A Review on Data Driven Machine Learning Models For Forecasting Remanufacturing Costs Of EOL Products

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Abstract- *End-of-life product remanufacturing represents a crucial component of sustainable business practices. By extending the life of products, minimizing waste, and supporting economic growth, remanufacturing aligns with the principles of a circular economy. As industries and consumers increasingly recognize the environmental and economic benefits, the integration of end-of-life product remanufacturing is likely to grow, contributing to a more sustainable and responsible approach to resource utilization and waste management. Hence it is necessary to remanufacture wherever possible. Typically end of life (EoL) products are remanufactured based on their remaining useful life. For the purpose cost estimation for end of life products is essential. This paper presents a survey on statistical techniques as well as previous work done in the domain.*

Keywords- EoL Products, Remanufacturing Cost Forecasting, Evolutionary Algorithms, Forecasting Error, Accuracy.

I. INTRODUCTION

End-of-life product remanufacturing is a sustainable and environmentally conscious approach to handling used goods. This process involves restoring used products to a like-new condition, thereby extending their lifecycle and reducing the overall environmental impact associated with manufacturing new items. Remanufacturing contributes significantly to the concept of a circular economy, where resources are maximized, waste is minimized, and environmental sustainability is prioritized. One of the key benefits of end-of-life product remanufacturing is the reduction of electronic waste and the conservation of valuable resources. In sectors like electronics and automotive industries, remanufacturing allows for the recovery and reuse of components and materials from discarded products. This not only reduces the demand for raw materials but also decreases the amount of waste that would otherwise end up in landfills, posing environmental hazards.

Moreover, end-of-life product remanufacturing can have economic advantages. It creates job opportunities in the remanufacturing industry, contributing to economic growth. The remanufacturing process often requires skilled labor for disassembly, inspection, repair, and reassembly of products, fostering employment opportunities in various sectors. Additionally, remanufactured products are generally more cost-effective than their brand-new counterparts. Consumers can benefit from lower prices while still enjoying products with comparable performance and quality. This affordability can contribute to a more widespread adoption of remanufactured goods, further promoting sustainable consumption practices.

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II. INTRODUCTION TO EVOLUTIONARY ALGORITHMS.

Evolutionary algorithms try to mimic the human attributes of thinking which are:

1) Parallel data processing
2) Self-Organization
3) Learning from experiences

Some of the commonly used techniques are discussed below:

1)Statistical Regression: These techniques are based on the time series approach based on the fitting problem that accurately fits the data set at hand. The approach generally uses the auto-regressive models and means statistical measures. They can be further classified as:

a) Linear
b) Non-Linear
Mathematically:
Let the time series data set be expressed as:

$$Y = \{Y1, Y2 \ldots\ldots\ldots\ldots\ldots\ldots..Yt)$$

Here,
Y represents the data set
t represents the number of samples
Let the lags in the data be expressed as the consecutive differences.

The first lag is given by:

$$\Delta Y_1 = Y_{t-1}$$

Similarly, the jth lag is given by:

$$\Delta Y_j = Y_{t-j}$$

2) Correlation based fitting of time series data: The correlation based approaches try to fit the data based on the correlation among the individual lags. Mathematically it can be given by:

$$A_t = corr(Y_t, Y_{t-1})$$

Here,
Corr represents the auto-correlation (which is also called the serial correlation)
Y_t is the tth lagged value
Y_{t-1} is the (t-1)st lagged value
The mathematical expression for the correlation is given by

$$corr(Y_t, Y_{t-1}) = \frac{conv(Y_t, Y_{t-1})}{\sqrt{varY_t, varY_{t-1}}}$$

Here,
Conv represents convolution given by:

$$conv\{x(t), h(t)\} = \int_{t=1}^{\infty} x(\vartheta)h(t-\vartheta)d\vartheta$$

Here,
ϑ is a dummy shifting variable for the entire span of the time series data
t represents time
Y_t is the tth lagged value
Y_{t-1} is the (t-1)st lagged value
X is function 1
H is function 2
Var represents the variance given by:

$$var(X) = X_i - E(X)$$

Here,
Xi is the random variable sample
E represents the expectation or mean of the random variable X

3) Finite Distribution Lag Model (FDL): This model tries to design a finite distribution model comprising of lags fitted to some distribution such as the normal or lognormal distributions. Mathematically:

$$Y_t = \alpha_t + \delta_1 z_1 + \cdots \ldots \ldots \ldots \ldots \delta_t z_t + \mu_t$$

Here,
Y_t is the time series data set
α_t is a time dependent variable
δ_1 is a time-varying co-efficient
z is the variable (time variable)
t is the time index
μ_t is the time dependent combination-coefficient

4) Artificial Neural Networks (ANN): In this approach, the time series data is fed to a neural network resembling the working of the human based brain architecture with a self-organizing memory technique.

The approach uses the ANN and works by training and testing the datasets required for the same. The general rule of the thumb is that 70% of the data is used for training and 30% is used for testing. The neural network can work on the fundamental properties or attributes of the human brain i.e. parallel structure and adaptive self-organizing learning ability. Mathematically, the neural network is governed by the following expression:

$$Y = f(\sum_{i=1}^{n} X_i . W_i + \theta_i)$$

Here,
X_i represents the parallel data streams
W_i represents the weights
θ represents the bias or decision logic

The second point is critically important owing to the fact that the data in time series problems such as sales forecasting may follow a highly non-correlative pattern and pattern recognition in such a data set can be difficult. Mathematically:

$$x = f(t)$$

Here,
x is the function
t is the time variable.
The relation f is often difficult to find being highly random in nature.
The neural network tries to find the relation f given the data set (D) for a functional dependence of x(t).

The data is fed to the neural network as training data and then the neural network is tested on the grounds of future data prediction. The actual outputs (targets) are then compared with the predicted data (output) to find the errors in prediction. Such a training-testing rule is associated for neural network. The conceptual mathematical architecture for neural networks is shown in the figure below where the input data is x and fed to the neural network.

III. PREVIOUS WORK

Zhigang Jiang et al. [1] proposed A Data-driven Based Decomposition-integration Method for Remanufacturing Cost Prediction of End-of-Life Products. Principal component analysis (PCA) is a dimension-reducing tool Remanufacturing cost prediction is conducive to visually judging the remanufacturability of End-of-Life (EOL) products from economic perspective.

The general method for predicting the remanufacturing cost of EOL products is very low precision. To this end, a data-driven based decomposition-integration method is proposed to predict remanufacturing cost of EOL products. The approach is based on historical remanufacturing cost data to build a model for prediction. And proposed method can be utilized as an effective tool to analyze and predict remanufacturing cost of EOL products.

Zhang Yingfeng et al. [2] presented Cleaner production (CP) is considered as one of the most important means for manufacturing enterprises to achieve sustainable production and improve their sustainable competitive advantage. However, implementation of the CP strategy was facing barriers, such as the lack of complete data and valuable knowledge that can be employed to provide better support on decision-making of coordination and optimization on the product lifecycle management (PLM) and the whole CP process. Fortunately, with the wide use of smart sensing devices in PLM, a large amount of real-time and multi-source lifecycle big data can now be collected. To make better PLM and CP decisions based on these data, in this paper, an overall architecture of big data-based analytics for product lifecycle (BDA-PL) was proposed. It integrated big data analytics and service-driven patterns that helped to overcome the above-mentioned barriers.

Lingling Li et al. [3] proposed integrated approach of reverse engineering aided remanufacturing process for worn components. With the aid of reverse engineering (RE) technologies, a quick and accurate acquisition of the damaged areas of the worn part is attainable and thereby facilitates remanufacturing operations necessary to bring the parts back to like-new conditions. In this paper, a reverse engineering based approach is proposed to aid the remanufacturing processes of worn parts. The proposed approach integrates 3D surface data collection, nominal model reconstruction, fine registration, extraction of additive/subtractive repair, tool path generation and actual machining process, seeking to improve the reliability and efficiency of manual repair process. For nominal model reconstruction, a Prominent Cross-Section algorithm embedded with curvature constraint is proposed to automatically identify the boundary of the part's damaged area and thereby eliminate the defective point clouds from the reconstruction process.

Y Bowen et al. [4] proposed The research of application big Data analytics to the parts remanufacturing economic evaluation. The proposed model makes a comparison of the benefits of AR products and original products from the three aspects of economy, environment and user experience, and highlights the AR advantages of in-service mechanical products. Firstly, after collecting and analyzing various feedback information from the original manufacturers (OM), retailers (Rs), maintenance personnel (Ms) and end users, quality function deployment (QFD) is used to forecast the AR cost and evaluate of the economic benefits employing the smoothing index method. Secondly, the environmental benefits of different products are evaluated when analyzing the actual operating environment, operating specifications and remanufactured energy consumption of in-service products.

Winifred L. Ijomah et al. [5] proposed a research on Development of design for remanufacturing guidelines to support sustainable manufacturing. Developing sustainable approaches to manufacture is a critical global concern. Key measures towards this include practicing design for environment (eco design), for example by improving remanufacturing efficiency and effectiveness. Remanufacturing is a process of bringing used products to a ‘‘like-new’’ functional state with warranty to match. Its significance is that it can be both profitable and less harmful to the environment in comparison to conventional manufacturing. Remanufacturing has a low profile in world economies and is poorly understood because of its relative novelty in research terms. However, environmental and competitive pressures are changing the global and business environment and this is fuelling interest in the practice. This paper provides the background to remanufacturing together with the findings from workshops recently undertaken in the UK as part of research into design and manufacturing approaches to facilitate remanufacturing.

IV. EVALUATION PARAMETERS

Since errors can be both negative and positive in polarity, therefore its immaterial to consider errors with signs which may lead to cancellation and hence inaccurate evaluation of errors. Therefore we consider mean square error and mean absolute percentage errors for evaluation. The other evaluation parameters are:

1) Mean Square Error (mse)
2) Mean Absolute Error (MAE)
3) Mean Absolute Percentage Error (MAPE)
4) Accuracy

$$MSE = \frac{1}{N}\sum_{I=1}^{N}(V_t - \widehat{V}_t)^2 \quad \textbf{(12)}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|V_t - \widehat{V}_t|$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|e_t|$$

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{|V_t - \widehat{V}_t|}{V_t}$$

$$Accuracy = 100 - error(\%)$$

Here,
N is the number of predicted samples
V is the predicted value
$\widehat{V}_t$ is the actual value
e is the error value
It is desirable to attain high values of prediction accuracy.

V. CONCLUSION

It can be concluded that remanufactured products are generally more cost-effective than their brand-new counterparts. Consumers can benefit from lower prices while still enjoying products with comparable performance and quality. This affordability can contribute to a more widespread adoption of remanufactured goods, further promoting sustainable consumption practices. However, challenges exist in establishing widespread adoption of end-of-life product remanufacturing. Design complexities, variability in used product conditions, and the need for specialized knowledge can make the remanufacturing process intricate. Overcoming these challenges requires collaborative efforts between manufacturers, policymakers, and consumers to develop standardized practices, regulations, and incentives that encourage the incorporation of remanufacturing into mainstream production cycles. This paper presents a survey on the statistical models for EOL cost prediction.

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