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Reliability Simulation Mechanism Model of Big Data Mileage Prediction for Automotive Warranty

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Abstract

Stiff competition among automotive manufacturers to secure market share results in a short period of product development until production. Thus, there is a gap of limited attention concerning effective early detection tools leveraging information technology to identify product quality by optimising warranty data towards expediting market action. A big data simulation analysis model of warranty prediction is proposed based on parameter mileage using the Weibull statistic platform. Input of warranty prediction analysis based on warranty historical data, continued with data cleaning and selection. The algorithm model is applied to support big data analysis based on the application of Weibull statistics. The product with the highest failure rate in terms of warranty amount and quantity, part number PN312, was selected. The shape β value is 2.308, which matches the Rayleigh distribution with the shape η of product failure at 403,948km when the incidence is 63%. The model orchestrated the future warranty outcome and consequences. Relatively, the warranty prediction system simulates the evaluation costs of poor quality. The development of a new prediction simulation model will enhance the application of QC tools, expedite the selection of poor-quality products, eliminate wasteful resources such as time and manpower, and simplify the investigation process.

1. Introduction

In emerging countries, over the past decade, there has been significant growth in automotive sales and production. The automotive industry plays a significant role in strengthening the national economy and simplifying people's lives. It is an important branch of business in certain aspects compared to other initiatives. With the fast pace of information technology development, reform the automotive constitution with a competitive product. Such differentiation positions automotive companies as superior to others. Unfortunately, with fast development and execution to market, there is a risk of poor quality. Thus, customer satisfaction with product quality is their highest expectation [1].

Product failure may not be possible to eliminate, but it can be controlled in many ways. Thus, warranty prediction analysis is key to managing the cost of poor quality and further elevating customer satisfaction. Automotive sales and production in emerging economies over the past decades have experienced significant growth, with China being the largest automobile market since 2009 [2]. With intense competition, the automotive industry today strives for fast development to secure market share and meet customer expectations. It triggered a risk of poor quality with low development and production costs. The fast technology and complex product development with the application of information technology contribute to high potential failure [3]. Identifying product defects at an earlier stage is a challenge in securing future profit and protecting brand reputation [3][4].

High product defects in the market result in engineering and management decisions towards market activities such as product recall through re-design and reliability improvement, which are often reactive and less ideal for the manufacturer. Thus, proactive practical action in detecting a serious product reliability problem over time is a must in minimizing losses and reputation damage [3][5][6]. Almost for all products nowadays, customers demand good after-sales services with a product warranty as the offered mechanism [7]. In addition, it is a competitive strategy for encouraging market demand and increasing the brand's perceived value. It is one consideration factor for customers deciding on the product purchase, expecting high-quality products, after-sales services, and a warranty period. All of these factors affect profit return by providing warranty provision at the cost of poor quality [8].

Two-dimensional warranty policies are the automotive consideration factor with application period and mileage [9]. For example, a new car is covered for 5 years with unlimited mileage [10]. In sustaining the business and meeting customer expectations, setting up a warranty policy is fundamental, which is merely a business perspective in deciding the warranty policy's cost and cycle [11][12]. A research study by L. Jie et al. showed that applying a warranty strategy was able to increase customer satisfaction with after-sales service and increase profit for the manufacturer [8]. The definition of warranty claims is free replacement vehicle components for repair, replacement, or maintenance claims made by customers within the warranty period. The claims often indicate quality issue performance recorded throughout the warranty period and the main selling factor to appeal to customers by the manufacturer's sales [6].

Studies institute a gap of limited attention concerning effective early detection tool development based on warranty data [12]. The seriousness of reliability problems is assessed through an appropriate statistical method that represents trends in future warranty claims. In the Industry 4.0 initiative, scholars address the lack of guidance in developing robust simulation mechanism methodology as a result of a lack of models in discovery, empirical research guidance, and critique through information technology advancement [13]. Early detection of reliability problems through a dynamic control charting scheme signifies the development of warranty claims that monitor one period after another over the product life cycle [14]. Application of modern statistics is used for reliability analysis through managing overwhelming data volumes of unique complexity in the analysis of big data [1][15][16]. Four main methods were applied throughout the literature review by the latest researchers, such as the Weibull distribution application, the Non-Homogeneous Poisson Process (NHPP) application, the machine learning application, and the Monte-Carlo simulation algorithm application.

The first method is the Weibull distribution application. The procedure to estimate system reliability failure related to wear-out initial and random reliability is based on the Weibull distribution [17]. It determines the best-fit life distribution as a function of time when forecasting product reliability [18]. In reliability and warranty forecasting applications, the estimation of the parameters and the number of defective units in the underlying distribution is very important, as studied by Koutsellis, T., et al [19]. In the case of long-range forecasting, the researchers acknowledge the challenging task and emphasize the selection analysis method, which has many uncertainties. The Weibull distribution is very popular for lifetime probability prediction. With two parameters, the Weibull analysis reliability system would be able to predict system reliability. Historical research shows the application of model development only to the targeted problem of warranty improvement [20]. Most of the researchers widely applied the Weibull distribution application in their reliability research. However, the fundamental analysis of the significant factor of failure attributes is not considered.

The second method is Non-Homogeneous Poisson Process (NHPP) application. The NHPP is applied to model failure counts of repair products of two-dimensional warranty, with the potential effect of application rate on product deterioration [21]. Compared to traditional models, the proposed model significantly improved forecasting. This includes monitoring warranty claims one period after another by a dynamic control charting scheme over the product life cycle through that the false alarm rate at each period can be controlled at a desired level promptly [14]. The researcher observed a limitation in improving the detection ability if the values of β are small.

The third method is Machine Learning application. Machine Learning can forecast the product failure ratio using statistics that tied up over a telematic connection and vehicle records for predictive maintenance [22]. Using past data, the failure ratio was generated based on the auto-regression model and performed better with small data. The individual model performs better with sufficient data for the period using the aggregation method [4][22]. Some applications of reliability study analysis use a bivariate copula model by combining the one-dimensional distribution of two components. By emphasizing the warranty condition, applying the Archimedean copula model and Bayesian model can estimate two-component failure before product failure [23]. However, gaps are observed where the correlation between the past failures could affect the failure ratio prediction over time, including the evaluation of the regression mark that may fail. In addition, the limited number of positive samples also brings inconsistency to data compilation and targeting specific components.

Finally, the fourth method is the Monte-Carlo Simulation Algorithm Application. A solution approach based on a metaheuristic Monte-Carlo simulation (MCS) algorithm integrated with dynamic programming is suggested to solve the imperfect repair model. The application study only applies to a vacuum cleaner with model development and its solution procedures. A similar model is suggested for a two-dimensional warranty decision-making problem for automotive products due to the lack of a benchmark for a similar model for the automotive industry [24].

This study considers product quality failure prediction by leveraging warranty data simulation for automotive by applying the Weibull distribution application as the selected model. Warranty data is derived from field returns of products as a result of warranty quality feedback. It portrays the life data and outcomes of functional and environmental testing of the product. The method is appropriate for defining the best-fit life distribution and predicting product reliability as a function of time [16]. To evaluate the degree of relative parameters, The predictive simulation mechanism of warranty claim analysis by graphical and analytical means is suggested for better output analysis [25].

The aims of this study were:

- To apply the warranty simulation model based on the Weibull distribution
- To identify Weibull's prediction for mileage as characterized by analytics and graphs

In alignment with the study objective, the Weibull distribution application method is suitable for product quality failure prediction related to warranty claims analysis due to its statistical study method in forecasting product reliability and determining the best-fit life distribution. The expected outcome of the proposed simulation method is to simplify techniques and produce better output analysis.

The content of this paper is organized as follows: The second part sets out establishing the mechanisms of data compilation and cleaning, followed by modelling development and mechanism establishment, and finally model computing. The paper explanation continued with the third part, which elaborated on the results and discussion. Finally, the conclusion is in the fourth part.

2. Research Method

In this paper, the warranty prediction simulation mechanism is associated with business constitution measurement. Parameter warranty evaluation is based on mileage or distance of vehicle travel, in which simulation data linked with warranty parts returns through warranty claim analysis. The main features of the modelling application as per Fig. 1, where they are segregated into 3 areas namely data compilation and cleaning, modelling process, and model credential.

Firstly, the main business performance control items were compiled, cleaned, and consolidated. Only selected components were analysed through extraction and applied to the model. Secondly, the model process is established through selected data grouping into the structure of the model Weibull statistic forecast chart. Then, continue with the model calculation, which is derived from the calculation process of selected parameters and forecast output. The warranty simulation mechanism of the Weibull graph model reflects the future warranty claim, which thoroughly links the cost of poor quality with the exact manufacturer data. Combining the architecture of warranty simulation with real-data input expedites the measurable analysis of warranty forecasts. Finally, the model application verifies the warrant data, measuring future warranty impact via the build algorithm.

2.1 Data Compilation and Cleaning

Vehicles that completed warranty repair work at the service centre were collected. The study comprises the automotive brand ABC and Model XYZ. Total cars sell 50,740 units with an agreed-upon warranty policy of 5 years and unlimited mileage. However, the supplier warranty agreement is 3 years or 100,000 km, whichever comes first.

In this term, the supplier accepts a valid claim for manufacturer reimbursement should the product fail within the warranty period. However, the manufacturer has extended another 2 years with unlimited mileage in consideration of the business's intention to retain customers before repurchasing a new vehicle. Based on part number PN312, a total of 1,533 cases were recorded, and the data were consolidated on the centralised database server. The principal objective of data cleaning is to ensure the main data is free from error and replication before proceeding with the warranty analysis.

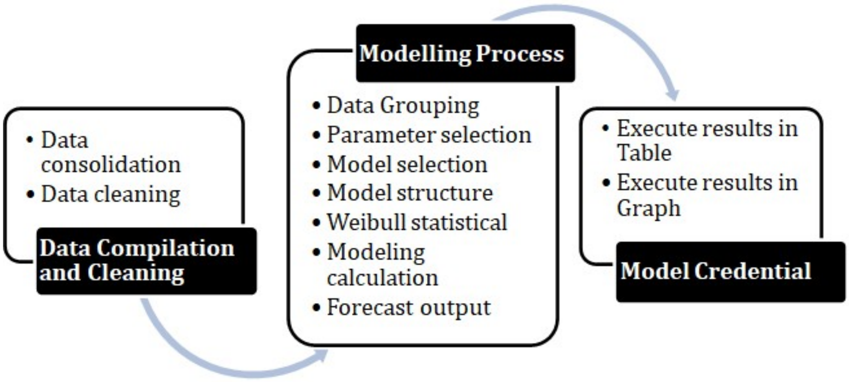

Fig. 1 *Warranty simulation mechanism modelling process*

Data cleaning was controlled by the computer, which administered the accuracy of the data. In Fig. 2, the cleaning process comprises an assessment of vehicle sales against product failure information. This is followed by warranty information screening, which constitutes sales data. This approach allows researchers to eliminate data scattering problems, duplication, and errors in main storage data. Administering quality information accuracy before executing analysis is imperative in certifying that the main data meets the objective of the study. Therefore, the importance of data cleaning lies in ensuring that the main data selection aligns with the analysis requirements before the warranty simulation predictive analysis is executed.

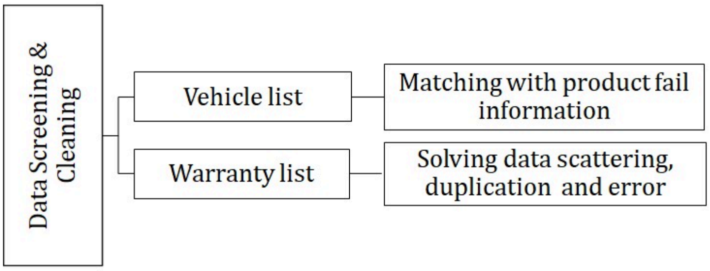

Fig. 2 *The data screening and cleaning process*

The main variable for the simulation development model is warranty mileage. The quality concerns data extracted from the warranty claims record on mileage, in which assessment of the data was conducted upon completion of data cleaning as per Table 1.

Table 1 *Assessment of product failure by mileage*

Parameter	Attribute	Meaning	Effect
Mileage	Records	Product or system failure based on distance	Warranty repairs were conducted and recorded

2.2 Model Architecture and Mechanism

Big data application of warranty simulation mechanism forecasting based on Weibull statistics is a fundamental criterion in suppressing market quality problems by proving countermeasures in the shortest time. In this study, the main variable is mileage based on assessing the product failure data within the warranty period. The definition of the warranty period is a time aspect that permits part replacement under car manufacturer expenses. At an unidentified period at τ, there is a possibility of an unforeseen change in the warranty claim rate of an unknown measure that requires attention and recognition. It is accomplished through the dynamic study of collective warranty claims over time. However, in understanding the overall warranty application in automotive, one should understand the basic concept of warranty claims. To illustrate further this work, the reference claim rate of a product set by the manufacturer with the assumption of known priors is denoted as $\lambda_0(g)$, $g>0$, and the field warranty claim rate for units manufactured in period i, known as $\lambda(g|i)$, $g>0$. Both $\lambda_0(g)$ and $\lambda(g|i)$ are functions of unit age, g [14]. It can be formulated as an assessment of the hypothesis of warranty forecasting simulation as follows:

$$H_0 : \lambda\,(g|i) \leq \lambda_0\,(g),\ g > 0 \tag{1}$$

against

$$H_0 : \lambda\,(g|i) > \lambda_0\,(g),\ g > 0 \tag{2}$$

from a certain point in time onwards, i.e., $i > \tau$.

To validate the hypothesis, sales and warranty claim data were collected periodically and analyzed. The duration of data collection varies depending on the complexity of securing data availability, monitoring data accuracy, and managing administrative difficulties, among others. In this study, the assumption warranty policy period length of free and non-renewable is measured and attached to the sold vehicle, denoted with w. Within this warranty period, unit sold assumed at period t. Manufacturers tolerate failure for the period of f (t, t + f) where f defined as origin of period, with no cost to customers of parts and labour. The balance warranty period alters to w – (f – t). Based on manufacturer feedback, there is a make-to-stock situation where, after manufacturing, the product is not sold immediately. It happens to anticipate a high volume of sales based on projected demand. To illustrate the nature of produce and sale as per Table 2. A further explanation should be the vehicle volume, V_k units (in the kth, where k = 1, 2, . . . , p, interval), and how these units might be sold in the current and or following intervals. Let $C_{k,l}$ represent the total units produced in interval k and sold in interval l, l = k, k + 1, . . . , e. In manufacturing business operations, production stops prior to the stoppage of sales, p ≤ e. Thus, the overall units sold in the lth period can be stated as

$$Sl = \sum_{k=1}^{l\wedge e} C_{k,l} \tag{3}$$

where $k\wedge p = \min\{k,p\}$. In addition, there is a situation where $C_{k,l}$ might be zero for certain intervals, when l is much larger than k or the distinct time interval is too quick.

Table 2 *Relation between the production and sale process*

Production		Sales					
No	Total	S1	S2	…	l(l ≥ k)	..	m
1	V_1	$C_{1,1}$	$C_{1,2}$	…	$C_{1,l}$	..	$C_{1,m}$
2	V_2		$C_{2,2}$	…	$C_{2,l}$	..	$C_{2,m}$
3	V_3			…	$C_{3,l}$	..	$C_{3,m}$
…	…	…	…	…	…	..	…
k	V_k			…	$C_{k,l}$	..	$C_{k,m}$
…	…	…	…	…	…	..	…
p	V_p			…		..	$C_{p,m}$

where the summary expression is as follows:

Production Total :	$\sum_{k=1}^{p} V_k$	Total l(l ≥ k):	$S1 = \sum_{k=1}^{l\wedge p} C_{k,1}$
Total Sales, S1:	$\sum_{k=1}^{1} C_{k,1}$	Total m:	$Sm = \sum_{k=1}^{m\wedge p} C_{k,m}$
Total Sales, S2:	$\sum_{k=1}^{2} C_{k,2}$		

The dismissal of vehicle sales is at the eth interval, where at interval one the first sales occur; the vehicle is not available for sale beyond that period. By way of explanation, the mth interval is the end of the vehicle model's life cycle. Take note that within the interval (m, m+w), warranty claims are still valid because at the mth interval, the warranty of units sold closely will end at interval m+w. Within this frame of reference, our monitoring organisation is extends beyond the vehicle model life cycle. By the origin of period f, the size of the observed population (i.e., the warranted base) can be considered by

$$\Omega_f = \sum_{1=1\vee(f-w)}^{(f-1)\wedge m} S1 = \sum_{1=1\vee(f-w)}^{(f-1)\wedge m} \sum_{K=1}^{l\wedge e} C_{k,l} \quad f=2,3,.... \tag{4}$$

where $1\vee(f-w) = \max\{1, k-w\}$, and $\Omega 1 = 0$.

The outcome of this analysis is the ability to identify failure rates based on mileage at a given confidence interval. It defines the distance the vehicle travels until component failure. Retrospectively evaluating vehicle component durability based on distance under continuous static and dynamic conditions. The probable output from this function is a prediction of component product failure based on the lapse mileage interval.

Secondly, the model mechanism is established by connecting it with Weibull analytic and simulation mechanism models. The model development is based on the Weibull statistical measurement and actual market feedback information. Thus, the computing process is derived from quality failure simulation. Table 3 represents the first part of the analysis, which is the output of analytic calculations based on Weibull statistics. It evaluates the first level of the model mechanism for mileage that covers the main evaluation criteria of occurrence rate.

Table 3 *Product failure forecast based on mileage*

Lapsed mil ('000km)	CDF, F (t)	No. Occ (Max)	Est. No. of units	Lapsed mil.	Lapsed mil ('000km)
Y_1	B_1	ΣN_1	ΣNm_1	$Logm_1$	Lnm_1
Y_2	B_2	ΣN_2	ΣNm_2	$Logm_2$	Lnm_2
Y_3	B_3	ΣN_3	ΣNm_3	$Logm_3$	Lnm_3
…..	…..	…..	…..	…..	…..
y	b	n	Σn	log	ln
…..	…..	…..	…..	…..	…..
Y_n	B_n	ΣN_n	ΣNm_n	$Logm_n$	Lnm_n

Where;

Y_n : Selected Lapse Month; B_n :Occurrence rate by mileage; ΣN_n : Total Occurrence by mileage; ΣNm_n : Number Generated in Future by mileage; $Logm_n$: Logarithm by mileage; Lnm_n : Linear equation by mileage.

Continue with the third part of the Weibull prediction graph model; the graph generates evaluation results for product failure occurrence rate against mileage (km). It is also a known factor that measures the product failure occurrence rate. The output of the Weibull analytics and graph reflects the product quality failure, which closely connects to the cost of poor quality for the automotive car manufacturer. Thus, expediting the evaluation of quality analysis and prediction. Finally, the model credential verified the market feedback via a constructed algorithm. Such an implementation procedure produces results that meet the planned business model requirements. This parameter completes the process aspect of evaluating product failure through a warranty forecasting simulation mechanism.

2.3 Model Calculation

Prior to reaching to the final output of the warranty forecasting evaluation. There are three steps namely consolidate warranty data, execute warranty analysis, and equate the simulation output. In the first step, clean warranty data on mileage consolidates and rearranges for evaluation by Weibull statistics. This initiates the second step of executing forecasting analysis and generating analytical and graphical output. Then, finally, all criteria and selected parameters execute with final simulation warranty forecasting. These steps are explained in Fig. 3.

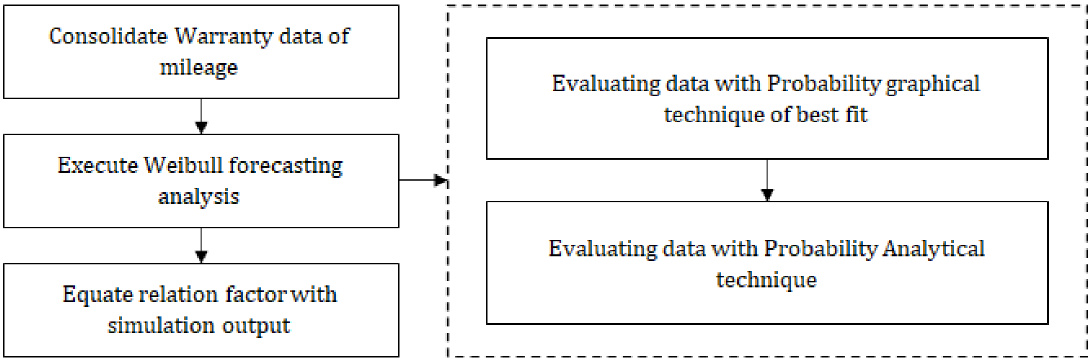

Fig. 3 *Steps in calculating warranty simulation*

2.3.1 Execution of Weibull Forecasting Model

The warranty forecasting simulation mechanism model evaluates overall product failure in a given category. In simulation calculations, the forecasting varies according to the changes caused by the changes in warranty data collected throughout the vehicle warranty. Such output depends on the overall quality improvement action input received by manufacturing and the results experienced by the customer against the customer through a warranty claim received from the service center. The main computation is based on Weibull statistical functions. The Weibull distribution is a Probability Density Function (PDF) of variable X, which has 2 parameters of η and β where β>0. It is illustrated as follows:

$$f(x:\eta,\beta) = \begin{cases} \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} e^{-\left(\frac{x}{\eta}\right)^{\beta}}, & x \geq 0 \\ 0, & \text{else} \end{cases} \tag{5}$$

This follows a condition where the shape parameter β and the scale parameter η, are less than or equal to x. This observation is known as the Cumulative Distribution Function (CDF), which derives as follows:

$$f(x:\eta,\beta) = \begin{cases} 1 - e^{-\left(\frac{x}{\eta}\right)^{\beta}}, & x \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

In reliability engineering, the Weibull distribution is widely used by leveraging several characteristics of other types of distributions [26]. Its flexibility includes different values of β as the universal distribution that allow the applications to analyze the lifetime of a system [27].

2.3.2 Reliability Functions

The reliability function of a system or unit conforming to a surrounding condition defines its likelihood to execute its functions over a projected period. The reliability function, or R(t), provides continuity and reliability over time. It is expressed as:

$$\mathrm{R}\ (\mathrm{t}) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{7}$$

Where t ≥ 0, β > 0, η > 0. In addition, the expression also applies by subtracting from CDF

$$\mathrm{R}\ (\mathrm{t}) = 1 - \mathrm{F}\ (\mathrm{t}) \tag{8}$$

The Weibull failure rate function, or hazard function, is given by

$$\mathrm{h}\ (\mathrm{t}) = \mathrm{f}\ (\mathrm{t}) \ / \ \mathrm{R}\ (\mathrm{t}) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{9}$$

The functions depend on the values of the distribution's parameter of β where the failure rate may decrease (when β<1), or increase over time (when β>1), or constant (when β=1 at 1/η). It controls the density function of the overall shape. The shape (or power) parameter, β having a value range between 0.5 and 0.8, which controls the density functions of the overall shape. Below is the β condition, which was recorded by previous scholars as follows:

- If the Weibull distribution matches the exponential distribution denoted by β = 1
- If the Weibull distribution matches the Rayleigh distribution denoted by β = 2
- If the Weibull distribution came close to the lognormal distribution denoted by β = 2.5
- If the Weibull distribution came close to the normal distribution denoted by β = 3.6

2.3.3 Weibull Probability Graph

In this study, the recommendation graph is a convenient way to oversee the overall situation of the failure pattern. Through the Weibull graphical technique best able to determine the output based on the data set of a given population. The evaluation is based on PDF and CDF, expressed as

$$\text{PDF} = f(t) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} e^{-\left(\frac{x}{\eta}\right)^{\beta}} \tag{10}$$

$$\text{CDF} = F(t) = 1-e^{-\left(\frac{x}{\eta}\right)^{\beta}} \tag{11}$$

Continued with the formula expression for the average failure, also known as the Mean Time to Failure (MTTF) which as follows:

$$\text{MTTF} = E(t) = \eta\Gamma(1+\frac{1}{\beta}) \tag{12}$$

For Weibull distributions, systems or components under analysis are expected to fail at 63.2% at the given age, known as η [28]. It is also known as the spread characteristic, which represents independent parameters of the failure distribution where the failure probability is at a point in the life of the part or system.

For β = 1, MTTF and η are equal. The relationship between MTTF and η is the gamma function:

When β < 1, MTTF > η,

When β = 0.5, MTTF = 2η,

When β = 1, MTTF = η, the exponential distribution

When β > 1, MTTF < η,

Finally, the analysis includes the variance and standard deviation, which is the square root of the variance.

$$\sigma^2 = \eta^2\left[\Gamma\left(1+\frac{2}{\beta}\right)-\left(\Gamma\left(1+\frac{1}{\beta}\right)\right)^2\right] \tag{13}$$

$$\sigma = \sqrt{\eta^2\left[\Gamma\left(1+\frac{2}{\beta}\right)-\left(\Gamma\left(1+\frac{1}{\beta}\right)\right)^2\right]} \tag{14}$$

3. Results and Discussion

Scope of the simulation mechanism study is based on a confidence interval of 10,000km to 100,000km. This is to oversee the warranty forecasting of product failures of supplier products within the agreed durability specification. The results of the analysis will determine the overall cost of poor quality incurred by the supplier.

3.1 Pattern of Warranty Claims Period

The warranted base differs progressively in the extent to which the aspect of Ωf as in equation 4 upholds the earlier description; refer to Fig. 4 as an example. Firstly, it displays initially that Ωf increases over time, then varies, and lastly reduces as f increases. Secondly, the sizes of the sold units in distinct age groups similarly fluctuate with f.

In summary, at earlier commencement, for example, earlier new model launch ages at the beginning were less than w, while at a later stage, near to the end of the warranty period of w, the ages of most units almost ended.

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The aforementioned time-dependent analysis structures make the vehicle warranty claims to observe issues more complex than others, which presents adversity in the development of the monitoring structure.

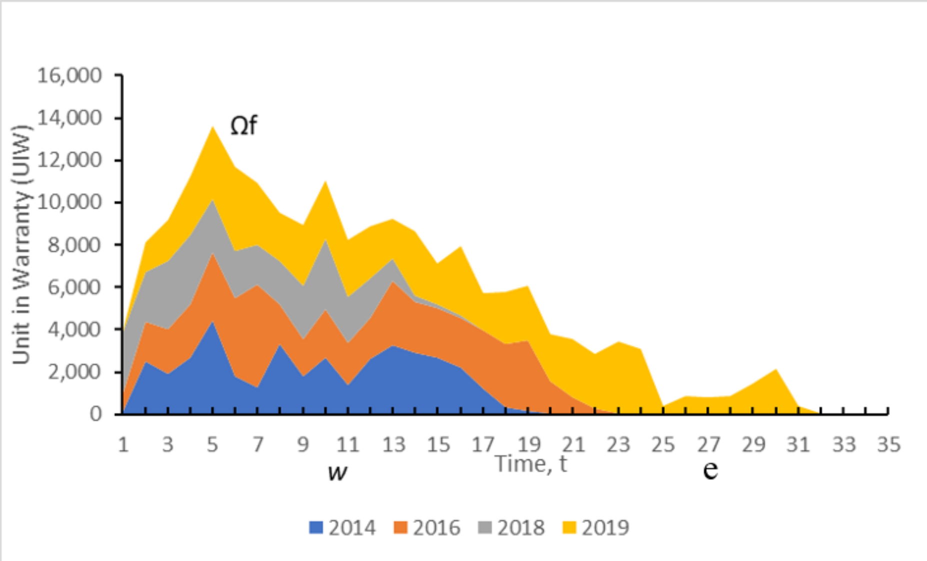

Fig. 4 *Warranted base over the vehicle lifecycle*

3.2 Pattern Warranty Claims Feedback

A total of 1,533 warranty claims for the highest warranty amount and quantity with frequent failure product of part number PN312 were selected. The product failure rate was 3.02% from a total of 50,740 units Model XYZ sales. The product failure pattern from registration to repair is represented in the warranty occurrence pattern graph in Fig. 5. Warranty treatment for product replacement only applies within the agreed period.

In addition, product failures can be monitored by production month, enabling the estimation of the starting point for quality improvement activity. This trend, represented in Fig. 6, allows the engineers to focus available resources on the root cause finding for the given production month. Similarly, with the mileage failure forecast prediction, the results for failure intervals between 10,000km and 100,000km are indicated in Tables 4 and 5. The expected outcome of the analysis is that products that fail within the warranty period can be interpreted as improvement activities. In Table 4, it is observed that mileage components produced a lower shape (β) value of more than 2.0.

The Weibull distribution matches the Rayleigh distribution. Proceed with criteria η that product failure occurred at 403,948km when the incidence occurred at 63%. The average life of the Mean Time to Failure (MTTF) is 357,878km. The following variance, σ^2, and standard deviation, σ, are 27,067,873,101 or 27.1x109 and 164,523km, respectively. Table 5 explains the lapse mileage impact over a maximum distance of 400,000km.

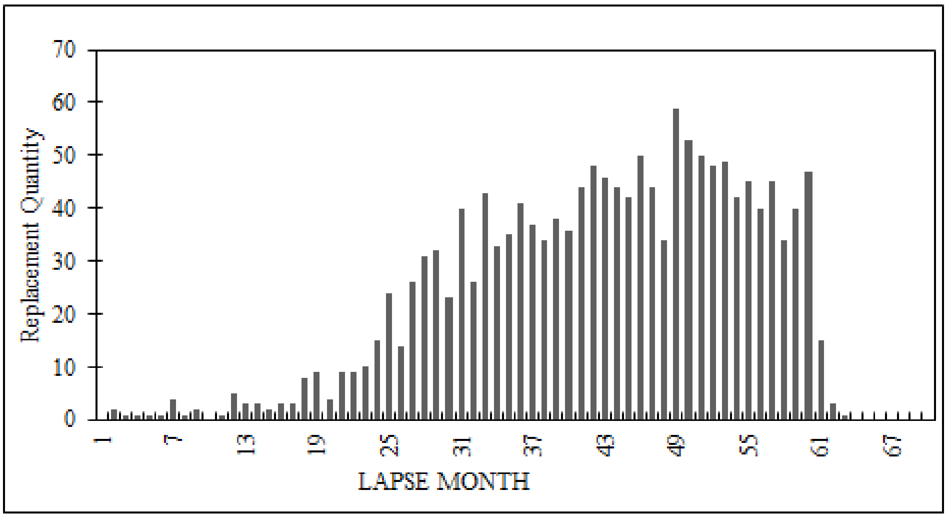

Fig. 5 *Warranty occurrence (Registration to repair)*

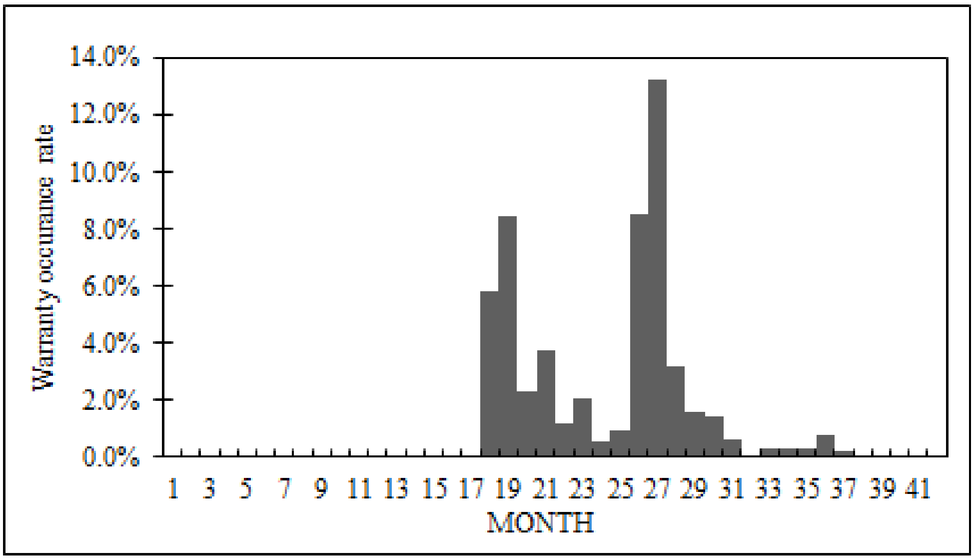

Fig. 6 *Warranty occurrence rate by production month*

This is merely to simulate the future impact of warranty claims on the respective year models of the vehicles. Selecting CDF, F(t), as the main key element in predicting occurrence shares the same pattern as in period evaluation. Based on mileage evaluation of targeted lapsed mileage analysis between 10,000km and 100,000km, it ranges from 0.02% to 62.38%. The number of occurrences is forecast to be between 0 and 452 units. Further observation pointed out that the highest probability of product failure rate is 62% and above once mileage reaches 400,000km.

Table 4 *Occurrence prediction based on mileage*

Criteria	Results
Value of m of y = mX + c, where m=β	2.308
Value of c of y = mX + c, where c=βln	-29.789
*η (when the incidence is 63%)	403,948
Average life *MTTF	357,878
Variance, σ^2	27.1×10^9
Standard deviation, *σ	164,523

Note: *Unit in km

Table 5 *Occurrence prediction by mileage*

Lapsed mil ('000km)	CDF, F (t)	No. Occ (Max)	Est. No. of units	Lapsed mil. (Log)	y value
10	0.02%	10	0	9.21	-8.54
20	0.10%	49	0	9.90	-6.94
30	0.25%	126	0	10.31	-6.00
50	0.80%	407	0	10.82	-4.82
80	2.36%	1195	0	11.29	-3.74
100	3.91%	1984	452	11.51	-3.22
160	11.13%	5647	4115	11.98	-2.14
200	17.92%	9092	7560	12.21	-1.62
300	39.55%	20067	18535	12.61	-0.69
400	62.38%	31651	30119	12.90	-0.02

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Final assessment of accessing an early detection scheme through graphical interpretation based on the y value of CDF, F(t). The line arch of shape (β) in Fig. 7 illustrates the warranty failure simulation line with a high degree of line pattern gradient in the given confidence interval plot. The signal indicates that the lower slope of the 100% plot line gives shape (β) low compared to the scope of the evaluation. Thus, the user can interpret the overall Weibull warranty simulation probability of failure relatively well at any distance given.

Finally, the application of the model validates field measurements of product quality performance through the prediction of warranty part returns. The product quality judgment will be improved through the speed of quality theme-up ratio in expediting countermeasure activity in the market, thus reducing the warranty claim rate as early as possible, as per Fig. 8. Such implementation produces results that reflect the intended business model environment.

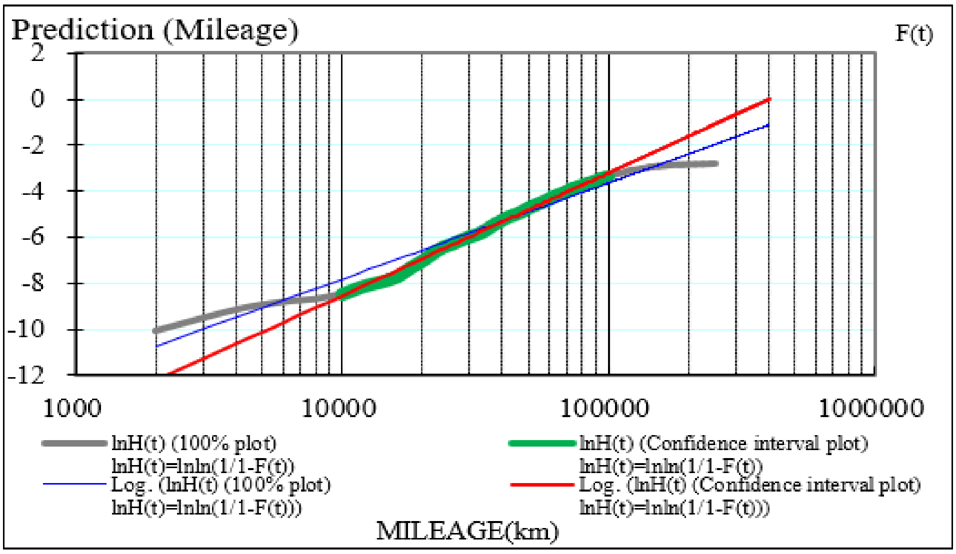

Fig. 7 *Graphical prediction trend by mileage*

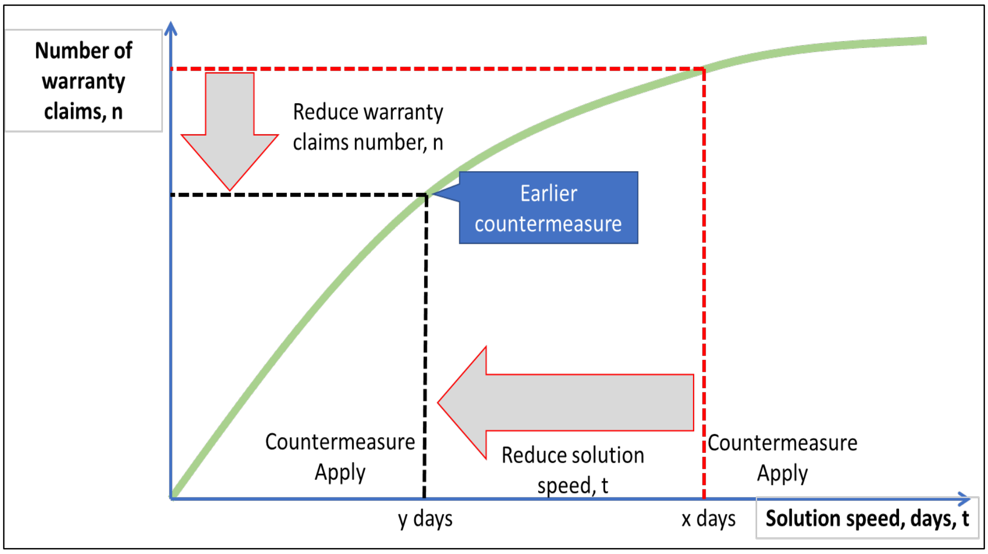

Fig. 8 *The expected outcome of early detection countermeasures*

3.3 Managerial Implication

The outcome of this study gives better guidance to engineers as problem-solving tools in improving vehicle products and systems based on the utilization of this simulation mechanism program in consolidating resources efficiently. Thus, the model application, combined with the selected warranty data, consistently tracks the focus product in evaluating future product failure. In future studies, the application model can be leveraged to predict another variable or parameter of product failure, such as the warranty period.

4. Conclusion

The warranty simulation mechanism model was developed and built based on the Weibull distribution as a recommended model to forecast the future cost of poor quality for the warranted base product. The model combines the evaluation of process regimes and overall warranty prediction, which creatively uses the company data to evaluate product failure, and can be applied to big data analysis as an algorithm model. The results of the model can reflect the prediction of product failure against mileage. It was also able to trigger attribute changes. Thus, give better guidance to engineers in improving vehicle products and systems based on practical advantage utilization. Based on big data analytics, the computation algorithm fundamentally generates a simulation of a forecasting graph and analytic table as per the stated objective. The application model reflects the objective of the study as follows:

- Successfully apply the simulation mechanism program based on the Weibull statistic for the variable parameter of mileage.
- The results of the study identify future warranty returns based on mileage parameter through selected confidence intervals simulated analytically and graphically.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Syahrul Nizam Samsudin, Bulan Abdullah;* ***data collection:*** *Syahrul Nizam Samsudin;* ***analysis and interpretation of results:*** *Syahrul Nizam Samsudin, Bulan Abdullah, Noriah Yusoff;* ***draft manuscript preparation:*** *Syahrul Nizam Samsudin, Bulan Abdullah. All authors reviewed the results and approved the final version of the manuscript.*

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