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Predicting Heavy Equipment Replacement in Diverse Private Sector Industries Using Neural Network Analysis: A Case Study

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ABSTRACT

Maintenance is essential for the sustainable use of heavy service equipment in both the government and private sectors. Therefore, there is a need to adopt an effective and efficient maintenance management system to ensure that machines and equipment in service departments operate in optimal conditions, thus achieving user satisfaction. This research aims to determine the optimal time for the replacement of various heavy service machines and equipment within a particular private company operating in diverse operational environments. For this purpose, an integrated model covering all maintenance expenses and costs was developed and implemented using actual data records. A neural network model was developed to predict the optimal equipment replacement time. The results of this research are expected to guide engineers and shop managers in determining when machinery and equipment in private companies should be replaced.

The primary motivation behind this research was the ignorance and misconceptions of many business owners regarding the optimal time to replace equipment. Hence, this research serves as an excellent guide for both the public and private sectors in determining the critical replacement point. One advantage of this research is that the replacement time is flexible, as it depends on the equipment's operating data and conditions.

Keywords: Equipment replacement, Neural network modeling, Heavy machinery, Asset lifecycle.

INTRODUCTION

Machinery and equipment deteriorate over time, eventually making maintenance costs unsustainable. To reduce financial losses, businesses must replace equipment when operating it becomes economically unviable due to high repair and maintenance expenses. Consequently, maintenance management is a key concern for both public and private sectors (Edward Patrick O'Connor, 2014).

Service departments in private companies use heavy machinery for private and public projects. Equipment deteriorates from intensive use under varying conditions, and is often replaced after a fixed number of years, assuming a 5% annual deterioration rate (Zonta et al., 2022). This benchmark does not reflect actual conditions, as equipment may require earlier or later replacement. The primary objective of this research is to determine equipment useful life and identify the optimal replacement time, considering operating conditions, maintenance costs, environmental factors, and residual value (Abed & Mutlag, 2020; Hamid et al., 2025).

Using a fixed replacement schedule can lead to financial losses by either keeping uneconomical equipment or replacing functional equipment prematurely. This research addresses the problem by analyzing real operational data from several machines to determine their useful life and optimal replacement point (Hamid et al., 2025).

The study's significance lies in guiding private-sector decision-makers, helping avoid excessive costs, delays, and project interruptions. Proper timing of replacement ensures efficient operations and minimizes ownership and operational expenses (Er-Ratby et al., 2025).

The main research problem addressed in this study grows from the absence of a data-driven framework that enables private companies to identify the optimal replacement time for heavy equipment. Current replacement decisions often rely on fixed administrative rules rather than on actual operational and maintenance data, leading to unnecessary costs and reduced efficiency. Therefore, there is a critical need for a predictive method that reflects real performance conditions and supports more accurate replacement planning.

The aim of this study is to develop a predictive model based on Artificial Neural Networks (ANNs) capable of predicting the optimal economic replacement time for heavy machinery using real operational and maintenance data. The study aims to provide decision-makers with a practical tool that minimizes costs, enhances operational efficiency, and improves asset management strategies within private-sector environments.

LITERATURE REVIEW

The management of equipment maintenance, repair, and replacement has significant economic implications. Optimizing replacement timing is critical to reducing costs and improving operational efficiency (Mutlag & Dawood, 2020). Various studies have explored methods to determine the economic life of equipment. For instance, uncertainty theory has been applied to age replacement policies, treating equipment age as an uncertain variable to optimize lifespan decisions (Yao & Ralescu, 2013; O'Connor, 2014). However, accurately estimating operating costs remains challenging, as annual-based estimates can overstate expenses by 20%-40%, affecting competitiveness and utilization (John & Don, 2018).

Predictive approaches have gained attention for improving reliability and availability of construction equipment. Time series analysis and artificial intelligence techniques have been shown to effectively forecast failures and minimize unexpected downtime in large construction projects (Hongqin Fan et al., 2015). Routine maintenance is also crucial, with delays often caused by part availability and equipment location contributing significantly to downtime (Janith & Bhasuri, 2019). Moreover; ageing equipment increases maintenance costs and failure risks, and technological obsolescence can justify early replacement to remain competitive (Wani et al., 2023).

Economic modeling and optimization frameworks have been developed to guide replacement decisions. Several studies proposed lifecycle cost analyses or analytical models to determine optimal replacement times, accounting for wear, breakdowns, and maintenance policies (Akeel, 2016; Sobczak-Piąstka et al., 2020; Palik, 2022; Almobarek, 2021; Pourrahimian et al., 2023). Optimization techniques, including Improved Particle Swarm Optimization (IPSOM), have demonstrated substantial reductions in project duration, costs, and quality improvement when applied to machinery selection in construction projects (Alshboul et al., 2025). Similarly, integrating automated construction with climate-adaptive technologies has shown long-term maintenance savings and extended equipment lifespan. Game-theoretic approaches also provide effective solutions for cost allocation, risk mitigation, and supply chain coordination (Shehadeh & Alshboul, 2025).

Machine learning and Artificial Neural Networks (ANNs) are increasingly applied for predictive maintenance, cost estimation, and lifespan optimization. ANNs can forecast failures, predict remaining useful life (RUL), and enhance equipment cost efficiency across industries (Huang et al., 2021; Boyko et al., 2023; Gustavo et al., 2019; Gajewski & Vališ, 2021; Kang et al., 2021). These models leverage operational data to improve decision-making, offering flexibility and accuracy superior to traditional statistical methods. Data-driven frameworks have been shown to support informed replacement strategies, comparing lifecycle costs under scenarios, such as refurbishment, replacement with used equipment, or acquisition of new machines (Pourrahimian et al., 2023).

Recent advances in the construction and

infrastructure sectors show a growing reliance on predictive analytics, digital transformation, and intelligent decision-support systems. Studies have demonstrated the effectiveness of machine learning, ensemble models, and belief-function approaches in enhancing occupational safety, risk classification, and shoring/reshoring reliability (Shehadeh & Alshboul, 2025a; Shehadeh et al., 2024g). Parallel research has emphasized the importance of integrating labor and insurance regulations, improving construction quality management, optimizing equipment management, and applying game theory-based strategies for cost and risk coordination (Alshboul & Shehadeh, 2025h; Alshboul et al., 2025i; Alshboul et al., 2025j; Shehadeh & Alshboul, 2024k). Moreover, significant progress has been made in BIM–VR integration (Building Information Modeling combined with Virtual Reality), digital twins, and machine learning-enhanced design tools to strengthen sustainability and resilience in the built environment (Shehadeh et al., 2025c; Shehadeh et al., 2024f; Shehadeh et al., 2025m). Additionally, climate-responsive pavement management and climate-adaptive pavement technologies have shown positive impacts on long-term infrastructure performance (Shehadeh et al., 2025b; Shehadeh, Alshboul & Tamimi, 2025n; Shehadeh & Alshboul, 2025d; Shehadeh et al., 2024e). Overall, this body of research underscores a clear trend toward AI-driven optimization.

Previous studies in the field of decision-making highlighted an increasing reliance on data-driven analytical frameworks for evaluating asset performance and supporting maintenance-related decisions. Setiawan (2022) demonstrated that service-life estimation is strongly influenced by actual operating and environmental conditions rather than fixed administrative replacement intervals, reinforcing the need for empirical approaches to replacement planning. Similarly, Noori and Varaee (2022) showed the effectiveness of ANNs in modeling non-linear behaviors within civil engineering systems, supporting the methodological direction adopted in recent research. Forecasting-oriented research has also gained traction, with studies employing time-series and computational models to predict engineering responses under varying conditions (Khasawneh et al., 2022; Al-Omari et al., 2022). In parallel, recent research on maintenance prioritization and decision analysis (Hamid et al., 2025) emphasized the importance of structured, data-supported frameworks for managing operational assets efficiently.

Generally, previous studies demonstrated a clear shift toward analytical, data-driven methodologies in engineering decision-making. However, despite these advancements, very few investigations have addressed equipment replacement within the private sector using real operational and maintenance datasets—particularly those capable of linking cost behaviour, deterioration patterns, and predictive modeling within a unified ANN framework. Most existing works rely on assumptions, limited datasets, or focus on either cost or reliability in isolation, offering no predictive tools grounded in actual field data.

To address this gap, the present study develops an ANN-based predictive model that integrates maintenance records, operational conditions, and cost dynamics to estimate equipment economic life and determine the optimal replacement timing using real data from a private company. This approach provides a practical, data-supported framework that can be generalized to other private-sector environments operating under similar conditions.

METHODOLOGY

This research aims to identify the economic life of many heavy service machines and equipment used by a specific private company, with a focus on determining the optimal time for their replacement. To achieve this ambitious goal, several key steps need to be taken.

Firstly, it is essential to analyze the maintenance costs and intervals to determine the economic life of the machines and equipment currently in operation. This step involves examining the maintenance timelines and associated costs, offering a clearer understanding. These insights form the foundation for a thorough economic assessment.

Secondly, to achieve our objectives, we employed the analysis of historical data using Artificial Neural Networks (ANNs). This dynamic integration aims to identify the optimal time for replacing each machine currently in operation.

The use of ANNs is of paramount importance in our research, as it adds a crucial predictive dimension to determining the optimal replacement point for machinery. This predictive capability enhances the accuracy of our model, reliably forecasting the ideal time for equipment replacement, thus optimizing decisions related to maintenance and replacement management. The ideal replacement time is determined in years, regardless of the replacement rules applied in the government or private sectors. By leveraging the advantages of ANNs, our methodology seeks to provide decision-makers with a data-driven approach to maximize operational efficiency and minimize costs associated with replacing heavy service machinery.

To achieve this, data was collected, including not only maintenance intervals and costs, but also approved policies and replacement rules or laws maintained by the company in question. The study focuses on a private company in Fallujah, Iraq, affiliated with the private services sector, utilizing data collected over six years, to illustrate the methodology and extract the implemented results.

The company is a medium-sized private service organization that operates a fleet of eight heavy machines, including excavators, shovels, dump trucks, rollers, water tankers, and graders, as listed in Table 1.

Our approach adds significant value by providing a predictive, data-driven tool that estimates the optimal replacement time for the company's entire equipment fleet within seconds. Unlike traditional statistical or optimization methods based on theoretical assumptions, the ANN model uses actual operational data to improve accuracy, efficiency, and practical applicability.

Recent studies highlighted a growing reliance on data-driven analytical methods for asset evaluation and maintenance decision-making. Prior research has shown that equipment service life is shaped by real operating and environmental conditions rather than fixed replacement schedules (Setiawan, 2022), and that ANN models are effective in capturing non-linear engineering behaviours (Noori & Varaee, 2022). Forecasting and maintenance prioritization studies further emphasized the value of predictive, data-supported frameworks (Khasawneh et al., 2022; Al-Omari et al., 2022; Hamid et al., 2025). Despite this progress, limited work has examined equipment replacement in the private sector using actual operational and maintenance data, particularly studies that integrate cost behaviour, deterioration patterns, and predictive modeling into a single framework. To fill this gap, the present study develops an ANN-based model that uses real field data to estimate economic life and identify optimal replacement timing, offering a practical decision tool for private-sector equipment management.

Although developed and validated with data from a single private company, the methodology can be applied to other organizations with available maintenance and cost records. Its main strengths lie in predictive efficiency, easy updating with new data, and adaptability over time, while its main limitation concerns the need for rich and reliable datasets for neural network training.

One of the research limitations of this research is that it relied on actual data of operation and maintenance from a single private company, where complete long-term equipment records are rarely available for it, naturally limiting dataset size. Despite this, each record represents several years of detailed cost and performance data, ensuring reliability and depth. The objective was precision within realistic conditions rather than large-scale generalization, making the ANN model valid for similar industrial contexts.

NEURAL NETWORK ANALYSIS

ANN Modeling

The ANN model is a formation of a parallel structure consisting of numerous interconnected processing elements known as neurons, organized into layers. It serves the purpose of mapping input data to output data without relying on a known a priori relationships between them. Neural networks have found widespread application in the analysis of problems in science and technology, demonstrating their ability to learn, generalize from experiences, adapt to changing situations, and establish both causal and inverse mapping models (Hambli et al., 2011; Khaterchi et al., 2015; Ömer Civalek, 2004; Hung & Nguyễn, 2023; Saha Dauji, 2021; Sakdirat et al., 2021).

A set of examples is presented in the process of training an NNs in the form of patterns (input patterns) with known values and outputs (target outputs) to the system. The weights of the internal connections are adjusted to reduce the error rates between the network output and the target output. Knowledge is encoded and stored in the strengths (weights) of connections between neurons.

Once adequately trained and tested, the NN can generalize rules and swiftly respond to input data, predicting the required output within the domain covered by the training examples. This capability enables the NN to perform rapid predictions, typically within seconds, leveraging the knowledge acquired during the training phase. (Hambli et al., 2011). Within the network, each neuron operates by summing the sum of its weighted inputs ($W_{ij}O_i$), output of neuron i in the current layer(O_i), bias associated with neuron i (θ_i), and the result is passed through a non-inear activation function (f), which is expressed mathematically as follows (Hung & Nguyễn, 2023; Naif et al., 2022):

$$O_i = f\left(\sum_j w_{ij}O_j + \theta_i\right) \tag{1}$$

The activation function employed in this study is given by:

$$f(x) = \frac{1}{1+e^{-\beta x}} \tag{2}$$

where β is a convergence constant. The network calculates the weighted connections to minimize the total mean squared error (Eq. 4) between the actual and the desired outputs. Weight adjustments are made in the presence of momentum, as indicated by the equation:

$$\Delta_p W_{kj}(n) = \eta\delta_{pk}O_{pj} + a\Delta_p W_{kj}(n-1) \tag{3}$$

Here, η is the gain term, δ_{pk} is a term for the error node k, and α is the momentum term, which contributes to faster convergence. $\Delta_p w_{kj}(n)$ is the weight update for iteration n, α is the momentum coefficient that accelerates convergence, and $\Delta_p w_{kj}(n-1)$ is the weight value from the previous iteration.

The primary parameter used during training to evaluate the fit of the metamodel is the mean square error (MSE), defined as follows:

$$MSE = \frac{1}{2}\sum_{j=1}^{P}\sum_{i=1}^{N}\left(t_{ij} - y_{ij}\right)^2 \tag{4}$$

where t_{ij} represents the desired output, y_{ij} is the induction model representing the expected response, P in the training database represents the total combinations, and N is the total number of outputs.

Training a neural network involves presenting input patterns with their corresponding target outputs. During this process, the internal weights are adjusted to minimize the difference between predicted and expected values, with the learned knowledge stored in these interconnections.

Various algorithms can be used for training; in this study, the back-propagation (BP) algorithm was applied. This iterative, gradient-based method updates weights to reduce the mean square error (MSE) between actual and target outputs. Training starts with random weights and continues through successive iterations until the prediction converge with the expected results.

Data Analysis

To conduct the data analysis, the gathered data encompassed the operational costs of eight distinct types of equipment. The dataset from the private company included six years of operational and cost data for eight equipment types, totaling 48 data points. Of these, 40 (~83%) were used for training and 8 (~17%) for validation, ensuring that the ANN model was tested on unseen data to prevent overfitting.

Operational costs were collected for each equipment type over six years, expressed in Iraqi dinars. The Kawasaki Shuffle 85 was used as a representative case, analyzing six key cost components: fuel consumption, lubrication per kg, oil per liter, maintenance and repair per hour, tire cost per hour, and operator hourly wage.

The assumed operational lifespan (number of years) for the equipment is set at 20 years, with an annual depreciation rate of 5%. The costs of special items are not taken into account, as special items are supplied from the spare parts store, and their costs are already incorporated into the purchase cost of the equipment. Moreover, it is noted that the tire replacement costs lead to exceed the sum of average values at certain times, which disturbs the analysis of cost data. Therefore, in order to equalize the data, sudden cost changes due to tire replacement are distributed linearly over the entire period, making the analysis more homogeneous while maintaining the content of the actual cost data.

RESULTS AND DISCUSSION

To initiate the analysis, input data and output data have been selected and organized based on historical records of equipment operating under similar conditions. Unique codes are assigned to all equipment, as illustrated in Table 1. Also, the average annual maintenance frequency is calculated using the recorded operating hours. Concurrently, annual working hours are extracted, as summarized in Table 2 (supplementary data).

Table 1. Equipment code

Equipment name	**Equipment code**
Komatsu 201 Excavator	1
Komatsu dash-5 excavator	2
Kawasaki Shuffle 85	3
Small Komatsu shuffle	4
Dump Truck	5
German Bomac steel roller grooved	6
Daewoo Korean water tank	7
Komatsu Grader	8

After completing the input data, the subsequent step involves clearly defining and specifying the required output data. In Table 3 (supplementary data), the columns utilized in the output process are presented, representing the costs associated with fuel, drivers' wages, oils, lubrication, tires, repairs, and the total cost.

The correlation matrix in Figure 1 illustrates the relationships between different variables. A strong positive correlation (0.95) exists between annual maintenance times and annual working hours, indicating that the more a machine operates, the more maintenance it requires. Additionally, total annual cost is moderately correlated (0.65) with both maintenance times and working hours, suggesting that increased operation and maintenance lead to higher costs. On the other hand, equipment code shows negative correlations with all other variables. These insights highlight that optimizing equipment selection and maintenance strategies could help reduce costs while ensuring efficiency. Figure 2 supports the findings from Figure 1 by providing a detailed visualization of the relationships between variables through scatter plots and histograms Paragraph: the first paragraph in a section, or to continue after an extract.

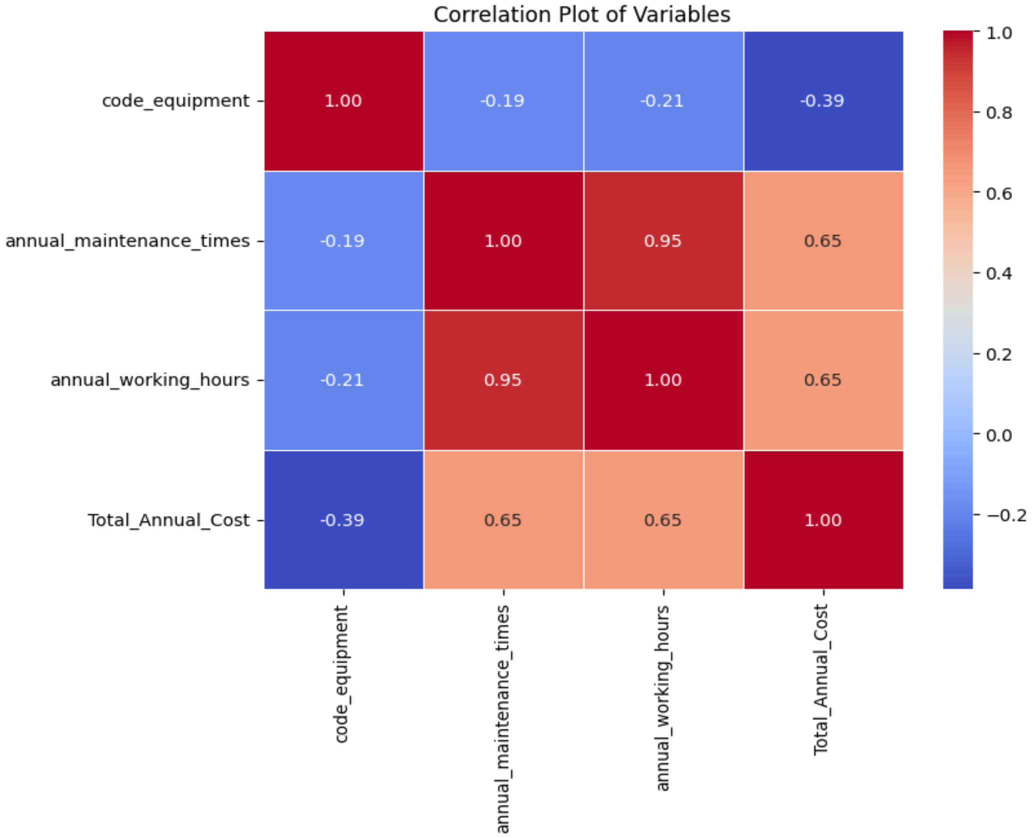

Figure 1. Correlation matrix of variables

The patterns presented in Tables 2 (supplementary data) and 3 (supplementary data) are further reinforced by the correlation visualizations shown in Figures 1 and 2. As seen in Table 2 (supplementary data), machines with higher annual working hours exhibit a proportional increase in maintenance frequency, a trend that is strongly confirmed by the correlation coefficient (r = 0.95) in Figure 1. This reflects a highly linear and predictable relationship between equipment utilization and required maintenance interventions. Figure 2 provides additional clarity through a scatterplot of distributions, illustrating that the rise in annual costs is not random, but closely aligned with increases in both working hours and maintenance frequency. Moreover, the cost components in Table 3 (supplementary data) clearly escalate with greater machine utilization, particularly in fuel consumption, tire wear, and repair activities. The correlation matrix in Figure 1 shows that total annual cost is moderately correlated with both working hours (r = 0.65) and maintenance times, indicating that operational intensity is a key driver of cost accumulation. These findings are consistent with previous studies (Huang et al., 2021; Gajewski & Vališ, 2021), which similarly attribute cost escalation to increased operational loads and mechanical fatigue. The combined evidence from the tables and figures emphasizes that equipment deterioration varies across machine types, supporting the need for predictive ANN-based modeling rather than fixed replacement rules.

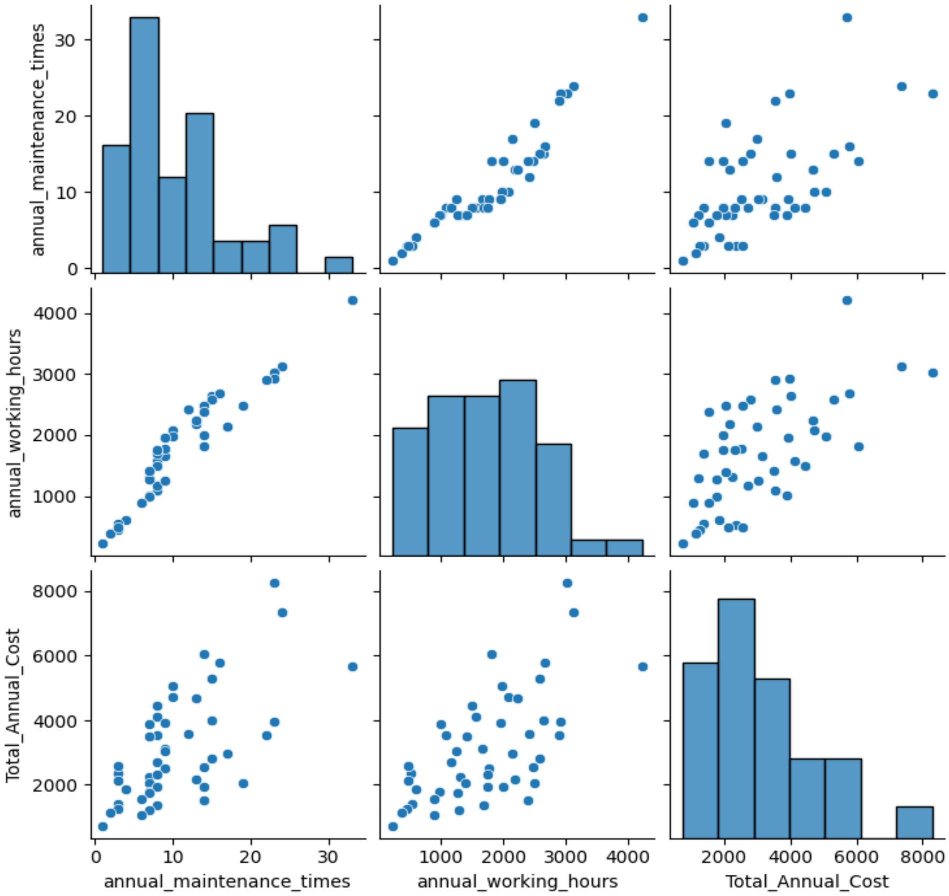

Figure 2. Correlation plot of variables (annual maintenance times, annual working hours, and total annual cost) of equipment performance

ANN Validation and Result Analysis

In the current study, an in-house ANN program developed in FORTRAN was employed to predict output data. The training phase begins with an initial configuration, typically one hidden layer with the number of hidden units set to half the sum of input and output units. Multiple calculations are performed iteratively for each configuration, retaining the best network based on the Mean Square Error (MSE). In Figure 3, the cost curve variations predicted by the ANN with different hidden layer nodes are superimposed. This comparison evaluates predicted responses against the desired ones.

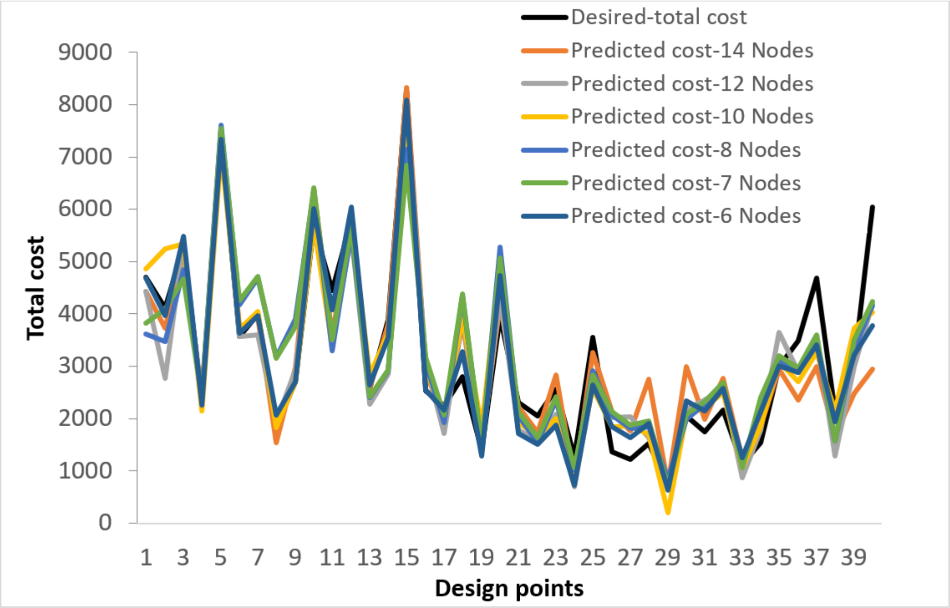

Figure 3. Comparison between the target value of total cost and the curves predicted by the ANN for total cost forecasting

Tables 2 (supplementary data) and 3 (supplementary data) served as the database for training the neural network. Different architectures were tested with varying hidden layer neurons, and their performance was assessed using MSE. The network adjusts its weighted connections to minimize total MSE (Eq. 4) between actual and desired outputs. Training revealed that 11 hidden nodes provide the best alignment with actual data, showing the lowest error. This configuration was therefore chosen to predict operating costs. Figure 4 (supplementary data) compares the neural network–predicted cost curve with the desired curve *versus* design point number. Increasing training repetitions reduces MSE significantly, stabilizing at 0.05 after 20,000 epochs. Figure 5 presents linear regression coefficients from training, validation, and testing stages. The R-plots show the relationship between target values and ANN outputs, with R² reaching 1 and a very low MSE, demonstrating the high accuracy and efficiency of the developed model.

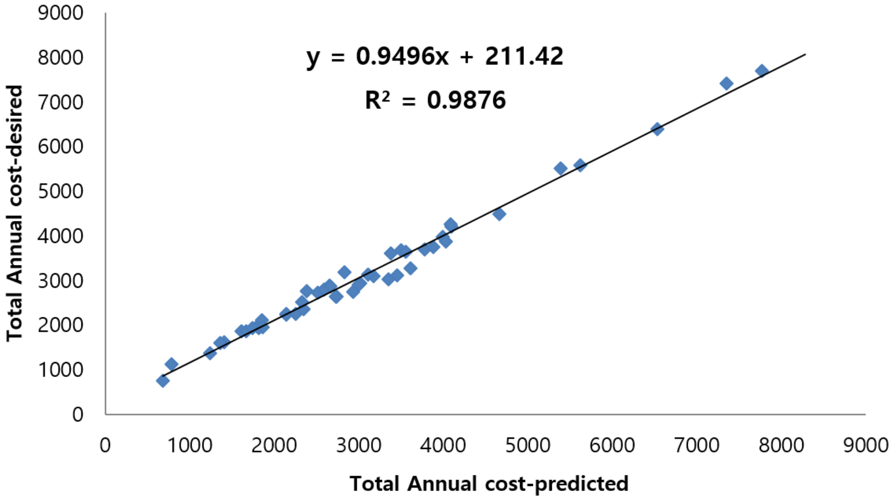

Figure 5. Linear regression analysis of the correlation between target values and ANN outputs

The optimal network architecture identified during training includes three input nodes (Annual Working Hours, Annual Maintenance Times, and Equipment Code), one hidden layer with eleven neurons, and seven output nodes representing Total Annual Cost (CT), Lubrication, Oils, Tire, Repair, Driver, and Fuel. The modeling phase involved detailed data analysis to determine this structure. Figure 6 illustrates the optimized architecture.

After training and architecture optimization, the model was tested using the validation dataset shown in Table 4 (supplementary data). Figure 7 (supplementary data) compares actual and predicted total annual costs, showing strong agreement with an R^2 of 0.92. This high correlation confirms the model's reliability and robustness for predicting equipment replacement timing in real operational contexts.

The results in Table 4 (supplementary data) of validation and Figures 3 to 7 (supplementary data) demonstrate that the ANN model accurately captures the relationship between working hours, maintenance frequency, and total annual cost. The strong alignment between predicted and actual values, as illustrated by the regression plot in Figure 7 (supplementary data) (R^2=0.99), confirms the model's high predictive performance. Also, Figures 3 and 4 (Supplementary data) show that the architecture with eleven hidden neurons provides the best match to the target cost curve, while Figure 5 further supports this through minimal deviation between actual and predicted outputs. Collectively, these results indicate that the ANN structure used in this study is effective in modeling the non-linear cost behaviour of heavy equipment. This reinforces the model's suitability for predicting equipment economic life and aligns with previous studies that demonstrated the robustness of ANN models in similar predictive maintenance applications (Huang et al., 2021; Kang et al., 2021).

Building on this validated model, forecasts are generated by aggregating the average working hours for the upcoming years. The Kawasaki Shuffle 85-wheeler is selected as a representative model, featured in the 20-year future forecast columns. In this study, it is revealed that there is an annual degradation rate of 5% in private sector equipment, as detailed in Table 5 (supplementary data). Results for the remaining devices will be presented in subsequent tables and figures, and the outcomes derived from this prediction will be visualized in Figure 8 for future values.

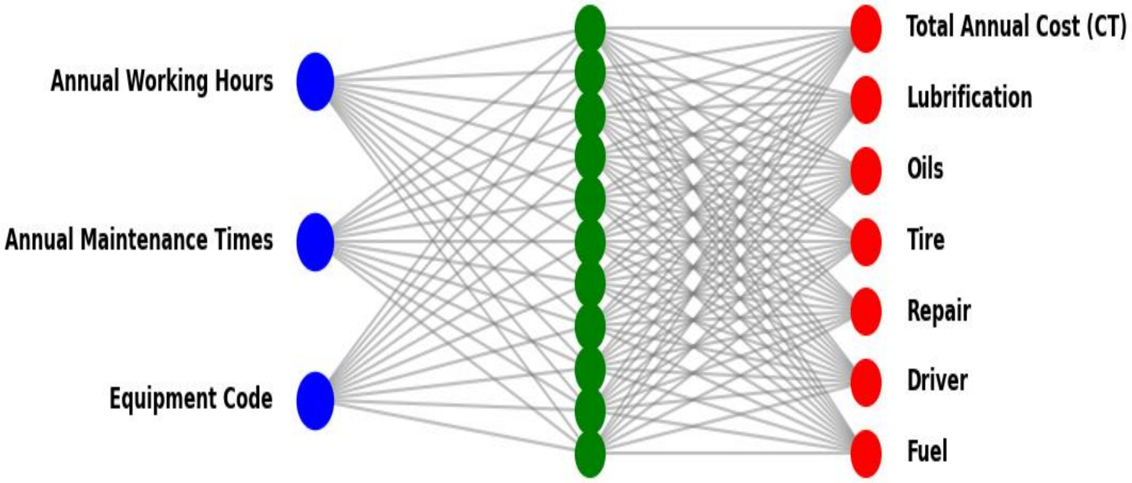

Figure 6. The architecture of the NN model

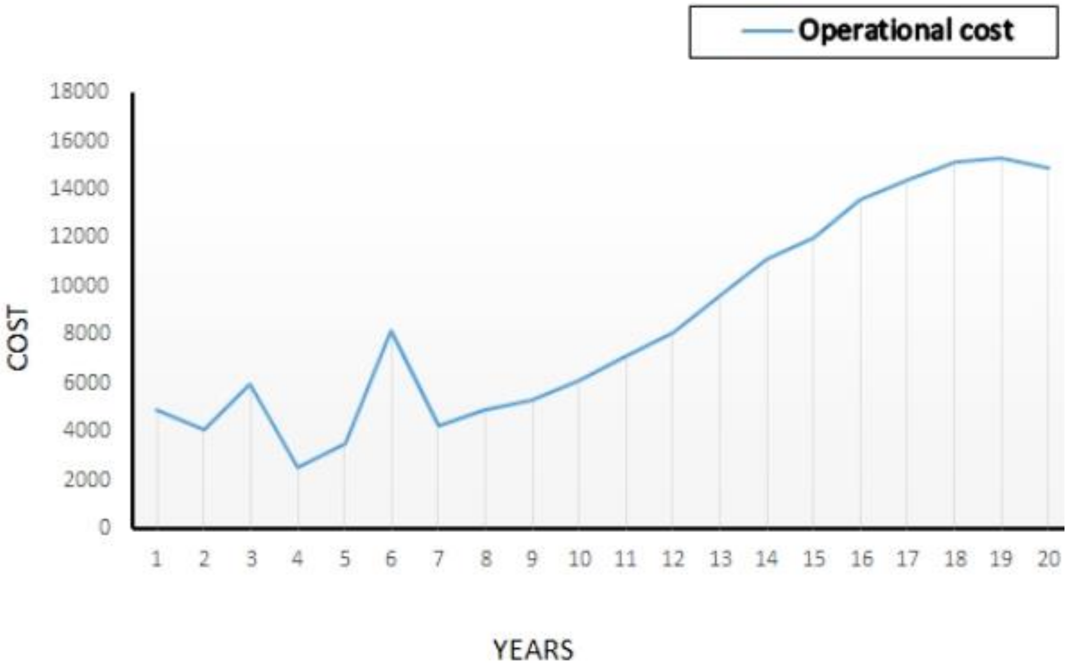

Figure 8. Kawasaki shuffle 85 estimated operating cost curve

For data prediction, the number of annual working hours (WH) was selected based on the historical average, which is approximately 1778 hours.

After entering the data of the Kawasaki Shuffle 85-wheeler into the trained program and adding the average working hours for the expected subsequent years to reach the life of the equipment, the estimated future cost is obtained, as shown in Figure 8, as predicted by the neural network. Facilitating the future estimation process and indicating the replacement date give a clear vision to the machinery and equipment fleet manager in making the right decisions in disposing of equipment approaching the replacement date by selling it. At the auction, selling equipment and benefiting from the financial returns (salvage value) lead to renewing the fleet by purchasing modern equipment and keeping up with latest technology.

The results in Table 5 (supplementary data) shows the progressive increase in maintenance frequency and the workload for the Kawasaki 85 machine, reflecting the natural escalation of deterioration over time. This upward trend is clearly captured in Figure 8, where the forecasted operational cost curve rises steadily after year 6 and accelerates toward the end of the lifespan equipment. The consistency between the empirical degradation patterns in Table 5 (supplementary data) and the predicted cost escalation in Figure 8 demonstrates the ANN model's ability to replicate realistic ageing behavior. This alignment supports the validity of the model in forecasting future operating costs and identifying the economic replacement point.

Figure 8 shows the magnitude of the Kawasaki 85 stochastic operating cost curve for the estimated period obtained from the neural network artificial intelligence program. We notice the fluctuation of operating costs at the beginning of the curve at a period of 6 years represents the period of actual costs, while the next period after 6 years represents the operating costs for the estimated period. Next, we can intersect the operating cost curve with the salvage value curve and determine the ideal point for replacement time.

- **Regression Analysis for Validation**

In this study, regression equations are used to validate the neural network predictions. Regression analysis provides a robust method to assess the accuracy and reliability of the ANN model by comparing its outputs with experimental target values. This approach evaluates the fit between observed and predicted values, confirming the model's effectiveness and validity. Rigorous regression analysis ensures the robustness and generalizability of the ANN predictions across different datasets and real-world scenarios.

The regression analysis will be illustrated using the example of Kawasaki Shuffle 85. Initially, we started by determining the regression equation for the data collected from the private sector. Then, we will use this equation to extend the computation and compare the results with those predicted by the ANN. To generate the regression equation, we used the Minitab software.

The regression equation relates the total annual cost to the number of annual maintenance and working hours:

$$C_T = 1991 + 0.155 * WH + 245.5 * NMH \tag{5}$$

Here, C_T is the Total Cost, *WH* is Working Hours, and *NMH* is the Number of annual maintenance hours.

The correlation coefficient (R^2) is observed to be nearly 1. Figure 9 (supplementary data) shows a curve, which establishes striking similarities between the results from regression analysis and the desired data.

This equation is employed for forecasting the total annual cost in the future and to compare these projections with those obtained by the Artificial Neural Network (ANN). By utilizing this regression equation, we assess the effectiveness of the ANN model in forecasting the total annual cost, which allows us to better understand its predictive capabilities and potential areas for improvement.

Figure 9 (supplementary data) compares the actual total annual cost values presented earlier in Table 3 (supplementary data) with the corresponding values estimated using the regression equation defined as Equation (5). The close similarity between the two curves indicates that the regression model successfully reflects the cost behavior observed in the recorded data. The slight deviations at some points do not affect the overall trend consistency, confirming that Equation (5) provides a reliable analytical fit for the empirical cost pattern in Table 3 (supplementary data). This agreement reinforces the validity of the regression equation as a supporting tool alongside the ANN model.

Figure 10 (supplementary data) shows that the ANN-predicted total annual costs closely match the values computed using the regression equation (Equation 5), both derived from the empirical dataset presented in Table 3 (Supplementary data). This strong alignment indicates that the two methods capture the same underlying cost behavior despite their different analytical approaches.

Figure 10 (supplementary data) shows curves from both regression analysis and ANN predictions, which have striking similarities in both trends and values. This remarkable agreement underscores the robustness and effectiveness of the ANN in modeling and predicting the total annual cost. The consistency of the results between the two approaches enhances confidence in the predictive capabilities of the ANN, proving that it can accurately capture the complex relationships between input and output variables. This also confirms that the ANN is an effective tool for modeling and prediction in situations where relationships between variables are non-linear or difficult to describe analytically.

The correlation between the regression equation results and those of the ANN outputs is shown in Figure 11 (supplementary data), where the ANN-predicted costs closely match the regression-based estimates generated from Equation (5) using the empirical dataset in Table 3 (supplementary data). The near-perfect correlation ($R^2 \approx 1$) demonstrates not only numerical agreement, but also that both approaches capture the same functional relationship linking working hours, maintenance frequency, and total annual cost. The strong alignment between the two curves indicates that the cost behavior exhibits a dominant linear structure, enabling both the regression model and the ANN to learn consistent patterns despite their differing computational frameworks. This level of stability directly supports the study's objective of developing a reliable predictive tool for equipment replacement planning.

Results of Salvage Value Analysis

In adherence to Iraqi law regulations, the annual deterioration rate is estimated at 10% for equipment and machinery operating in the government services sector. Therefore, regardless of equipment type, replacement is mandated to be after 10 years of operation period. In contrast, the private sector follows a 5% equipment deterioration rate, meaning that the equipment is replaced after 20 years. Our research is directed toward verifying the condition and determining the replacement time for each type of equipment individually. It explains the validity of the decisions taken by the government sector or the private sector, and explains the correct and appropriate decision in determining the optimal replacement time.

Calculating the salvage value is a complex task, because it depends on several variables, including the economic situation of the country, as well as the supply and demand factor in the Iraqi market, in addition to the state’s policy in allowing companies to import heavy equipment or not. Accordingly, the progression period will be assumed over 20 years, according to the following equation:

$$S(n) = Ic - ((5\% * n) * Ic) \quad (6)$$

where S_n is the salvage value rate in a specific year, n is the number of years and I_c is the primary cost.

Table 6 (supplementary data) shows the details and calculations of the salvage value used in the private sector. Figure 12 (Supplementary data) illustrates the intersection of the salvage value and operating cost curves for the Kawasaki Shuffle 85, occurring at year 11 (19,560 h), which represents the optimal replacement time when total operating cost and residual value are balanced. Replacing the equipment at this point minimizes expenses and maximizes asset utilization. However, this optimal time depends on the accuracy of cost and operational data; variations in usage or maintenance may shift the intersection, emphasizing the need for periodic reassessment.

This indicates that replacement decisions made by both the private and government sectors were inaccurate. Replacing the Kawasaki Shuffle 85 before or after the optimal point leads to significant additional costs. Delaying replacement beyond the optimal point increases expenses for private companies.

Table 7 (supplementary data) summarizes the replacement times for various equipment types studied. It provides a useful reference for optimal replacement periods for each equipment category, assisting decision-makers in maintenance and fleet management. The table clearly shows the diverse replacement timelines across the equipment types analyzed.

Table 7 (supplementary data) summarizes the optimal replacement times for all equipment types, while Figure 12 (supplementary data) graphically illustrates the replacement point for the Kawasaki 85 by showing the intersection between the rising operational cost curve and the declining salvage value curve. The intersection represents the economic life of the equipment, confirming that replacement becomes financially justified once operating costs exceed the remaining asset value.

These results directly support the study's objective of establishing a data-driven method for identifying optimal replacement timing, replacing the traditional fixed-year rules used in practice. From an industrial engineering perspective, the integration of ANN-predicted costs with salvage-value analysis provides a systematic and economically grounded decision framework that reduces lifecycle costs and enhances fleet management efficiency.

CONCLUSIONS

The findings of this paper highlight the practical value of adopting a data-driven method to estimate the economic life of heavy equipment in private-sector (private company) operations. The ANN model demonstrated strong predictive capability, as evidenced by the close alignment between actual and predicted total annual costs, as in Figures 7-11 and the high correlation coefficient ($R^2 \approx 1$) obtained during validation. These findings confirm that equipment deterioration and cost escalation follow consistent patterns that can be captured more accurately by ANN compared to fixed administrative replacement rules. The proposed model successfully identified optimal replacement times (6 and 16 years) depending on machine type, which is significantly shorter than the traditional model rule (20 years). This difference reinforces the limitations of static replacement policies and emphasizes the need for flexible planning based on real operating and maintenance data.

Furthermore, integrating ANN predictions with salvage-value analysis enhanced the precision of determining economic replacement points, as demonstrated by the intersection of cost and salvage curves in Figure 12 (supplementary data) (for example, the Kawasaki Shuffle 85, occurring at year 11 (19,560 h)). This combined approach supports more efficient fleet management by reducing unnecessary maintenance expenses and preventing delayed replacement. Overall, the findings illustrate that a predictive ANN-based framework provides a more reliable and economically grounded basis for replacement decisions in private-sector environments.

Conflict of interests

The authors declare that they have no conflict of interests regarding the current research.

Data Availability

Data sharing is not applicable to this article, as no new data was created or analyzed in this study.

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