Neuro-Fuzzy System Identification for Remaining Useful Life of Electrolytic Capacitors

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***Abstract*—The remaining useful life of electrolytic capacitors is most important to guarantee the safety and reliability of the electric systems. The remaining useful life is a nonlinear function, which dramatically changes by different internal and external effects in the capacitors. Soft computing approaches can be used as a powerful tool to analyze data and identify complex systems. Neuro-fuzzy approach is one of the important and widely popular topics in soft computing that are used for nonlinear system identification of dynamic functions. In this paper, an adaptive neuro fuzzy inference system based on subtractive clustering algorithm with 12 inputs is presented for system identification of remaining useful life in the electrolytic capacitors. An experimental dataset is considered to model the remaining useful life, which was provided by the Prognostics Data Repository of NASA. Comparing between simulations and experimental results has illustrated the accuracy of the purposed method to identify nonlinear systems. According to the results, mean squared error of the training and test data are 3.489×10^{-4} and 1.476×10^{-2} respectively.**

Keywords-ANFIS; NASA; capacitor; system identification; remaining useful life; soft computing; system reliability

I. INTRODUCTION

Computational intelligence is a branch of artificial inelegance such as Artificial Neural Networks (ANNs), Adaptive Neuro Fuzzy Inference System (ANFIS), and fuzzy systems Fuzzy. These methods are widely used by many researchers in different fields of humanities, engineering, and medical [1-5]. Fuzzy systems have a special place among the computational intelligence methods for nonlinear system identification [6-10]. The ability to implement human knowledge using the concepts of language tags and fuzzy rules, nonlinearity and the compatibility of these systems and their better accuracy compared to other methods in terms of data constraints are among the most important features of these systems. An important point of fuzzy logic is the ability to find a relationship between space inputs that the initial mechanism for doing this is a list of if- then sentences, which are called the rule. On the other hand, ANNs, due to the educational capabilities using different educational patterns, can create an appropriate connection between input and output variables. ANFIS is a combination of fuzzy inference system and ANN as a powerful tool that can identify results using numerical data is introduced as a neuro-fuzzy comparative inference system [11, 12]. Fuzzy systems are knowledge and rules-based systems. The heart of a fuzzy system is a knowledge base, which is formed from if-then rules. An if-then rule is an if-then expression that some of its words are identified by continuous membership functions.

The capacitor is an electric element that can store electrical energy by electrostatic field (electric charge). Different types of capacitors are used in diverse electrical circuits in fields of electronic, aerospace, robotic, mechatronics and other area of electrical systems [13, 14]. Given that the charge is stored in the capacitor, a capacitor can be used to create uniform electrical fields. Capacitors can hold electrical fields in small volumes; they can also be used to store energy. The capacitor is an electrical device that produces a capacitive effect in electrical circuits. In other words, capacitors are elements that can store electricity energy in the form of an electrostatic field.

Capacity is a criterion to measure the ability to maintain electrical energy. High capacity means that the capacitor is able to hold more electrical energy. Generally, the capacity determines Remaining Useful Life (RUL) in the capacitors [15]. RUL is the most important parameters in increasing reliability and safety in applications of engineering systems. Actually, RUL is a physical quantity that depends on the capacitor's structure, circuit, potential difference, operation range and its work environment [16, 17]. Therefore, RUL is as a nonlinear multivariate function, which has many uncertainties and nonlinearities. Recently, prediction and estimation of RUL in the capacitors, batteries, and other electric and electronic components has been considered by many researches[18]. In this paper, an ANFIS method based on subtractive clustering algorithm has been used for system identification of RUL in the electrolytic capacitors. In this work, we use capacitance loss and Equivalent Series Resistance (ESR) of the capacitors for estimation of RUL.

II. CASE STUDY

The case study includes a dataset of experimental data of electrolytic capacitors that was established by a significant test in NASA [9]. This dataset is available for researchers in The Prognostics Data Repository website [19]. The data was collected from the electrolytic capacitors at about 4500 hours of under operation. These types of capacitors are commonly

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found in electric circuits. The electrolytic capacitors are the same as the constant capacitors, but their size and capacity are larger than the fixed capacitors. The chemical capacitor is the other name for these capacitors. The actual amount of their capacity and tolerable voltage is also included on the body. Fig. 1 and Fig. 2 show ESR and capacitance loss of six capacitors respectively. Fig. 3 depicts target of ANFIS model, which is RUL of the capacitors.

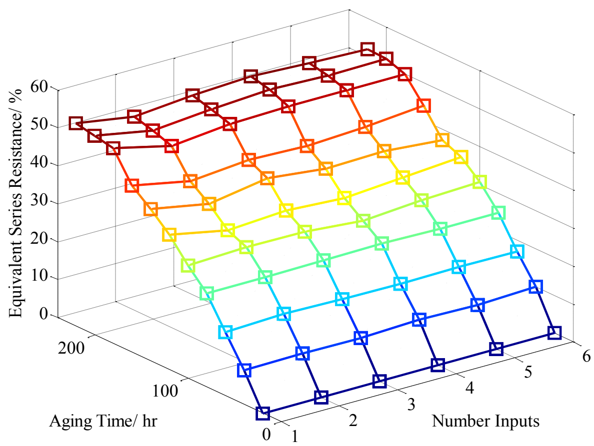

Figure 1. Equivalent series resistance for six capasitors as inputs.

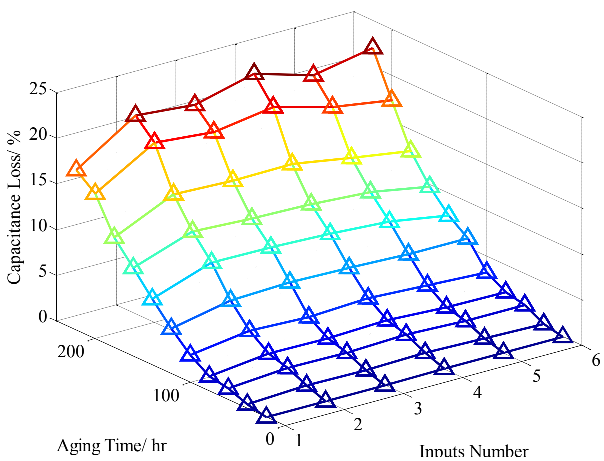

Figure 2. Capacitance loss for six capasitors as inputs.

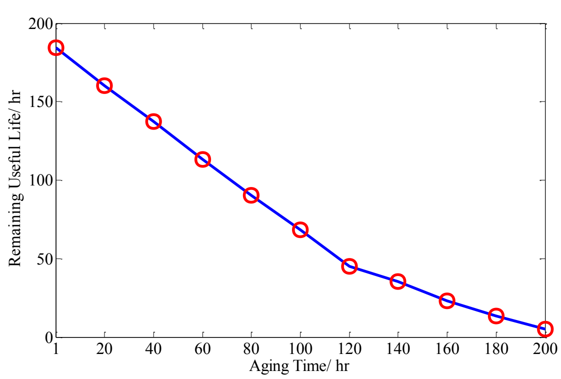

Figure 3. Remaining useful life as a target for estimation.

III. PROPOSED ANFIS APPROACH

Modeling means getting a relationship between input and output of the system. The main axis of modeling a system can be the physical rules governing a given system or the use of the results of a test on the real system. The system identification is a specific method of modeling a system that is done through using the results of a practical experiment. Mathematical modeling means obtaining a mathematical relation between the input and output of the system, so that if a similar input signal were applied to a simulated system and model, the outputs of the original system and the model are approximately the same.

ANFIS is a 5-layer network consisting of nodes and nodes connecting arcs[12]. The proper structure of the neuro-fuzzy system is chosen proportional to the input data, the degree of membership, the rules, and the rule and functions of membership degree [20]. Fig. 2 shows a neural-fuzzy network architecture with two inputs, one output, and two rules. In the first layer (input layer), the value of each entry dependency to different fuzzy intervals is specified by the user. By multiplying the input values to each node in each other, the weight of the rules is obtained in the second layer. The relative weight of the rules is calculated in the third layer. The fourth layer is the rule layer that operations on incoming messages are performed on this layer. The final layer is the network output, which aims at minimizing the difference between the output from the network and the actual output. At the training stage, by adjusting the degree of membership parameters based on the acceptable error rate, the input values are closer to the actual values. The main training method in this system is the error propagation method. In this method, using the error retarder algorithm, the error value is distributed to the inputs and the parameters are corrected. The points that need to be considered about neuro-fuzzy network education are:

1. The information chosen for test and training must be selected randomly.
2. Model is not able to simulate information that is outside the scope of information
3. Input information to the model should be normalized to achieve better results
4. The higher the number of model training data, a model gets better training

In this paper, the proposed approach has been set upped by Fuzzy Logic Toolbox of MATLAB. The structure of ANFIS model for system identification of RUL is depicted in Fig. 4. As illustrated in Fig. 4, there is a structure of ANFIS model with 12 inputs and 1 target. In addition, this figure clearly display neuron’s arrangement of the subtractive clustering algorithm to identify the nonlinear parameters of the capacitors. Fig. 5 to Fig. 8 provide information about surface function of the obtained output with inputs by three dimension graphs. The x-axis and the y-axis illustrate inputs 1-2, 1-6, 7-8, and 7-12 (x-y) respectively for Fig. 5 to Fig. 8. In addition, the z-axis indicates output of the model that is RUL of the capacitors.

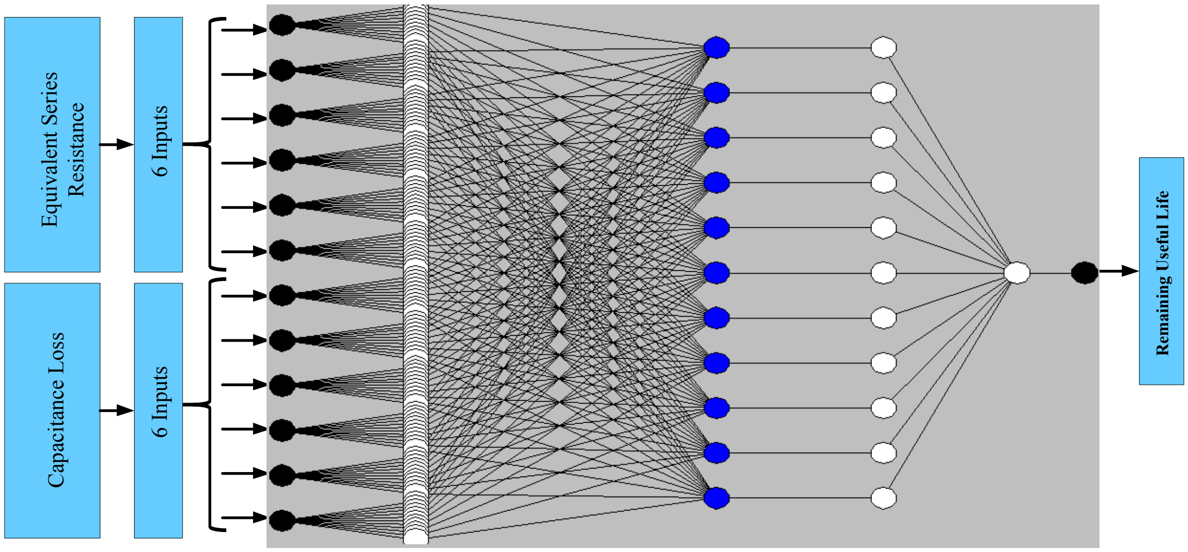

Figure 4. The structure of ANFIS model for system identification of RUL.

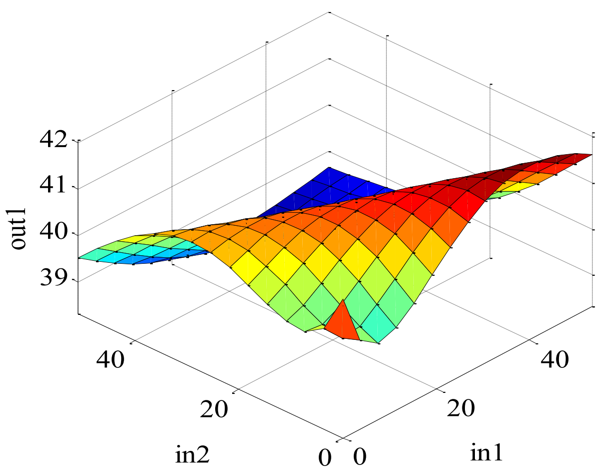

Figure 5. A surface function of the obtained output with input 1 and input 2 by a 3D graph.

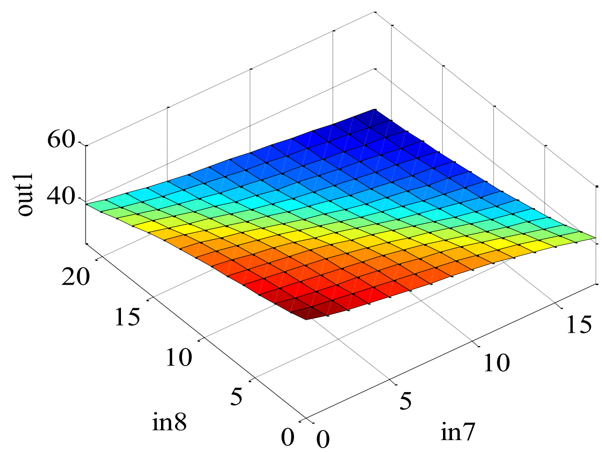

Figure 7. A surface function of the obtained output with input 7 and input 8 by a 3D graph.

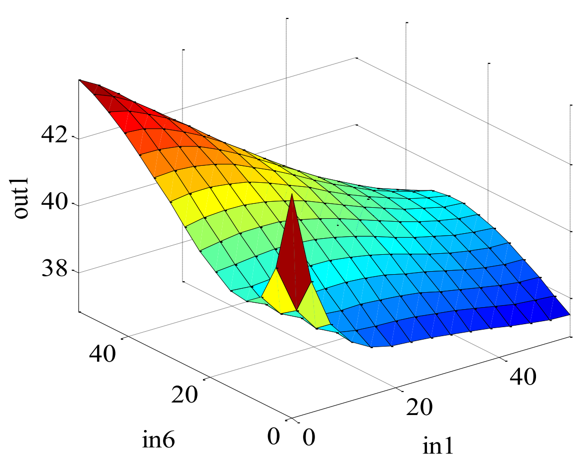

Figure 6. A surface function of the obtained output with input 1 and input 6 by a 3D graph.

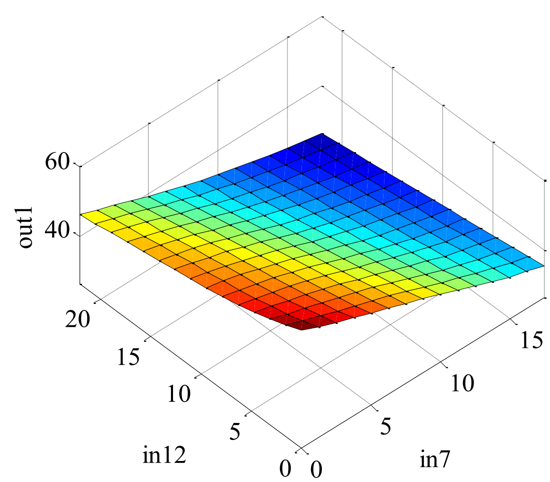

Figure 8. A surface function of the obtained output with input 7 and input 12 by a 3D graph.

IV. RESULTS AND EVALUATION

The last step in modeling and system identification is evaluation and validation of the obtained model and function. There are many uncertainties and nonlinearities in process of system identification. In this part, a number of criteria and graphs to compare and evaluate the results of simulation is brought. These graphs and criteria help us to accurate analyses the responses of the ANFIS model. Figure 9 gives information about comparing between data of real RUL and estimated RUL in the training state. As shown in the figure, there is an excellent response ANFIS model in training the data of the capacitor. Fig. 10 indicates a comparison between the estimated RUL, which is obtained by presented ANFIS method, and the real RUL of the capacitor in the test state. According Fig. 10, the response of the purposed ANFIS model is goodness to identify RUL of the capacitors. Fig. 11 and Fig. 12 clearly display error regression of training and test data respectively. According in the figures, the training data with R=1 has better response than test data with R=0.998. Finally, Table I presents information about evolution of errors. As illustrated in the table, there are 4 criteria for validation of the proposed ANFIS that include Root-Mean-Square Error (RMSE), mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

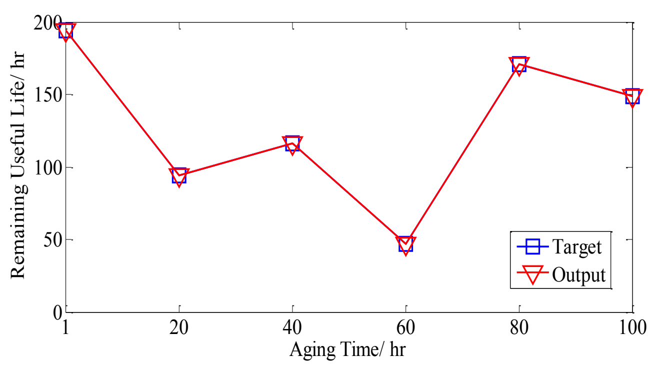

Figure 9. A comparison between the out put RUL and the real RUL in the training state of the ANFIS model.

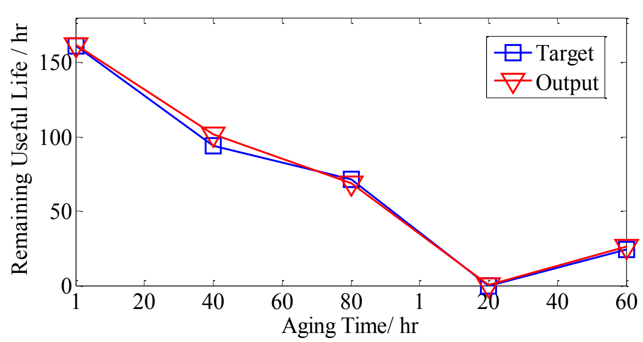

Figure 10. A comparison between the out put RUL and the real RUL in the test state of the ANFIS model.

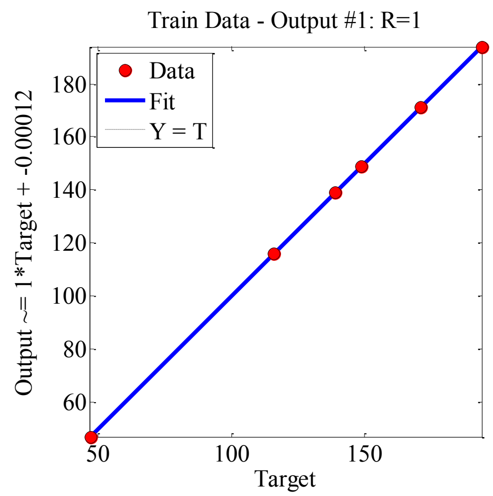

Figure 11. Error regression of training data.

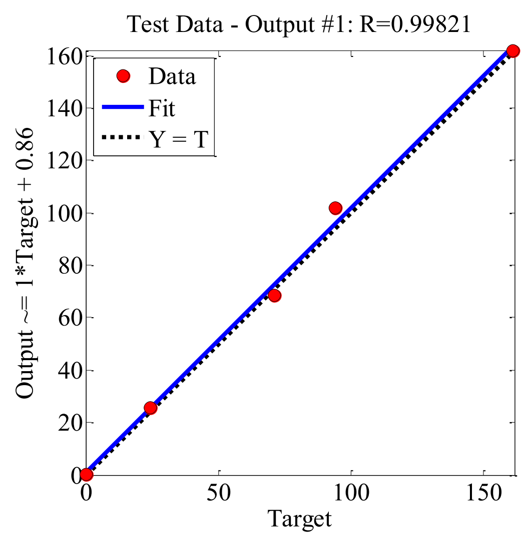

Figure 12. Error regression of test data.

TABLE I. ERRORS OF THE SYSTEM IDENTIFICATION METHOD

Errors of the ANFIS model in training state	***Errors of the ANFIS model in test state***
RMSE = 1.867×10^{-5}	RMSE = 1.724×10^{-2}
MSE = 3.487×10^{-4}	MSE = 1.471×10^{-2}
MAE = 9.339×10^{-4}	MAE = 1.561×10^{-2}
MAPE = 2.160×10^{-4}	MAPE = 1.482×10^{-2}

V. CONCLUSION

A soft computing approach for estimation of Remaining Useful Life (RUL) of electrolytic capacitors with capacitance loss and Equivalent Series Resistance (ESR) parameters using Adaptive Neuro Fuzzy Inference System (ANFIS) based on subtractive clustering has been presented. ANFIS model can be used in algorithms for system identification of dynamic systems, which have many uncertainties and nonlinearities. The case study includes a dataset of electrolytic capacitors parameters such as RUL, ESR, and capacitance loss, which was obtained as an experimental dataset by a test in NASA. The main goal of this work is on the estimation of complex systems and performing neuro-fuzzy system identification as a black box model, instead of analytical and mathematical method. To estimate the RUL using the soft computing method, an ANFIS structure with 12 inputs was selected, which its 6 number for ESR and its 6 other inputs for capacitance loss. The model of RUL have been identified and simulated using Fuzzy Logic Toolbox of MATLAB, and verified by several criteria. The simulation results indicated that the proposed method has goodness response to identify RUL of electrolytic capacitors with mean squared error of the training and test data 3.489×10-4 and 1.476×10-2 respectively.

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