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Short communication

Remaining life estimation of used components in consumer products: Life cycle data analysis by Weibull and artificial neural networks

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Abstract

Environmental awareness and legislative pressures have made manufacturers responsible for the take-back and end-of-life treatment of their products. To competitively exploit these products, one option is to incorporate used components in "new" or remanufactured products. However, this option is partly limited by a firm's ability to assess the reliability of used components. A comprehensive two-step approach is proposed. The first stage phase statistically analyzes the behavior of components for reuse. A well-known reliability assessment method, the Weibull analysis, is applied to the time-to-failure data to assess the mean life of components. In the second phase, the degradation and condition monitoring data are analyzed by developing an artificial neural network (ANN) model. The advantages of this approach over traditional approaches employing multiple regression analysis are highlighted with empirical data from a consumer product. Finally, the Weibull analysis and the ANN model are then integrated to assess the remaining useful life of components for reuse. This is a critical advance in sustainable management of supply chains since it allows for a better understanding of not only service requirements of product, but the remaining life in a product and hence its suitability for reuse or remanufacture. Future work should assess: (1) reduction in downtime of process equipment through the implementation of this technique as a means to better manage preventative maintenance; (2) reduce field failure of remanufactured product; (3) selling-service strategy through implementation of the proposed methodology.

Keywords: Remaining life; Reuse; Reliability

1. Introduction

Considering the limits of natural resources, dramatically increasing global population and the effects of environmental impacts, products need to be considered for their entire life cycle from design, manufacture, and sale, through to use and end-of-life in order to optimize the production processes and to reduce impacts on the environment. Manufacturers have encountered increasing pressures from both governments and environmentally focused groups to 'reduce', 'recycle' and 'reuse' their industrial waste (Linton et al., 2002). The introduction of international and national legislations on industrial production and waste management are demanding remarkable changes in the manufacturing culture. These regulations make the Original Equipment Manufacturer (OEM) responsible for the end-of-life treatment of their products (Seliger et al., 2004). This follows the principle of Extended Producer Responsibility (Klausner and Hendrickson, 2000) according to

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which producers should be responsible for the entire life cycle of their products and especially for the take-back, the recycling and the final disposal of their products (Kiritsis et al., 2003). Thus, supply chain management needs to focus on the integration of activities across the whole life of the product including recycling, reuse, and final disposal of products. To embrace these challenges, increasing interest in promoting an inverse supply chain (Shibata et al., 2001) and sustainable production has led many companies to scrutinize the ways in which they deal with the end-of-life treatment of their products.

Depending on the product type, manufacturers choose between methods of reuse, recycling, incineration and disposal. Minimizing Wasted Resources (Yamagiwa et al., 2001) can be achieved by two strategies—product recovery through product reuse and material recovery through recycling. Manufacturers are struggling to find ways to smooth the flow of returned products and to recover maximum value from these products. This goal can best be achieved by selecting the higher levels of material recovery such as reuse. Research reveals (Fleischmann et al., 1997) that economical and ecological motivation is the driving force behind increasing interests in reuse in the recent past. Reuse is more environment friendly than recycling or first-time manufacturing as remanufacturing (through reuse) uses fewer materials and less energy since it reuses several parts from the used product (Ferrer and Whybark, 2001). Products returns continue to grow in volume worldwide, in part due to customer service and laws pertaining to manufacturer responsibility. These developments require companies to explicitly consider the product reuse in the early stages of new product development (Guide et al., 2003b). Remanufacturing and recoverable manufacturing systems (Guide et al., 2000), in which parts are reused, are at the heart of reverse logistics (Dowlatshahi, 2000).

Revalorization (Parkinson and Thompson, 2003) through reuse of a product or its components would yield an economically competitive treatment of products as it would reduce the energy required to process raw material and components and make less demand on the environment by preventing premature discarding of products. Several other researchers (Griese et al., 2004; Guide et al., 2003a; Kaebernick et al., 2002; Kobayashi, 2001) have also emphasized that the reuse of the components, subassemblies or the entire product is a competitive and efficient strategy. Reusing of used parts has already been applied to industrial products. For instance, parts are reused in products such as one-time-use cameras, photocopying machines and toner cartridges of printers in Japan (Okumura et al., 2001). A wide-spread implementation of the reuse strategy could be triggered, subject to the availability of reliable methods to assess the useful remaining life of parts.

Since the essential goal of the reuse strategy is to reuse parts, the reliability of used parts becomes a central point. Research indicates (Kara et al., 2004; Klausner et al., 1998) that reuse is technologically feasible, associated with a significant manufacturing cost saving, and it does not compromise product quality. However, it is not easy to be applied in reality. There are several uncertainties associated with reuse, the most common is the uncertainty of the product's quality after use (Kaebernick et al., 2001, 2002). The unavailability of reliable methods to assess the reliability of used parts is one of the major barriers in reusing used parts. The evolution of such a methodology would play a pivotal role in making decisions on the supply chain process and the recovery value of returned products.

Reliability assessment by life cycle data analysis is the basis of the proposed methodology. The suggested strategy considers statistical as well as condition monitoring data analysis for decision-making on reuse. The methodology addresses the problem of reliability assessment of used parts by considering two important aspects. Firstly, it assesses the overall reuse potential of components with a clear understanding of the failure mechanism. Secondly, it determines the actual (used) life of the components by analyzing the operating history of components.

2. Estimating the remaining useful life

The remaining useful life is a function of the component's overall life and the actual (used) life under the operating conditions of use. Mathematically,

$$L_R = L_M - L_A \tag{1}$$

where L_R is the remaining useful life, L_M the mean life and L_A represents the actual life of components under given conditions of use. L_M and L_A represent two distinct perspectives – static and dynamic – and therefore they need to be addressed accordingly. L_M basically represents the component's total functional life under stated conditions of use, and it is estimated by analyzing time-to-failure data of a family of components operated under the same conditions of use. The accuracy and authenticity of the L_M estimation becomes better with increasing amounts of available statistical data. On the other hand, L_A is dynamic in the sense that it mainly depends upon the real conditions of use, and its assessment is based on the actual conditions of use.

2.1. Mean life L_M

The mean life is determined by analyzing time-to-failure data of the same category of components under the same conditions of use. Time-to-failure data was collected for the electric motor and the gearbox of a top loading washing machine from the leading manufacturer of home appliances in Australia.

Weibull analysis (Cole, 1998; Li, 2004; ReliaSoft-Corporation, 2001), extensively utilized in maintenance procedures, is a powerful tool for reliability assessment that can be used to classify failures and to model failure behaviour. The methodology has applications in a wide range of industries such as military, automotive, electronics, composites research, aerospace, electrical power, nuclear power, dental research, advertising, even the mortality of mailing lists (Abernethy, 1993). Weibull analysis can be used to determine the optimum replacement/repair interval for components, subject to wear-out failure. The very common form of the Weibull distribution is

$$F(t) = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right], \qquad (2)$$

where $F(t)$ represents the fraction of units failing and 't' is the time-to-failure. The distribution is characterized by two parameters, the scale parameter η and the shape parameter β. The value of the parameter β identifies the mode of failure. For example, $\beta < 1$ means infant mortality, $\beta = 1$ indicates random failure and $\beta > 1$ describes wear-out failure. The scale parameter η is defined as the life at which 63.2% of units will fail.

The mean life L_{M} is measured by using the relationship between the scale parameter η and gamma function (Γ) of the shape parameter β.

$$L_{\mathrm{M}} = \eta\Gamma\left[\frac{\beta + 1}{\beta}\right] \qquad (3)$$

The results for the washing machine as shown in Table 1 indicate that the electric motor and gearbox possess immense potential to be considered for reuse.

One of the most import aspects of the above results are the remarkably high values of the shape parameter, which show that both of these subassemblies follow a well defined wear-out failure mechanism. These high values also associate a higher level of certainty to the mean life estimates.

Table 1
Weibull analysis results (Mazhar et al., 2004)

	Gearbox	Electric motor
Shape parameter (β)	3.2	4.973
Scale parameter (η) (years)	35.44	46
Mean life (years)	31.74	42.26

2.2. Actual (used) life L_A

As discussed above, the proposed procedure for life estimation is aimed at making reuse decisions by analysing the operating data collected during the usage phase of a product. One of the major obstacles for the development of a methodology based on life cycle data analysis is the unavailability of operating information, particularly in the case of consumer products such as washing machines, refrigerators, etc.

In order to collect operating data of a washing machine, accelerated lifetime testing was carried out in the laboratory. The acceleration is basically usage rate acceleration (ReliaSoft-Corporation, 2001) in which the machine operates continuously. The other conditions and assumptions (Mazhar et al., 2005) are:

- top loading medium size washing machine;
- atmospheric pressure, ambient temperature, pressure and humidity;
- average operational load;
- water level medium;
- machine operating continuously for 24 h a day, 7 days a week;
- average household load—40 min per wash cycle, 10 wash cycles per week.

The following parameters have been monitored and recorded during the spin cycle of the washing machine: motor rotation speed, winding temperature, power, current and voltage. The spin cycle was selected because this is the only cycle during which the motor spins in a single direction. Furthermore, to ensure consistency in data recording, the data was always taken at the same moment in time (i.e., just before the spin cycle ends) during the complete cycle.

Fig. 1 shows the behaviour of some of the monitored parameters over the life of the machine. It can be seen that motor speed and power are related to the age of the machine in the first 16 and 9 years of operation respectively. However, the winding temperature shows a delayed and slow trend in the later years of the machine age.

Previous studies (Mazhar et al., 2004, 2005) show that regression analysis and dynamic kriging method can be employed to determine the used life of components at given conditions of use. However, these techniques are only suitable under particular conditions (Kara et al., 2005). For example, regression analysis

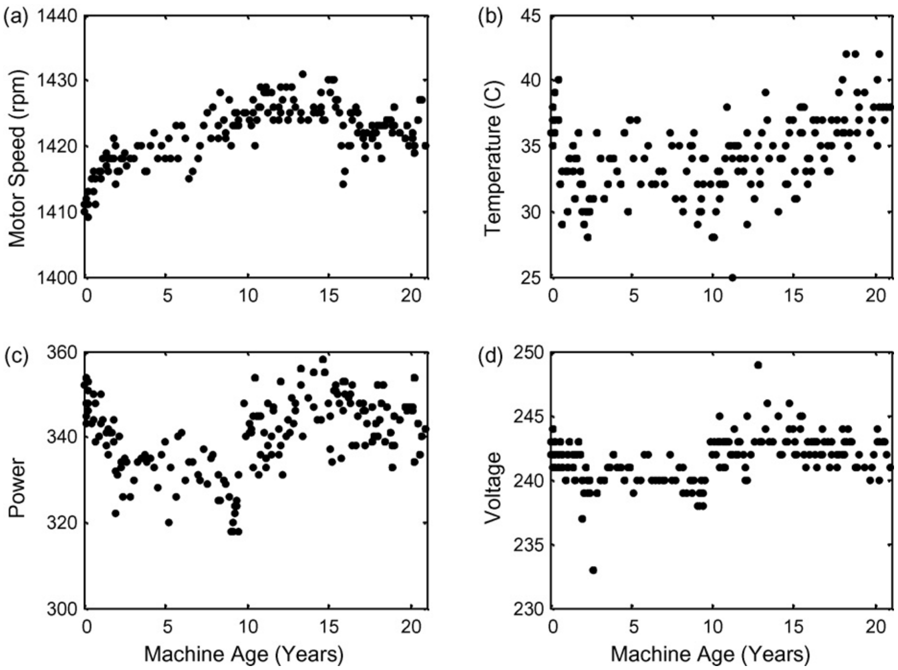

Fig. 1. Life cycle data: (a) motor speed, (b) temperature, (c) power, and (d) voltage.

produces reasonably acceptable results in situations where the input variables follow a well-defined positive trend over the age of the machine, but this method has been found struggling to maintain its estimation accuracy when the input variables exhibit a complex trend. This fact is explained by conducting regression analysis on different sections of data as the behaviour of functional parameters keeps changing over the entire age of the washing machine. The regression coefficients, as shown in Table 2, were calculated by the method of least squares estimation (Albright et al., 1999). The actual (used) life is then determined by the following regression equation:

$$L_A = a + b_1(\text{rpm}) + b_2(\text{tmp}) + b_3(\text{pow}) + b_4(\text{cur}) + b_5(\text{vol}) \quad (4)$$

The output is compared by estimating the R^2 at every year starting from the 10th year of the machine age by considering all the data until that particular year. The results of the detailed stepwise regression analysis as shown in Fig. 2 reveals the fact that the motor speed is the dominant parameter in establishing a good correlation between the estimated and experimentally measured machine life.

Table 2
Regression coefficients at different years of machine life

Year	Parameter					
	b_1	b_2	b_3	b_4	b_5	a
10	239.0751	36.0916	−88.6174	11450.7949	−33.4411	−319890
11	0.5988	−0.0423	−0.1169	27.0683	0.0359	−859.2130
12	0.6749	−0.0116	−0.0635	22.8489	−0.0623	−955.0391
13	0.6989	−0.0254	−0.0547	24.8532	−0.0694	−993.2748
14	0.7221	−0.0108	−0.0282	25.0357	−0.0901	−1030.9558
15	0.8103	0.0095	0.0606	10.0190	−0.1111	−1152.913
16	0.6821	0.0491	0.0066	59.5659	−0.5457	−933.6174
17	0.7559	0.0784	0.0979	46.4665	−0.6421	−1027.3751
18	0.7524	0.2555	0.0999	49.0128	−0.7374	−1009.9026
19	0.7553	0.4973	0.0521	57.0808	−0.7683	−1012.0664
20	0.7730	0.5753	0.0837	64.4035	−1.0899	−985.4825
21	0.8047	0.7110	0.1116	52.730	−1.0477	−1034.2963

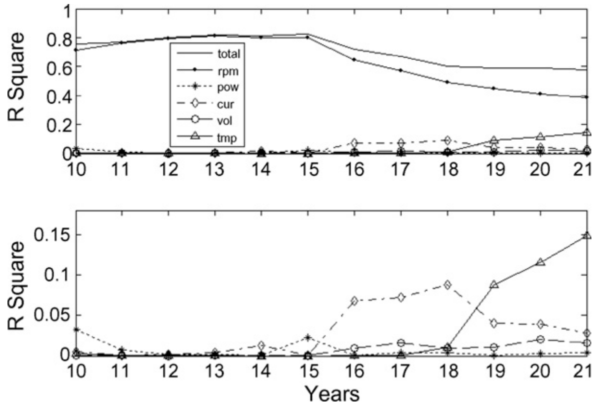

Fig. 2. Contribution to R^2 by functional parameters.

The correlation coefficient R^2 is heavily dependent on motor speed, particularly in the first 15 years of machine life. The contribution of the other four parameters (temperature, power, current and voltage) is noticeably very low. However, the temperature shows an increasing trend in the later years of machine age whereas power demonstrates a very consistent, although not very significant, behaviour over the entire age of the machine.

The decline in R^2 in the later years of machine age is contributed to the fact that regression analysis is unable to handle the complex and fluctuating behaviour of monitored parameters.

2.2.1. *Neural network approach*

Neural networks are becoming more popular among researchers because of their proven ability to recognize complex relationships between input and output variables. Artificial neural networks are adaptive and have parallel information-processing structures that have the ability to build functional relationships between data and provide a powerful toolbox for nonlinear, multidimensional interpolations. This aspect of neural networks makes it possible to capture and interpret the existing highly complex nonlinear relationships between input and output parameters that are most of the time not well understood (Eskandari et al., 2004).

2.2.1.1. The proposed model. The proposed neural network model is a multilayer feed-forward back-propagation (Haykin, 1999) neural network as shown in Fig. 3. The back-propagation neural network model has the advantages of handling nonlinear problems with learning capability (Zhang and Qi, 2005).

The layer outputs of the network are given as:

$$y_1 = f_1(\mathrm{IW}_{1,1}P + b_1) \tag{5}$$

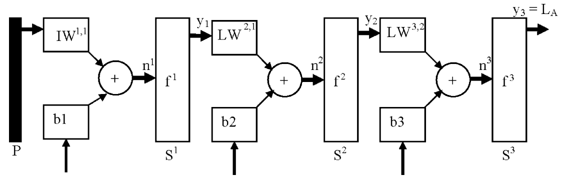

Fig. 3. Structure of the proposed neural network. Where P is input to the model, L_{A} the output of the model (actual life of component at given conditions), S_i number of neurons in layer i, n number of layers in the model, y_i output of layer i, f_i the transfer function in layer i, IW the input to layer 1 weights, $\mathrm{LW}_{i,j}$ layers weights from layer j to i, b_i the bias in layer i, f_i is the transfer function for the output of layer i.

$$y_2 = f_2(\mathrm{LW}_{2,1}y_1 + b_2) \tag{6}$$

$$y_3 = f_3(\mathrm{LW}_{3,2}y_2 + b_3) \tag{7}$$

$$L_{\mathrm{A}} = y_3 = f_3(\mathrm{LW}_{3,2}f_2(\mathrm{IW}_{2,1}f_1(\mathrm{IW}_{1,1}P + b_1) + b_2) + b_3) \tag{8}$$

$$L_{\mathrm{A}} = \mathrm{Purelin}(\mathrm{LW}_{3,2}\mathrm{Tansig}(\mathrm{IW}_{2,1}\mathrm{Tansig}(\mathrm{IW}_{1,1}P + b_1) + b_2) + b_3) \tag{9}$$

To make the back-propagation neural network more flexible in terms of acknowledging complex relationships it is important to be able to calculate the derivatives of any transfer functions used. Both of the transfer functions—`tansig` and `purelin` used in the proposed network have a corresponding derivative function `dtansig` and `dpurelin`, respectively.

The architecture of the proposed network of a three layer network is shown in Fig. 3. It consists of two hidden layers of sigmoid (`tansig`) neurons followed by an output layer of a linear neuron (`purelin`). The purpose of hidden layers with nonlinear transfer functions is to allow the network to learn nonlinear and linear relationships between input and output variables. The linear transfer function in the output layer lets the network produce outputs outside the range [−1,1].

2.2.1.2. The data. One of the major problems with neural network models is the requirement of huge amounts of data before a network can be trained to produce acceptable results (Lucifredi and Mazzieri, 2000). At the same time it is very difficult to gather a sufficient amount of condition monitoring information, particularly in consumer products.

To fulfil the data requirement, a statistical basis for random data generation was established by conducting statistical data analysis of the lifetime testing data, collected by the accelerated lifetime testing of a washing machine. Analysing the condition monitoring data by employing the most commonly used 95% statistical control limits, yields the lower and upper control limits for generating the random data. The data generation procedure is detailed below:

(a) Plotting the measured data. For example, speed versus age of the washing machine. In this case, there are 180 data points recorded over the 21-year age of the machine.
(b) Determining the best fit. In this case, it is a ninth order polynomial.
(c) Applying 95% control limits and determining the upper and lower control limits (UCL and LCL). As shown in Fig. 4, the calculated control limits provide a reasonably wide space to allow more variation in the data generation process.
(d) Generating random data points. Every time, 180 data points are generated randomly over the age of machine (0–21).
(e) Generating a random value of the functional parameter (e.g. speed) between the UCL and LCL at each of the randomly generated data points in the above step.
(f) Repeating the step ‘e’ for all of the five functional parameters.

A total of 3600 data points were generated by this procedure. Including the experimentally measured data, the neural network training and test data set has 3780 data points altogether.

This procedure produces unique combinations of condition monitoring parameters as every data value is generated randomly. Furthermore, the data generation algorithm produces more scattered data as the LCL and UCL provide more space than the area occupied by the experimental data.

2.2.1.3. Principal component analysis. There is a very useful function `prepca` in Matlab. This function is used to eliminate the highly correlated (redundant) components of the input vectors. The procedure `prepca` preprocesses the network input training set by applying a principal component analysis. This analysis transforms the input data so that the elements of the input vectors will be uncorrelated. In addition, the size of the input vectors may be reduced by retaining only those components which contribute more than a specified fraction of the total variation in the data set. In this study, the function `prepca` has been used to eliminate those principal components that contribute less than 3% to the total variation in the data set.

The results indicate that there was significant redundancy in the training data set since the principal component analysis has reduced the size of the input vectors from 5 to 3. Vectors representing current and voltage are eliminated. Interestingly, these findings are very consistent with the results of the stepwise regression analysis.

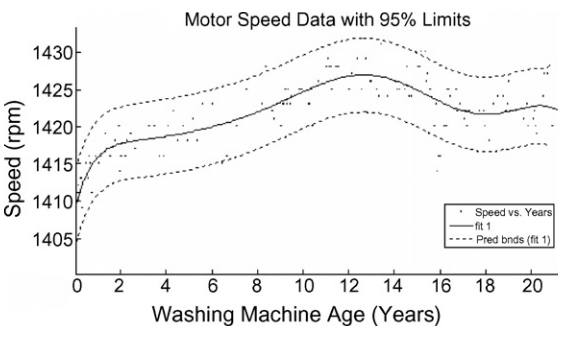

Fig. 4. Statistical data analysis—motor speed (rpm).

2.2.1.4. Training the network. The training style is the supervized learning in which the learning rule is provided with a set of examples (the training set) of proper network behaviour. The training set consists of inputs and the corresponding correct outputs (targets).

One of the most powerful learning algorithms, the Levenberg–Marquardt algorithm (Haykin, 1999), has been used to train the network. On function approximation problems, this algorithm is considered to be one that has the fastest convergence. One of the problems that occur during neural network training is ‘over-fitting’ or ‘over-training.’ In this case, the network memorizes the training examples but it has not learned to generalize to new situations. The MATLAB function `trainbr`, which was used to train the proposed network, has a built-in procedure, Bayesian regularization, a technique designed to overcome the over-fitting problems. This technique has been documented as a better generalization procedure for function approximation problems.

To produce the most efficient training, the input data has been pre-processed before training. The selected training function (`trainbr`) works best when the network inputs and targets are scaled so that they fall approximately in the range $[-1,1]$. This pre-processing has been done by using the function `prestd`.

2.2.1.5. Network optimization and performance testing. The architecture of a multilayer network is not completely constrained by the problem to be solved. The number of inputs to the proposed network is given by the number of available inputs (speed, power and temperature), and the number of neurons in the output layer is constrained to one as the output required contains one parameter (actual life of machine) only. However, the number and size of layers between network inputs and output layer are determined by testing several combinations of numbers of layers and the number of neurons in each layer. Each of the selected combinations is tested with several different initial conditions to guarantee that the proposed model is the best solution. The resulting network consists of three inputs, two hidden layers of 20 and 50 neurons respectively and an output layer of one neuron.

After the training was completed, the network was tested for its learning and generalization capabilities. The test for its learning ability was conducted by testing its ability to produce outputs for the set of inputs (seen data) that was used in the training. For this purpose, 154 out of 180 experimentally measured data points were selected and it was observed that the network's outputs had a correlation coefficient of about 0.866 with the desired (actual) outputs (Fig. 5a).

The test for the network's generalization ability was carried out by investigating its ability to respond to the input sets (unseen data) that were not included in the training process. The test data set was created by picking the data as equally spaced points throughout the experimentally measured data. A total of 26 out of 180 experimentally measured data points were selected. It was observed that outputs had a correlation coefficient of about 0.81 with the desired outputs of test data. The results are shown in Fig. 5b.

3. Analysis and discussion

Artificial neural networks have been widely used for various prediction and forecasting problems, ranging from engineering to business applications. Their flexible nonlinear modelling ability is predominantly useful for many complex real-world problems.

This study investigates the effectiveness of neural networks for estimating the remaining life by analysing complex and nonlinear life cycle data. The research further explores and highlights the advantages of using artificial networks over multiple regression for the development of a reliability assessment model based on life cycle data analysis.

The multiple regression method produced good results during the first 15 years of machine life, but when applied to the whole life span (21 years) of the washing machine, the correlation coefficient was very low (below 60%). On the other hand, the proposed neural network has the ability to adapt data that has been presented to it in the form of input–output patterns. The model's output was obtained and compared to the experimentally measured values by using the `postreg` function. This function basically performs linear regression between targets (experimentally measured values) and the network response to the presented inputs (condition monitoring data). The model's response to all the three sets of life cycle data was remarkably accurate especially for the seen and entire data sets as shown in Fig. 5a and c.

A comparison summary as given in Table 3 shows that regression analysis is no longer capable of producing reasonable results in situations where input–output relationships are nonlinear and complex. Whereas, once trained, the neural network model yields outputs very closely related to the desired outputs.

The proposed model can be used to estimate the remaining useful life of components at the given conditions of use. The mean life L_M remains the same for this particular category of washing machine components, whereas the actual (used) life L_A is determined by the neural network at the given conditions (speed, temperature and power). Eq. (1) is then used to determine the remaining useful life. Table 4 shows an example of how the proposed methodology determines the remaining useful life of a component (motor in this case) at the given conditions.

Remaining life estimation with nonlinear inputs is far more complicated than with linear inputs, especially in the case of an intricate mixture of fluctuating and unpredictable trends.

The results produced by the proposed integrated methodology for remaining life assessment are associated with higher levels of certainty due to the fact that in both stages of the analysis well-known reliability assessment and statistical analysis techniques have been

Table 3
Comparison of estimation accuracy—ANN model and regression analysis

Remaining life estimation method	R^2		
	Seen data	Unseen data	Entire data
ANN model	0.866	0.81	0.857
Regression analysis	0.5539	0.5288	0.5451

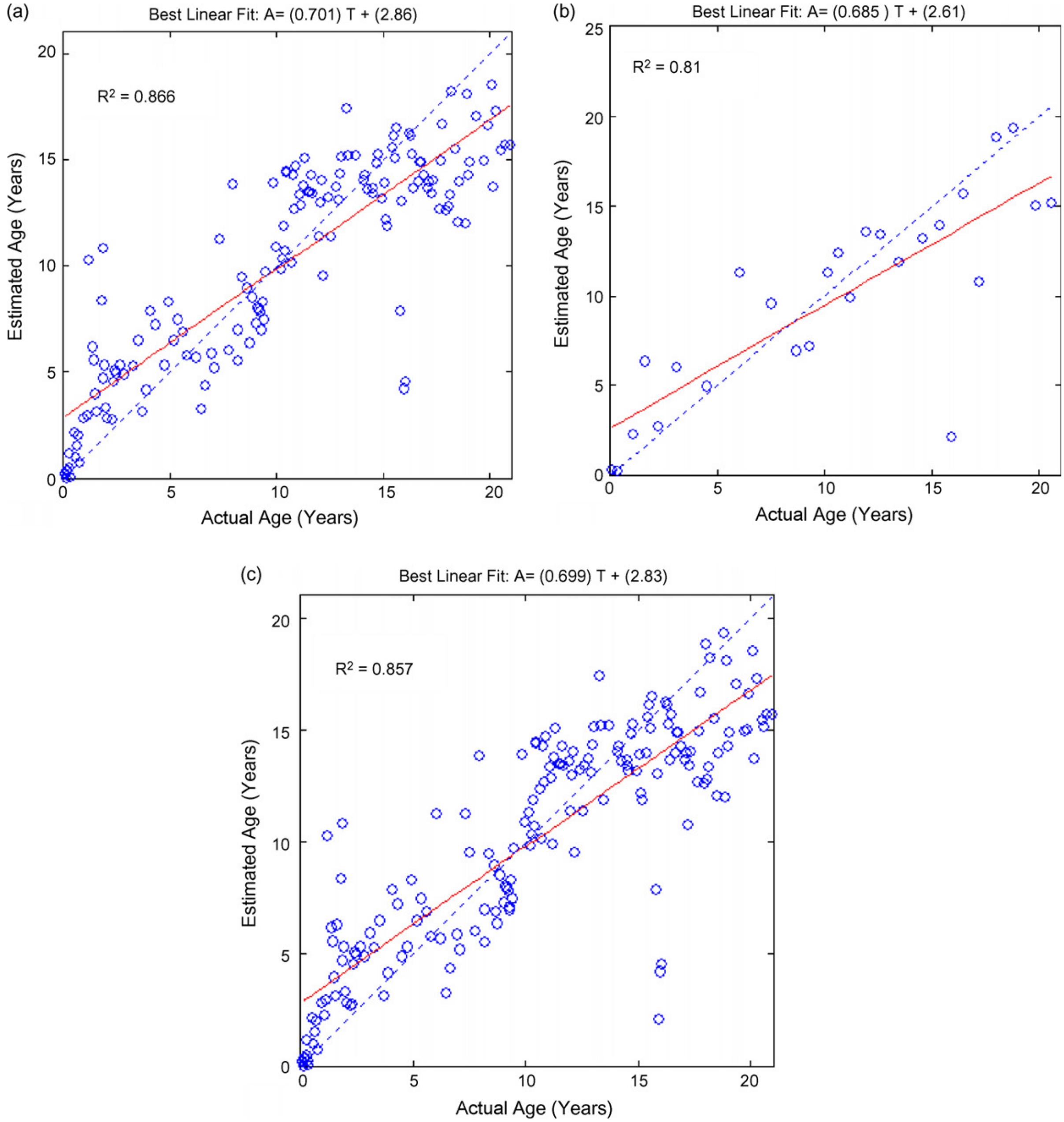

Fig. 5. Neural network's performance: (a) seen data; (b) unseen data; (c) entire data.

employed. Furthermore, the best available functions and procedures have been utilized to pre-process the inputs, train the network and post-process the outputs of the model.

4. Managerial implications of the results

A sustainable society and a business can only be achieved if the current business practice of an open-loop system is transformed into a close-loop system by establishing an integrated supply chain. This will allow organizations to consider the whole life cycle of their products from the concept design to disposal. Implementation of such a concept requires significant changes to the way products and services are traditionally designed. The entire product life cycle provides opportunities to preserve resources while reducing the environmental impact. Participation of

Table 4
Remaining life estimates

Given conditions of use		Mean life of motor (Weibull) (years)	Used life of motor (ANN) (years)	Remaining useful life (years)
1				
Speed	1424	42.26	11.31	30.95
Temperature	28			
Power	343			
2				
Speed	1420	42.26	18.81	23.45
Temperature	40			
Power	352			

operation managers in this process is crucial since they play a key role to reduce cost and to preserve scarce resources at three different stages, namely design, production, usage and disposal stages. In this environment, they are forced make decisions and provide feedback on product and service design for the environment, design for end-of-life, environmentally friendly materials and process selection, maintaining products' functionality during the usage phase and finally selecting an environmentally friendly end-of-life options. The integrated approach proposed in this paper helps operation manager in strategic and operational decision making during the design, usage and disposal stages of a product's life cycle. At the design stage, it helps the user to assess the design life built into a component of a product. If the design life of a component exceeds the product's life, the component may be over designed for the intended use unless it is designed for reuse at the end of product's life cycle. In this context, the proposed methodology helps the user to make the decision of whether the remaining life of the component is long enough for a second life. In addition, the lifetime data collected during the first life cycle is also invaluable for decision making on Condition Based Monitoring (CBM), which, based on sensing and assessing the current state of the system, emerges as an appropriate and efficient tool for achieving near-zero breakdown time through a significant reduction and elimination of downtime due to process or machine failure. Furthermore, the lifetime prediction methodologies as proposed in this paper are one of the key elements for implementing selling the service associated with the product rather than selling physical products.

5. Conclusion

This paper presents an integrated approach to estimating the remaining useful life of components for reuse. It has been shown that once trained, the proposed neural network model produces life time estimates with higher levels of certainty. The results were validated by utilizing life cycle data from a washing machine. Furthermore, it has been shown that motor speed, winding temperature and power can be used for estimating the remaining life of a washing machine electric motor.

The methodology proposed in this paper aims at bridging the gap that currently exists in the literature by providing a decision making tool for achieving closed-loop systems. In this context, the integrated approach helps users to make sound end-of-life decisions during the product's life cycle. Determining how this technique can be utilized in order to reduce process and equipments' down time as a means of preventative maintenance and reduce field failure of remanufactured products would be a useful extension of this research. Furthermore, it will be interesting to how this approach can be used in implementing selling-service strategy, which will be one of the strategies influencing the manufacturing organizations in the near future.

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