Data-driven fleet management using MOORA: a perspective of risk management

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Abstract

Purpose – The purpose of this study is to investigate the best fleet for a new purchase based on multi-objective optimization on the basis of ratio (MOORA), reference point and multi-MOORA methods. This study further identifies critical parameters for fleet performance monitoring and exploring optimum range of critical parameters using Monte Carlo simulation. At the end of this study, fleet maintenance management and operations have been discussed in the perspectives of risk management.

Design/methodology/approach – Fleet categories and fleet performance monitoring parameters have been identified using the literature survey and Delphi method. Further, real-time data has been analyzed using MOORA, reference point and multi-MOORA methods. Taguchi and full factorial design of experiment (DOE) are used to investigate critical parameters for fleet performance monitoring.

Findings – Fleet performance monitoring is done based on fuel consumption (FC), CO_2 emission (CE), coolant temperature (CT), fleet rating, revenue generation (RG), fleet utilization, total weight and ambient temperature. MOORA, reference point and multi-MOORA methods suggested the common best alternative for a particular category of the fleet (compact, hatchback and sedan). FC and RG are the critical parameters for monitoring the fleet performance.

Research limitations/implications – The geographical aspects have not been considered for this study.

Practical implications – A pilot run of 300 fleets shows saving of Rs. 2,611,013/- (US$36,264.065), which comprises total maintenance cost [Rs. 1,749,033/- (US$24,292.125)] and FC cost [Rs. 861,980/- (US$11,971.94)] annually.

Social implications – Reduction in CE (4.83%) creates a positive impact on human health. The reduction in the breakdown maintenance of fleet improves the reliability of fleet services.

Originality/value – This study investigates the most useful parameters for fleet management are FC, CE, CT. Taguchi DOE and full factorial DOE have identified FC and RG as a most critical parameters for fleet health/performance monitoring.

Keywords Decision-making, Risk analysis, Data analysis, MOORA, Multi-MOORA, Project risk management, Taguchi DOE, Full factorial DOE and Monte Carlo simulation

Paper type Technical paper

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1. Introduction

Fleet management involves purchasing, placement and maintenance of the fleet, out of which the maintenance and placement sections of fleet management are very dynamic and complex. In the placement section of fleet management, operators and fleets are assigned the tasks based on their availability. Fleet management systems are useful for fleet owners, manufacturers, transportation service providers and maintenance providers for improving productivity and safety. A fleet management system is designed to use the fleet in a most efficient, economical and productive manner. However, many researchers have contributed toward solving the problems related to fleet management using different tools and techniques, out of which few are discussed below from the year 2005 to 2018. Bigras and Gamache (2005) used classical shortest path algorithm by taking into account the displacement mode (forward or in reverse) of vehicles for solving the shortest path problem. King and Topaloglu (2007) presented a model to coordinate the pricing and fleet management decisions of a freight carrier. Minis *et al.* (2009) discussed essential design aspects of the "taxi (car)" used for transporting very important persons during the Athens 2004 Olympic games and developed a system based on robust operating principles for fleet management. Galletti *et al.* (2010) developed competitive benchmarking strategies for increasing the cost efficiency of operating fleets used in private fleet management. Mathew *et al.* (2010) proposed a three-dimensional model based on the choice of a fleet improvement program for efficient fleet management. Fazel-Zarandi *et al.* (2013) addressed a stochastic facility location and vehicle assignment problem in the scenario of full return trips service of fleet for customers. Moradi Afrapoli and Askari-Nasab (2017) reviewed industrial fleet management systems and used the leading academic algorithms for the mine fleet management systems. Xu *et al.* (2018) proposed a cloud-based fleet management platform by integrating the internet of things (IoT) and cloud technology. Lukman *et al.* (2018) developed optimization approach based on mathematical graph theory for the fleet management and evaluated in the city of Maribor, Slovenia. This scenario of the literature survey motivates to monitor real-time fleet performance for making a correct decision with justification for a given situation.

This study considered renowned fleet service provider to understand the operations of fleet management, which are associated with more than 0.1 million fleets out of which most of the fleets are outsourced for increasing the profit. Fleet service providers have developed the system for managing the outsourced fleets, which starts with the step of adding a rental vehicle into a system based on three stages such as vehicle details (owner name, vehicle number plate, etc.), uploading of documents (rental agreement, operator card, vehicle inspection report, vehicle insurance, etc.) and request to activate the rental vehicle. Similarly, fleet service providers have developed the driver's application to get an alert, to know the next move, to track the earning and to plan the day with ease. This application helps the driver to activate or deactivate the fleet from the system. The activated status of the fleet helps the service provider to assign the ride and track the vehicle. The fleet service providers have established a two-way rating system to ensure a safer and comfortable experience for the customer. In this rating system, the drivers and customers are required to provide feedback on every trip. A customized mobile application is developed for customers, drivers and operations teams to ensure the smooth fleet allocation. As soon as the driver logs into the application, the system shows the active signal for fleet and driver, which helps the operations team to assign the job to a specific fleet based on location and availability. However, the developed mobile application is inefficient for monitoring fleet health and performance, which results in different risks for fleet service providers such as the sudden breakdown of the fleet, discomfort to the customer and high maintenance time. This scenario of fleet management motivates to monitor health and performance of fleet to reduce the risk associated with fleet management. The decision-makers also need a solution to identify the best fleet for outsourcing or purchasing, which involves lots of multi-objective decision-making.

Different multi-criteria decision-making (MCDM) methods are available for decision-making such as analytical hierarchy process (AHP), the technique for order preference by similarity to ideal solution method, graph theory and matrix approach, Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) and multi-objective optimization on the basis of ratio (MOORA). The selection of a suitable method for solving the fleet management issues is a significant challenge and not explored to the extent required. Chakraborty (2011) listed few advantages of MOORA over the other multi attributes decision-making, as it needs less computational time for performing the mathematical calculations and requires minimum parameters as compared with VIKOR and grey relational analysis methods. Karande and Chakraborty (2012) observed that the rankings of the alternatives are affected by the criteria weights and normalization procedure. Some of these methods are also quite difficult to comprehend and complex to implement, as it requires extensive mathematical knowledge. Thus, the decision-makers needed a simple, logical and systematic approach for solving the issues related to fleet management. MOORA, reference point and multi-MOORA methods are selected to fulfill the requirements of decision-makers.

In this paper, three categories of fleets [compact (C), hatchback (HB) and sedan (S)] are considered as it provides more services and business to fleet service providers. C fleets are comfortable air conditioner (AC) cars that can accommodate three persons and gives excellent value for money, which further offers economical fare for short distance. HB fleets are comfortable AC cars having a hatch-type rear door, which opens upward and often has a shared space for the passengers and cargo. It is an economical option for the daily commute and the S fleets have a closed body with a separate compartment for the engine, passenger and cargo, with extra legroom and boot space. The scope of this study includes the selection of the best alternative for a new agreement or new purchasing in a given situation and the identification of critical parameters for real-time monitoring of fleet performance. Further, Monte Carlo simulation (MCS) has been used to optimize the range of the critical parameters, which can help to monitor the risk involved in fleet management. This analysis did not consider the effect of fleet age.

This paper is organized in various sections. In Section 2, literature survey on MOORA, project risk management (PRM), Delphi method, design of experiment (DOE) and MCS has been performed to understand the concept and applicability of methods and tools and the gaps have been identified for further research. Section 3 discussed the research methodology, Section 4 shows data collection plan and Section 5 shows implementation of selected methods. Section 6 represents sensitivity analysis, Section 7 represents results, Section 8 shows discussion on results based on perspectives of risk management with suitable situations. Finally, conclusions are shown in Section 9.

2. Literature survey

In this section of the paper, the literature survey is performed in the domain of the MOORA, PRM, Delphi method, DOE and MCS to understand the concepts and tools used for different applications. The detailed literature survey has been carried out in Sections 2.1, 2.2, 2.3, 2.4 and 2.5 for the period of 2009–2018.

2.1 Literature survey on multi-objective optimization on the basis of the ratio

MOORA method was developed by Brauers and Zavadskas (2006) for the optimization of multi-objective optimization problems. This method considers beneficial and non-beneficial objectives for selecting or ranking the alternatives from a set of available options. MOORA method requires less computation time, as it involves simple and logical mathematics. Brauers and Zavadskas (2009) used the test data of facilities centers for evaluating the robustness of MOORA method. Stanujkic *et al.* (2012) proposed an extended MOORA method by combining the concept of interval grey numbers and MOORA method for solving many complex real-world problems.

Karande and Chakraborty (2012) applied MOORA method to solve some of the standard material selection problems and tested the performance of the multi-MOORA and reference point methods for the considered problems. Brauers (2013) used the MOORA method for ranking the best location for a new seaport or the expansion of existing seaport. Kumar Sahu *et al.* (2014) applied a multi-MOORA with the grey number for evaluating appraisal of the candidate. Patel and Maniya (2015) presented the application of the AHP and MOORA method for selecting the optimal value of output parameters of wire cut electrical discharge machining process. Aytaç Adalı and Tuş Işık (2017) demonstrated MOORA, full multiplicative (multi-MOORA) and multi-objective optimization on the basis of simple ratio analysis methods for selecting the laptop. Jain (2018) used MOORA and preference selection index for the ranking of performance factors of flexible manufacturing systems. Arabsheybani *et al.* (2018) applied a fuzzy-MOORA for evaluating the supplier's overall performance. Chand *et al.* (2018) identified issues in green supply chain management and analyzed the issues for the implementation of the green concept in industries. Majumder and Maity (2018) integrated fuzzy logic and MOORA approach for optimizing different correlated responses such as discharge current (I), pulse-on time, wire feed, wire tension and flushing pressure. Steps invovled in MOORA method are discussed as follows,

Step 1: Develop the decision matrix based on a number of criteria and alternatives, as shown below Karande and Chakraborty (2012). Where X_{ij} is the performance measure of *i*-th alternative on *j*-th criteria, m is a number of alternatives and *n* is a number of criteria:

$$X = \begin{bmatrix} X_{11} & X_{12} & \ldots. & \ldots. & X_{1n} \\ X_{21} & X_{22} & \ldots. & \ldots. & X_{2n} \\ \ldots. & \ldots. & \ldots. & \ldots. & \ldots. \\ \ldots. & \ldots. & \ldots. & \ldots. & \ldots. \\ X_{m1} & X_{m2} & \ldots. & \ldots. & X_{mn} \end{bmatrix}$$

Step 2: Develop a normalized matrix based on equation (1) Aytaç Adalı and Tuş Işık (2017), so that the matrix becomes dimensionless and comparable to each other. In this step, the performance value of alternative for criteria against the other alternative performance on that criteria is computed as:

$$X^*_{ij} = \frac{Xij}{\sqrt{\sum_{i=1}^{m} X^2_{ij}}} \quad i = 1, 2, \ldots\ldots, m \, \text{and} \, j = 1, 2, \ldots, n \tag{1}$$

X^*_{ij} is a dimensionless number between (0, 1). The value shows the normalized performance of *i*-th alternative on *j*-th criterion.

Step 3: Compute the assessment value (Y_i) of *i*-th alternative with respect to all the criteria based on equation (2) Karande and Chakraborty (2012). In this step, sum the normalized performance values of beneficial and non-beneficial criteria. Finally, the sum of non-beneficial criteria is subtracted from beneficial criteria, as shown in equation (2):

$$Y_i = \sum_{j=1}^{g} X^*_{ij} - \sum_{j=g+1}^{n} X^*_{ij} \tag{2}$$

where g is the number of criteria to be maximized, (*n*-g) is a number of criteria to be minimized.

Step 4: Finally, arrange the Y_i values of all alternatives in descending order. The best alternative is decided based on the highest assessment value.

The full multiplicative MOORA approach consists of multiple criteria such as maximization and minimization of a purely multiplicative utility function (U_i). Equation (3)

Karande and Chakraborty (2012) is used to compute the degree of utility for an *i*-th alternative of full multiplicative MOORA approach:

$$U_i = \frac{A_i}{B_i} \tag{3}$$

where $A_i = \prod_{j=1}^{g} X_{ij}^{*}, B_i = \prod_{j=g+1}^{n} X_{ij}^{*}$

In equation (4), the criteria to be maximized (beneficial attributes) are taken in the numerator and the criteria to be minimized (non-beneficial attributes) are taken in denominator Karande and Chakraborty (2012). If any of the X_{ij}^{*} value is 0, which signifies the absence of a particular criterion in the decision matrix and a foregoing filtering stage or withdrawal of that criterion from the decision matrix can be considered.

The reference point approach used the normalized performance of i-th alternative on j-th criteria [Equation (1)]. In the next step, choose maximization as a reference point, which has the highest coordinate per criteria of all the candidate alternative (r_i). Similarly, for minimization, the lowest co-ordinate is chosen. In this approach, the performance index (P_i) is calculated based on equation (4) and the minimum value of P_i gives the best alternative Karande and Chakraborty (2012):

$$P_i = \mathrm{Min}_i\left(\mathrm{Max}_j\left|r_i X_{ij}^{*}\right|\right) \tag{4}$$

2.2 Literature survey on project risk management

PRM is the process or strategy of risk identification, evaluation, prioritization and monitoring. The project involves different risks and its contribution decides the success rate of the project, i.e. the minimum probability of risk ensures a high success rate of the project. Many researchers have contributed in the domain of PRM and developed different frameworks, strategies, guidelines and risk matrix to monitor and mitigate the risks.

Ahmed *et al.* (2005) developed a framework for an intelligent risk management system based on the Australia/New Zealand risk management standard (AS/NZS 4360). Han *et al.* (2008) reviewed basic decision-making processes in global construction projects and presented a web-based decision support system for PRM. De Bakker *et al.* (2010) presented a meta-analysis of the empirical evidence for PRM, which contributed for success of Information Technology (IT) projects and validated the assumptions made for risk management. Kirkire *et al.* (2015) explored risks involved in medical product development (MPD) process of a dental product manufacturing company and proposed a model for risk mitigation during the MPD process to minimize failure events. Jadhav *et al.* (2015) explored and categorized significant supply risks in just in time (JIT) implementation from a buyer's perspective. Dandage *et al.* (2016) represented various barriers of business houses, who have already signed an agreement for investing to risk management in domestic and international projects under the Make in India scheme. Rane and Kirkire (2017) explored risk sources in the medical device development process and developed a model of interaction among these sources. Dandage *et al.* (2018) presented various risk categories and barriers for risk management in domestic and international projects through a literature survey and feedback from project professionals. Dandage *et al.* (2018) explored eight different risk categories in international projects and presented the ranking of risk categories according to their importance in project success. Kirkire *et al.* (2018) implemented PRM practices in a dental-product-manufacturing company for MPD. (Dandage *et al.*, 2019) used interpretive structural modeling and Matrice d'Impacts Croisés Multiplication Appliqués à un Classement for risk prioritization in international projects. Rane *et al.* (2019) developed a PRM framework based on Industry 4.0 technologies and demonstrated the developed framework using IoT technology. Rane *et al.* (2019) developed strategies to improve agility in the project procurement management process. This survey has given an understanding of the risk management approach and its applicability, which can help to identify the risk associated with fleet management.

2.3 Literature survey on Delphi method

The Delphi method is helpful in situations where analytical techniques cannot solve the problem and historical data or relevant information is unavailable (Ferreira and Monteiro Barata, 2011). Many researchers have used the Delphi method in a different field for solving the problems. Campos-Climent *et al.* (2012) used the Delphi method with strengths weaknesses opportunities and threats analysis for meaningful assessments of horticultural cooperatives. Bazzani and Canavari (2013) applied the Delphi method to obtain judgments of different experts regarding the driving forces of the tomato industries located in Italy and Germany. Mehnen *et al.* (2013) discussed appropriateness of the Delphi method for obtaining information about governance. Ribeiro and Pereira da Silva (2015) demonstrated the Delphi method to determine the prospects of using microalgae into the production of biofuels within a time scale extending up to 2030. Chun and Lee (2017) developed a service evaluation index for internet addiction in South Korea based on the Delphi method. In this study, the Delphi method is used for problem identification and selection.

2.4 Literature survey design of experiment and Monte Carlo simulation

Many researchers have used DOE for different applications such as, investigation of tribo-mechanical properties of CrAlCN coatings (Tillmann *et al.*, 2016), optimization of the Candida Antarctica lipase B mediated epoxidation of monoterpenes (Ranganathan *et al.*, 2016), optimization of the electrophoretic deposition process parameters for peeking base coatings (Atiq Ur Rehman *et al.*, 2017) and optimization of design configurations of channels in plastic injection molds (Jahan *et al.*, 2017). Similarly, many researchers have contributed to MCS and used it for different applications such as chemotactic bacteria on the basis of the kinetic model (Yasuda, 2017), beta radiation transport within radioactively-contaminated food samples (Merk *et al.*, 2017), optimization of a sintering process (Matsuda *et al.*, 2017) and building a time-dependent diffusion equation (Dumonteil *et al.*, 2017). This section gives the roadmap to investigate and optimize the critical parameters.

2.5 Research gaps based on literature survey

The literature survey reveals a need to focus on real-time fleet health monitoring and to leverage the usage of MCDM methods for fleet management. The survey motivates to adopt PRM practices for improving fleet management.

2.6 Requirements of stakeholders

2.6.1 Requirements of industries.

- Enhance the fleet maintenance management.
- Improve decision-making in fleet management activities.
- Enhance fleet health monitoring and utilization (U).

2.6.2 Requirements of customers.

- The assigned fleet should be in good condition.
- Fleet selection should be quick and waiting time should be as less as possible.

2.7 Problem definition

In this section, problem identification and selection are done based on the Delphi method and Table 1 shows the details of the expert panel, which is decided based on a literature survey. The experts are selected from different fleet manufacturing organizations and service providers to demonstrate the Delphi method. The selected experts are further categorized based on years of experience, i.e. 0–3 years, 4–6 years, 6–10 years and above 10 years. Experts are further involved in identifying the problems and parameters along with their weights. In the first discussion, experts have suggested more than eight problems and a few parameters. The most prominent problems and parameters are recommended by experts to develop the matrix. The developed matrix (Table 2) is further shared with the experts to give their preferences based on the scale [strong effect (10), moderate effect (7), low effect (5) and no effect (3) (Potdar and Rane, 2018)]. The responses were received from a total of 31 experts in the form of a matrix (Table 2), which shows the highest frequency of expert responses on a particular scale. The data is further analyzed by considering parameters weight, scale and expert frequency. The expert frequency is considered in the calculation of rating to know the effect of expert frequency on the rating. The sample calculation of rating is as shown below, where 'n' is a number of parameters:

$$\text{Rating} = \sum_{i=1}^{n}\left[\left(\frac{\text{Maximum frequency}}{\text{Total number of expert}}\right)\times \text{Scale}\times \text{Weight}\right]$$

$$\text{Rating} = \left[\left(\frac{12}{31}\right)\times 10\times 0.5\right]+\left[\left(\frac{15}{31}\right)\times 5\times 0.3\right]+\left[\left(\frac{15}{31}\right)\times 5\times 0.2\right] = 3.15$$

The analysis shows that there are two significant problems such as fleet health monitoring and utilization and identification of the best fleet for a new purchase.

2.7.1 Research objectives. This research focuses on the following objectives:

- Identification of the parameters for fleet health monitoring and utilization.
- Identification of the best fleets for a new purchase using MOORA, reference point and multi-MOORA methods.
- Identification of the most critical parameters for fleet performance monitoring using DOE.
- Identification of the optimum range of critical parameters using MCS.
- Discussion of risk management perspective using fleet maintenance management.

Table 1.
List of expert panel

Sr. no.	Expert	No. of experts	(%)
1	Top management	4	13
2	Fleet managers	9	29
3	Fleet design engineer	5	16
4	Managers from fleet manufacturer	7	23
5	Service engineer	6	19

3. Research methodology

The research methodology flow chart (Figure 1) starts with the selected domain, i.e. fleet management, followed by a literature survey (Section 2) and discussion with experts. The literature survey and Delphi method are used to select a problem and to identify a few parameters for fleet performance monitoring. Research objectives are mentioned in Section 2.7.1. In the next step, some sensors are identified and installed on an appropriate location of fleet to capture the data of selected parameters, which is explained in Section 4.2. The data collection plan is developed to collect the data (Section 4.3) and collected data is further analyzed by selected MCDM methods (Section 5). In Section 6.1, DOE is used to investigate the most critical parameters and MCS is used to identify the optimum range of critical parameters. In Section 7, the statistical, technical and business results are discussed. Risk management perspectives are demonstrated using different situations (Section 8). Conclusions were derived at the end of the methodology (Section 9).

4. Data collection

The data collection is an essential step of any research as it helps to know the current situation of the process and also gives the future direction for improvement. The data collection is a process, which starts from parameter identification, sensor selection, installation, data collection plan and ends with data collection.

4.1 Parameter identification

In this step, initially experts have suggested some parameters for fleet performance monitoring such as fuel consumption (FC), speed, CO_2 emissions (CE), engine working hours, coolant temperature (CT), velocity, fleet rating (FR), revenue generation (RG), driver behavior, U, noise, ambient temperature (AT), total weight (TW), displacement and vibration. In the next discussion, experts have selected some beneficial and non-beneficial parameters to solve the identified problems. The finalized nonbeneficial parameters are FC, CE, CT, TW, AT and beneficial parameters are FR, RG, U. In the analysis, the displacement of the fleet has not been considered separately, as it depends on FC, CE and fleet utilization, as displacement of fleet has a direct impact on FC and CE.

4.2 Sensor selection and installation

In the second step of data collection sensors are selected and installed as shown in Table 3 MG-811 CO_2 sensor module is placed on the exhaust system (silencer) to measure the quantity of CO_2 and the supply is given through battery. The Wi-Fi module is also placed on

		Parameters with weights							
		Business value (0.5)		Cost saving potential (0.3)		Customer satisfaction (0.2)			
Sr. no.	Problem	*F*	*S*	*F*	*S*	F	*S*	Rating (%)	
1	Fleet health monitoring and utilization	12	10	15	5	15	5	3.15	30.38
2	Fleet maintenance planning	11	5	9	7	9	3	1.67	16.14
3	Fleet scheduling	8	5	11	5	9	3	1.35	13.06
4	Monitor driver behavior	10	3	9	3	10	5	1.07	10.31
5	Identify best fleet for new purchase	14	7	16	7	14	5	3.12	30.10

Table 2. Problem selection matrix (*F* – frequency of experts, S – scale)

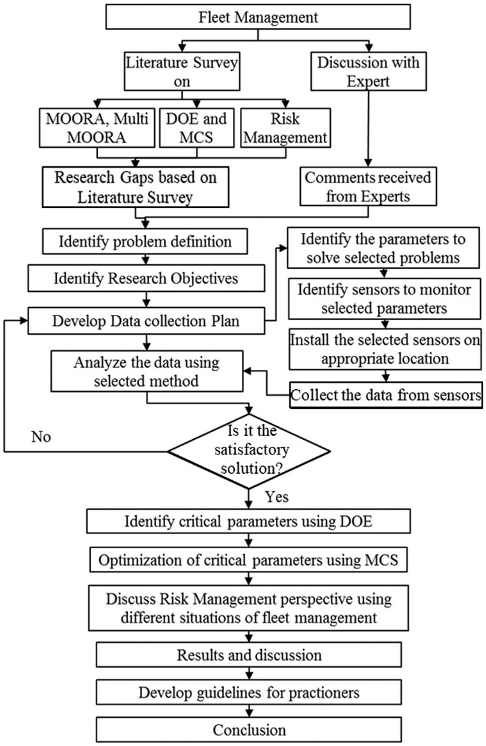

Figure 1.
Research methodology flow chart

the sensor to transfer the data into the system. The connectors are used to install global positioning system (GPS) on the on-board diagnostic system. This system helps to monitor FC, CT and AT. The system is further integrated with Android and iOS systems to transfer the data. Table 3 shows additional arrangements for supporting sensors. Similarly, customer rating, RG, TW and fleet U data is collected from the enterprise resource planning system. The approximate total installation cost of sensors is Rs. 18,000–20,000 (US$250– US $280) per fleet.

4.3 Data collection plan

The data collection plan is shown in Table 4, which presents the data of 12 fleets of each category and ensures optimization in the installation cost, time and computation efforts. Further, data is captured in 5 min to reduce the data volume and velocity, which can confirm the smooth functioning of the system.

4.4 Data collection method

Data collection method helps to develop the check sheet and to collect the relevant data. The sensors are placed on the selected 12 fleets of each category to capture the data in the time interval of 5 min, which generates a maximum of 288 entries per day for a single parameter. A similar number of entries are expected for other parameters, which generates big data. Architecture was developed (Figure 2) to manage and analyze the captured big data. The architecture starts with the sensor level, as shown in Figure 2. In the next step, the captured data is available on the local area network, which is sent to the cloud with the help of the transmitter and receiver mechanism. The data is securely stored on the cloud and shared with the fleet manager, design engineer and mechanic to make a decision, which is known as the application layer of the system. This system floats the data from the bottom layer to the top layer and actions are floating from top to the bottom layer. In the data collection process, the TW is calculated by adding the curb weight of the vehicle, luggage and passenger weight. The curb weight depends on the manufacturer and model of the fleet, which is collected from fleet specification catalog. The maximum weight of luggage and passengers ensures the critical environment for analysis. The calculated TW and collected maximum AT are as shown in Table 5.

5. Implementation of methods

This section helps to solve the problem related to the purchasing of the new fleet and the real-time fleet health monitoring by monitoring the selected parameters.

5.1 Multi-objective optimization on the basis of ratio

The steps involved in MOORA implementation are discussed in Section 2.1. The decision matrix is developed based on a number of criteria and alternatives, as shown in Table 5. In the next step of MOORA, a normalized decision matrix is formed based on equation (1) and the assessment value is calculated by equation (2), as shown in Table 6. The highest assessment value gives the best alternative. Obtained the ranking by MOORA method for fleet categories (C, HB and S) is as shown in Table 9.

Sr. no.	Parameter	Specification of sensor/equipment	Cost in US$
1	CE	Heating voltage: −6.0 ± 0.1V, AC or DC, heating resistor:- ~30.0 Ohm, heating current:- ~200mA, heating power:- ~1200mW, operating temperature:- −20°C–50°C, storage temperature:- −20°C–70 °C, output:- 100–600mV, 400–10,000 ppm CO_2	100
2	FC, CT	Brand:- Rollr lithium-polymer with 220 mAH, battery backup up to 4 h, in-built SIM card, rollr app (available for Android and iOS)	100

Table 3. Details of sensor/equipment for selected parameters

Sr. no.	Subject head	Details
1	Select the fleet category	C, HB and S
2	How many fleets must select for each category?	Collected data for 12 fleets of each category
3	How to capture the data of selected parameters?	Using sensors
4	What is the frequency of data collection?	5 min
5	Who will collect the data?	GPS, Wi-Fi module and smartphone
6	Which type of data was captured?	Continuous stream
7	Data considered for analysis	Three months data captured

Table 4. Data collection plan

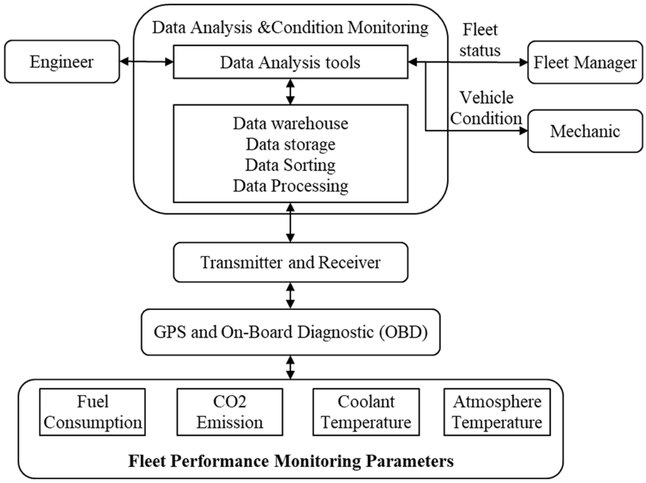

Figure 2.
Fleet management architecture

5.2 Reference point approach

The reference point approach starts with a normalized matrix, as shown in Table 6. The highest value of the beneficial attributes (FR, U, RG) and lowest value of the nonbeneficial attributes (FC, CE, CT, TW and AT) are selected from the normalized matrix as r_i. In the next step, equation (4) is used to calculate the performance index and results are shown in Table 7. The ranking is done based on the lowest value of P_i and ranking of the fleet categories (C, HB and S) are shown in Table 9.

5.3 Multi-objective optimization on the basis of ratio approach

This method also starts with a normalized matrix, as shown in Table 6. The U_i value is calculated based on equation (3) and as shown in Table 8. In this method, the ranking is done based on the highest value of U_i. The multi-MOORA method obtained the ranking for the fleet categories (C, HB and S) is as shown in Table 9.

The rank is given by MOORA, reference point approach and multi MOORA method for a C, HB and S fleets are as shown in Figures 3–5, respectively, which show variation in the ranking by methods but suggested the same best alternative for the fleet category. The variation has been observed in fleet ranking because of variation between parameter values. In the next step of research, a sensitivity analysis was performed to check the effect of parameter variation on fleet ranking and for more sound decision-making.

6. Sensitivity analysis

Sensitivity analysis is a technique to check the response of the method for a different scenario. In this step, the total 20 iterations (Table 10) of each fleet are taken to perform the sensitivity analysis. The results of MOORA and multi MOORA method for 10 iterations are shown in Figures 6 and 7, respectively. The analysis shows the variation in ranking for different alternatives, but most of the iterations shows the same best alternative for the given conditions, i.e. C-9 has received the first rank for 8 out of 10 iterations for MOORA and multi MOORA method, which shows that the variation in data doesn't have any significant effect on the best alternative. In Figure 7, iteration-6 has received 12th rank by multi-MOORA method because of high values of CE and CT and low FR given by customers as

Type of fleet	Fleet ID	Average FR	Average FC (MPG)	Average CE (g CO_2/km)	Average U (hours)	Average CT (°C)	RG		TW	AT
							In Rs x 10	In US$	(Kg)	(°C)
C	C-1	3.5	25	106	16	80.7	8,858	123.0	1,328	36
	C-2	3.2	26	106	14	81.9	11,832	164.3	1,178	38
	C-3	3.9	25	105	16	78.3	9,801	136.1	1,414	33
	C-4	3.4	24	105	12	79.4	9,351	129.9	1,344	35
	C-5	3.9	25	104	14	79.5	11,659	161.9	1,257	36
	C-6	3.6	26	105	18	80.0	12,749	177.1	1,446	37
	C-7	4.2	26	107	12	80.6	9,407	130.7	1,163	36
	C-8	3.4	25	106	16	80.4	9,782	135.9	1,289	37
	C-9	4.0	24	104	13	79.9	10,316	143.3	1,379	35
	C-10	3.5	25	105	14	79.4	12,613	175.2	1,283	34
	C-11	3.9	26	106	12	79.1	11,659	161.9	1,154	37
	C-12	4.0	25	105	15	81.7	10,250	142.4	1,278	36
HB	HB-1	4.3	25	105	15	78.7	12,027	167.0	1,886	37
	HB-2	4.9	25	105	15	78.8	9,149	127.1	1,696	29
	HB-3	3.9	25	105	13	80.7	9,480	131.7	1,749	29
	HB-4	3.7	25	104	12	82.7	13,501	187.5	1,794	36
	HB-5	3.8	25	104	14	80.5	14,142	196.4	1,377	36
	HB-6	4.2	24	104	11	80.5	9,751	135.4	1,869	34
	HB-7	4.3	25	104	13	80.0	10,612	147.4	1,530	37
	HB-8	3.3	25	105	12	78.7	11,862	164.8	1,668	35
	HB-9	4.4	26	104	16	82.2	12,253	170.2	1,377	39
	HB-10	3.2	25	107	15	79.9	10,754	149.4	1,539	34
	HB-11	5.0	26	104	14	81.2	12,598	175.0	1,682	34
	HB-12	3.8	25	105	15	81.9	14,006	194.5	1,656	33
S	S-1	4.3	24	106	18	79.1	12,492	173.5	2,017	32
	S-2	4.7	25	106	11	82.9	12,744	177.0	2,091	36
	S-3	3.1	25	104	15	81.0	13,903	193.1	1,879	33
	S-4	3.4	24	104	16	78.7	8,895	123.5	1,882	36
	S-5	3.6	26	104	13	79.1	10,861	150.8	1,843	31
	S-6	3.5	26	105	14	77.0	10,416	144.7	1,611	34
	S-7	4.0	25	103	13	79.5	14,548	202.1	1,946	35
	S-8	4.1	26	106	13	80.1	12,880	178.9	1,578	38
	S-9	4.2	25	105	16	77.2	10,705	148.7	2,232	33
	S-10	4.7	26	105	15	80.5	12,140	168.6	1,997	32
	S-11	3.1	25	105	16	81.2	12,271	170.4	2,176	36
	S-12	4.0	24	107	14	81.7	10,320	143.3	2,097	38

Notes: FC, CE, CT, TW, AT, FR, RG, U

Table 5.
Data collection check sheet

compare to Iterations-5 and 6. The ranking shows that the best alternative remained the same for different values of parameters for a certain period, but it may change as the fleet gets older. Further, Taguchi and full factorial DOE are used to investigate the critical parameters for fleet performance monitoring.

Table 6. Sample calculation of normalized matrix

Type of fleet	Fleet ID	Average FR	Average FC (MPG)	Average CE (g CO_2/km.)	Average U (hours)	Average CT (°C)	RG	TW (Kg)	AT (°C)	Y_i
C	C-1	0.272	0.287	0.290	0.313	0.291	0.238	0.296	0.289	−0.630
	C-2	0.247	0.298	0.290	0.275	0.295	0.317	0.262	0.310	−0.617
	C-3	0.303	0.287	0.288	0.329	0.282	0.263	0.315	0.265	−0.542
	C-4	0.266	0.275	0.288	0.247	0.286	0.251	0.299	0.279	−0.664
HB	HB-1	0.303	0.288	0.290	0.308	0.282	0.294	0.328	0.309	−0.591
	HB-2	0.345	0.288	0.290	0.308	0.283	0.224	0.295	0.245	−0.523
	HB-3	0.275	0.288	0.290	0.272	0.289	0.232	0.304	0.245	−0.638
	HB-4	0.261	0.288	0.287	0.261	0.297	0.330	0.312	0.304	−0.635
S	S-1	0.316	0.276	0.291	0.364	0.286	0.302	0.298	0.267	−0.436
	S-2	0.346	0.288	0.291	0.221	0.300	0.308	0.309	0.304	−0.616
	S-3	0.227	0.288	0.286	0.303	0.293	0.336	0.277	0.274	−0.551
	S-4	0.250	0.276	0.286	0.310	0.285	0.215	0.278	0.298	−0.647

Table 7. Reference point approach (sample)

Type of fleet	Fleet ID	Average FR	Average FC (MPG)	Average CE (g CO_2/km.)	Average U (hours)	Average CT (°C)	RG	TW (Kg)	AT (°C)	P_i
C	C-1	0.054	0.011	0.005	0.038	0.008	0.104	0.039	0.023	0.104
	C-2	0.080	0.023	0.005	0.076	0.013	0.025	0.005	0.044	0.080
	C-3	0.023	0.011	0.003	0.022	0.000	0.079	0.058	0.000	0.079
	C-4	0.061	0.000	0.003	0.104	0.004	0.091	0.042	0.014	0.104
HB	HB-1	0.051	0.012	0.003	0.036	0.000	0.052	−0.088	−0.064	0.052
	HB-2	0.009	0.012	0.003	0.036	0.000	0.122	−0.055	0.000	0.122
	HB-3	0.079	0.012	0.003	0.072	0.007	0.114	−0.065	0.000	0.114
	HB-4	0.094	0.012	0.000	0.082	0.014	0.016	−0.072	−0.059	0.094
S	S-1	0.031	0.000	0.008	0.000	0.008	0.050	0.065	0.008	0.065
	S-2	0.001	0.012	0.008	0.142	0.021	0.044	0.076	0.044	0.142
	S-3	0.119	0.012	0.003	0.061	0.014	0.016	0.044	0.014	0.119
	S-4	0.097	0.000	0.003	0.053	0.006	0.137	0.045	0.039	0.137

Table 8. Full multiplicative MOORA approach (sample)

Fleet ID	U_i	Fleet ID	U_i	Fleet ID	U_i
C-1	9.784	HB-1	11.526	S-1	18.984
C-2	10.362	HB-2	13.986	S-2	10.011
C-3	13.460	HB-3	9.632	S-3	12.648
C-4	8.684	HB-4	9.683	S-4	8.968

6.1 Investigation of critical parameters

6.1.1 Taguchi design of experiment. In this section of the study, Taguchi DOE L12 suggested 12 combinations (Table 11) for eight parameters and considered the range of different parameters are FR (3–5), FC (20–26 MPG), CO_2 (100–108 g CO_2/km), U (10–16 h), CT (64°C–84°C), TW (1,000–2,500 Kg), AT (25°C–40°C) and RG in Rs.[(8,000–15,000) x 10]. The fleet performance for 12 combinations is observed and main effect plots for SN ratio and mean are shown in Figure 8. Main effect plot shows that the FC, CT and RG contributed significantly to fleet performance. Linear analysis is performed between SN ratio vs all parameters and the result (Figure 9) shows that the p-value for FC, CT and RG is lesser than 0.05 at 95% confidence level. Thus, the Taguchi DOE helps to reduce the number of parameters from eight to three with sound justification.

6.1.2 Full factorial design of experiment. In further analysis, the full factorial DOE is used to investigate the critical parameters from selected parameters (FC, CT and RG). The full factorial DOE suggested eight combinations for three parameters. The performance of the fleet for the different combinations are computed and analyzed using a normal plot of effect (Figure 10), main effect plot (Figure 11), Pareto chart (Figure 12) and interaction plot (Figure 13).

	C			HB			S		
Rank	MOORA	RPA	Multi-MOORA	MOORA	RPA	Multi-MOORA	MOORA	RPA	Multi-MOORA
1	C-6	C-6	C-6	HB-9	HB-9	HB-9	S-1	S-1	S-1
2	C-10	C-12	C-5	HB-5	HB-1	HB-5	S-10	S-10	S-10
3	C-5	C-5	C-10	HB-11	HB-11	HB-11	S-7	S-9	S-7
4	C-3	C-10	C-3	HB-12	HB-7	HB-12	S-3	S-6	S-8
5	C-12	C-3	C-12	HB-2	HB-12	HB-2	S-8	S-12	S-3
6	C-11	C-8	C-11	HB-1	HB-5	HB-1	S-9	S-7	S-9
7	C-9	C-2	C-9	HB-7	HB-4	HB-7	S-6	S-8	S-6
8	C-8	C-9	C-8	HB-10	HB-3	HB-10	S-2	S-5	S-2
9	C-7	C-7	C-7	HB-4	HB-6	HB-4	S-5	S-3	S-5
10	C-2	C-1	C-2	HB-3	HB-2	HB-3	S-4	S-11	S-4
11	C-1	C-4	C-1	HB-8	HB-8	HB-8	S-11	S-4	S-11
12	C-4	C-11	C-4	HB-6	HB-10	HB-6	S-12	S-2	S-12

Table 9. Ranking of fleets

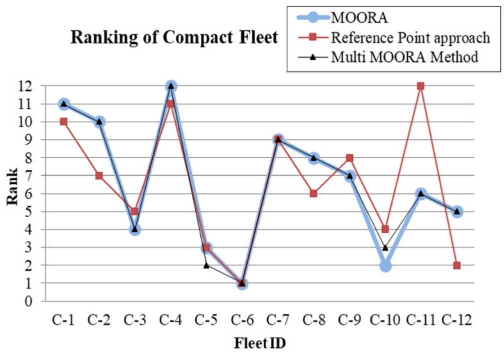

Figure 3. Ranking of C fleet

The normal effect plot (Figure 10) at 95% confidence level shows that the RG and the FC have significant effect on fleet performance. RG has a positive impact on fleet performance as compared to FC. The main effect plot identified that fleet performance is higher than 70% for 20 MPG FC and for Rs.150,000 (US$2,083.34) RG. Fleet performance is higher than 60% at a CT of 60°C. Pareto chart confirmed RG and FC are the most significant parameters for fleet performance. The interaction plot shows the interaction between all selected parameters with fleet performance. It represented that the fleet performance is higher for less FC and lower CT. At the end of the full factorial DOE, the functional equation is developed and shown below to predict the fleet performance.

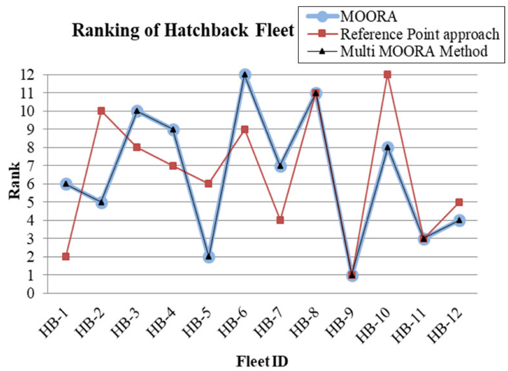

Figure 4.
Ranking of HB fleet

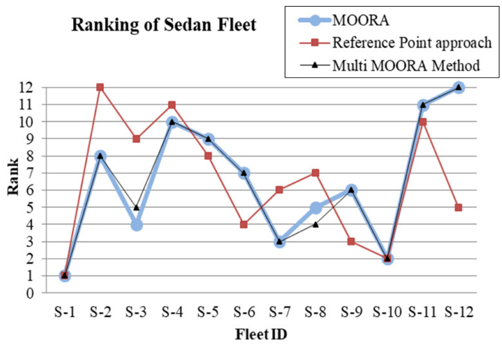

Figure 5.
Ranking of S fleet

Table 10.
Captured data for fleet 1 (sample)

Iteration	Average FR	Average FC (MPG)	Average CE (g CO_2/km.)	Average U (hours)	Average CT (°C)	RG	TW (Kg)	AT (°C)
I-1	3.4	26	105	13	79	9,893	1,346	35
I-2	3.6	26	103	14	84	6,642	1,267	36
I-3	3.8	24	105	11	83	9,381	1,379	35
I-4	3.4	26	105	12	78	8,173	1,283	34

$$\text{Fleet Perfrormance} = 3.549 - 0.1123FC - 0.03917CT - 0.000079RG + 0.001157\ FC \times CT + 0.000003\ FC \times RG + 0.000002\ CT \times RG - 0.00000 \times FC \times CT \times RG$$

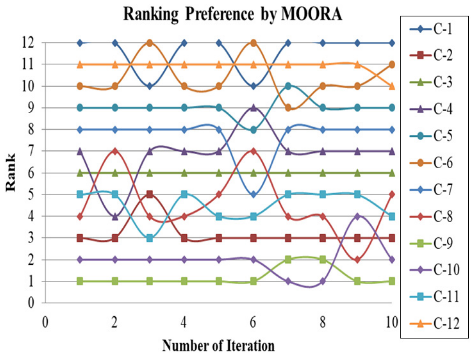

Figure 6.
Ranking by MOORA

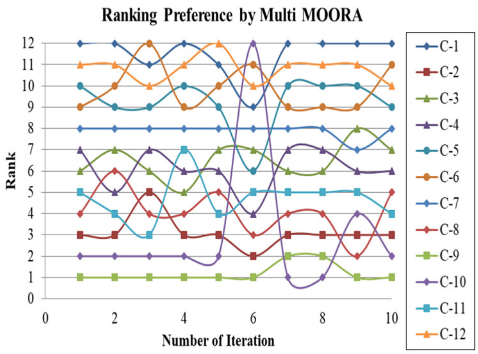

Figure 7.
Ranking by multi MOORA

Table 11.
Taguchi DOE L12

Sr. no.	FR	FC	CO_2	U	CT	RG	TW	AT	Performance
1	3	20	100	10	64	8,000	1,000	25	0.80485
2	3	20	100	10	64	15,000	2,500	40	0.932
3	3	20	108	16	84	8,000	1,000	25	0.71385
4	3	26	100	16	84	8,000	2,500	40	0.5819
5	3	26	108	10	84	15,000	1,000	40	0.6092
6	3	26	108	16	64	15,000	2,500	25	0.74115
7	5	20	108	16	64	8,000	2,500	40	0.7639
8	5	20	108	10	84	15,000	2,500	25	0.7643
9	5	20	100	16	84	15,000	1,000	40	0.786
10	5	26	108	10	64	8,000	1,000	40	0.6729
11	5	26	100	16	64	15,000	1,000	25	0.8436
12	5	26	100	10	84	8,000	2,500	25	0.62285

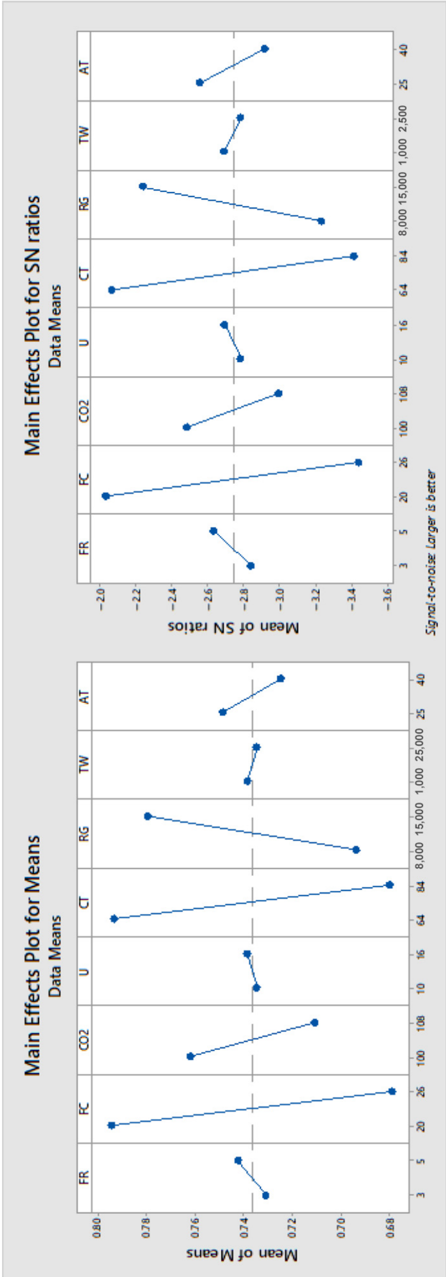

Figure 8.
Main effect plots for SN ration and means

Linear Model Analysis: SN ratios versus FR, FC, CO2, U, CT, RG, TW, AT

Estimated Model Coefficients for SN ratios

Term	Coef	SE Coef	T	P
Constant	−2.73592	0.1238	−22.102	0.000
FR 3	−0.10324	0.1238	−0.834	0.465
FC 20	0.70413	0.1238	5.688	0.011
CO2 100	0.25566	0.1238	2.065	0.131
U 10	−0.04578	0.1238	−0.370	0.736
CT 64	0.67646	0.1238	5.465	0.012
RG 8000	−0.49894	0.1238	−4.031	0.027
TW 1000	0.04790	0.1238	0.387	0.725
AT 25	0.17930	0.1238	1.448	0.243

Analysis of Variance for SN ratios

Source	DF	Seq SS	Adj SS	Adj MS	F	P
FR	1	0.1279	0.12789	0.12789	0.70	0.465
FC	1	5.9495	5.94953	5.94953	32.36	0.011
CO2	1	0.7844	0.78436	0.78436	4.27	0.131
U	1	0.0252	0.02515	0.02515	0.14	0.736
CT	1	5.4912	5.49116	5.49116	29.86	0.012
RG	1	2.9873	2.98730	2.98730	16.25	0.027
TW	1	0.0275	0.02753	0.02753	0.15	0.725
AT	1	0.3858	0.38577	0.38577	2.10	0.243
Residual Error	3	0.5516	0.55164	0.18388		
Total	11	16.3303				

Model Summary

S	R-Sq	R-Sq(adj)
0.4288	96.62%	87.61%

Figure 9.
Results of linear model analysis

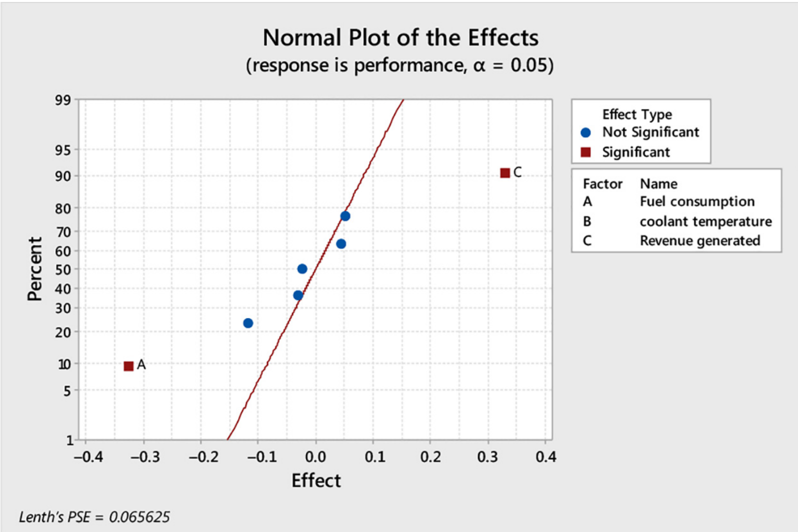

Figure 10.
Normal plot of effects for parameter

6.1.3 Monte Carlo simulation. MCS optimizes the range of the critical parameters. The random data is generated with 10,000 data points for three parameters (FC, CT, RG) using the normal distribution. Then, the simulation was performed to compute the performance using the above equation and the result is shown graphically in Figure 14. The result shows that the mean performance of the fleet is 1.6670 based on 10,000 samples. The variation in the results of the standard deviation is 0.2869; the minimum performance of the fleet is 0.6538 and a maximum of 3.0146, which shows the fleet performance range.

6.1.4 Validation of results. In this study, *F*-test and *t*-test are used to validate the results of improvement in fleet performance by monitoring critical parameters. (Mishra and Rane, 2018) used $\chi 2$, *F* and *t*-test to validate business results of improvement in iron casting

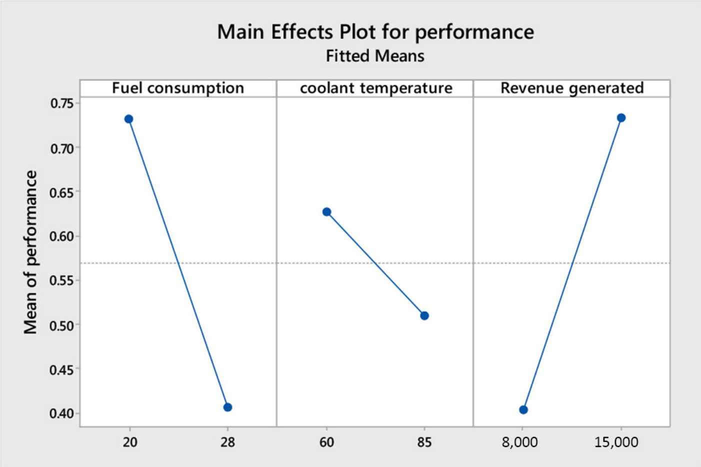

Figure 11.
Main effect plot for performance

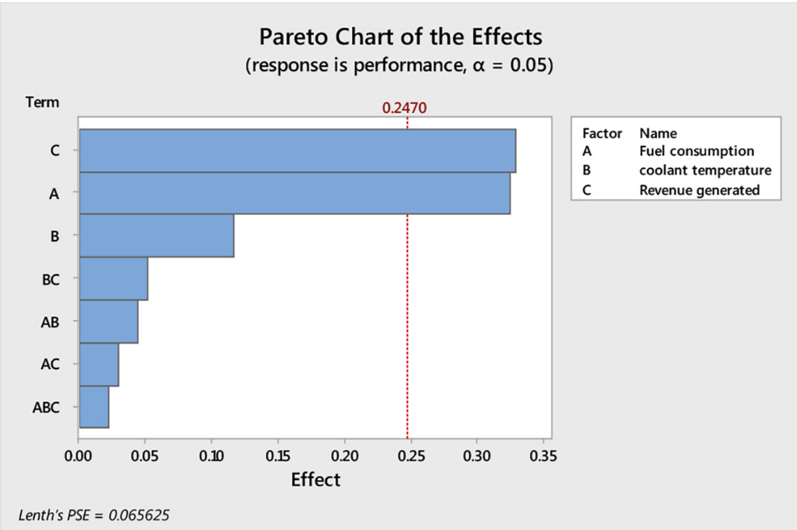

Figure 12.
Pareto chart of parameters effect on performance

quality based on hypothesis statements. (Rane and Mishra, 2018) demonstrated the *F* and *t*-test to validate the impact of the discover-innovate-predict-perform-sustain model on analytical goal achievement. *F* and *t*-tests are performed with 95% confidence level as shown in Figure 15, which also shows *P* value equal to zero (i.e. $p < 0.05$). *F*-test results confirmed a reduction in standard deviation (Table 12) and *t*-test results confirmed improvement in a mean (Table 13).

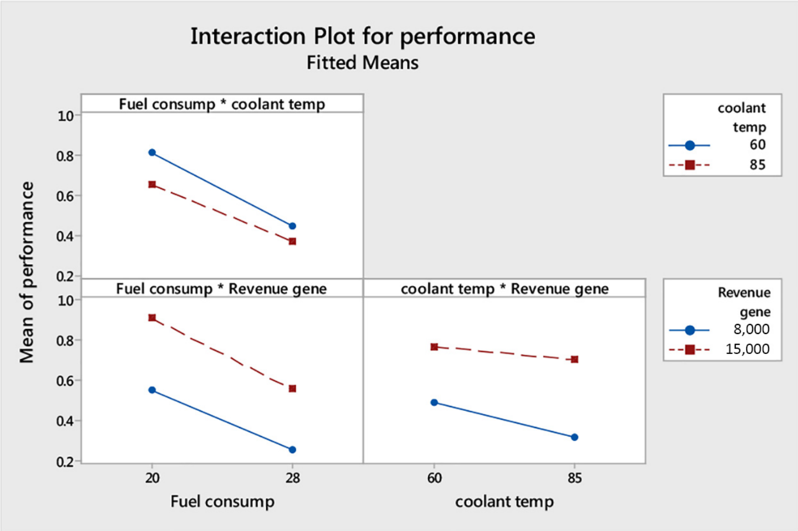

Figure 13.
Interaction plot for performance with different parameters

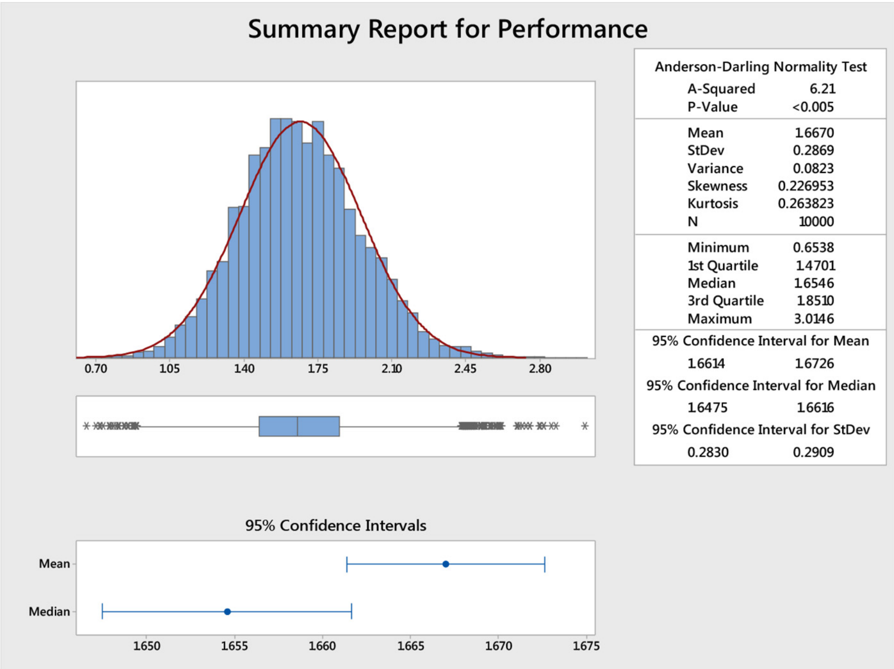

Figure 14.
Summary of fleet performance for random data

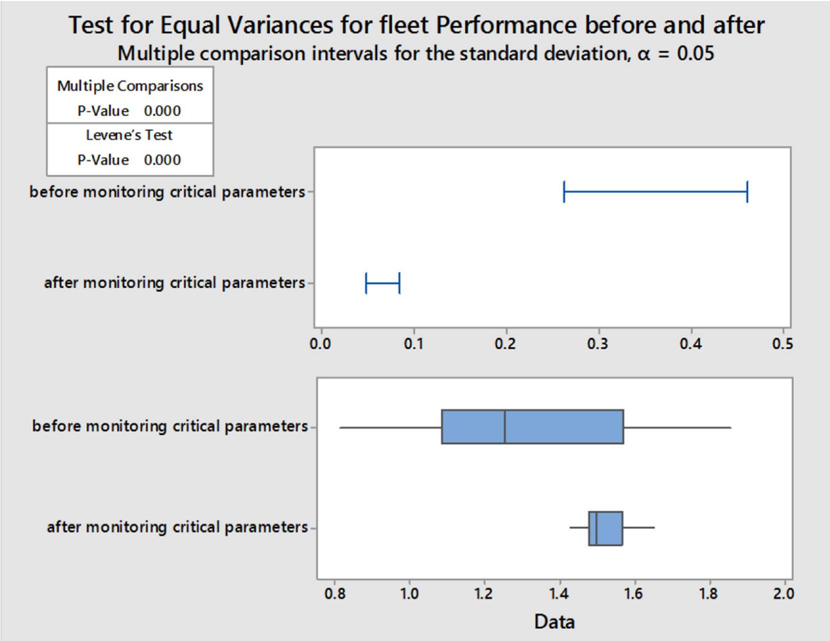

Figure 15.
Test for equal variances of fleet performance for before and after the situation

Table 12.
Results of F-test for fleet performance

Factor	Before	After
Standard deviation	0.330351	0.060031
p-value	0.000	

Table 13.
Results of t-test for fleet performance

Factor	Before	After
Mean	1.3099	1.5127
p-value	0.000	

Table 14.
Comparative study of statistical results

	Best alternative for purchasing	
Fleet category	Before	After
C	C-6	C-6
HB	HB-5	HB-9
S	S-7	S-1

7. Results

7.1 Statistical results

In this section, comparative statistical results are shown in Table 14. Full factorial DOE investigated that FC and RG are the critical parameters for fleet performance monitoring. Pareto chart confirmed the results of full factorial DOE. MCS has identified the optimum range of FC (23 to 24 MPG) and RG in [Rs. (10,000–11,500) x10] or (US$1,389–US$1,598) to maintain the average performance of the fleets.

7.2 Technical results

The technical results are derived for 300 fleets and results are shown in Table 15.

7.3 Business results

In this section, the business results are derived for 300 fleets and results are shown in Table 16. When the concept is used for all the fleets (0.1 million) across all the cities of the country, the total revenue generated will be a huge value worth US$12,088,022.

8. Discussion on results

8.1 Perspective of risk management

In this section of the article, we discussed the perspective of risk management for environmental, financial and operational risk using particular conditions and shows how the MOORA helps to take a correct decision for fleet maintenance management.

8.1.1 Fleet maintenance management. The fleet maintenance management focused on three types of maintenance, i.e. scheduled maintenance, non-compliance maintenance and critical maintenance. Noncompliance maintenance is unpredictable maintenance of the fleet, whereas critical maintenance involves the replacement of components and scheduled maintenance is periodic maintenance, which is helpful to improve the performance and life of the fleet. In this research, the scheduled maintenance is considered to discuss risk management perspective and data is captured on June 10th 2018 (Table 17). There is scheduled maintenance for fleet C-2 and C-5 after four and seven days, respectively, as shown in Table 17. The risks associated with scheduled maintenance are delays in scheduled maintenance, failure to perform maintenance as per schedule, assignment of the

Table 15. Comparative study of technical results

Sr. no.	Parameters	Before	After	(%)	Remark
1	CE (Kg CO_2/km) per year	3,022,680	2,876,566	4.83	Reduction in %
2	Fleet U in hours per year	1,353,609	1,576,460	16.46351	Improvement in %

Table 16. Comparative study of business results

		Before		After		Cost saved per year	
Sr. no.	Parameters	In Rs.	In US$	In Rs.	In US$	In Rs.	In US$
1	Total maintenance cost per year	5,708,627	79,286.47	3,959,594	54,994.36	1,749,033	24,292.125
2	FC cost per year	6,923,862	96,164.75	6,061,882	84,192.80	861,980	11,971.94
Total cost saved per year						2,611,013	36,264.065

wrong fleet for maintenance activities and increase in the maintenance time. The architecture (Figure 2) is developed to respond the identified risk, as it shares the data of fleet with an engineer, fleet manager and mechanic to take quick action. The captured data of selected parameters (June 13th 2018) is analyzed using MOORA and results are shown in Table 18. The highest-ranking by MOORA method shows the worst condition of the fleet and vice-versa. The ranking shows that the C-4 is in excellent condition and suggested to go with the scheduled maintenance. However, C-2 required maintenance on urgent bases, i.e. on June 14th 2018 or before, based on MOORA analysis. The MOORA analysis shows that C-7 and C-6 required maintenance in the next five to six days. However, if the maintenance activity goes as per the schedule, there is the probability of critical maintenance, which can increase maintenance cost and time.

Similarly, C-5 shows that scheduled maintenance is after seven days, but MOORA assigned the third rank to C-5, which shows that the fleet is in excellent condition and suggested that the maintenance is not required after seven days, but can be performed approximately after a month. This way, MOORA helps to make the correct decision, i.e. some schedule maintenance is confirmed (C-2), postponed (C-5) and preponed (C-6, C-7). This way, the MOORA helps to reduce or mitigate the risk associated with the assignment of the wrong fleet for maintenance. The ranking of a C fleet for maintenance management is shown in Figure 16. It shows that both methods suggested the same rank for C-2, which implies that the scheduled maintenance is required. Similarly, scheduled maintenance is assigned rank 7 for C-7, but MOORA assigned rank 2, which implies urgent maintenance of C-7 is required to avoid critical maintenance. The ranking of C-1 shows that the maintenance can be performed as per the schedule.

8.1.2 Environmental risk. Environmental risk can be defined as the "actual or potential threat of adverse effects on living organisms and the environment by effluents, emissions, wastes, resource depletion, etc., arising out of an organization's activities." The

Table 17.
Details of scheduled maintenance

Sr. no.	Fleet ID	Date of scheduled maintenance	Remark (unavailable after following days)	Rank
1	C-1	23/06/2018	13	3
2	C-2	14/06/2018	04	1
3	C-3	03/07/2018	23	5
4	C-4	01/07/2018	21	4
5	C-5	17/06/2018	07	2
6	C-6	03/07/2018	23	6
7	C-7	09/07/2018	26	7

Table 18.
Captured data (average) and MOORA ranking

Sr. no.	Fleet ID	FC (MPG)	CE (g CO_2/km.)	CT (°C)	MOORA Ranking
1	C-1	25	106	80.7	4
2	C-2	26	106	81.9	1
3	C-3	25	105	78.3	6
4	C-4	24	105	79.4	7
5	C-5	25	104	79.5	5
6	C-6	26	105	80.0	3
7	C-7	26	107	80.6	2

environmental risk is identified and controlled by real-time monitoring of CE. The maximum permitted value of CE is around 120 gCO_2/Km, which is the reference value for monitoring environmental risk. If the CE values are breaches to threshold values, then there is a probability of increasing environmental risk, legal risk and financial risk in terms of penalty charged by the government. Further, CE values are useful to check the performance of the fleet and the likelihood of physical risk for the fleet. The real-time monitoring of CE helps to reduce the risk associated with the environment, physical damage and legal risk.

8.1.3 Financial risks. Financial risks are categories into market risk, credit risk, liquidity risk and operational risk. In this study, the operational risks are discussed based on two situations such as selection of fleet for a new purchase fuel theft and consumption. In an earlier section of the article, MOORA and multi-MOORA are performed to select the best fleet for a new purchase, which gives different alternatives than the existing approach. The suggested alternative by MOORA can help an organization to increase return on investment. This study also monitors FC and RG for knowing the FC rate and fuel theft, e.g. if the FC is high with respect to RG, then there is the possibility of fuel theft or unnecessary fleet travel. Both the conditions develop the financial risk for the organization. The real-time FC monitoring minimizes the risk associated with fuel theft. Further, if FC is high as compared to average consumption, it indicates fleet under-optimum performance condition, which may lead to the physical risk of the fleet. The continuous monitoring of FC can help to avoid the physical risk of the fleet. Thus, the identified parameters and MCDM techniques help to reduce the financial risk associated with fleet management.

8.2 Guidelines for practitioner

- Select both beneficial and non-beneficial attributes for analysis.
- Select the most demanded fleet for analysis.
- Select appropriate numbers of attributes to reduce error and analysis efforts.
- The ranking preference may vary between the methods but ensure that all method suggests the same best solution for a given situation.

9. Conclusions

In this study, two critical problems of fleet management are identified based on a literature survey and Delphi method 1) identification of the best fleet for a new purchase and 2) fleet

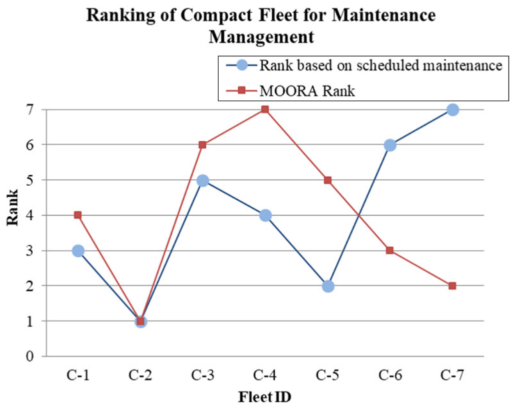

Figure 16. Ranking of C fleet for maintenance management

health monitoring and U. The useful parameters for fleet performance monitoring are identified such as FC, CE, CT and AT, which are monitored using sensors in the interval of every 5 min. This generates approximately more than 190 entries per day for a single parameter. The real-time monitoring of selected parameters presents the current condition of fleet health. Fleet utilization, customer rating and RG are monitored once in a day. However, maximum AT and TW develop a critical environment for fleet management analysis. The selection of the best fleet is simple and logical based on MOORA, reference point and multi-MOORA approaches, as these methods considered beneficial and non-beneficial parameters for selecting the best alternative. The MOORA and other two methods have suggested (C-6, HB-9 and S-1) as the best alternatives for a new purchase or agreement in given conditions. The deviation between MOORA and Multi-MOORA method is very less as compared to the deviation between MOORA and the reference point approach. The different operating mathematics introduced deviation in the results of the MOORA and reference point approach.

The sensitivity analysis shows that the best alternative remains the same for most of the different values of parameters. Taguchi and full factorial DOE identified FC and RG are the critical parameters for fleet performance monitoring. MCS optimized the range of critical parameters such as FC (23 to 24 MPG) and RG [Rs. (10,000–11,500) × 10] or (US$1,389–US $1,598), which helps to monitor the average performance of the fleet. The results of DOE and MCS are validated using F and *t*-test to ensure the significant effect of monitoring critical parameters on fleet performance. This study also discusses the perspective of risk management using different situations of fleet management, which helps to identify, mitigate and monitor risks associated with operations, finance and environment. The fleet management architecture helps to reduce the response time for risk management.

In future studies, a similar method can be used for asset propelled industries, manufacturing industries, service industries with the same or different parameters and different MCDM methods with a fuzzy scale can also be used for a similar or different problem.

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