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Research paper

Bearing fault prognostics using Takagi-Sugeno of extended fuzzy with recursive least square algorithms

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Abstract

This paper presents the detection of fault prognostics in bearings with the application of extended Takagi-Sugeno fuzzy recursive least square algorithms (exTSFRLSA). The nonlinear system is decomposed into a multi-model structure, consisting of linear models that are not inherently independent, due to the fuzzy regions defined in exTSFRLSA. The exTSFRLSA was developed to tune, adjust and adapt the parameters involved in the propagation model, as it tends to update itself with the availability of new data. This method is suitable for the online identification of systems because of its unsupervised learning pattern which dwells on a mechanism cantered on rule-based evolution. Scenarios considered for the rule-based modification and upgrade are quite diverse, thereby ensuring effective comparison of measured and predicted defect size. An estimation of the remaining useful life was determined successfully with the proposed method, showing that the system performance health indicator reflects bearing degradation, and it was concluded that exTSFRLSA can be used for fault prediction of bearing where rolling element are involved, especially while its operation is associated with fluctuating speed and load conditions.

1. Introduction

Takagi-Sugeno of extended form assumes a fixation on the rule-based fuzzy program structure. It is equally important to note that the rule-based Fuzzy structure is approximators of universal functions.

These are ideal for the extraction of interpretable information which provides a promising structure for effective and strong prognostics, for the effective arrangement of systems and control designs.

Attenuated faults used to estimate their remaining useful life, especially in bearings of rotating machinery usually result from adverse vibration.

Using vibration or acoustic signature analysis, and most especially the adopted method in this work is a widely used technique to avoid breakdowns in machinery where taper and rolling element bearings are often used. Such signals are usually correlated with in-order reference measurements to establish bearing conditions [1, 2].

Identification and fault detection in systems at the very early stage will greatly reduce system downtime, thus encouraging smooth production processes in industries, thereby enhancing productivity, efficiency, and profitability. The prognostics process is very important in fault detection; it entails the anticipation of possible manifestation of failure in a system and taking appropriate measures or solution procedures without postponement. The success of prognostic methods is a function of its ability to accomplish “accurate” estimates or predictions, a measure of reliability follows. In this research, the extended Takagi-Sugeno is applied in conjunction with one of the popular equations for fault detection known as Paris law to supplement and make the remaining useful life more expressive. Fuzzy Neural Networks, a hybrid metaheuristic technique, is a combination of neural network and fuzzy logic useful for solving complex combinatorial and stochastic problems in a diverse area of engineering like pattern recognition, control system modelling, robotics, and bioengineering applications, and other engineering problems.

A good number of hybrid applications associated with the feed-forward process include combined fuzzy and neural networks known as (adaptive neuro-fuzzy inference system) model. Another popular aspect associated with hybrid metaheuristic application is the online adaptive fuzzy neural network and neural network combined with fuzzy [3-6].

Despite some discrepancies in the literature associated with fault detection, predictions, and prognostics, the International Organization for Standardization defines prognosis as the calculation of the time for failure to occur having modes of failure that are incipient and which could be one or more in number [7].

One of the important aspects of failure mode is time estimation of failure, which is associated with risk in such complex systems. Prognostics is defined [8, 9] as a process of systems analysis, which involves fault detection associated with impending conditions of design parameters with durable life.

The complexities and dynamics of real-world problems in engineering and manufacturing require advanced methods and techniques for developing intelligent and adaptive systems (ISs) online. Systems in these industries should be able to evolve as they function and be able to improve the model by communicating with the environment as well as updating their knowledge.

Coyle et al. [10] were able to use a hybrid heuristic fuzzy combined with a neural network for the robustness of their work and to expand on the efficiency of the computation of related research. New methods were suggested for validating the network architecture after effective modification. There is no doubt that hybrid algorithms, specifically the creative ones of fuzzy neural models, are capable of adapting to complex structure, especially where neurons are needed. There is no doubt that the research presented by Coyle et al. [10] is very similar to that presented by Rubio [11] and quite related to the self-organizing fuzzy modified least-square network. He developed an online algorithm that is able to reorganize the model and adjust to a changing environment in which both the structure and the learning parameters are simultaneously carried out. His network avoids the singularity produced by the widths in the antecedent part for online learning.

A clustering technique at the incremental level takes into consideration the non-stationary existence of the pattern of dataset presented which further produces clusters in online mode used as the first stage of the non-iterative learning process to form fuzzy rule-based structures of a previous existence in component forms. The breaking down of the learning recursive clustering leads to a powerful principle known as Takagi-Sugeno in extended, which is known for its powerful recursive estimation technique [12, 13].

The novelty introduced in this work is in the method of determining the remaining useful life of taper bearing (which can also be used for roller bearings) which as proposed for fault extraction is based on fuzzy rules and the use of recursive least square. This helps to look closely at the control perspective showing deep attention to the system structure that is usually overlooked in other methods. More attention is usually given to the recognition from system parameter point of view, especially focusing on adaptation of the system, tuning process and modification process [14]. Fuzzy theory is often known to be the most suitable approach to real-life problems, especially problems associated with mathematical models especially stochastic cases or problems under uncertainty [15, 16].

The hybrid system, of extended fuzzy and neural network recursive least square, has robust application and is very fast in terms of processing speed and practical application, as it can utilize linguistic terminologies associated with fuzzy rules for high performance [17]. Therefore, it is worthy to note that hybrid application of fuzzy and neural network with recursive least square is very significant in systems, especially where the remaining useful life of rolling element bearingss running and maintaining varying speed and load conditions are to be investigated [18-23].

The concept of the method in view is such that, considering fuzzy rules, components of fuzzy sets, and other variables of the occurrence elements, it is necessary to come up with a standard fuzzy rule-based model structure with alpha cuts from rule viewer [24].

The adapted and hybrid fuzzy system functions like a creative or nature inspired system which is capable of mimicking real life natural systems like humans by looking at the system behavior and programmed to function based on their process of operation, especially looking at key features associated with the human system like learning pattern, developmental pattern, operational pattern, pattern of growth, and development to develop rules for data manipulations using linguistic terminologies [25]. With the Takagi-Sugeno of extended form being a technique with high level of creativity for solving complex problems with multiple modes of operation, online recognition methods have recently begun to see application [26]. In combination with model recognition, monitoring, fault detection, and signal processing, the issue associated with its online application has also been discussed.

The model is a high-level fuzzy model of qualitative form using linguistic terminologies for effective rule development which has to be in line with membership function space and parameters by taking alpha cuts on the developed platform. This same algorithm is a function of recursive estimation of possible information based on dataset and rule development with expressive linguistic terminologies. The technique is qualitative hence the name extsfrls algorithm [27, 28]. An approach for modelling bearings degradation function is provided in this work, thus providing a relevant update on the bearings' remaining useful life by using the creative algorithm process, which is based on Takagi-Sugeno fuzzy of extended form and the least square recursive algorithm (exTSFRLSA) for the purpose of ensuring effective prognostics. Changing the parameters of a model is very possible using the proposed creative model as used in this study. The selected parameters are modified, tuned and properly adapted by relating measured and expected defect sizes in a structure under investigation [27]. Despite the variability defect growth behavior, the instantaneous rate of defect propagation was recorded, and there is also an improvement in the computation processing time.

This method has been used extensively in this work to demonstrate the expressive power of exTSFRLSA, using small amount of dataset compared to the solution obtained from common problem of inducing expert opinion considering robust dataset, as seen in previous research work based on fuzzy models has a high level creative algorithms. Another benefit of this research has to do with the ability of the process to function with other nonlinear expression [28-31]. The hybrid algorithm technique uses the concepts of the Extended Takagi-Sugeno also known for its linguistic based ability on developed rules from dataset alpha-cuts and from membership function of the fuzzy system [13]. Paris law in combination with the recursive least squares method thus capture's the crack growth in the systems relevant to data capture online which is 1.5 mm wide by 1mm deep simulated groove made on the bearings outer raceway by spark erosion machine.

The approach adopted in this study is based on unsupervised learning, with a focus on the recursive, non-iterative building of the Fuzzy network with rule from the available dataset. The method adopted further provides awareness of the online detection of the existence of bearings defects growth, thereby offering possible forecasting. It has a higher convergence speed and gives the fuzzy network better fine-tuning as shown in the conclusion.

2. Takagi-Sugeno fuzzy of extended type and recursive least square model

Real structures are complex, and sometimes their behavior appears to be non-stationary and often non-linear. The statement is true for bearings with rolling components working under fluctuating speed and load conditions. Monitoring systems are advanced; however, the online analyzes are now simple to perform with the help of the systems. Thus, creative and data-driven methods are being applied increasingly to systems other than prognostics Fig. 1. The aforementioned creative algorithm Takagi-Sugeno of extended form fuzzy models as an expert system has high-level expressive power and has demonstrated superior performance over traditional methods, so there is no doubt that the method can effectively perform prognostic degradation modeling [32-35].
This hybrid creative model can be defined as a collection of the following type of fuzzy rules as shown in the system of Eq. (1), [13, 27]:

$$R^i: IF\left(x_i.\text{is.close.to.}ב_1^{i^*}\right) AND \dots AND \left(x_n.\text{is.close.to.}ב_n^{i^*}\right)$$

$$\text{then } \left(y^i = x_e^T \pi^i\right) \quad i = 1,2, \dots, R \tag{1}$$

where R^i denotes the i^{th} fuzzy rule, R is the number of fuzzy rules, x_e is the extended input vector; $x_e = [1, x^T]^T$ which is formed by appending the input vector $x = [x_1, x_2, \dots, x_n]^T$, x_j.is.close.to.$x_j^{i^*}$ denotes the i^{th} fuzzy sets of the j^{th} fuzzy rule; $j = [1, n]$, $ב^{i^*}$ is the focal point of the i^{th} rule antecedent, $y^i = [y_1^i, y_2^i, \dots, y_m^i]$ represents the output i^{th} sub-system.
The output of the hybrid fuzzy model is calculated by considering the developed rules and sectioning the weighted average of individual rules' as shown in the system of Eq. (2).

$$y = \sum_{i=1}^{R} \tau^i(x) y^i = \sum_{i=1}^{R} \tau^i(x) x_e^T \pi^i = \Psi_k^T \theta_k \tag{2}$$

where $\tau^i(x) = \frac{\mu^i(x)}{\sum_{j=1}^{R} \mu^j(x)}$ stands for the i^{th} rule firing level, and Ψ_k^T is the vector of the inputs weighted by normalized firing τ of the rules.
Considering the recursive least squares algorithm, there is no doubt that the algorithm is a powerful tool for the forecasting and filtering process. This can generate an unstable quantization effect and divergence problem, especially when applied in a finite precision setting. As with the use of exponentially forgetting components, this results in separate effects, where in most cases there is exponential growth associated with the errors. A vital feature of the recursive least squares is the calculation of the input data estimation associated with the correlation matrix in an inverse form which helps the process of minimization. There are certain limitations associated with the creative algorithm, which have to do with complex computation and dynamic variables of the algorithm. This is resolved through incorporating fuzzy into the recursive least square. The significance of the least square model compared to the RLSM algorithm is to optimize the difference in the sum of the squares between the filter output and the target signal.
In terms of speed, the creative fuzzy model has a fast convergence, but not as fast compared with the the recursive least squares model. One of the interesting features of the recursive least squares is that it does not show the spread problem of its own value. A deterministic Takagi-Sugeno fuzzy of extended form is found to have less square defect-propagation model as built in the system to estimate the size of the defect and the rate of defect growth. A power law, which is closely related to the Paris law, has always taken the form of the defect growth model.

$$\frac{dD}{dt} = C_0 (\Delta D)^n \tag{3}$$

As presented in Eq. (3), dD/dt represents the diameter of crack with respect to time, equally, ΔD represents the instantaneous defect area of the system under study, and C_0 and n represent material constants. This has been noted to vary with factors different from instantaneous defect size. As can be seen in Fig. 1, the figure clearly represents the flow chart of the hybrid system designed to estimate the growth rate of the defect size.

The creative hybrid approach, due to its superiority, has been used for effective error prediction, thus it is capable of fine-tuning parameters of the established model with the RLS algorithm. It provides continuous improvement in the level of accuracy by adopting the defect growth behavior, which is a function of time. It is also worthy to note that there are three key parameters, which include α, β and t_0. These parameters are to be obtained using the established model defined in the system of Eqs. (4-6), respectively.

$$\alpha = \frac{1}{n-1}\log\left(\frac{C_0}{1-n}\right) \tag{4}$$

$$\beta = \frac{1}{1-n} \tag{5}$$

$$t_0 = \left(\frac{C_0}{1-n}\right) D_0^{n+1} \tag{6}$$

As presented in the equations, it is important to define the necessary parameters that make up the equations. According to the chart presented in Fig. 1, $C_0 = 0.0702$ and $n = 0.6875$, they both represent material constants, and D_0 represents the area of the smallest defect, which is capable of deflecting from size.

To effectively update the desired values of the parameters presented in systems of Eqs. (4-6), including α, β and t_0, which are necessary for effective model estimation, it is important to make use of the forgetting factor in RLS.

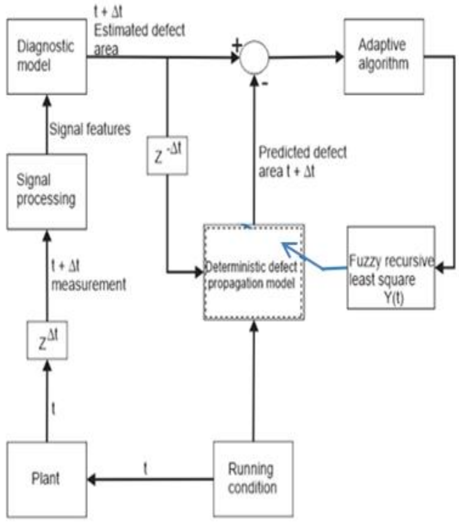


Fig. 1. Flow chart of exTSFRLSA prognostic system.

To obtain the output of the fuzzy network, Eq. (7) is further presented, thus:

$$Y(t) = \log(\Delta \mathrm{D}) \tag{7}$$

$\Delta \mathrm{D}$ represents the range of strain in the course of fatigue cycle.

$$Y(t, \vartheta(t-1)) \quad \rightarrow \textit{estimate of } Y(t)$$

The output Y estimation is a function of the defect area due to the range of strain during the fatigue cycle of time (t) and the filter parameter ϑ.

The recursive least squares algorithm is given as follows:

$$Y(t) = [\Psi^T(t-1)\vartheta(t-1) + \varepsilon(t)] \tag{8}$$

The output $Y(t)$ is a function of the vector of the input Ψ, the filter parameter ϑ and the error which are all functions of time.

where:

$$\Psi^T(t-1) = \begin{bmatrix} y(t-1), y(t-2), \dots\dots\dots \\ y(t-n), \end{bmatrix}$$
$$u(t-1-N), \dots\dots\dots u(t-r-N), 1]$$
$$\vartheta^T(t-1)$$
$$= [a_1, a_2, \dots\dots\dots a_n, b_1, b_2, \dots\dots\dots b_r, d]$$

A small amount of data is involved at the minimization of the filter parameter, which affects the signal sensitivity needed. Hence, Eq. (9) is given below:

$$\min_{\hat{\vartheta}} \sum [\underbrace{\Psi^T(i-1)\vartheta(i) - y(i)}_{\substack{\text{"least squares"} \\ \text{prediction value of } y}}]^2 \tag{9}$$

As shown in the system of Eq. (9), it is important to properly define some parameters such as y, which represent the value of the output. Then, u which represents the input value of the system, and d represent the noise or disturbance in the system during operation, N represents the time for system delay. The system of Eq. (10) present s a (3×3) matrix, which is a covariance matrix $p(t)$.

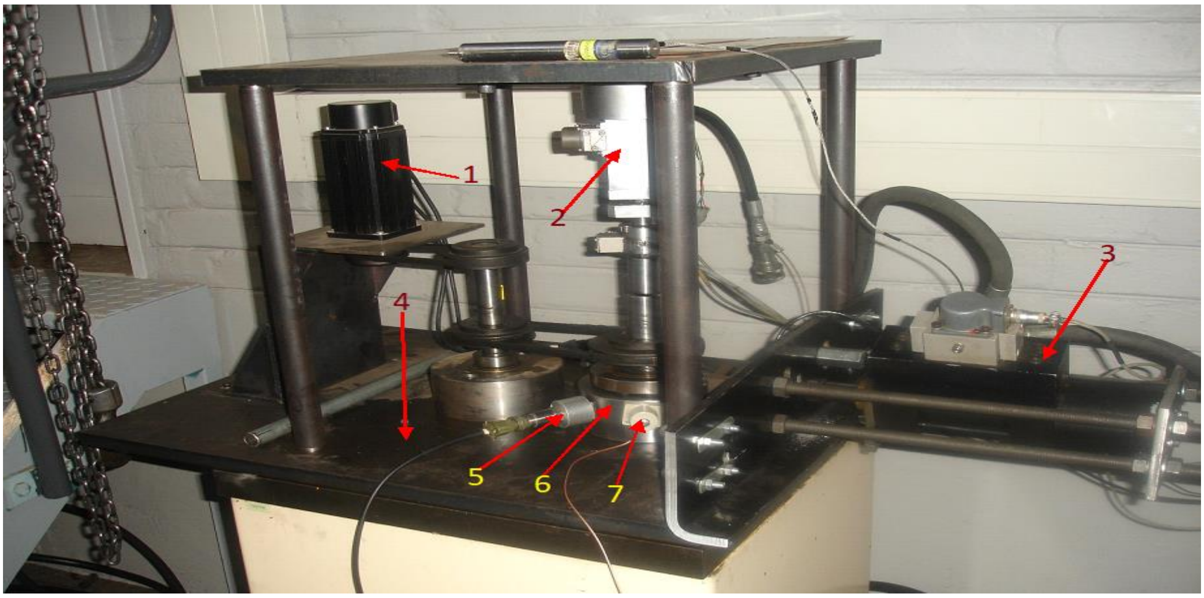
$$P(t) = \lambda^{-1}\left(\begin{matrix} P(t-1) - \\ \frac{P(t-1)\Psi(t)\Psi^T(t)P(t-1)}{\lambda+\Psi(t)P(t-1)\Psi(t)} \end{matrix}\right) \tag{10}$$

As shown in the equation, λ totally represents the forgetting factor and the range is between 0 and 1, that is $0 < \lambda \leq 1$. A unit matrix scale, which represent the initial covariance matrix, is chosen by a positive scalar and has a set of boundary conditions or functions between 1-1000 (Fig. 1).

$$\vartheta = [\alpha \;\; \beta \;\; t_0]^T \tag{11}$$

3. Experimental procedure

Fig. 2 shows the test rig setup, which was used in the experiment. As shown in the figure representing the test rig, three bearings have been considered (Timken HR 30307 J); out of the three, two were selected to undergo artificially placed defects because they can be removed from the outer raceway. The test rig includes different parts; one of the very important parts is the servo-hydraulic actuators (two sets) for mounting the different vertical and horizontal load amplitudes on the bearing been tested. Two actuators were added for successful simulation, a situation that aided the coupling of the vertical and horizontal course to be considered. The rotational bearing speeds were quite slow and were between the range of values 70 and 90 rpm. The force applied was sinusoidal. To further demonstrate the machine operation process, an AC motor of brushless type, with specification standard, Rockwell Automation MPL-B680B, was placed on a single row bearing with the name NSK 6309. The motor drive analog outputs were used to measure the angular velocity on the motor (BM-01 series Rockwell Automation Kinetix 6000).



1.Variable speed motor, 2.Axial hydraulic actuator, 3.Radial hydraulic actuator, 4.Test rig, 5.Acoustic transducer 1, 6.Test bearing housing, and 7.Acoustic transducer 2

Fig. 2. Experimental test rig.

This system makes continuous variable velocities between 0 and 3600 rpm. An AE sensor, which have a frequency range of 25-530 kHz (model number: SR 150 M), was added to the test rig. A bearing was added which was tested with a crack using the process of spark erosion. Fig. 3 represents a display of full schematic diagram of the test rig constructed.

Fig. 4 shows the seeded crack test bearing details. The bearing details used are given in Table 1. The rated speed of the bearing, when used with grease, was 4800 rpm; however; for this work; the bearing via a variable motor speed at low speeds of 70 and 90 rpm was operated because of the unique experience observed at such speed under variable loads and speeds.

The three bearings were sinusoidally loaded 500N vertically at a frequency of 2Hz and 900N and horizontally at a frequency of 1Hz. The addition of the load helps the model real-life scenarios. The servo motor speed for the bearings was set at 70 and 90 rpm, respectively, as reported earlier. At all these speeds the test-bearing vibration signatures were obtained using an FFT analyzer, NI card acquisition (BNC-2110) with BNC connector block acting as a shield.

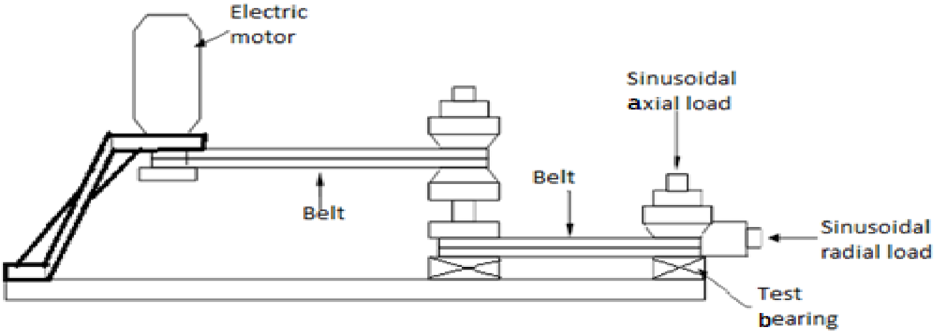
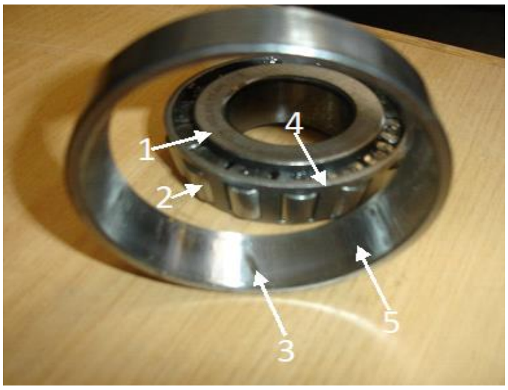


Fig. 3. Schematic diagram of test rig setup.

Table 1. Bearing information**.**

Contents	**Parameters**
Bearing specification	Timken taper roller bearing HR 30307 J
Bearing outer diameter	80 mm
Bearing inner diameter	35 mm
Bearing width	22.75 mm
Bearing roller diameter	12 mm
The number of rollers	14
Rated speed with grease	4800 rpm



1. Bearing inner ring, 2. Bearing roller, 3. Seeded crack, 4. Rollers cage, and 5-Bearing outer ring
Fig. 4. Crack on outer race.

4. Results and discussion

The tests conducted were halted after some random pits sprawled on both bearings, following operating for approximately 16 days each. Then the damaged data-bearing were sectioned, and each was used for the creative hybrid algorithm exTSFRLSA for effective analysis. The test results were collected on the damaged bearing, and the first category was identified as Data 1. It was measured and worked at a speed of 70 revolution per minute (rpm). The second group, sectioned as Data 2, was equally tested on the damaged bearing, and the speed of operation was recorded at 90 rpm.
The training process was observed for data 1, which was observed at a slow and steady rate for groups in data 1. The learning rate used to verify the performance result for data 2 after the model was further trained was 0.5. The data groups 1 and 2 contain 52 sets of data of 60,000 samples each. Group in Data 1, was further partitioned into 2 groups, one containing a dataset of roughly 25 used to train the algorithm, while the other group of a dataset of roughly 27 was used to evaluate and verify the algorithm that was further trained. Upon presentation of each input vector for individual samples, the gradual training using the creative algorithm shows some level of adjustment of the set of weights and biases of the fuzzy model. This is a total shift from classical algorithms known as online training or the adaptive training process. The process demonstrated is purely creative using an expert learning algorithm, in this case, biases and weights are structured to modify the system by responding to available input variables. As demonstrated in the experiment, the Data 2 set was equally validated by considering the obtained set of data categorized into 27 sets. This is part of data 1 classification. It was further noted that the result obtained at this level is valid when compared with dataset 1.
Fig. 5 shows a continuous simulation of defects with noticeable growth consisting of the estimated plot for parameters in the defect propagation model. The simulation process performed, at the first stage is four simulation procedures. The initial estimate is represented as $\alpha = -4.5$, $\beta = 3.2$, and $t_0 = 1.5$. The estimation of the initial defect propagation parameters model is shown in Table 2.
A clearer view of Fig. 5 demonstrates the obtained value of defect propagation model parameters which consist of the two bearings 1 and 2. It was observed that the bearings obtained a speed of 70 and 90 rpm, respectively. It was further observed via the performed simulation at the very first time on dataset 1, that the obtained value of α_1 gave a range of values far from zero. It was also observed that t_{01} increases due to convergence experience, at a close range of value of 10×10^4 cycles. It was further investigated that as α_2 maintained a shift towards the zero, t_{02} was observed to be smaller. A close look at Fig. 6, reveals a divergence in the simulation process parameter not from the predicted but the actual value

Table 2. The estimation of the initial defect propagation parameters model in continuous growth of defect area simulation.

	Simulation of continuous growth of defect area on data group 1 at 70 rpm		
Prediction no.	α_1	β_1	t_{01}
1	-4.5	3.2	3.6
2	-4.2	3.4	2.4
3	-5.0	2.5	2.0
4	-4.0	2.5	2.4
Simulation of continuous growth of defect area on data group 2 at 90 rpm			
Prediction no.	α_2	β_2	t_{02}
1	-3.5	2.2	1.4
2	-3.5	2.2	1.5
3	-3.5	2.5	1.3
4	-2.0	2.2	1.3

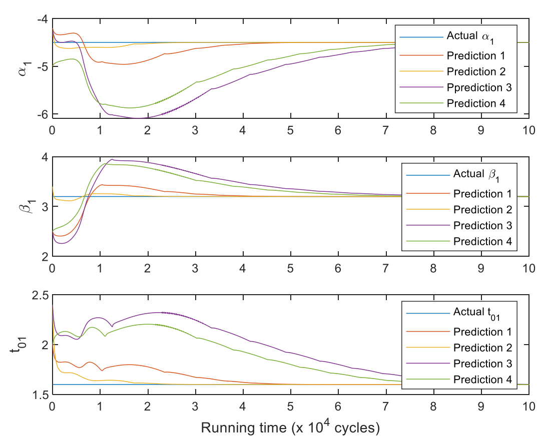


Fig. 5. Data 1 at 70 rpm using exTSFRLSA estimated defect propagation parameters model.

In running the simulation, it took a time of 154.22 secs. This shows that it was quite fast covering a percentage value of 81 % compared to the recursive least squares process simulation. This is because the creative hybrid system of the fuzzy network was introduced and quite superior to the classical recursive least square algorithms. Fig. 7, shows the prediction plot, which reveals adaptation at the growth of the crack. 0.3 standard deviation was considered with a zero mean added for normally distributed portion of noise. This is sufficient to account for the effect of the distortion inherent in in-direct measurement signal processing. For the simulation γ was 0.99 and was the forgetting factor.

Considering the creative hybrid model exTSFRLSA, and the result of the simulation performed, testing the viability of the prognostic method became very necessary. It was further noted from the plots that the level of prediction differs, though there was not much deviation between the predicted and actual plot, considering the two vital bearings used. In the first set of simulations, according to the deterministic propagation model of both Eqs. (2, 10), a defect is assumed to evolve continuously. Eq. (10) is therefore, very useful for use with Eq. (2) because it allows the estimation of many data. The unsupervised exTSFRLSA algorithm uses training, demonstrating the development of an evolving rule-based framework for evolution. The time series centroid input was gradually modified based on the dataset.

There is a clear indication, as shown in Fig. 8, that the system is quite suitable for online identification, and it can depend on the previous value received; for example, if the method begins from time t0, it is possible to use the integrator block, this is done to enable the new value to align with the previous value, the time t2 is dependant on the value of t1.

It is further shown from the graph by comparing the growth defect area using the creative hybrid model Takagi-Sugeno fuzzy of extended form and the classical model, recursive least square as a general diagnostic model. After demonstrating the solution strength of the classical recursive least squares, it is very clear that the creative hybrid exTSFRLSA algorithm is robust and quite suitable for prognostic rolling element bearing functioning at fluctuating speed and load conditions.

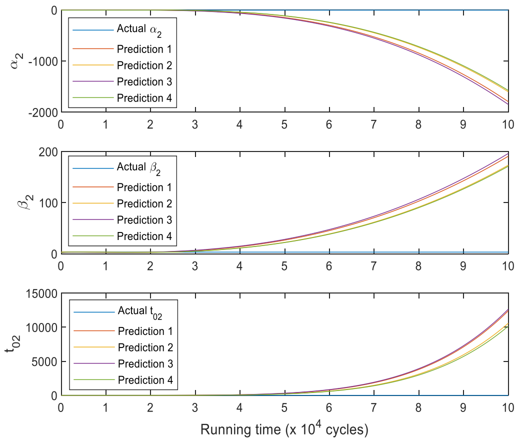


Fig. 6. Data 2 at 90 rpm using exTSFRLSA estimated defect propagation parameters model.

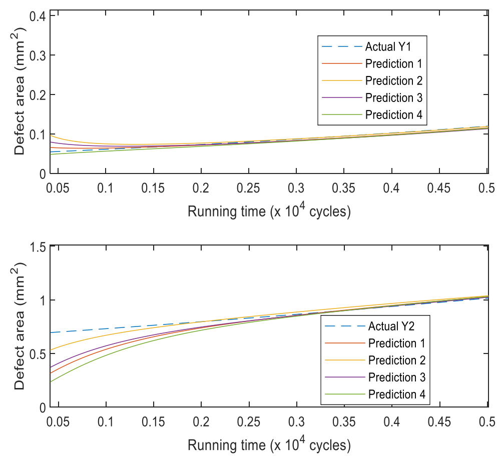


Fig. 7. Rls prediction plot with adaptation at the crack growth.

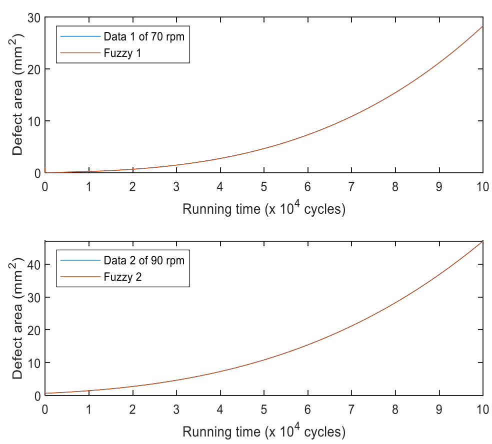


Fig. 8. Plot comparison between RLS and exTSFRLSA.

5. Conclusions

This study is a demonstration of the creative hybrid system, as an online-based identification of the exTSFRLSA model, developed for fault detection in bearings, which is a creative hybrid Takagi-Sugeno fuzzy of extended form for system maintenance (condition and predictive based). This process is based on noniterative, recursive rule development through the creative or adapted learning process. The concept adopted is a hybrid classification considering an inspired creative algorithm, Takagi-Sugeno fuzzy, and a classical recursive least squares, combined with popular Paris law with simulation work, which demonstrated the solution strength for remaining useful life application in the prediction of bearing fault prognosis.

A close view of the performance strength of exTSFRLSA shows a good performance in terms of defective prediction and analysis. The response strength is fast, in terms of bearing defect propagation, before failure. The application of this hybrid algorithm, Takagi-Sugeno fuzzy of extended form, showed a high level of superiority over the classical recursive least squares approach, which involves less computational task but more computational resources, better sensitivity analysis, fast and accurate fine-tuning process, and well-structured parameters. In summary, the adopted model is computationally efficient and reliable.

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