65 <= 156.34678649902344 AND ZVCT <= 74.13337707519531 AND BHTV
<= 0.9730818867683412 AND CAXOFF <= -0.5239526629447937 AND UPRZ <= 340.31561279296875 AND CRETIV <= 1.7202269475546927e-07 AND
ZINST85 <= 534.458984375 AND ZINST56 <= 2.532994747161865 AND ZINST87 <= 528.1591796875 AND WSPRAY <= 0.0 AND BHV1 <= 1.0 AND
BRHCV <= 0.9960347414016724 AND ZINST66 <= 0.0 AND ZINST103 <= 87.17401885986328 AND ZINST86 <= 534.44580078125 AND CXEMPCM <=
2663.744140625 AND URHXUT <= 152.58592224121094 AND ZCOND <= 0.7789534330368042 AND ZINST108 <= 39.857906341552734 AND ZINST68
<= 1.0066975355148315 AND ZINST1 <= 99.2776107788086 AND BPORV <= 0.0 AND BFV122 <= 0.5474188923835754 AND WBOAC <=
0.5432032942771912 AND WFWLN1 <= 528.3328247070311 AND WFWLN2 <= 534.641845703125 AND UHOLEG2 <= 326.6001281738281 AND
ZINST81 <= 98.3774642944336 AND ZINST67 <= 1.0065896511077879 AND ULPHOUT <= 155.545166015625 AND ZINST72 <= 88.75724029541016
AND ZINST78 <= 50.02643585205078 AND ZINST69 <= 1.0549740791320799 AND UFUELM <= 747.944580078125 AND QOVER <=
1.0877995491027832 AND UUPPPL <= 326.5968322753906 AND ZINST101 <= 99.62583923339844 AND KBCDO15 <= 15.0 AND ZINST79 <=
100.08946990966795 AND KBCDO7 <= 201.0 AND BFV488 <= 0.9244197010993958 AND WFWLN3 <= 534.5620727539061 AND UAVLEG1 <=
308.53863525390625 AND BFV479 <= 0.5183502435684204 AND UPRT <= 40.007659912109375 AND ZINST100 <= 226.3286590576172 AND ZINST74
<= 65.31446075439453 AND ZINST99 <= 64.78323364257811 AND BFV478 <= 0.87298184633255 AND ZINST2 <= -3.3531486988067627 AND ZINST80
<= 100.09034729003906 AND UHOLEG1 <= 326.5968322753906 AND ZINST71 <= 88.72502899169922 AND WCHGNO <= 4.3999223709106445 AND
ZINST121 <= 3.514105319976806 AND BPSV10 <= 0.0 AND UCOLEG1 <= 290.48046875 AND ZINST15 <= 0.24127197265625 AND WDEWT <=
8.91982650756836 AND UAVLEG2 <= 309.36810302734375 AND BFV498 <= 0.8781413435935974 AND UCOND <= 31.42851638793945 AND QPROLD
<= 0.9927760362625122 AND ZINST70 <= 88.72418975830078 AND ZINST73 <= 65.31695556640625 AND ZINST124 <= 997.6688232421876 AND
ZINST76 <= 50.029296875 AND UCTMT <= 34.67035675048828 AND ZINST102 <= 9.999999974752427e-07 AND BLV459 <= 1.0 AND BFV499 <=
0.5221828222274779 AND UCOLEG2 <= 292.1361083984375 AND BFV489 <= 0.43492591381073 AND ZINST77 <= 50.03113174438477 AND ZINST75
<= 65.30826568603516 AND UAVLEG3 <= 309.36700439453125 AND EBOAC <= 99998.78125 AND UHOLEG3 <= 326.5968322753906 AND UCOLEG3
<= 292.13714599609375 AND ZAFWTK <= 9.718579292297363 AND UAVLEGM <= 309.09124755859375 AND BTV418 <= 0.0 AND ZINST48 <=
0.29459047317504883 AND FRQGEN <= 60.0 AND PVAC <= 721.2213134765625 AND KBCDO22 <= 997.0 AND BHV2 <= 1.0 AND PVCT <=
1.7339204549789429 AND KBCDO11 <= 160.0 AND ZINST36 <= 29.2335205078125 AND UAVLEGS <= 309.3218078613281 AND BHV6 <= 1.0 AND
ZINST3 <= 0.0 AND KBCDO19 <= 1800.0 AND KBCDO6 <= 228.0 AND ZINST26 <= 0.2516960799694061 AND KBCDO16 <= 402.0 AND BHTBY <= 0.0
AND FSRMDPM <= -1.6815581571897805e-44 AND H2CONC <= 0.0 AND BHV22 <= 0.0 AND BHV302 <= 0.0 AND BFV13 <= 0.0 AND KBCDO8 <=
228.0 AND ZINST22 <= 2.07918119430542 AND BHSV <= 1.0 AND KLAMPO15 <= 1.0 AND BLV48 <= 0.0 AND KBCDO5 <= 228.0 AND KBCDO20 <=
998.0 AND KBCDO10 <= 228.0 AND BTV143 <= 1.0 AND KLAMPO48 <= 0.0 AND KLAMPO69 <= 0.0 AND KBCDO4 <= 228.0 AND KLAMPO221 <=
1.0 AND KLAMPO234 <= 1.0 AND BHV41 <= 0.0 AND BPV145 >= 0.645190417766571 AND ZCNDTK >= 9.474410057067873 AND CIODMPC >=
99.29403686523438 AND UCHGUT >= 272.32571411132807 AND BLV614 >= 0.0 AND QPRZH >= 0.8720238208770752 AND ZREAC >=
6.462434768676758 AND ZINST63 >= 54.97410202026367 AND UNRHXUT >= 52.1552963256836 AND ZINST65 >= 156.20016479492188 AND ZVCT >=
73.89144134521484 AND BHTV >= 0.9729109406471252 AND CAXOFF >= -0.5240284204483032 AND UPRZ >= 340.17596435546875 AND CRETIV >=
5.765338784158304e-08 AND ZINST85 >= 534.4403076171875 AND ZINST56 >= 2.389007806777954 AND ZINST87 >= 528.1431884765625 AND

WSPRAY >= 0.0 AND BHV1 >= 1.0 AND BRHCV >= 0.9959763884544371 AND ZINST66 >= 0.0 AND ZINST103 >= 87.14859771728516 AND ZINST86
>= 534.4196166992189 AND CXEMPCM >= 2663.735107421875 AND URHXUT >= 142.6816864013672 AND ZCOND >= 0.7786016464233398 AND
ZINST108 >= 39.829673767089844 AND ZINST68 >= 1.0066565275192259 AND ZINST1 >= 99.26520538330078 AND BPORV >= 0.0 AND BFV122 >=
0.4949208199977875 AND WBOAC >= 0.543174147605896 AND WFWLN1 >= 528.0573120117189 AND WFWLN2 >= 534.3208618164061 AND
UHOLEG2 >= 326.58795166015625 AND ZINST81 >= 98.3693618774414 AND ZINST67 >= 1.0065691471099854 AND ULPHOUT >=
155.53285217285156 AND ZINST72 >= 88.75226593017578 AND ZINST78 >= 50.01876449584961 AND ZINST69 >= 1.0549527406692505 AND UFUELM
>= 747.891357421875 AND QOVER >= 1.0877978801727295 AND UUPPPL >= 326.58636474609375 AND ZINST101 >= 99.6245346069336 AND
KBCDO15 >= 15.0 AND ZINST79 >= 100.08570861816406 AND KBCDO7 >= 201.0 AND BFV488 >= 0.9239929914474488 AND WFWLN3 >=
534.270751953125 AND UAVLEG1 >= 308.5282287597656 AND BFV479 >= 0.5182148218154907 AND UPRT >= 40.007659912109375 AND ZINST100
>= 226.3286590576172 AND ZINST74 >= 65.30299377441406 AND ZINST99 >= 64.77167510986328 AND BFV478 >= 0.8725782036781311 AND ZINST2
>= -3.3532030582427983 AND ZINST80 >= 100.08714294433594 AND UHOLEG1 >= 326.58636474609375 AND ZINST71 >= 88.71971130371094 AND
WCHGNO >= 3.8864009380340576 AND ZINST121 >= 3.514094829559326 AND BPSV10 >= 0.0 AND UCOLEG1 >= 290.4700927734375 AND ZINST15
>= 0.23052978515625 AND WDEWT >= 8.91979694366455 AND UAVLEG2 >= 309.3565673828125 AND BFV498 >= 0.877232766151428 AND UCOND
>= 31.42851638793945 AND QPROLD >= 0.992651343345642 AND ZINST70 >= 88.71894836425781 AND ZINST73 >= 65.30547332763672 AND
ZINST124 >= 997.6653442382812 AND ZINST76 >= 50.02112579345703 AND UCTMT >= 34.67035675048828 AND ZINST102 >= 9.999999974752427e-
07 AND BLV459 >= 1.0 AND BFV499 >= 0.5220410823822021 AND UCOLEG2 >= 292.12518310546875 AND BFV489 >= 0.4347801208496094 AND
ZINST77 >= 50.02268600463867 AND ZINST75 >= 65.29682159423828 AND UAVLEG3 >= 309.3566589355469 AND EBOAC >= 99998.78125 AND
UHOLEG3 >= 326.5865478515625 AND UCOLEG3 >= 292.12677001953125 AND ZAFWTK >= 9.718579292297363 AND UAVLEGM >=
309.0804748535156 AND BTV418 >= 0.0 AND ZINST48 >= 0.29459047317504883 AND FRQGEN >= 60.0 AND PVAC >= 721.2213134765625 AND
KBCDO22 >= 997.0 AND BHV2 >= 1.0 AND PVCT >= 1.731525182723999 AND KBCDO11 >= 160.0 AND ZINST36 >= 29.03362274169922 AND
UAVLEGS >= 309.3218078613281 AND BHV6 >= 1.0 AND ZINST3 >= 0.0 AND KBCDO19 >= 1800.0 AND KBCDO6 >= 228.0 AND ZINST26 >=
0.2516960799694061 AND KBCDO16 >= 402.0 AND BHTBY >= 0.0 AND FSRMDPM >= -1.6815581571897805e-44 AND H2CONC >= 0.0 AND BHV22
>= 0.0 AND BHV302 >= 0.0 AND BFV13 >= 0.0 AND KBCDO8 >= 228.0 AND ZINST22 >= 2.07918119430542 AND BHSV >= 1.0 AND KLAMPO15 >=
1.0 AND BLV48 >= 0.0 AND KBCDO5 >= 228.0 AND KBCDO20 >= 998.0 AND KBCDO10 >= 228.0 AND BTV143 >= 1.0 AND KLAMPO48 >= 0.0 AND
KLAMPO69 >= 0.0 AND KBCDO4 >= 228.0 AND KLAMPO221 >= 1.0 AND KLAMPO234 >= 1.0 AND BHV41 >= 0.0 AND KLAMPO119 = 0 AND
KLAMPO118 = 0 AND KLAMPO117 = 0 AND KLAMPO28 = 1 AND KLAMPO29 = 0 AND KLAMPO9 = 0 AND KLAMPO241 = 1 AND KLAMPO198 = 1
AND KLAMPO195 = 0 AND KFV610 = 0

----- Subgroup 2 ------
Rule N° 1: IF BPV145 <= 0.6524736285209656 AND ZCNDTK <= 9.45296859741211 AND CIODMPC <= 99.29264831542969 AND UCHGUT <=
211.93014526367188 AND BLV614 <= 0.0 AND QPRZH <= 1.4012984643248168e-45 AND ZREAC <= 6.462461471557617 AND ZINST63 <=
57.19255065917969 AND UNRHXUT <= 45.94796752929688 AND ZINST65 <= 159.32032775878906 AND ZVCT <= 70.39556121826172 AND BHTV <=
0.9745541214942932 AND CAXOFF <= -0.5233811736106873 AND UPRZ <= 340.19256591796875 AND CRETIV <= 1.0358860436099349e-07 AND
ZINST85 <= 534.2867431640625 AND ZINST56 <= 0.6326019763946533 AND ZINST87 <= 528.2058715820311 AND WSPRAY <= 1.4012984643248168e-
45 AND BHV1 <= 1.0 AND BRHCV <= 0.9947968125343324 AND ZINST66 <= 4.313003540039063 AND ZINST103 <= 87.05277252197266 AND
ZINST86 <= 534.3170776367189 AND CXEMPCM <= 2663.6357421875 AND URHXUT <= 114.27513122558594 AND ZCOND <= 0.7815900444984436
AND ZINST108 <= 39.83956146240234 AND ZINST68 <= 1.0064274072647097 AND ZINST1 <= 99.35131072998048 AND BPORV <= 0.0 AND BFV122
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Fig. 4. A portion of the rule extraction results from the CNS data-based anomaly detection.

5. Conclusion

AI-based decision support systems are actively being researched to reduce human error in the operation of NPPs. However, the black-box characteristics of AI can be an obstacle to the practical application of such research. Recently, XAI methods have been applied to solve this problem. However, most XAI applications are limited to supervised learning-based algorithms. However, many researchers are also developing anomaly detection models using unsupervised learning algorithms. Therefore, applying XAI methods to unsupervised learning algorithms is necessary.

In this study, we consider the applicability of the OCSVM with rule extraction method, which combines the OCSVM method, an unsupervised learning algorithm, with the rule extraction method, an XAI algorithm. The case studies were performed to assess the applicability of: (1) anomaly detection using accelerated aging data of IGBT and (2) anomaly detection using NPP simulation data. The extracted rules reveal the logical structure of the OCSVM method-based anomaly detection models. These results are expected to enhance the interpretability of unsupervised learning-based anomaly detection models. However, a limitation exists: each input variable contributes to a rule, potentially complicating interpretation as the number of variables increases. This limitation is difficult to address because we ultimately extract rules based on the characteristics of the OCSVM model. In future work, we plan to explore other AI models or supplement the rule reduction technique to better reflect the characteristics of the data and derive interpretable rules.

Acknowledgment

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE) (20224B10100120, Development of commercialization technology for failure diagnosis of reactor control and digital I&C systems) and (20224B10100130, Development of operational state simulator for operating nuclear power plant and commercialization technology for artificial intelligence decision-making support system to prevent human error in accident operation).

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