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Procedia CIRP 105 (2022) 296–301

www.elsevier.com/locate/procedia

29th CIRP Life Cycle Engineering Conference

An AI-enhanced Approach for optimizing life cycle costing of military logistic vehicles

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Abstract

Individual usage profile (aka true usage profile) of military logistic vehicles (MLV) is highly dependent on types of operations, duration and areas of use. Compared to non-military vehicles, the operation life is considerably longer, mileage tends to be several times lower and the characteristics of the application area, including environmental factors, is much more diverse. Transparent and realistic determination of MLV’s true usage profile facilitates, inter alia, optimal life cycle costing in particular operation costs. In practice, however, effects of non-usage, such as material degradation or damage during service of the vehicles are not explicitly recorded. Important aspects of assets management, such as identifying maintenance measures and logistic disposition calculations, are often conducted non-systematically and non-data driven but rather based on human experiential knowledge and manufacturer's specifications. Hence, the modelling and predictive analysis of MLV’s true usage profile is subject to significant uncertainties. The body of knowledge in assets management does not consider the aforementioned problems. Therefore, lack of novel AI-enhanced approaches for modelling MLV’s true usage profile is evident. This paper introduces an integrative, data-driven approach for identifying the true usage profile and thus improving the life cycle costing of MLV. The proposed approach involves an AI-enhanced analysis of heterogeneous data sources, such as sensor-, vehicle control-, GPS-, and logistics data as well as textual logbooks. It enables a transparent and realistic identification of MLV’s true usage profiles, which facilitates accurate and timely calculation of life cycle costs under consideration of data quality properties. Finally yet importantly, classification of usage profiles enables a data-driven decision support system to provide i) proactive maintenance measures, and ultimately ii) to optimize distribution of vehicles and spare parts in decentralized warehouses.

Keywords: Life Cycle Costing, Maintence Planning, Asset Management, Disposition Model, AI

1. Introduction

Assuring reliability of military logistic vehicles (MLV) and their failure-free operation during a mission is the most vital task within a military unit [1]. Monitoring the ongoing technical condition of various MLV’s subsystems based on operational data is, therefore, important in order to derive optimization measures [2]. Original equipment manufacturers in civil sector collect an extensive data set through built-in sensors (e.g. interior temperature, exterior temperature, GPS sensors, etc.), as well as through the evaluation of vehicle control systems, which enables high-quality conclusions of individual “true usage profiles” of vehicles [3, 4]. However, MLV’s usage profiles are fundamentally different from those of non-military vehicles [5]. The useful life is considerably longer, mileage tends to be several times lower and characteristics of the application area, including environmental factors, is much more diverse. In the military sector, analysis

10.1016/j.procir.2022.02.049

of operation data and maintenance of vehicles has not been the focus of research so far. Currently employed maintenance methods in this field are not sufficient for data-driven optimization of life cycle costing and associated key performance indicators (KPIs) [6]. Fundamental KPIs, such as reliability, availability, and maintainability (RAM), are currently only occasionally considered where intensive inspection and constant improvement are planned [7], while careful consideration of RAM parameters is the key for successful maintenance management and life cycle costing [8]. In practice, operation and maintenance cost of a MLV fleet is a large expense for the owner, while existing standard methods lack providing adequate proactive and accurate handling measures. The existing off-the-shelf and best-practice methods to select maintenance strategies are mainly based on experience of the operators and manufacturers' recommendations. Over the last few years, pressure on optimizing operating costs and on time delivery have dramatically gained importance to optimize maintenance processes [5]. Frequently, logistics and maintenance objectives are optimized separately and further the resulted optimization outcomes have only a modest effect [7]. Hence, AI technologies and knowledge-based maintenance approaches should be evaluated in order to lay the ground for the next steps of enhancement in life cycle costing and maintenance of MLV, in particular to assure MLV's failure-free operation [9]. Documenting the true usage profile of the MLV fleet of a military unit accurately using multi-structured data, inter alia sensor and text, enriches the existing experiential knowledge-base and shapes a heterogeneous data basis for improving cost and maintenance planning.

To bridge the aforementioned gap in research and practice, this paper proposes an integrative, data-driven approach for identifying the true usage profile and thus improving the life cycle costing of MLV. The proposed approach focuses on multi-structured data analytics, i.e. collection and evaluation of accurate heterogeneous data sources, such as sensor-, vehicle control-, GPS-, and logistics data as well as logbooks. Further, it systematically explores transparent and realistic identification of usage profiles of MLV, based on an AI-enhanced analysis of vehicle information. The evaluated MLV's true usage facilitates calculation of life cycle costs, considering data quality properties. Further, classification of MLV's true usage profiles enables a data-driven decision support system to provide i) proactive maintenance measures, and ultimately ii) to optimize distribution of vehicles and spare parts in decentralized warehouses.

Considering the above introduction, the rest of the paper is structured as follows: Section 2 discusses theoretical principles of life cycle costing and provides a state-of-the-art literature review on machine learning algorithms for MLV usage classification. On this basis, the missing link between life cycle costing and true usage profiles is identified, which leads to a concept model for optimized life cycle costing and further contributes into a data-driven approach for modelling and predictive analysis of MLV's true usage profile, cf. Section 3. Section 4 concludes the discussion and identifies the future pathways of research.

2. State of the Art

2.1. Life cycle costing based on usage profiles

Several reports and articles provide holistic models calculating life cycle costs of military equipment. However, there is an evident lack in the body of knowledge for understanding, integrative modeling, capturing data and monitoring the true usage of MLV linked to life cycle costing. This issue is briefly discussed in this section, through a review of state-of-the-art approaches.

Life cycle costs (LCC) refer to costs associated with the design, development, acquisition, operation, maintenance, overhaul and support from the inception of the concept to the disposal of the asset. LCC are determined by understanding all factors contributing to the cost of the asset and compiling the individual costs to develop a total lifetime cost for the asset [10, 11]. From military perspective, the Defense Acquisition Guidebook (DAG) defines LCC as costs consisting of R&D costs, investment costs, operating and support costs, as well as disposal costs over the entire life cycle. For a defense acquisition program not only the direct costs, but also indirect costs that would be logically attributed to the program are included, regardless of funding source or management control [12]. Thus, the LCC are composed of the acquisition costs C_P, the maintenance costs C_{OM}, the operational costs C_O and the disposal costs C_D as follows [13]:

$$LCC = C_P + C_{OM} + C_O + C_D \tag{1}$$

LCC in defence acquisition projects are usually calculated over the i) concept and development stage, ii) acquisition stage, iii) operation and maintenance stage and the iv) disposal stage of the product as shown in Fig. 1 [14, 15].

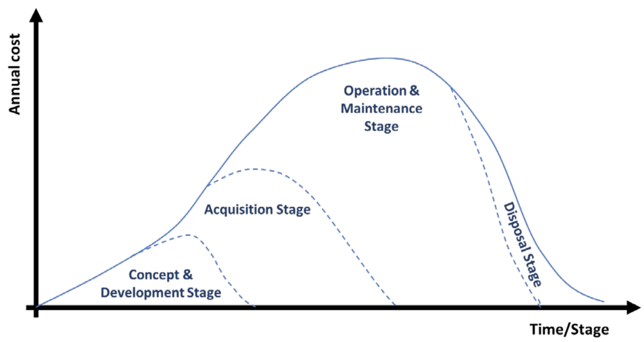

Fig. 1. Four stages of life cycle costing in military context

A life cycle model requires to identify key factors that affect operational readiness and cost of achieving expected readiness [16, 17]. Modelling needs complex and time-consuming research to examine various input parameters and possible scenarios, that is why existing models usually cover only specific systems or only parts of a life cycle. As an example, maximizing availability and profitability of the product system by varying both maintenance strategies and logistic factors is discussed in [18]. However, LCC are highly dependent on understanding individual and correlative effect of these parameters. Notably, maintenance and operation of vehicles dependent on the vehicle's usage profile, which also has the greatest impact on lifecycle costs. Therefore, in aviation or maritime systems, LCC is often calculated based on the so-called "true usage profiles" [19]. MLV's true usage profile is determined mainly by operation time, area of use (i.e. terrain type) and storage. Based on the true usage of components or a system, a remaining useful lifetime span can be assigned in relation to the planned load [20]. Compared to civilian vehicles, MLV are exposed to a substantial additional load, due to off-road use. Therefore, accurate recording and classification of usage data can have a highly positive impact in optimization of LCC, in the concept and development stage as well as during operation and maintenance stage [21].

2.2. Machine learning algorithms for usage classification

In order to classify usage profiles of vehicles accurately, usually "multiclass classification algorithms" are applied. These kind of algorithms are basically applied to a wide range of use-cases, e.g. in prediction of stock market prices, hydrology or health monitoring [22]. Multiclass classification describes the process of classifying input data into two or more categories, whereas binary classification addresses the classification of instances into simply two classes. Applying supervised multiclass classification enables the prediction of a class of data, based on labelled training data [23]. For this purpose, Support Vector Machine (SVM), Random Forests (RF) and Artificial Neural Networks (ANN) are applied widely. For the classification of usage profiles in order to predict particular events, the body of literature has already provided several approaches. These approaches mostly rely on vehicle control data, using aforementioned multiclass classification algorithms. For instance, scholars made efforts to predict the fuel consumption of vehicles, cf. [22, 24, 25]. In particular, Wickramanayake et al. discusses how machine learning is used for the prediction of fuel consumption, based on correlated vehicle data [22]. The approach of Nie et al. uses regression models, in order to predict the fuel consumption of trucks, based on historical vehicle time series data, as well as further correlated time series data, i.e. the distance travelled, the average speed and the average road slope [25]. However, only very few approaches considered deriving handling measures, e.g. for maintenance actions in order to reduce the LCC of vehicles. Zhang et al. recommend that considering maintenance actions based on the true vehicle usage, instead of pre-defined schedules, improves efficiency considerably [26]. Markudova et al. focuses on deriving preventive maintenance actions for heterogeneous industrial vehicles, based on historical vehicle usage data, exploring both, linear and non-linear regression models [27]. It is worth noting that, the authors mainly confronted a lack of sufficient data and were, therefore, forced to include data from different, but similar vehicles. Yet, none of the identified approaches covers the application of MLV, and their respective characteristics.

2.3. Research Gap and Contribution

Optimal LCC of MLV is significantly dependent on understanding the influencing factors across design, development, storage, operation, maintenance, and repair of an equipment, as well as their correlative effects. Standard calculation method is currently, based on derived and generalized usage profiles as well as empirical values of the respective vehicle types. Furthermore, the calculation results are oftentimes inaccurate due to the large variance in the usage of the individual vehicles. Non-usage costs are currently only estimated based on empirical values. In the military sector, as well as in the civilian sector, maintenance planning is usually based on mileage or, due to the sometimes-low mileage, on service life. Nevertheless, the lifespan of components such as engines or bearings, based on milage or operating hours, is often an estimated, inaccurate value, because the real life span of components and the whole system is massively influenced by environmental factors such as usage, load or temperatures. The lack of insight into the true usage profile of the individual vehicles, leads to a de facto situation that some vehicles are over-maintained or worse, not sufficiently maintained, leading to increased planned and unplanned costs [28].

A data-driven decision support system that enables maintenance schedules, based on true usage profiles and according to the calculated necessity could lead to significant savings in maintenance costs. The decreasing costs of sensory equipment enables the estimation of LCC, based on a well-founded data base from real-time collected data, which is not yet common in military asset management especially for MLV. Incorporating experiential knowledge of manufacturers and users of MLV into the data-driven analysis, an optimized LCC calculation with improved estimation accuracy is achieved.

3. True Usage Concept and related Data-driven Model

3.1. Concept for Optimized MLV's LCC

In order to overcome the research gaps, identified in Sect. 2.3, a concept of procedural multi-level model for the implementation of an AI-enhanced traceable recording and monitoring of MLV's true usage profile is introduced, which enables an informed decision support providing maintenance measures as well as an optimized logistic distribution calculation for MLV, thus leading to reduced LCC, as depicted in Fig. 2.

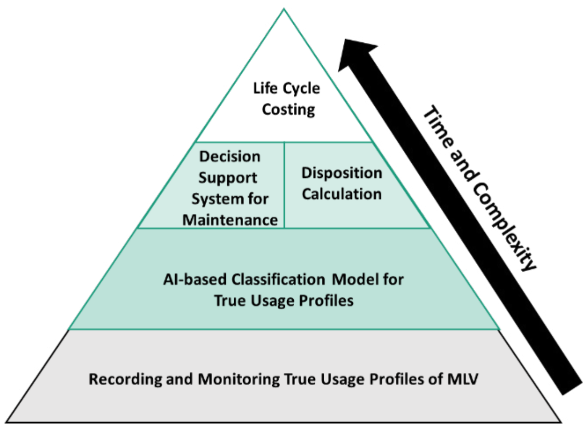

Fig. 2. Procedural Approach for Optimizing MLV's LCC

The true usage of MLV is recorded and monitored, using vehicle control data, data from externally installed sensors as well as respective logbooks. In a second stage, an AI-based

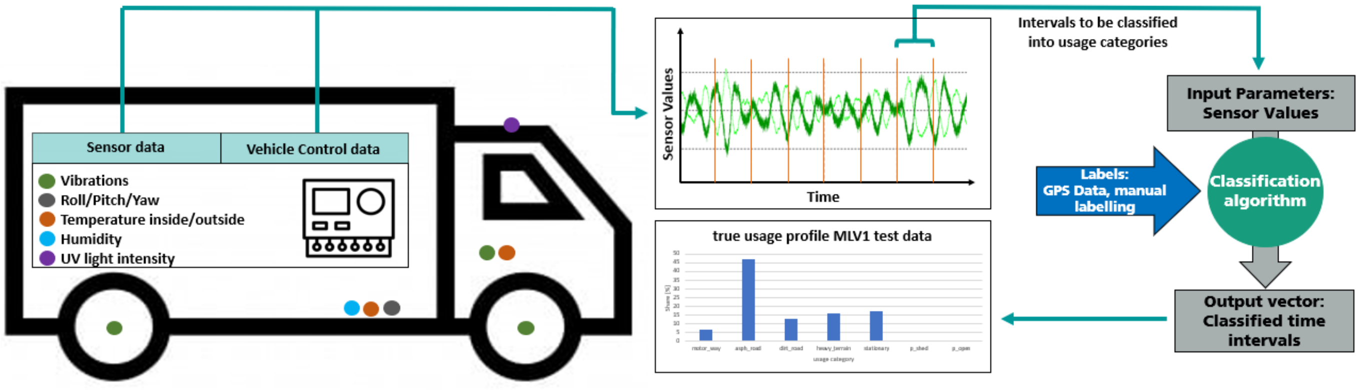

Fig. 3. Concept of True Usage AI-based Classification

classification model analyzes the captured true usage data cf. Fig. 3. Apart from the surface on which the vehicle is operating, storage or parking conditions are believed to have major impact on wear and overall health condition of the vehicle. Several usage categories have been identified, which impact the vehicle's health status. The categories of usage correspond partly with categories found in literature [29, 30] but have been expanded in order to incorporate storage and parking conditions, cf. Table 1.

Table 1. Identified Usage Profiles in driving, parking, storage and idle mode

Driving Mode	**Parking/Storage/Idle Mode**
Road – motor way	Stationary but engine running
Road – paved or asphalted	Parking in garage/shed roof
Dirt roads (tracks)	Parking in open terrain
Heavy terrain/open country	

The true usage profiles, then facilitate the implementation of a decision support system for identifying proactive maintenance measures for each monitored vehicle. Critical vehicle parts, correlated to the usage behaviour, can be identified based on the vehicle's true usage as well as data from the logistics information system. Therefore, the maintenance strategy is not limited to regularly scheduled maintenance actions specified by the manufacturer but is customizable for every vehicle. By proactively planning maintenance actions based on the usage of the vehicle, unexpected failures can be reduced, and the reliability is increased. Due to an improved spare part disposition, the mean time to repair (*MTTR*) is reduced which leads combined with reduced downtimes to an increased availability (*A*) i.e. uptime, according to the formula below.

$$A = \frac{t_{uptime}}{t_{uptime} + t_{downtime}} \tag{2}$$

Further, the maintainability is improved, since maintenance actions can be performed on time and efficiently based on true usage estimations [7].

In order to classify usage profiles precisely, the proposed concept for an AI-enhanced model incorporates data at two levels i) vehicle control data and ii) external sensor data. At a first level, vehicle control data is collected in order to provide information such as vehicle speed, engine temperature, selected gear etc. However, captured information is not sufficient to determine the detailed usage profile of the vehicle. Therefore, to gain more in-depth insights on the actual usage of the vehicles, information from additional applied sensors is analysed, cf. Fig. 3. For that matter a sensor concept is introduced, capable of tracking relevant additional data, to the vehicle control data. Notably, these sensors provide information about vibrations within the vehicle, the vehicle behaviour (pitch, roll, yaw, etc.) as well as temperatures, uv-radiation and humidity. Hence, further information about the true usage profiles of the MLV is collected.

3.2. Data Preparation and Modeling

To improve maintenance decisions, disposition calculation and life cycle costing, a clear understanding of the true usage of the vehicles is necessary. Therefore, different data from the vehicle control and applied sensors as well as logbooks are collected, analyzed, and modeled to determine the surface on which the vehicle is operated and hence the true usage profile of a vehicle. The step-wise data-preparation and modeling process is described below.

Data Basis: In test drives, vehicles have been equiped with a prototypical sensor installation with a variety of sensors (cf. Fig. 3) in order to capture mean and peak loads during operations as well as environmental conditions. Furthermore, 186 variables from the vehicle control system have been constantly recorded, including torques, pressures, temperatures, speed, etc. Data from the sensor installation and vehicle control system has been recorded during several test runs, covering all aformentioned usage categories. The relation of the input variables with the usage profile has been visualized in a heatmap in order to sort out features in the data which are not related to the classification task. The best predictores of the usage profile have been fed into the classifaction algorithm. To classify the usage categories of the vehicle, where the recorded data has been split into discrete time intervals of 10 sec.

***Data Labelling Process**:* In order to apply and train a supervised machine learning algorithm to classify the usage categories, all time intervals of the training data are assigned their associated category. As this is a resource-consuming task, a GPS position sensor has been used to provide latitude and longitude coordinates of the vehicle, and partly automate this process. Textual data from logbooks has been used for cross-check validation. The labelling process of the usage profiles has been automated using a geolocation API to obtain the vehicles current position and add the identified types of the roads to the data set. The distinction between dirt road and heavy terrain has been added manually, as the automatic labelling approach has not been able to distinguish these categories effectively.

Classification Model: Due to technical limitations, parking and storage categories have not been considered in the model, since the chosen sensor installation was not able to collect data with the ignition switched off. In the explorative data analysis (EDA), it has been revealed, that depending on the surface, front axle speed, demanded engine torque, fuel rate, current gear, shaft speed, vertical-acceleration, vertical-displacement and roll/pitch/yaw are the best predictors to classify the surface and thus the true usage profile. Three different algorithms have been applied to classify the surfaces. A multilayer perceptron (MLP) neural network with two hidden layers and 15 hidden units respectively, a Random Forest Classifier (RFC), as well as a support vector machine (SVM) have been used for the classification task. All three algorithms take as an input vector the mean, median and standard deviation values of the time intervals of the aforementioned variables, and provide as an output vector the predicted category. On a previously unseen test data set, all models reached an average model performance measurement, which has been found sufficient for the subsequent tasks of disposition calculation, decision support for maintenance measures and life-cycle costing. However, the RFC provided the best results, cf. Table 2.

Table 2. Average model performance measurement of 3 different algorithms and detailed model performance of RFC

Average model performance measurements (mean values)			
	SVM	**MLP**	**RFC**
Precision	76.0%	76.9%	79.7%
Recall	69.6%	74.7%	77.5%
F1-Score	71.6%	75.5%	78.3%
RFC model performance measurements			
Class	**Precision**	**Recall**	**F1-Score**
0	86.6%	86.1%	86.3%
1	73.4%	83.6%	78.1%
2	67.4%	53.8%	59.8%
3	79.6%	76.5%	78.0%
4	91.3%	87.5%	89.4%

As shown in Fig. 4, the distinction between the categories 1 and 2, which correspond to heavy terrain and dirt road, shows the smallest precision. This phenomenom can be accounted to the fact, that there is no clear demarcation between the two categories. Dirt roads with many potholes can justifiably be counted as heavy terrain and vice versa. It is worth noting that the model has been trained on around 3.5h of training data with a sampling rate of 10Hz. Another 1.5h of data has been used for validating the model. Expanding the data basis and varying the sampling rate could lead to considerable improvement of the model's classification performance.

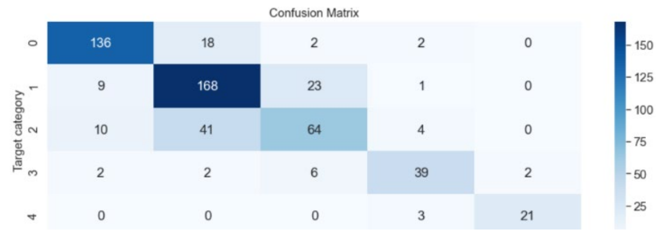

Fig. 4: Confusion Matrix for the Random Forest Classifier

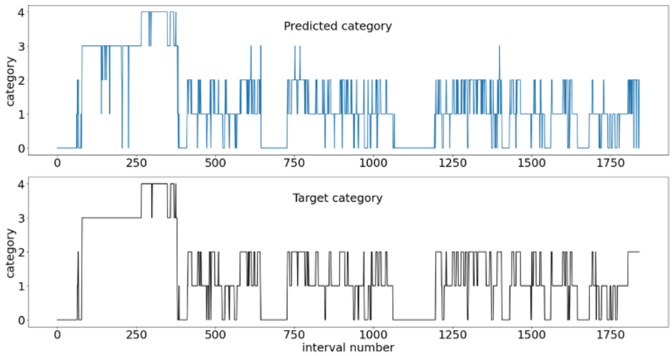

Fig. 5: Graphic comparison between target and predicted categories per time interval

4. Conclusion and Future Research Agenda

This paper presents an AI-enhanced approach for the classification of the true usage profiles of MLV. Using both prototypical sensor installation and multi-structured data including the vehicle control system and logbooks, it has been shown that the true usage profiles of MLV can be classified with a high precision. Future research focuses on analysis of the true usage profiles of MLV to enable a data-driven decision support that allows proactive identification and prescription of maintenance measures based on the vehicles usage. Further, a more precise forecast of the spare parts supply, leading to reduced LCC should be explored. Although the proposed concept already addresses the LCC saving opportunities enhanced by a data-driven decision support, there are still challenges for deployment as:

- The current classification model still needs to be expanded to incorporate parking and storage conditions of the vehicles, which is expected to have a major impact on the vehicle's health status;
- In order to improve spare part disposition and availability of the vehicles based on the true usage profiles, it is necessary to correlate the maintenance effort and spare part consumption of vehicles to the true usage profiles;
- In order to get a better understanding of the vehicle's true usage profile, based on a minimized sufficient sampling rate, a more light-weight sensor installation which can be powered through several months by the vehicle battery is required.

In sum, the AI-enhanced approach provides a practical solution for modeling and predicting the true usage profile of MLV, however, its deployment still confronts technical barriers for data collection. Last but not least, the effect of optimizing LCC on enhancing sustainability factors in design and operation of MLV is an unexplored topic subject to a separate research.

Acknowledgements

The authors would like to acknowledge the financial support provided by the Austrian Research Promotion Agency (FFG) through the research project "True_Usage", Grant number 879702.

References

[1] Verhoeff, M., Verhagen, W., Curran, R., 2015. Maximizing Operational Readiness in Military Aviation by Optimizing Flight and Maintenance Planning 10, p. 941.
[2] Krobot, Z., Turo, T., Neumann, V., 2017. Using vehicle data in virtual model for maintenance system support, in 6th International Conference on Military Technologies: ICMT 2017 conference handbook May 31 to June 2, 2017, Brno, Czech Republic, IEEE, Piscataway, NJ, p. 171.
[3] Louen, C.J., 2016. Datenbasierte Zustandsüberwachung in Personenkraftfahrzeugen mit Anwendung an einem Drei-Wege-Katalysator, Fakultät für Ingenieurwissenschaften.
[4] Barc, 2015. Predictive Maintenance in der Automobilbranche: AlexanderThamm data sience services.
[5] Ausseil, R., Gedik, R., Bednar, A., Cowan, M., 2020. Identifying sufficient deception in military logistics 141, p. 112974.
[6] Rabeno, E., Bounds, M., 032009. Condition based maintenance of military ground vehicles, in 2009 IEEE Aerospace conference, IEEE, p. 1.
[7] Djokic, I., Lazic, L., Pavlovic, A., Avdic, A., 2015. Simulation based life-cycle analysis of a vehicle fleet.
[8] Madreiter, T., Kohl, L., Ansari, F., 2021. A Text Understandability Approach for Improving Reliability-Centered Maintenance in Manufacturing Enterprises, in Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems, Springer International Publishing, Cham, p. 161.
[9] Ansari, F., Nixdorf, S., Sihn, W., 2020. Insurability of Cyber Physical Production Systems: How Does Digital Twin Improve Predictability of Failure Risk? 53, p. 295.
[10] Duran, O., Roda, I., Macchi, M., 2016. Linking the spare parts management with the total costs of ownership: An agenda for future research 9, p. 991.
[11] Passath, T., Huber, C., Kohl, L., Biedermann, H. et al., 2021. A Knowledge-Based Digital Lifecycle-Oriented Asset Optimisation 15, p. 226.
[12] Defense Acquisition University, 2013. Defense Acquisition Guidebook.
[13] Konecny, V., Furch, J. Methodology for Creating a Model of Vehicle Life Cycle Costs and the Methods of Modelling, in 2021 International Conference on Military, p. 1.
[14] Navarro-Galera, A., Ortúzar-Maturana, R.I., Muñoz-Leiva, F., 2011. The Application of Life Cycle Costing in Evaluating Military Investments: An Empirical Study at an International Scale 22, p. 509.
[15] Ghergari, V., Wang, L., 2016. Development of Cost Breakdown Structure for Defence Acquisition Projects.
[16] Djokic, I., Lazic, L., Pljaskovic, A., Pavlovic, A., 2013. Time between aircraft overhauls optimization by maximizing fleet total flying hours.
[17] Biedermann, H., Vorbach, S., Posch, W., 2019. Industrial Life Cycle Management: Innovation durch Lebenszyklusdenken. Rainer Hampp Verlag.
[18] Achermann, D., 2008. Modelling, Simulation and Optimization of Maintenance Strategies under Consideration of Logistic Processes.
[19] Tinga, T., Tiddens, W., Amoiralis, F., Politis, M., 2017. Predictive maintenance of maritime systems: Models and challenges, in Safety and Reliability – Theory and Applications, CRC Press, CRC Press Taylor & Francis Group 6000 Broken Sound Parkway NW, Suite 300 Boca Raton, FL 33487-2742, p. 68.
[20] Tomas Turo, Vlastimil Neumann, Zdenek Krobot, 2019. Health and Usage Monitoring System Assestment. Springer Berlin Heidelberg, New York NY.
[21] Banks, J.C., Crow, E., Reichard, K., Ruark, R. A cost-renefits analysis of the effect of condition-based maintenance strategies for military ground vehicles, in IEEE Aerospace Conference Proceedings, p. 3227.
[22] Wickramanayake, S., Dilum Bandara, H. Fuel consumption prediction of fleet vehicles using Machine Learning: A comparative study, in 2016 Moratuwa Engineering Research Conference, p. 90.
[23] Chaitra, P., Saravana, K., 2018. A Review of Multi-class classification algorithms.
[24] Çapraz, A.G., Özel, P., Şevkli, M., Beyca, Ö.F., 2016. Fuel Consumption Models Applied to Automobiles Using Real-time Data: A Comparison of Statistical Models 83, p. 774.
[25] Nie, J.-Y., Obradovic, Z., Suzumura, T., Ghosh, R., Nambiar, R., Wang, C., Editors, 2017. Application of Machine Learning for Fuel Consumption Modelling of Trucks: Dec 11-14, 2017, Boston, MA, USA proceedings. IEEE.
[26] Zhang, W., Yang, D., Wang, H., 2019. Data-Driven Methods for Predictive Maintenance of Industrial Equipment: A Survey 13, p. 2213.
[27] Markudova, D., Mishra, S., Cagliero, L., Vassio, L. et al., 2021. Preventive maintenance for heterogeneous industrial vehicles with incomplete usage data 130, p. 103468.
[28] Birgelen, A. von, Buratti, D., Mager, J., Niggemann, O., 2018. Self-Organizing Maps for Anomaly Localization and Predictive Maintenance in Cyber-Physical Production Systems 72, p. 480.
[29] Ludovici, D., Bray, M., Wickramanayake, V., 2013. Health and Usage Monitoring Proof of Concept Study Using Army Land Vehicles.
[30] Wang, S., Kodagoda, S., Shi, L., Wang, H., 2017. Road-Terrain Classification for Land Vehicles: Employing an Acceleration-Based Approach 12, p. 34.