Prognostics Health Management (PHM) System for Power Transformer Using Kernel Extreme Learning Machine (K-ELM)

by Awan Uji Krismanto

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ABSTRACT

A power transformer is one of the most important and valuable components for the power system network. This device is critical to ensure power quality and reliable electricity supply for consumers. When the power transformer could not work properly or out of service in unforeseen ways, it provides a severe impact on power system utilities and customers in term of the expensive of transformer's replacement cost and revenue lost caused by the electrical blackout. To overcome these issues, the proper prognostics health management (PHM) system as a tool for condition monitoring and health assessment of these valuable assets is required. This paper proposed a PHM system based on a kernel extreme learning machine (K-ELM) for power transformer's health assessment. Two sets of variable combinations called Set-1 and Set-2 were considered to examine the robustness and efficiency of the proposed method. In Set-1, the input variables were water content, total acidity, breakdown voltage, dissipation factor, dissolved combustible gases, and 2-furfuraldehyde. While the output of PHM system was the health condition which categorized as good, moderate, and bad circumstances. Set-2 utilized water content, total acidity, breakdown voltage, dissipation factor, and interfacial tension as input variables. Whereas, the PHM system outputs consisted of four categories: normal, good, moderate, and bad. The proposed method with two sets of variables had showed the satisfactory results for transformer's health condition assessment compared to an extreme learning machine (ELM), support vector machine (SVM), and least-square support vector machine (LS-SVM) in terms of learning and testing accuracies and computation time. The proposed PHM system using the Set-1 dataset could assess the transformer health as of 100% while in terms of the testing process, the proposed PHM system has an excellent accuracy result as of 68.67%. Furthermore, the proposed PHM system using the Set-2 dataset had successfully assessed the transformer health as of 100%. In the testing phase, the proposed PHM system model has a rigorous result for its accuracy result as of 93.61%.

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CCS CONCEPTS

Machine learning~Machine learning approaches~Kernel methods

KEYWORDS

Power Transformer, Power System Network, PHMS, K-ELM, SVM, LS-SVM.

1 Introduction

Nowadays, the electric power network capacity continues to grow due to electrical demand rises rapidly [1]. One of the most valuable assets utilized by power companies to deliver a higher quality of electric power services to their customers is power transformers. The performance of power transformer directly influences the operation of electric power networks. Any faults in the power transformer generally result in a widespread outage in the power grid, impact to the environment through oil leakages, pose a risk to utility personal by causing fire and explosions, and other enormous economic losses [2].

Additionally, the dependency of expert individuals to analyze the data extracted from transformers is still required by most electricity companies. Also, the conventional method is utilized to decide the health condition assessment of their power transformers. When the experts engaged are unavailable, it raises a difficult problem for the company. Meanwhile, conventional methods are occasionally incapable of generating exhaustive results. Thus, the development of prognostics health management (PHM) system based on artificial intelligence (AI) method for power transformer is a must to tackle the problem. In addition, proper health condition assessment of these valuable assets is essential [3].

Lately, the development of artificial intelligence (AI) method has attracted many researchers for solving a real-world problem in engineering areas. Some AI approaches have been proposed to solve prognostics health management (PHM) system problems such as fuzzy logic [4], neural network [5], neuro-fuzzy [6], support vector machine [7], and fuzzy support vector machine [8]. All AI techniques above have shown comprehensive results. Among the AI approaches above, there is a unique method, that is, a kernel extreme learning machine (K-ELM) method. This approach utilizes a kernel function to replace the hidden node in the ELM approach. The K-ELM method had successfully applied and provided satisfactory results for engineering field problems such as monitoring of dam leakage flow [9] and prediction of the diet energy digestion [10]. As the K-ELM method had successfully applied for solving various engineering problems, we employ a K-ELM approach as a PHM system model for power transformer health assessment as our contribution in this paper in the power transformer research area. Besides, the K-ELM method has an advantage in terms of learning accuracy and computation time speed. To examine the efficacy of the proposed PHM system model, we utilize two different datasets extracted from the power transformer are utilized. Simulation results have shown that the proposed PHM system predicted power transformer health conditions accurately and efficiently.

2 Kernel Extreme Learning Machine (K-ELM)

The extreme learning machine (ELM), proposed by G.B. Huang, et. all in 2006 [11], is one of the prominent machine learning algorithms (MLAs) that has attracted many researchers and applied worldwide for various engineering fields. The ELM model is composed by using a feed-forward artificial neural network with a single hidden layer known as a single hidden layer feed-forward neural network (SLFN). The merit of this algorithm can map the correlation between input and output datasets with exceptional speed.

So far, the ELM algorithm has been utilized in order to overcome the deficiency of conventional artificial neural networks (ANNs). ANN acquires a longer time in terms of learning due to its network parameter is updated by iteratively. To obtain predictive output accurately in training and testing phases, more training samples are included. In addition, learning algorithms in ANN minimize the empirical risks by minimizing training error to fit non-linear function based on input and output datasets.

Due to iteration process is unneeded to obtain the proper parameter of ELM model, the time speed of learning phase for ELM is faster than ANN. Although ELM approach has eminent compare to ANN technique, ELM has also a weakness. The drawback of ELM method is that the determination of the hidden neurons of ELM is conducted by the trial-and-error method (TEM). Moreover, the hidden layer of ELM technique acquires more neurons to obtain a good result of training process due to the weighting and bias parameters of ELM is chosen randomly. To overcome this problem, the neurons in the hidden layer part are replaced by using kernel function for mapping the data from the hidden input layer into higher dimensional feature subspaces, where the non-linear pattern becomes linear and avoids computationally intensive operations. Furthermore, this learning algorithm becomes more flexible and stable due to it does not need randomly chosen nodes parameters of both hidden and input layers.

Given N data samples $\{(\mathrm{x}_i,\mathrm{t}_i)|\mathrm{x}_i\in\mathrm{R}^n,\mathrm{t}_i\in\mathrm{R}^m,i=1,\ldots,N\}$, the ELM output model is defined as follows,

$$y_M(\mathrm{x})=\sum_{i=1}^{M}\beta_i h_i(\mathrm{x})=\mathrm{h}(\mathrm{x})\beta \quad (1)$$

where $\beta=[\beta_1,\beta_2,\ldots,\beta_M]$ is the weights between the hidden layer and output layer neurons. $\mathrm{h}(\mathrm{x})=[h_1(\mathrm{x}),h_2(\mathrm{x}),\ldots,h_M(\mathrm{x})]$ is the output of hidden layer related to input x. the goal is to minimize the error as much as possible as represented in (2).

$$Min:\|\mathrm{H}\beta-\mathrm{T}\|,\|\beta\|. \quad (2)$$

The Karush-Kuhn-Tucker (KKT) optimality condition is employed to solve the problem of (2), which can be written as follows.

$$\beta=\mathrm{H}^T\left(\frac{1}{C}+\mathrm{HH}^T\right)^{-1}\mathrm{T} \quad (3)$$

where H, C, T are output of hidden layer, regularization coefficient, and predicted output, respectively.

After the formulation of β (3) is obtained and substituted to (1). We can obtain the output function of ELM classifier as defined in Equation (4).

$$y(\mathrm{x})=\mathrm{h}(\mathrm{x})\beta=\mathrm{h}(\mathrm{x})\mathrm{H}^T\left(\frac{1}{C}+\mathrm{HH}^T\right)^{-1}\mathrm{T} \quad (4)$$

Kernel method based on Mercer's condition was suggested by G.B. Huang [11] to overcome if the feature mapping $h(x)$ is unknown. The kernel formulation can be written as follows,

$$\mathrm{O}=\mathrm{HH}^T:\mathrm{m}_{ij}=\mathrm{h}(\mathrm{x}_i)\mathrm{h}(\mathrm{x}_j)=\Omega(\mathrm{x}_i,\mathrm{x}_j) \quad (5)$$

The output function $y(\mathrm{x})$ of kernel extreme learning machine (K-ELM) can be defined as follows,

$$y(\mathrm{x})=[\Omega(\mathrm{x},\mathrm{x}_1),\ldots,\Omega(\mathrm{x},\mathrm{x}_M))]\left(\frac{1}{C}+\mathrm{O}\right)^{-1}\mathrm{T} \quad (6)$$

For multi-class classification using single output neuron, among all the multiclass labels, the forecasted class label of a defined testing sample is closest to the output of ELM classifier. For binary classification issue, ELM requires only one output neuron, and the decision function of ELM classifier is

$$y(\mathrm{x})=sign\left([\Omega(\mathrm{x},\mathrm{x}_1),\ldots,\Omega(\mathrm{x},\mathrm{x}_M))]\left(\frac{1}{C}+\mathrm{O}\right)^{-1}\mathrm{T}\right) \quad (7)$$

where $O = HH^T$ and $\Omega(x, y)$ is the kernel function of hidden neurons of SLFN.

Equation (7) is like the support vector machine (SVM) model but provides a closed-form expression for the kernel coefficients. In this work, we use radial basis function (RBF) as kernel to examine the performance of the ELM learning algorithm as defined in Equation (8).

$$\Omega(x, y) = \exp\left(\frac{\|x - y\|^2}{2\sigma^2}\right) \quad (8)$$

where σ is kernel parameter.

The performance of K-ELM is influenced by the regularization coefficient C and kernel parameter σ, where these parameters must be selected properly. The K-ELM learning algorithm is more stable compared to standard ELM and it is faster than SVM. The network structure of K-ELM algorithm is illustrated in Figure 1.

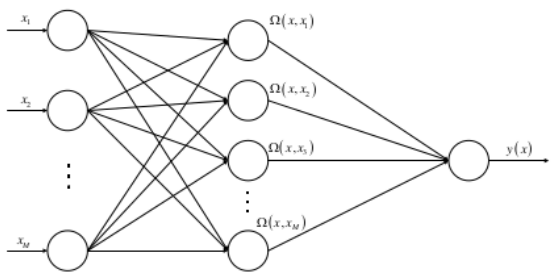


Figure 1: Network structure of K-ELM algorithm

3 PHM System based on Kernel Extreme Learning Machine (K-ELM)

The development of PHM system algorithm has been an active domain of research in various engineering applications in order to avoid the unforeseen failures and longer time for maintenance. Among PHM methods, power transformer is known to be a crucial field of application. The PHM system model is also considered as the main process in condition-based maintenance technology that is employed in power transformer. The PHM system framework using K-ELM approach in this research work is depicted in Figure 2, which the features chosen as input datasets include water content, total acidity, breakdown voltage, dissipation factor, and interfacial tension. While the output dataset is health condition of power transformer. In this research study, we split each dataset for PHM system into training and testing phases.

First, the procedures for the training process of proposed PHM system are described as follow:

1) Prepare the datasets such as water content, total acidity, breakdown voltage, dissipation factor, interfacial tension, and power transformer health condition.
2) Utilize water content, total acidity, breakdown voltage, dissipation factor, and interfacial tension datasets as input of K-ELM. While the dataset of transformer health condition is used as the output of K-ELM.
3) Transform the input datasets of K-ELM into high dimensional features using RBF kernel (8).
4) Set the K-ELM parameters including coefficient C and kernel parameter σ.
5) Do the training process through (1)-(7) to obtain the output result of K-ELM using (7).
6) Calculate the accuracy of the proposed PHM system. An accuracy rate was utilized as the performance metric for evaluating the outcome of the PHM system where it represents the ratio of the number of correct predictions to the total number of input samples. The accuracy rate is defined as follows:

$$Accuracy\,rate = \frac{Number\,of\,correct\,predictions}{Total\,number\,of\,predictions\,made} \times 100\% \quad (10)$$

Second, the parameters of proposed PHM system that obtained from training phase is utilized for testing process. The procedures of testing phase are described as follow:

1. Collect the datasets for testing phase such as water content, total acidity, breakdown voltage, dissipation factor, interfacial tension, and transformer health condition.
2. Employ water content, total acidity, breakdown voltage, dissipation factor, and interfacial tension datasets as input of K-ELM. While the dataset of transformer health condition is used as the output of K-ELM.
3. Set the regularization coefficient C and kernel parameter σ of K-ELM that obtained from training process.
4. Transform the data input of K-ELM to high-dimensional feature using kernel function in (8).
5. Compute the output result using (7).
6. Obtain the accuracy result of K-ELM output using (10).

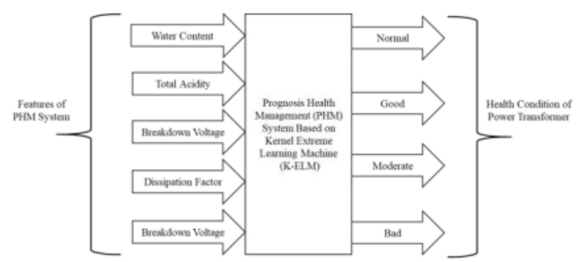


Figure 2: Proposed PHM system scheme

4 Results and Discussions

To develop the proposed PHM system algorithm for the power transformer health assessment, we divide the sets of variables into two groups called Set-1 and Set-2. In Set-1, following power transformer parameters as illustrated in Table 1 were employed as the features or input data of PHM system: water content in the transformer (Water), total acidity of the oil (Acidity), dissolved combustible gases (TDCG), oil breakdown voltage (DBV), dissipation factor in percent (DF), and 2-furfuraldehyde content in (Furan). These measurement datasets of 30 power transformers were taken from Refs. [4] and [12]. Furthermore, the power transformer health categories as PHM system output consisted of good (G), moderate (M), and bad (B) circumstances. The power transformer compositions utilized in Set-2 as input data of the PHM system were water content, total acidity of the oil, breakdown voltage, dissipation factor, and interfacial tension as depicted in Figure 3. Here, a database of 730 power transformers as shown in Figure 3 was utilized and collected from [14] for Set-2.

Table 1. Input and output data of prognostics health management (PHM) system for Set-1

No.	Water (ppm)	Acidity (mgKOH/g)	DBV (kV)	DF (%)	TDCG (ppm)	Furan (mg/L)	Health Categories
1	21.7	0.024	32.5	0.075	483	0.86	Good
2	26.9	0.098	40.5	0.894	254	0.65	Good
3	14.5	0.033	58	0.14	78	0.26	Good
4	21.2	0.226	48.7	0.424	215	5.53	Bad
5	10	0.01	75	0.111	126	0.06	Good
6	15.5	0.075	71	0.143	38	0.53	Good
7	16.8	0.167	70.1	0.255	149	0.78	Good
8	15	0.092	67.8	0.211	28	0.69	Good
9	17	0.035	62.7	0.113	9	0.21	Good
10	30	0.088	37.6	0.353	197	0.31	Good
11	16.2	0.181	25.5	0.201	35	8.76	Bad
12	15	0.155	37.5	0.182	53	7.29	Bad
13	16.8	0.115	25.6	0.174	78	9.6	Bad
14	15	0.21	57	0.22	53	6.69	Bad
15	27.6	0.089	30.4	0.128	336	5.12	Bad
16	23.5	0.106	45.8	0.207	30	0.24	Good
17	24.8	0.012	29.9	0.068	504	1.68	Moderate
18	23.6	0.07	39.2	0.203	22	0.5	Good
19	30.5	0.073	28.7	67	30	1.7	Bad
20	18.4	0.063	64.5	0.243	69	0.15	Good
21	21.1	0.019	28.4	0.025	144	0.02	Moderate
22	8.1	0.01	66.9	0.042	71	0.05	Good
23	19.6	0.216	41.1	0.264	48	7.54	Bad
24	6	0.01	67.6	0.126	427	0.08	Good
25	18.4	0.152	37.2	0.299	81	1.14	Moderate
26	11.1	0.032	67.2	0.089	119	0.04	Good
27	21.5	0.147	60.8	0.938	168	0.92	Good
28	7.5	0.16	70.1	0.448	10	0.06	Good
29	13	0.091	51.6	0.369	8	0.32	Good
30	35.7	0.229	41.4	0.639	24	1.07	Moderate

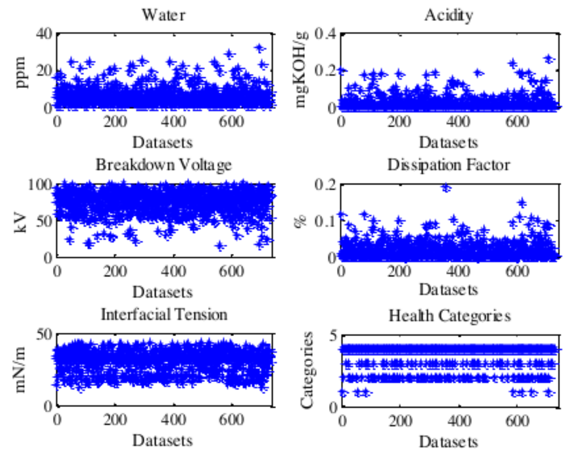


Figure 3: Input and output data of (PHM) system for Set-2

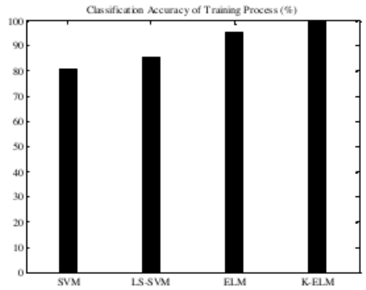
Furthermore, the PHM system outputs for Set-2 were divided into four categories: normal (N), good (G), moderate (M), and bad (B). All simulations were carried out using notebook i5 with 2.30 GHz, 8 GB of RAM Memory. The proposed PHM system was implemented using MATLAB software environment [15]. In this research work, the power transformer datasets were split as training and testing data where 70% of total datasets included as training data and the remaining datasets were utilized as testing data.

4.1 Simulation results for Set-1 variables

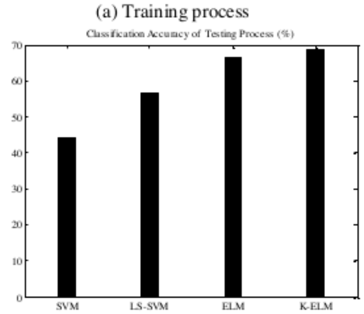
The parameters of four PHM system models using SVM, LS-SVM, ELM, and K-ELM methods are listed in Table 2. A radial basis function (RBF) was employed as an activation function for the ELM learning algorithm. While kernel type employed for SVM, LS-SVM, and K-ELM were radial basis functions (RBF). The accuracy result of proposed PHM system is depicted in Figures 4(a)-(b). The computation time process of proposed PHM system was figured out in Figures 5(a)-(b). For the training process, the best accuracy result is provided by the proposed PHM system using K-ELM method. The proposed PHM system could assess the transformer health as of 100% while the accuracy results of PHM system using SVM, LS-SVM, and ELM were 80.95%, 85.71%, and 95.24%, respectively. In terms of the testing process, the K-ELM approach has an excellent accuracy result as of 68.67%. The accuracy results of PHMS system using SVM, LS-SVM, and ELM were 44.44%, 56.67%, and 66.46%, respectively.

Table 2 Parameters of SVM, LS-SVM, ELM, and K-ELM for Set-1

SVM	LS-SVM	ELM	K-ELM
C = 50	C = 50	Hidden Neuron = 30	C = 50
$\sigma = 25$	$\sigma = 25$		$\sigma = 25$



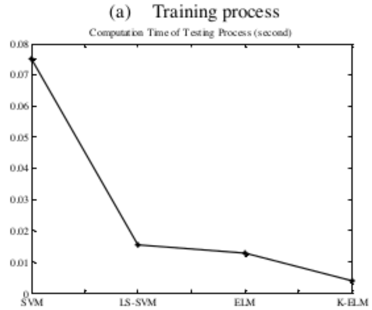
(a) Training process



(b) Testing process

Figure 4: The accuracy result of four PHM system models for Set-1

(a) Training process



(b) Testing process

Figure 5: The CPU times for Set-1

As shown in Figures 5(a)-(b), the best CPU time calculation is resulted by the proposed PHM system around 0.0177 second during the training phase. While the computational burden time of PHM system using SVM, LS-SVM, and ELM were 0.5156 second, 0.2031 second, and 0.0356 second, respectively. For testing phase, the proposed PHM system had showed best performance with 0.0039 second. While the CPU time of other PHM system models using SVM, LS-SVM, and ELM are 0.075 second, 0.0156 second, and 0.0129 second, respectively.

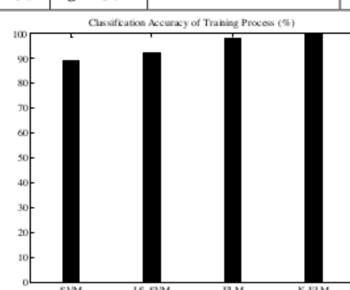
4 .2 Simulation results for Set-2 variables

To examine the efficacy of the proposed PHM system for Set-2 variables, the proposed PHM system parameters that utilized are provided in Table 3. The activation function for the ELM learning algorithm and kernel type for SVM, LS-SVM, and K-ELM were same as used in study with Set-1 variables. Figures 6(a)-(b) show the accurateness of PHM system output while Figures 7(a)-(b) provide the CPU time process of PHM system.

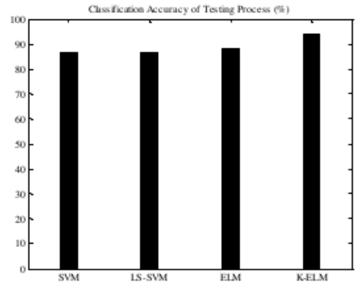
The proposed PHM system using K-ELM method had provided superior results among the other PHM system models during training phase as illustrated in Figures 6 (a)-(b) where it could assess the transformer health as of 100%. In the contrary, the accurateness of PHM system model output based on SVM, LS-SVM, and ELM were 88.85%, 91.98%, and 98.24%, respectively. In the testing phase, the proposed PHM system model has a rigorous result for its accuracy result as of 93.61% while the PHM system framework based on SVM, LS-SVM, and ELM have the accuracy results as of 86.75%, 86.76%, and 88.13%, respectively. The best computation time process is resulted by the proposed PHM system around 0.043 second during the training phase as depicted in Figures 7(a)-(b). While the CPU time of PHM system using SVM, LS-SVM, and ELM were 36.92 second, 0.78 second, and 0.051 second, respectively. In the testing phase, the proposed PHM system model had showed best performance with 0.012 second. While the CPU time of PHM system model using SVM, LS-SVM, and ELM are 1.88 second, 0.11 second, and 0.07 second, respectively

Table 3 Parameters of SVM, LS-SVM, ELM, and K-ELM for Set-2

SVM	**LS-SVM**	**ELM**	**K-ELM**
C = 100	C = 100	Hidden Neuron = 200	C = 100
$\sigma = 50$	$\sigma = 50$		$\sigma = 50$

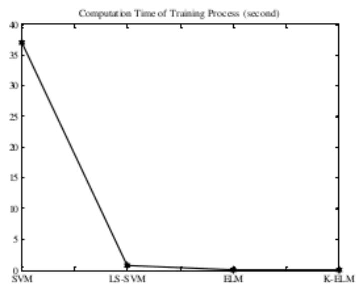


(a) Training process

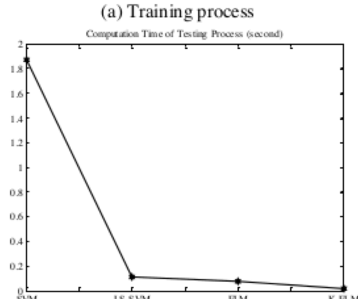


(b) Testing process

Figure 6: The accuracy results of four PHM system models for Set-2



(a) Training process



(b) Testing process

Figure 7: The CPU times for Set-2

Conclusions

In this research work, K-ELM has been proposed as PHM system to assess the health condition of power transformer. As shown from the simulation results, the proposed PHM system model in terms of accuracy provides better performance compared to PHM system model based on SVM, LS-SVM, and standard ELM both for training and testing processes. In viewpoint of speed of learning algorithm, the proposed PHM system model is faster than other PHMS system models tested in this paper. The proposed PHMS system can achieve better generalization performance and has more stable ability than other PHMS system models utilized in this paper in terms of accuracy rate and CPU time. Since the present proposed PHM system model is not optimized, the application of meta-heuristic approach to improve the performance of PHM system model is necessary in the futures.

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