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ARTICLE

Operational reliability evaluation-based maintenance planning for automotive production line

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ABSTRACT
Reliability evaluation plays a critical role in upgrading the availability and productivity of automotive manufacturing industries by adopting the well-planned maintenance. Due to the lack of operation management studies in automotive industry, this paper addresses an operational reliability evaluation through failure behavior trend in an automotive production line. The main approaches for reliability analysis in this study include statistical structure and Monte Carlo simulation model. The statistical structure consists of three steps: data acquisition and homogenization process, validity of the trend hypothesis and parameters estimation. The reliability evaluation under statistical approach identified the main bottlenecks through the recognized behavior trend of system so that needs to be considered as a priority. Besides, K–R algorithm as Monte Carlo simulation was carried out to simulate reliability regarding failure distribution function. The result of Monte Carlo simulation with different iterations provides a high prediction accuracy of reliability with the lowest error. In addition, regarding the computed reliability through the proposed approaches and total expected cost, a reliability-based maintenance optimization model was conducted. The proposed maintenance intervals could be useful for improving the operational performance of critical components in automotive system.

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KEYWORDS
Automotive industry; reliability; maintenance interval; Monte Carlo simulation; statistical structure

1. Introduction

With increasing systems' complexity and automation of manufacturing systems, having a reliable operation is one of the major challenges facing the implementation of industry 4.0 (Rüßmann et al., 2015; Shrouf, Ordieres, & Miragliotta, 2014). To achieve a reliable operating condition along with high productivity and quality in order to remain competitive in the global market, asset performance analysis such as reliability indices is necessary (Becker, Borst, & van der Veen, 2015; Xu, Xie, Tang, & Ho, 2003). Comprehensive knowledge of reliability plays a key role in predicting the spare parts and the unplanned downtime cost as well as suggesting the optimal maintenance intervals (Darghouth, Chelbi, & Ait-Kadi, 2017; Mokhtari, Mozdgir, & Abadi, 2012). The system reliability is defined as reaching a remarkable performance in a given time and under given conditions (Tortorella, 2005). In other words, reliability is the probability that a system functions adequately without any failure, within a specified period of time, when it is subjected to normal operating conditions (Cui, Chen, & Gao, 2018).

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In general, the reliability analysis methods can be classified into qualitative, quantitative and simulation methods, which have been conducted under various situations (Adefarati & Bansal, 2017; Kumar & Goel, 2017; Riascos-Ochoa, Sánchez-Silva, & Klutke, 2016; Tsarouhas, 2015). The special applicability of these approaches depends on different parameters, such as type of system or process, accessible data (e.g. real/historical data or expert knowledge), complexity of system, etc. (Ben-Daya, Kumar, & Murthy, 2016). The lack of quantitative data is one of the main issues driving researchers to apply the qualitative methods for reliability analysis (Yazdi & Soltanali, 2018). In recent years, a majority of studies have been accomplished to the application of qualitative approaches based on expert knowledge and overcoming their drawbacks by intelligent techniques. Besides, the operational data such as failure data set are known as main tool for quantitative and simulation methods to reliability evaluation (Ahmad & Kamaruddin, 2012; Görkemli & Kapan Ulusoy, 2010).

The present study focuses on quantitative and simulation methods according to the characteristics and nature of the accessible quantity data provided by automotive production equipment. Among the quantitative approaches, the statistical roles are the popular and efficient tools for evaluating reliability. In this direction, Barabady and Kumar (2008) proposed a statistical structure for reliability analysis in three steps including data collection, trend test and parameter estimation. Garmabaki, Ahmadi, Mahmood, and Barabadi (2016) improved a new statistical structure for reliability analysis that consists of data acquisition and homogenization process, validity of the trend hypothesis and parameters estimation. Recently, a system reliability performance based on a dependent two-stage failure process, including the defect initialization stage and the defect development stage with competing failures, has been improved by Qiu and Cui (2018). The dependence between these two stages was modeled by statistical role, namely nonhomogeneous Poisson process (NHPP) model. In another work, Qiu, Cui, Gao, and Yi (2018) developed the concept of sequential probability series system in failure states. They derived some analytical expressions for the optimal allocation solutions under certain assumptions. Also, an efficient genetic algorithm (GA) was conducted to search the optimal solutions, when the lifetime of units follows general distributions.

On the other hand, the analytical methods such as statistical models do not capture all characteristics of a system. Thus, uncertainty always exists in the hypothesis underpinning the model (model uncertainty) and in the values of its parameters (parameter uncertainty); these lead to uncertainty in the model output (Nutt & Wallis, 2004). To overcome such limitations, the simulation approaches are suggested as a useful alternative to analytical method for reliability analysis in repairable systems. They can provide a wide range of output parameters including all moments and complete probability density functions. They can also handle very complex scenarios, such as non-constant transition rate, multi-state systems and time-dependent reliability problems. Moreover, the simulation techniques provide remarkable flexibility in solving any type of complex problems (Hoseinie, Ghodrati, & Kumar, 2013; Rao & Naikan, 2016).

For this purpose, the stochastic simulation is an appropriate technique to evaluate and predict the reliability of a system, which can be applied in two ways (Hoseinie, Al-Chalabi, & Ghodrati, 2018): (a) sequential approach, by examining each basic interval of the simulated period in a chronological order and (b) random approach, by examining the randomly chosen basic intervals of the system lifetime. The random approach known as 'Monte Carlo' method is a numerical method that allows the solution of mathematical and technical problems by means of probabilistic models and the simulation of random variables. The Monte Carlo simulation is a powerful approach for the reliability analysis of large-scale complex networks that have been employed in different applications. In this method, the stochastic failure occurrence of the system is analyzed and the probability of the failure and success of the system operation are computed (Wang & Pham, 1997).

Therefore, there are many potentials to apply the simulation methods for predicting reliability and comparing their results with the statistical methods, because of existing complex systems and uncertain environment in process industry, particularly in automotive industry under real/operational data. In general, reliability studies in automotive sector can be divided into two categories: design reliability focusing on vehicle systems and operational reliability focusing on production process. Most studies have emphasized on design reliability of vehicle components. In such studies, the main purpose of reliability analysis is to improve the resilient and recoverability of automotive systems. In this context, the reliability of a vehicle body-door subsystem is examined by Zou, Mahadevan, Mourelatos, and Meernik (2002). Subsequently, reliability of automotive door subsystem is analyzed by Zou, Mahadevan, Mourelatos, and Meernik (2003) and also a vehicle reliability estimation model for improving performance of crank-case subsystem in a two-wheeler automobile has been suggested by Garg, Singh, and Singh (2010).

On the other hand, very few studies have been conducted on operation management in particular focusing on evaluating operational reliability in automotive production phase. The major studies include reliability analysis for robotic subsystem by Fudzin and Majid (2015) and operational reliability analysis for critical equipment in automotive assembly line by Li and Ni (2008). In such studies, the simple traditional distribution function such as Weibull was fitted on failure data and the main parameters such as homogenization process, validity of the trend hypothesis and correlation test have been ignored for reliability analysis. In other words, they assumed that the failure data follow the simple traditional distributions as well as the same homogenous environment. These issues may affect the accuracy of the estimated reliability and the proposed maintenance intervals. As a main contribution of this study, for making reliability model, most of these parameters were included in the proposed statistical structure, and then the optimal maintenance intervals were suggested. In addition, the application of maintenance planning based on proposed reliability structures has not yet been studied by researchers. In other words, they have only suggested the reliability analysis for deciding maintenance intervals as a future perspective in automotive production process.

Hence, the main objectives of this study are to evaluate the operational reliability based on statistical modeling and simulation like 'Monte Carlo' method, and their extension to cost-based maintenance models. Accordingly, this study contributes a reliability-based maintenance planning through the proposed approaches and total expected cost on fluid-filling system (as a case study) in an automotive production process.

2. Methodology

2.1. System description

To provide guidelines for reducing failure frequency in automotive assembly line, the fluid-filling system as the most critical and complex equipment was selected and the reliability-based maintenance planning was implemented. Study and analysis of the reliability of such system from the perspectives of both operational and non-operational aspects are important for the management. Firstly, because of the importance of the speedy nature of these manufacturing operations, a low reliability leads to an increase in operational costs and equipment failure, and ultimately a downtime in the production lines. Secondly, improvement of system reliability and availability can enhance the safety of operators and vehicle drivers by adapting well-planned maintenance interval. The main fluid-filling systems in automotive assembly line include six main equipment: washing, gearbox, coolant, fuel, brake and hydraulic fluid-filling equipment. Each of the fluid-filling equipment consists of six critical blocks, as shown in Figure 1. Generally, in different fluid-

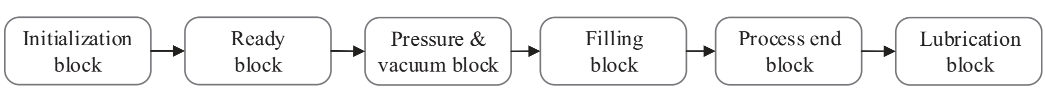

Figure 1. Process description of the fluid-filling system.

filling systems, most of the blocks are similar. In addition to the same block, even these systems have almost the same subsystems. The main subsystems of each fluid-filling system include the hydraulic-pneumatic circuit, the electrical circuit and the filling head set. In this regard, the data and required information such as failure frequencies, number of failures and time between to failures (TBFs) data of these subsystems related to the six fluid-filling systems were collected from the computerized maintenance management system of an Iranian automotive company. Then, the failure data set were sorted and screened. Subsequently, the outlier identification data were detected and removed using Minitab version 18 software. Each fluid-filling system takes care of leakage test through producing pressure and vacuum as well as filling and leveling different fluids in paths and pipes in vehicles. The filled amounts for types of vehicles based on appointed standards differ. The most important feature of the system is simultaneous activity of many components in different blocks. In addition, any failure of the important components in each of the components leads not only to system disability but also to downtime in the production lines.

Figure 2 shows a scheme of the fluid-filling subsystems including the hydraulic-pneumatic circuit, the electrical circuit and the filling head set. The filling pump is used for fluid injection, the pressure controlset (PCS) the required pressure, and the pipes and fittings are designed to carry air and other fluids. The electrical circuit includes a programmable logic controller (PLC) which comprises of different sensors, anti-lock braking system (ABS) and starter. The filling head set is mounted on the vehicles. The crucial components of this set include mini-valves, coupling and O-rings & seals.

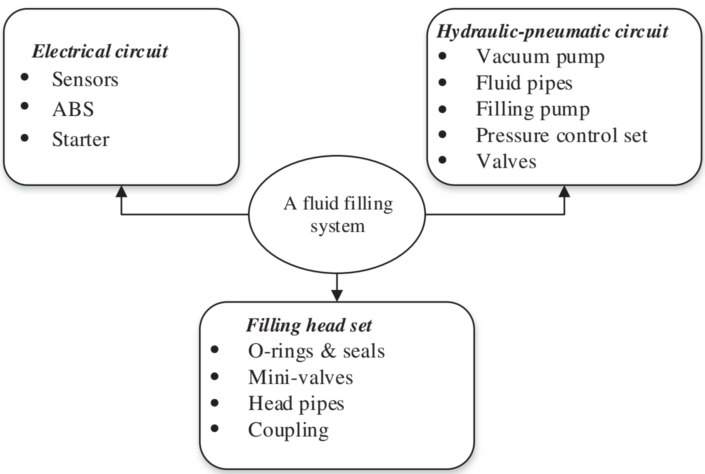

Figure 2. Structural diagram of the fluid-filling system.

2.2. Reliability and failure rate analysis

There are two popular methods for estimating the reliability: analytical and non-analytical approaches. Hence, in this study, a systematic decision algorithm under statistical methods was adapted. This is defined based on statistical distributions. On the other hand, the non-analytical method employs computer simulation tools like Monte Carlo simulation (Calixto, 2013).

2.2.1. Statistical structure

The process of evaluating reliability using statistical structure is shown in Figure 3 (Barabady & Kumar, 2008). After sorting and classifying the failure data, in the next step the homogeneous groups were created based on a checklist that is available from risk analysis for NASA manager's handbook (Stamatelatos et al., 2011). In this study to provide the homogeneous samples, the main items were considered with the same location and environment, manufacturer, installation and design and the same software and procedures. Then, the validity of the assumption of independent and identically distributed (iid) nature of the time between failure and the time to repair data of each component is assessed. This can be performed by the trend test and the serial correlation test approaches (Najafi, Asoodar, Marzban, & Hormozi, 2015; Tsarouhas, 2015). The null hypothesis and the alternative hypothesis are as follows: H_0: no-trend in the data (homogeneous poison process/renewal process) and H_1: trend in the data (non-homogeneous poison process).

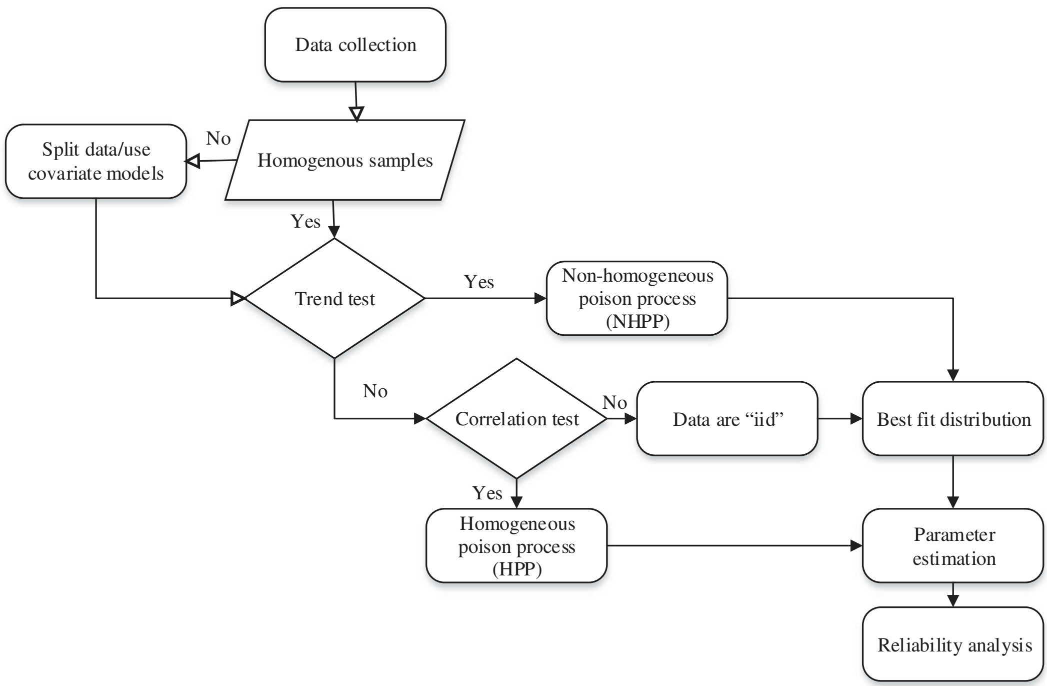

Figure 3. The statistical structure for the reliability analysis adapted from Barabady and Kumar (2008).

Moreover, the test statistic U is chi-square distributed with $2_{(n-1)}$ degrees of freedom (df) (Tsarouhas, 2015). The U statistic is calculated based on the experimental failure data, whereas the $\chi^2_{a,\ df}$ can be determined by the chi-square distribution given the df. If the statistic is $U > \chi 2_{a,\ df}$, the null hypothesis is plausible, otherwise the null hypothesis is rejected and the alternative hypothesis H_1 is accepted. The trend test results are compared with the statistical parameter U as follows (Najafi et al., 2015):

$$U = \sum_{i=1}^{n-1} \ln\left(\frac{T_n}{T_i}\right) \tag{1}$$

If the assumption that the data are '*iid*' is not valid, then classical statistical techniques for reliability analysis may not be appropriate'; therefore, a non-stationary model such as non-homogeneous poison process (NHPP) based on power law process (PLP) needs to be fitted. The PLP has been widely used in reliability growth and software reliability models. The intensity function of the PLP is given by (Tsarouhas, 2012)

$$\rho(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \quad \alpha, \beta > 0 \tag{2}$$

where α and β are the scale and shape parameters of the PLP, respectively, and t is the running time. The cumulative failure function is defined as

$$H(t) = \left(\frac{t}{\alpha}\right)^{\beta} \tag{3}$$

The scale and shape parameters of the PLP can be estimated as follows:

$$\beta = \frac{n}{\sum_{i=1}^{n} \ln\left(\frac{t_n}{t_i}\right)} \tag{4}$$

$$\alpha = \frac{t_n}{n^{1/\beta}} \tag{5}$$

where t_i is the total running time at the ith event and n is the number of failure events. If the shape parameter $\beta > 1$, reliability decreases. In the case of shape parameter $\beta < 1$, reliability improves. If $\beta = 1$, the PLP reduces to the homogenous poison process (HPP) with intensity of $1/\alpha$. Hence, the reliability and failure probability functions at time t are defined by (Tsarouhas & Arvanitoyannis, 2011)

$$R(t) = \exp[-H(t)] = \left[\exp - \left(\frac{t}{\alpha}\right)^{\beta}\right] \tag{6}$$

$$Q(t) = 1 - R(t) = 1 - \left[\exp - \left(\frac{t}{\alpha}\right)^{\beta}\right] \tag{7}$$

2.2.2. Monte Carlo simulation

The Monte Carlo simulations are performed by different algorithms for reliability evaluation which are mainly built up on the Kamat and Raily (K–R) algorithm. It is considered the most general reliability simulation method, and other methods, such as Rice and Moore (R–M), Chao and Huang (C–H), Lin et al. (L–D–L) and Lin and Donagh (L–D) are known as the modifications or specializations of K–R algorithm (Hoseinie et al., 2013; Rao & Naikan, 2016).

The K–R algorithm has been well adopted in system reliability analysis of complex systems. Furthermore, it is the first one in analyzing repairable systems and has a very simple substance and fast running process (Hoseinie, Ataei, Khalokakaie, Ghodrati, & Kumar, 2012; Wang & Pham, 2006). In this method, the random failure times for each subsystem are generated based on defined failure distribution functions, which are then applied to assess the success or the failure of the system. The main steps of K–R algorithm for reliability prediction are as follows (as displayed in Figure 4) (Hoseinie et al., 2013):

(I) Find all minimal tie-sets from system block diagram. Assume, we should obtain system reliability interval at some time t.
(II) Generate a random failure time t_i according to the life distribution of each subsystem where i represents the ith subsystem, $0 < i < t$.
(III) Compare t_i with t for all subsystems. If $t_i > t$ this shows that at the time t subsystem i holds proper functions. If $t_i < t$, the subsystem i has failed.
(IV) Determine whether the whole system is properly functioning or not according to the statue of its subsystems at t from step (III). Check all subsystems in a minimal tie-circuit.

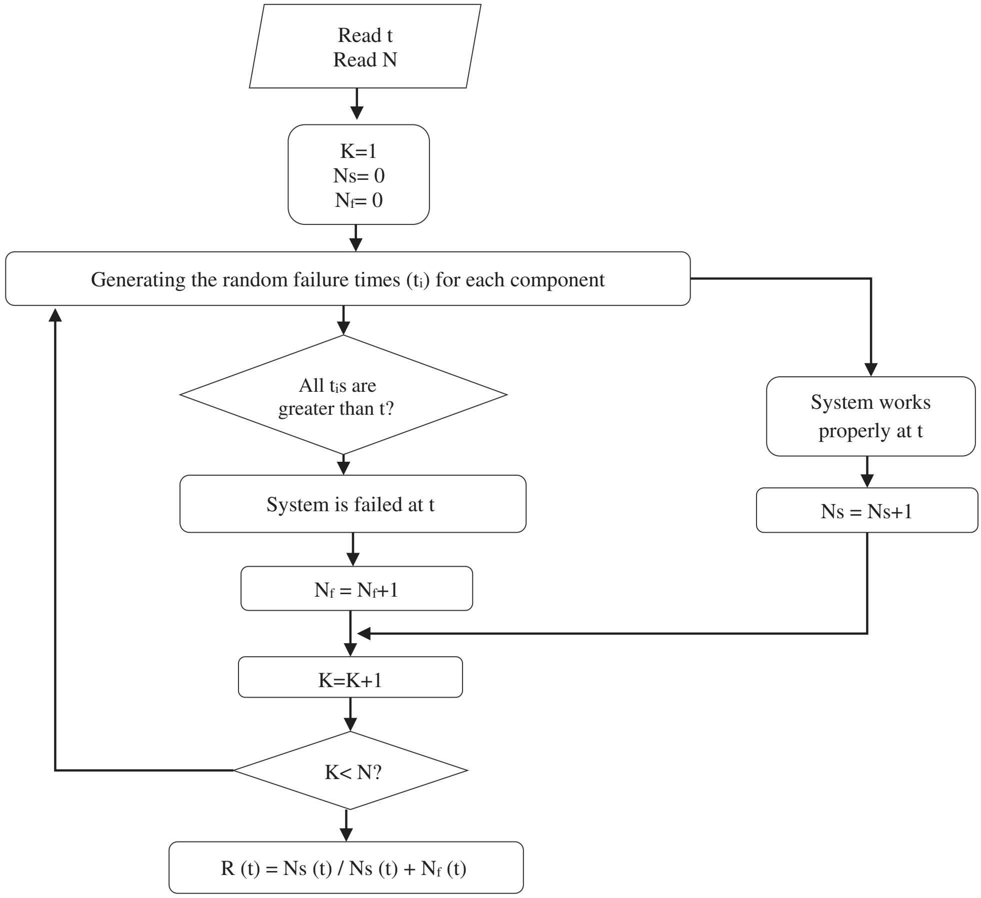

Figure 4. K–R algorithm to calculate the reliability at time t (Hoseinie et al., 2013).

If all are operational, the system is properly operating at time t. If one or more fails, the tie-circuit is broken (failure) at t. Check the next minimal tie-circuit until an unbroken one appears which means the system is operational at t. If all minimal tie-circuits are broken, the system fails at t.

(V) Repeat steps (II), (III) and (IV) for N times. Count the failure and success numbers of the system, respectively: N_s (t) and N_F (t). It should be mentioned that $N = N_s(t) + N_F(t)$.

(VI) The system reliability is estimated in period t by

$$R(t) = \frac{N_S(t)}{N_S(t) + N_F(t)} \tag{8}$$

2.2.3. Maintenance optimization model

The optimal maintenance interval for cycle T (planning horizon) has been suggested by Rezaei, (2015). The failures take place at times $k\tau(\tau, 2\tau, \ldots, k\tau)$, as well, repair are performed at the end of the cycle T (for $k = n$, at the time $n\tau$).τ is the time between two consecutive maintenances, i.e.τ = T/n. The objective is to find the optimal maintenance interval time to minimize the total expected cost of the system over the cycle T. The total expected cost incurred in the inspection k for each cycle (τ) is given by

$$E_\tau\left[C^T_{Total}\right] = \sum_{i=1}^{n}\sum_{k=1}^{T/\tau} E_\tau\left[C_i^{(k-1)\tau,k\tau}\right]$$

$$\left(\begin{array}{l} \sum_{i=1}^{n}\sum_{k=1}^{T/\tau}\left(\tau_i^I W^I + \tau_i^I P\right) + \sum_{i=1}^{n}\sum_{k=1}^{T/\tau}\left(\mathrm{Re}_i + \tau_i^R W^R + \tau_i^R P\right)(1 - R(k\tau)) + \\ \sum_{i=1}^{n}\sum_{k=1}^{T/\tau}\left(\tau_i^{PF} P + L\right)(1 - R(k\tau)) \end{array}\right) \quad (9)$$

$$\forall \tau = T, T/2, T/3, \ldots, T/T$$

where $E_\tau\left[C^T_{Total}\right]$ is the total expected cost, W is the inspection/preventive cost, Re is the repair/perfect replacement cost, P is the production loss cost and L is the downtime cost.

According to the work of Rezaei (2015), the optimal maintenance interval can be obtained as follows:

$$\eta C = \frac{\sum_{i=1}^{n}\sum_{k=1}^{T/\tau} E_\tau\left[C_i^{(k-1)\tau,k\tau}\right]}{k.\int_0^\tau R\ (k\tau)dt} \quad (10)$$

where ηC(kτ) is the optimal maintenance interval at $k\tau$ (τ, 2τ, …, kτ), $R\ (k\tau)$ is the computed reliability based on proposed methods (based on Sections 2.2.1 and 2.2.2).

3. Results and discussion

3.1. Statistical description

In order to facilitate the computation, the fluid-filling systems were divided into three major subsystems: filling head set, electrical circuit and hydraulic-pneumatic circuit. Based on data collected in recent years, the contributions of failure frequencies in fluid-filling system for the above subsystems were 42%, 35% and 23%, respectively. The descriptive statistics of the basic features of the TBF data are given in Table 1. The following observations were made: (a) the mean TBFs for three subsystems were 639, 336 and 225 h suggesting that in every 26, 14 and 9 days of operation a failure occurs in the fluid-filling system, respectively. (b) The coefficients of variance (CoefVar) at three subsystems were around 75.54, 125.59 and 88.64 h, respectively. Also, the subsystems had the greatest standard deviation (StDevs). To put it differently, they had high

Table 1. The descriptive statistics of the failure data for failure data at fluid-filling system.

Subsystem	Component	TBF (h)	St. dev	CoefVar	Minimum	Maximum	Skewness	Kurtosis
Hydraulic-pneumatic circuit	Vacuum pump	1293	633	48.90	316	2852	0.76	0.32
	Valves	3950	2669	67.56	1601	10635	1.66	2.33
	PCS	1685	934	55.41	553	4174	1.05	0.69
	Total	639	483.1	75.54	6.5	2050	0.66	−0.40
Electrical circuit	Sensors	1049	858	81.70	858	3411	1.13	0.84
	Starter	1623	1482	91.31	114	5469	1.29	1.10
	ABS	599	818.50	136.57	2.5	4520	2.40	6.76
	Total	336	422.20	125.59	0.5	3240	2.93	13.51
Filling head set	O-rings & seals	393	309.83	78.70	8.50	1698	1.31	2.17
	Coupling	1191	605.20	50.78	76	2602	0.33	−0.51
	Mini-valves	977	514.50	53.36	209	2269	0.45	−0.43
	Total	225	199.70	88.64	1.5	999	1.20	1.01

deviation from their means. (c) The minimum TBFs were observed at the filling head set with 1.5 h, and at the next rank electrical circuit with 0.5 h. Therefore, the maintenance personnel must pay due attention to these components. The maximum TBFs were estimated 2050, 3240 and 999 h at three subsystems levels, respectively. (d) The more distributions of TBF at system level showed positive skew values. This indicates that the tail on the right side is longer than on the left side.

3.2. Reliability evaluation result

The validity of the assumption for '*iid*' nature of the TBF data of each subsystem was checked. The validity of the trend for the TBF based on MIL-Hdbk-189 test and Laplace's test (A significant level of 0.05) are shown in Table 2. It is assumed that the null hypothesis and the alternative hypothesis are as follows: H_0: no-trend in data (renewal process/homogeneous Poisson process) and H_1: trend in data (non-homogeneous Poisson process). According to the values obtained in the two tests (>0.05), the null hypothesis is plausible. In other words, the data have not trended. Furthermore, Figure 5 represents a serial correlation graphical test for the components. Accordingly, TBF data set for these components with 5% significance level is '*iid*'. Therefore, they can be subjected RP models in forms of theoretical distributions to reliability evaluation.

Table 2. Trend tests results for failure data of fluid-filling system.

Subsystem	Component	MIL-Hdbk-189 test (U)	Laplace's test	Decision for H_0
Hydraulic-pneumatic circuit	Vacuum pump	0.61	0.63	>0.05 Not rejected
	Valves	0.36	0.31	>0.05 Not rejected
	PCS	0.61	0.33	>0.05 Not rejected
Electrical circuit	Sensors	0.12	0.41	>0.05 Not rejected
	Starter	0.60	0.28	>0.05 Not rejected
	ABS	0.56	0.47	>0.05 Not rejected
Filling head set	O-rings & seals	0.50	0.23	>0.05 Not rejected
	Coupling	0.91	0.22	>0.05 Not rejected
	Mini-valves	0.72	0.30	> 0.05 Not rejected

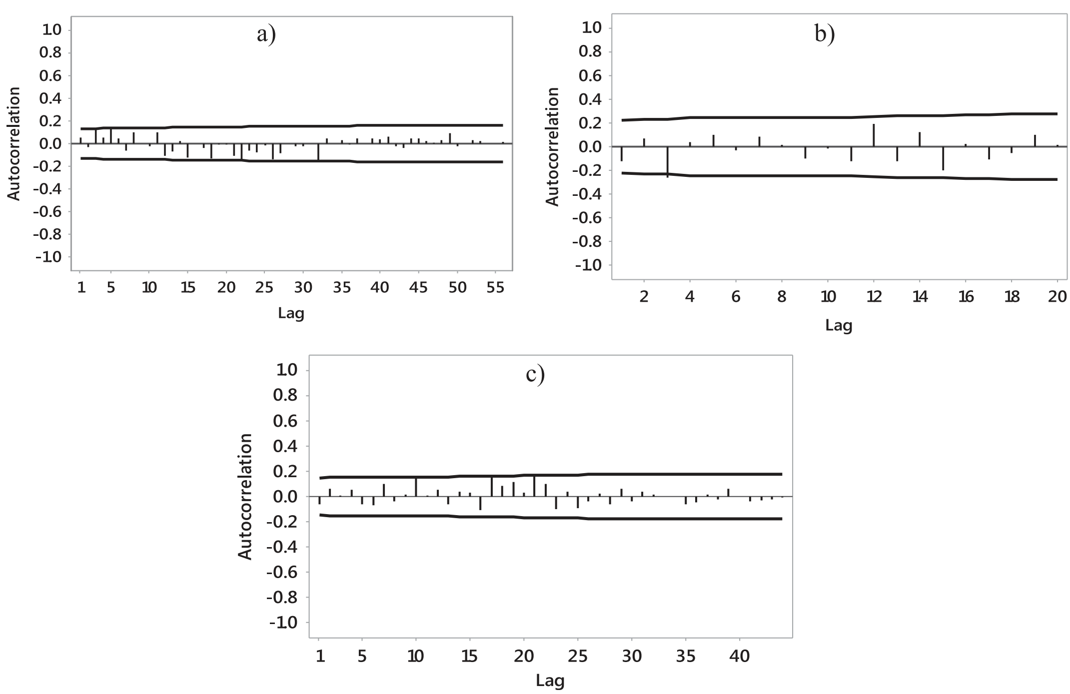

Figure 5. Autocorrelation test of failure data for (a) filling head set, (b) hydraulic-pneumatic circuit and (c) filling head set at 5% significance level.

Furthermore, the serial correlation (autocorrelation (ACF)) test for failure data of the subsystems is evident in Table 3. It is assumed that the null hypothesis H_0: *No-correlation in data*, and the alternative hypothesis H_1: *Correlation in data*. Considering that the *t*-test values are in the range of the confidence level (−1.96 <confidence level of 95% <+1.96), the null hypothesis (*No-correlation in data*) is plausible. In addition to, a serial correlation diagram represents the sketching of $\rho_{\tilde{k}}$ against lag k, where $\rho_{\tilde{k}}$ are the correlation coefficients and lag k are the lag-time periods separating the ordered data. Correlation coefficients range from −1 (a perfect negative relationship) to +1 (a perfect positive relationship). The value of 0 indicates no linear relationship that is no-correlation. Therefore, the failure data for the fluid-filling system are '*iid*'. Further, Figure 5 represents a serial correlation graphical test for the components. Accordingly, TBF data set for fluid-filling system with 5% significance level is '*iid*'. Therefore, they can be subjected RP models in forms of theoretical distributions to reliability evaluation.

Table 3. Serial correlation (autocorrelation) test for failure data of fluid-filling system.

Subsystem	Component	ACF	*t*-test	LBQ[a]	−1.96 < confidence level of 95% < +1.96
Hydraulic-pneumatic circuit	Vacuum pump	0.006	0.016	3.75	Not reject
	Valves	−0.14	−0.52	2.77	Not reject
	PCS	0.03	0.20	3.97	Not reject
Electrical circuit	Sensors	−0.02	−0.14	3.96	Not reject
	Starter	−0.02	−0.11	2.88	Not reject
	ABS	0.04	0.38	19.80	Not reject
Filling head set	O-rings & seals	0.01	0.14	37.65	Not reject
	Coupling	0.18	0.98	20.43	Not reject
	Mini-valves	0.18	1.07	26.13	Not reject

* With 5% significance limits for the autocorrelation. [a] Ljung–Box Q (LBQ).

The MLE method was applied to calculate the scale and shape parameters of theoretical distributions. The AD test was performed to select the best fit of the distributions (Table 4). It is well known that the smaller the statistic value is the better model fit. Therefore, making clear that the failure data have followed the Weibull distribution as best fit with the lowest value. Based on the competed parameters, since the most of failure rates are increasing (α > 1), it is implied that the fluid-filling system is in 'wear out' phase of their life cycle. This means that the current applied maintenance strategies are not adequate and must be upgraded immediately.

Table 4. The best-fit distribution for failure data of components.

Subsystem	Component	Weibull	Lognormal	Exponential	Logistic	Normal	Best exact parameter
Hydraulic-pneumatic circuit	Vacuum pump	0.67[a]	0.79	5.04	0.91	1.02	Shape = 2.18, Scale = 1468.00
	Valves	1.30[a]	1.46	2.34	2.12	2.05	Shape = 1.70, Scale = 4474.96
	PCS	0.69[a]	0.75	3.24	1.29	1.24	Shape = 1.94, Scale = 1920.69
Electrical circuit	Sensors	0.55[a]	0.90	0.99	1.46	1.71	Shape = 1.23, Scale = 1126.02
	Starter	0.71[a]	0.81	0.74	1.58	1.73	Shape = 1.15, Scale = 1692.30
	ABS	0.36[a]	0.92	5.25	7.09	9.32	Shape = 0.72, Scale = 489.14
Filling head set	O-rings & seals	0.40 [a]	1.29	2.59	3.00	3.70	Shape = 1.29, Scale = 426.47
	Coupling	0.44[a]	1.37	4.60	0.71	0.58	Shape = 2.06, Scale = 1342.08
	Mini-valves	0.97[a]	1.30	5.40	1.18	1.27	Shape = 2.04, Scale = 1090.67

[a] Indicates the lowest value.

In addition, exact parameters, estimating the confidence intervals (upper and lower) for the shape-parameter and the scale-parameter were discussed. The simultaneous Tukey test for reliability evaluation of the fluid-filling system considering three types of parameter estimation approaches is presented in Table 5. The mean comparison result revealed that there is no significant difference between the exact parameters and with the upper and lower parameters for reliability estimation (significant at 0.05). In other words, it can be concluded that the exact parameters could be a useful manner for estimating reliability function.

Table 5. Simultaneous Tukey test for comparison of exact versus upper and lower parameters.

Subsystem	Component	Lower value	Upper value	Significant reliability estimation (*P*-value)
Hydraulic-pneumatic circuit	Vacuum pump	Shape = 1.83, Scale = 1289.80	Shape = 2.65, Scale = 1701.95	0.42
	Valves	Shape = 2.18, Scale = 3872.82	Shape = 2.18, Scale = 5110.06	0.10
	PCS	Shape = 1.49 Scale = 1768.00	Shape = 2.40, Scale = 2123.74	0.81
Electrical circuit	Sensors	Shape = 0.98, Scale = 892.50	Shape = 1.38, Scale = 1438.00	0.27
	Starter	Shape = 0.86 Scale = 1283.93	Shape = 2.18, Scale = 2015.14	0.80
	ABS	Shape = 0.62 Scale = 890	Shape = 0.84, Scale = 572.11	0.41
Filling head set	O-rings & seals	Shape = 1.14, Scale = 382.38	Shape = 1.48, Scale = 481.05	0.27
	Coupling	Shape = 1.76, Scale = 1151.17	Shape = 2.63, Scale = 1564.64	0.19
	Mini-valves	Shape = 1.71, Scale = 955.00	Shape = 2.48, Scale = 1258.59	0.21

The failure rate of each component of the three subsystems including filling head set, hydraulic-pneumatic circuit and electrical circuit for fluid-filling system is presented in Figure 6, respectively. It can be seen that the min-valves of the filling head set and the vacuum pump of hydraulic pneumatic circuit have the highest failure rate with the most increasing trend (with the steepest slope). In addition, the electrical circuit has the lowest decreasing failure rate (with fairly negative slope) compared with the other subsystems in particular the starter.

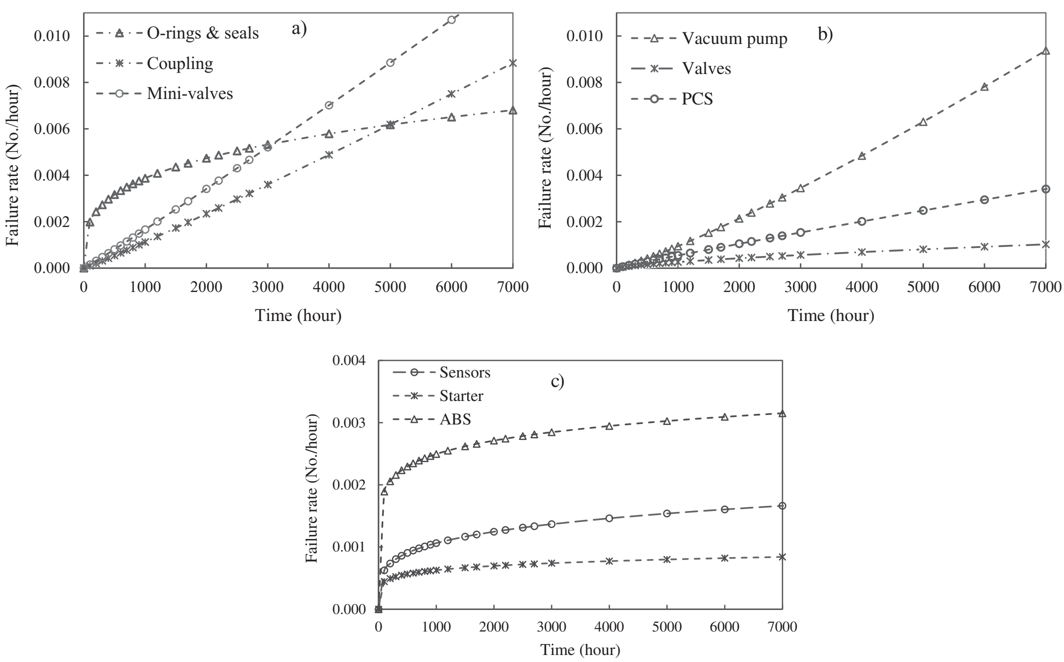

Figure 6. The failure rate functions: (a) filling head set, (b) hydraulic-pneumatic circuit and (c) electrical circuit.

Based on the failure rates, the reliability functions confirm that the components of filling head set including, O-rings & seals, mini-valves and coupling tend to reach zero earlier after 1500 and 2200 and 2400 h of operation, receptively (Figure 7 (a)). Corrosion of O-ring and seals due to chemical impact of fluids and more functioning can affect the leakage of couplings and mini-valves in the filling head set. In addition, the main aspect of coupling failure affected by frequently hit, because of operator's error that might be due to weakness of maintenance staffs in servicing and daily inspections, and also neglecting suitable training schedule of operators. Moreover, improving the design aspects of filing head set such as using light weight and appropriate material could reduce personal faults (prohibited form muscle and joint pressures) and hence improving the reliability.

Moreover, the reliability of hydraulic-pneumatic circuit components including, vacuum pump, valves and PCS set tend to reach zero earlier after 3000 and 7000 and 5000 h of operation, receptively(Figure 7 (b)). The majority of failures affecting the vacuum pump are related to fatigue and strain of spring, and filter failure due to its frequently use. Also, the reliability for the electrical circuit components such as ABS, starter and sensors tend to reach zero earlier after 2000 and 5000 and 6000 h of operation, receptively (Figure 7 (c)). Given the computed reliability, the suitable maintenance intervals should be initially focused on filling head set, followed by electrical circuit to improve the reliability of the whole fluid-filling system.

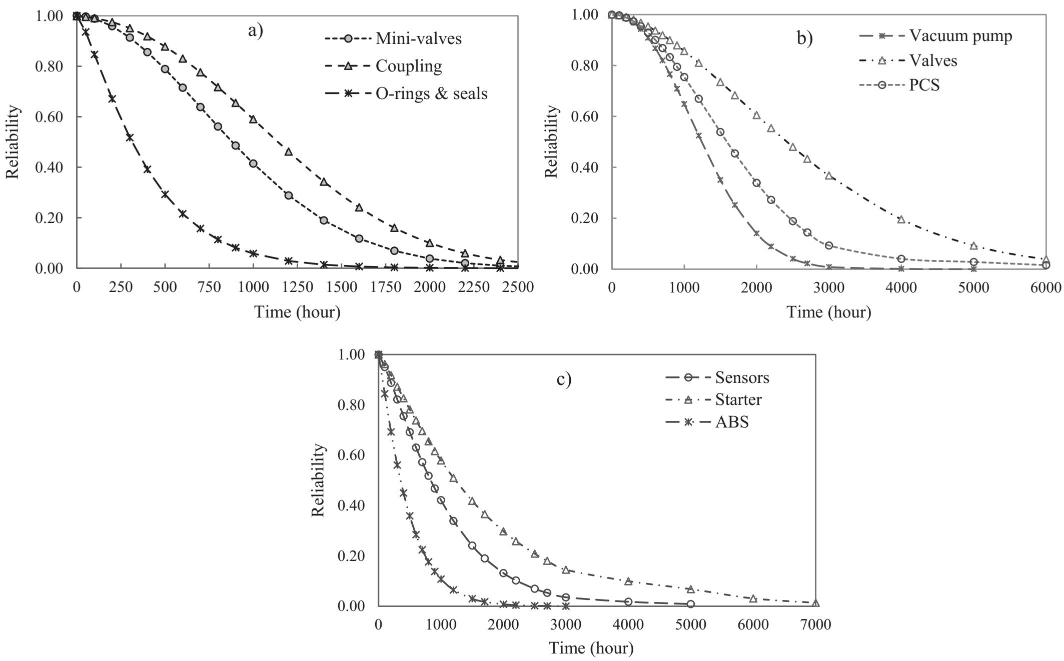

Figure 7. Reliability function: (a) filling head set, (b) hydraulic-pneumatic circuit and (c) electrical circuit.

If the three subsystems and their components of the fluid-filling system considered as a series configuration (the failure of any component causes the downtime of entire fluid-filling system), a comparison can be made between the results of simulation and statistical methods for evaluating the reliability (Figure 8). The result of analytical model reveals the reliability decreases approximately to zero after 1200 h of operation. Moreover, regarding the distributed function, gained by statistical method, the reliability has been simulated by Monte Carlo method. The reliability simulations were performed with 1000, 2000 and 3000 iterations and the results were 4.53%, 3.73% and 1.59% of errors, respectively. It can be seen that the Monte Carlo method with good enough iterations acquires a higher accuracy of reliability prediction with the lowest errors. In other words, the results of Monte Carlo method are very close to statistical model. Hence, the main advantage of this procedure is more accurate prediction of reliability for future failure data.

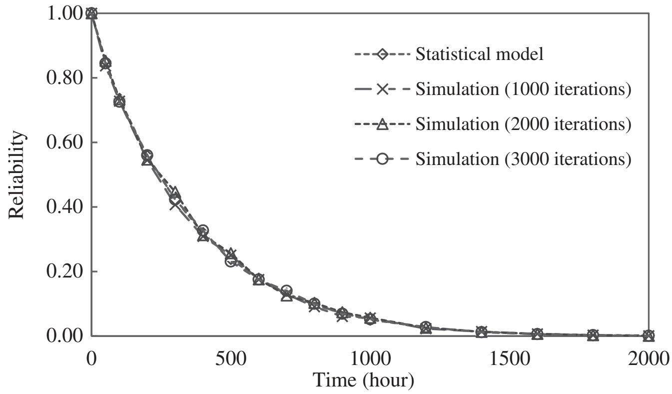

Figure 8. Comparison of the results of reliability estimation between simulations and analytical methods.

3.3. Maintenance optimization result

Figure 9 shows the maintenance intervals in particular focusing only on different proposed reliability levels for the critical components of fluid-filling system. If the assumption is 85% of reliability, these results are expected:

(a) The proposed maintenance intervals for the hydraulic-pneumatic circuit including the valves, PCS and vacuum pump were calculated as 1000, 750, and 716 h, respectively. (b) The optimal maintenance intervals for electrical circuit including the starter, ABS set and sensors were estimated as 230, 98, and 204 h, respectively. (c) The suitable maintenance intervals for the filling head set including the mini-valves, coupling, and O-rings & seals were achieved as 460, 550, and 105 h, respectively. In order to achieve a high level of reliability (90%), the proposed maintenance interval for the critical components such as vacuum pump with 483 h, ABS with 65 h, and O-rings & seals with 75 h are recommended.

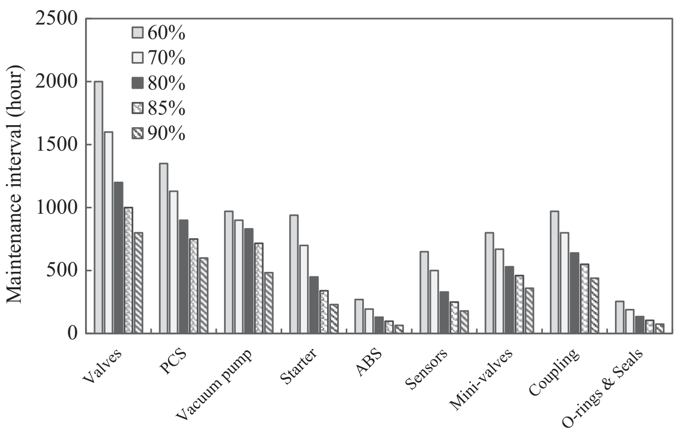

Figure 9. Maintenance intervals for the components of the filling systems with different reliability levels.

In addition to reliability decision levels, maintenance costs play a critical role to suggest optimal maintenance intervals. Also, total expected cost model through computed reliability to optimize maintenance intervals are shown in Figure 10. Thus, the main results of optimal maintenance interval in supposed finite period (short term planning), e.g. 2000 h of operation subject to total expected cost, can be suggested as follows:

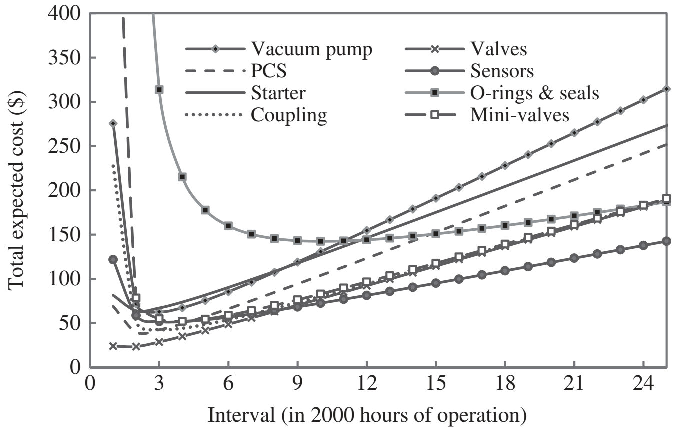

Figure 10. Total expected cost based on optimal maintenance intervals.

(a) For the hydraulic-pneumatic circuit, two maintenance intervals for valves with \$23.43 and three maintenance intervals for PCS with \$42.70 and vacuum pump with \$62.81 were obtained. (b) The optimal maintenance intervals for electrical circuit including the starter and sensors were estimated as two and four maintenance intervals with \$63.91 and \$51.56, respectively. Further, (c) The suitable intervals for the filling head set including the mini-valves, coupling, and O-rings & seals were obtained as four, three and 10 maintenance intervals with \$52.09, \$42.70 and \$40.42 in 2000 h, respectively.

4. Conclusion

The study aimed to propose a reliability-based maintenance planning for critical equipment in automotive production process. In this regard, the operational data, such as failure data named as time between failures were acquired from the computerized maintenance management system for the fluid-filling system in an automotive assembly line. Reliability was evaluated using the statistical structure and Monte Carlo simulation. In proposed statistical model, the validation of the assumption of independent and identically distributed nature for the failure data were examined based on trend and the serial correlation tests. The results of statistical model appointed that to achieve the high level of reliability, the critical subsystems (e.g. filing head set) as main bottleneck needs to be considered as a priority. In addition, the Monte Carlo simulations with different iterations were performed and the result of which shows a high prediction accuracy of reliability with the lowest errors. Therefore, it has a great potential to simulate and predict reliability for future failures data. To suggest the optimal maintenance intervals, a cost-based model including reliability function were applied. The proposed maintenance model could be useful to predict the systems' behavior trend and to provide a sustainable continuity of automotive production process. Furthermore, in the current study, the operational data by focusing on failure data has been used for reliability and maintenance modeling. As a future perspective, due to the rare operation management studies in automotive sector, the big data (sensor-based) acquisition and monitoring regarding big data techniques and intelligent algorithms can be suggested for evaluating system performance leading towards automotive 4.0 objectives.

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