VOL. 18, NO. 5, MARCH 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

SIMULATION OF VEHICLE MAINTENANCE AND REPAIR WORKSHOP

Evgeniy Sergeevich Kozin and Nikolay Olegovich Sapozhenkov
Department Service of Automobiles and Technological Machines, Transport Institute, Tyumen Industrial University
Volodarskogo Street, Tyumen, Russian Federation
E-Mail: kozines@tyuiu.ru

ABSTRACT

The article discusses the implementation and usage of information technologies in the field of automobile workshop management. A potential direction is the implementation of digital twins in various industries and technological processes. Digital twins by using a virtual environment make it possible to answer the question: "What if?" without experiments on real production and business processes of the company. The digital twin of an automobile workshop will increase the efficiency of the company by introducing an analytical system and a decision support system. The first phase of creating a digital twin is the development of a simulation model of an automobile workshop. The model must be able to generate data, analyze it and make optimization decisions based on it. Simulation is used to train and tune the digital twin. When implemented in real production, the source data simulation module can be replaced with a set of source information from the enterprise. The rest of the modules will be able to perform their functions without lengthy configuration. The article presents in detail the block of simulation modeling of the processes of operation of the vehicle fleet and automobile maintenance and repair workshops.

Keywords: vehicle fleet, digital twin, optimization, car maintenance and repair, simulation.

INTRODUCTION

Motor vehicles are in first place in terms of freight traffic among other types of transport (about 70% of all transported goods in Russia). Truck-based special vehicles are widely used for a variety of tasks. A large number of vehicles are concentrated in freight companies or taxi cab companies that provide transportation services to citizens or other organizations. These can be companies of vehicle fleet owners. Throughout the article, these companies will be called the vehicle-using company. A trucking company typically uses one of two strategies to keep vehicles running: car maintenance and repair by its own facilities or by third-party service organizations [8, 20]. When using the first strategy, the main structural element is the service department whose main tasks are the maintenance and repair of vehicles. The technical department consists of several mechanics (operators) who carry out work in an area equipped with car lifts and the necessary equipment [1].

The set of mechanics, equipment, and work area will be called a repair unit or unit. The unit is a channel for processing incoming requests for vehicle maintenance and repair. Motor transport enterprises are interested in reducing operating costs and increasing the efficiency of using cars. These measures can be achieved by optimizing the work of the technicians [21], maintenance scheduling and service interval optimization [25, 26 19], improvement of vehicle reliability factors, rational organization of the work of automobile service and repair workshops [7], and some other ways. The development of a digital twin of a trucking company has significant potential to improve the efficiency of vehicle-using company management. Digital twins are virtual prototypes of real production assets that reproduce the form and actions of the original and are synchronized with it. Digital twins are beginning to be widely used in various industries. For example, in the oil and gas sector, assets are being digitized to reduce operating costs and increase production and refining efficiency. In the automotive industry, digital twins are used mainly in the production of cars and in improving the reliability of their components and assemblies [2, 12, 18].

Digitalization of production can become the basis for a decision support system for the management team. Decision support systems are computer-automated systems, the purpose of which is to help people make decisions in difficult conditions for a complete and objective analysis of the subject activity. Decision support systems are based on the theory of decision-making, the methodological basis of which is the scientific basis of the systems approach. These topics lie in the focus of systems engineering, which is aimed at guiding the creation of complex systems [9]. Systems engineering is closely related to the concept of digital manufacturing.

Simulation is widely used in decision support systems. This method has advantages over analytical methods when modeling complex systems with a large number of random factors [5].

The aim of the work is to increase the efficiency of the vehicle-using company by developing a simulation model of the automobile maintenance and repair workshop. This is the first step in creating a digital twin for a company.

The paper is structured as follows. The materials and methods that disclose the algorithms and structure of the simulation model are presented in Section 2. Section 3 contains the initial data for modeling. Section 4 presents the results of modeling to determine the number of automobile repair units, and implement the algorithm for their loading. Section 5 provides an overview of the vehicle-using company digital twin web application. The last section summarizes the results and conclusions.

MATERIALS AND METHODS

The structure of the developed digital model of a vehicle-using company consists of several blocks (Figure-1).

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

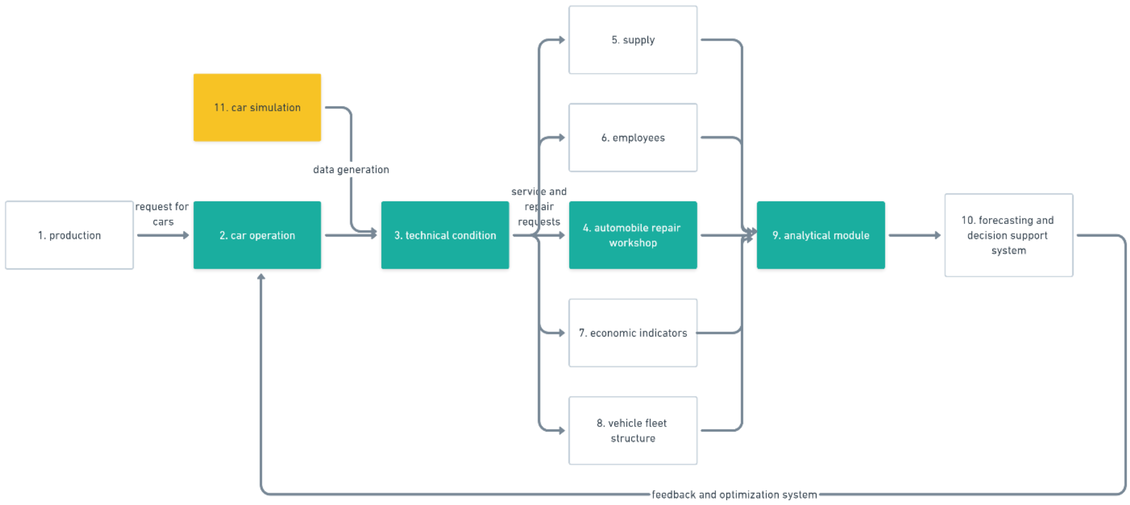

Figure-1. Digital model of a vehicle-using company.

The transport usually acts as a service for a particular production process (block 1). For example, oil and gas production companies form a request for automobiles and special vehicles to vehicle fleet owner companies or departments. Or the taxi company must service all received requests for the carriage of passengers. For these companies, the main production acts as an external environment. It forms the requirements for the size of the fleet of vehicles, its structure, the scope of work, and the conditions for operation. Trucking companies must continuously ensure that these requirements are satisfied by configuring the work of all services for this. The vehicle operation module (block 2) forms the daily mileage of vehicles and determines their technical condition (block 3) [3, 10]. The vehicle can be in working condition and perform the work assigned to it, or it can be idle while waiting for an order. Finally, it can be in a faulty condition or under maintenance. The manufacturer's technical reliability indicators of the vehicle may change under the influence of external conditions and the intensity of its operation [4]. Vehicle transition to a faulty condition forms a flow of requests for maintenance and repairs for the automobile repair workshop, which may be a part of the company's technical department (block 4). It is interconnected with other structural elements: the supply department (block 5), and employees (block 6), and affects the economic indicators (block 7) and the vehicle fleet structure (block 8) [6, 11, 14]. The digital model of a vehicle-using company makes it possible to trace the direction and relationship of information flows between the considered blocks, as well as to generate analytical reports of any complexity and depth in real-time (block 9). Preventive maintenance is an effective tool in fleet management [13]. Thus, company management has the opportunity to evaluate the effectiveness of production processes [16]. For example, the model allows to evaluate of the reliability indicators of a particular vehicle in comparison with others, considers the factors that influenced failures, determines the frequency of their occurrence and the duration of downtime in repairs, evaluate the work of mechanics and the logistics department, etc [15]. At the macro level, the model allows you to determine the performance indicators of the technical department determine the rational term of use of the vehicles' fleet, and its structure, draw conclusions about the correspondence between the number of vehicles and the flow of applications for them [23]. Also, the digital model includes a system for forecasting and decision-making support (block 10), which is able to give recommendations and evaluate the actions of personnel based on artificial intelligence and scientific patterns identified in the previous blocks. A feature of this approach is the presence of feedback, which allows management to adjust the parameters of any block based on an analysis of the company's current activities. For example, the model allows for adjustment of the number and composition of repair units (mechanics for car maintenance and repair, equipment, car lifters), depending on the annual program for using the vehicle fleet, formed at the request of the main production. Also, it could help to increase the number of customers [24]. With the help of a digital model, it is possible to determine the company's performance indicators when changing the car maintenance and repair strategy (for example, when the company completely refuses to service and repair cars) or when restructuring the fleet (changing the model range, the average age of cars, etc.).

The article discusses the implementation of the following modules of the company's digital model: a model of car operation, changes in its technical condition, and a model of a car maintenance and repair station.

Below are the schemes of the algorithms of the main modules mentioned above and a description of their work. The algorithm for the simulation model of car operation is shown in Figure-2.

VOL. 18, NO. 5, MARCH 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

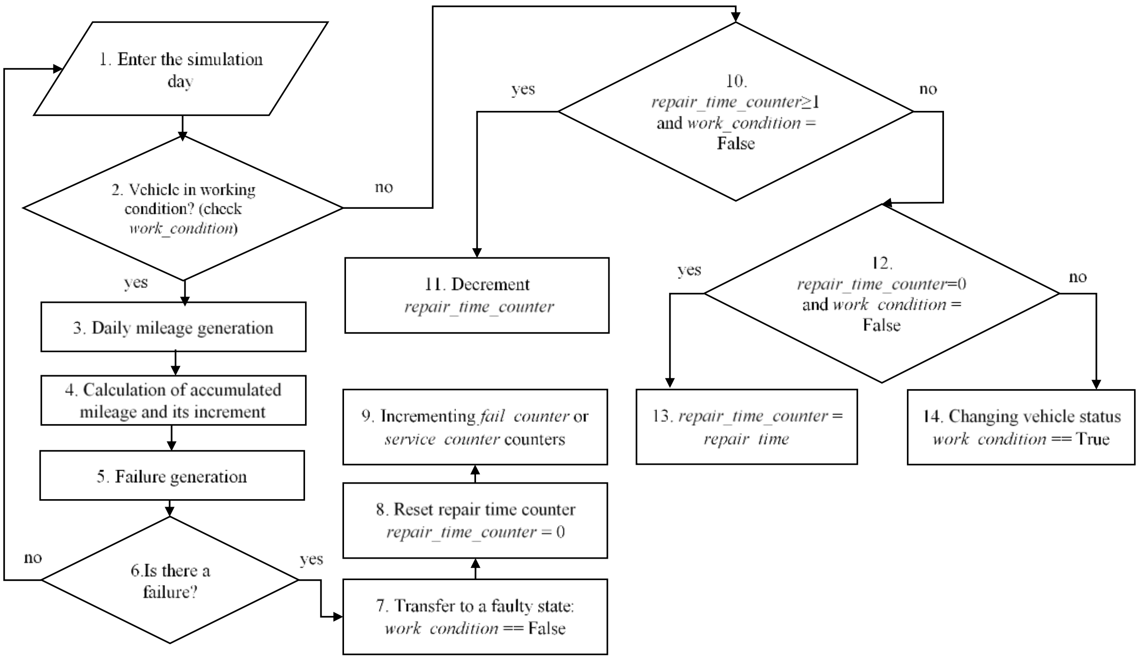

Figure-2. Algorithm for the simulation model of car operation.

The following is a description of the algorithm of the simulation model of car operation. The data on the required number of cars and the simulation period, which is 1 year or 365 days, are fed into the model. The simulation step is 1 day.

Before starting the simulation, a specified number of objects of the “Car” class are created with the following parameters: serial number, state registration number, make, model, year of manufacture, mileage from the start of the operation, frequency of maintenance, state (good, faulty), average maintenance time, average repair time. When a new day arrives, the condition of the vehicle is checked. If the car is serviceable and not under repair, daily mileage is generated, the accumulated mileage is calculated and the mileage is updated from the start of operation. At each step, according to a predetermined distribution, the failure moment is generated. The generated mileage at which the failure occurs is compared with the current mileage of the car and, if the failure did not occur, the indicators are recorded in the database and the next business day is simulated. When a failure occurs, the vehicle is transferred to a faulty state; the repair duration counter is reset to zero. If during the simulation the car was already under repair, then the repair duration counter is reduced by one. If the repair has been completed (the repair duration counter is zero and the vehicle state is faulty), then the vehicle is placed in a healthy state and the simulation continues.

The data generated by the previous module (block 11 in Figure-1) are the basis for the operation of other modules of the digital model of a trucking company. The sum of the daily number of failures and requests for maintenance for all cars is the initial information for the car repair zone modeling block, the block diagram of which is shown in Figure-3.

ARPN Journal of Engineering and Applied Sciences

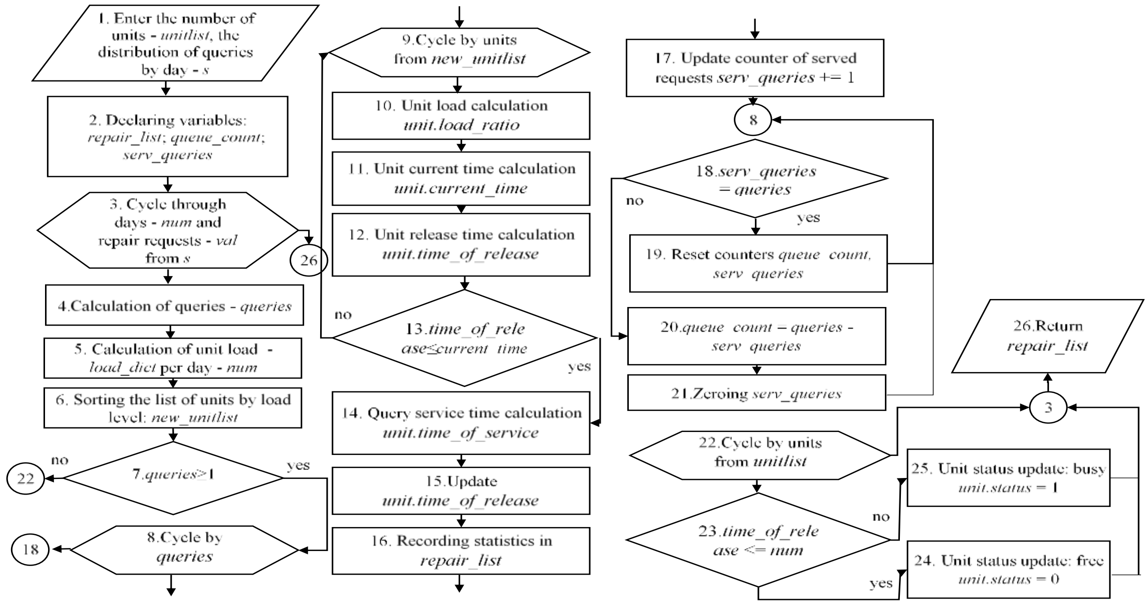

Figure-3. Scheme of the algorithm of the car repair zone.

At the input to the model, the number of units for servicing applications is set. The units operate on the principles of an n-channel non-Markovian queuing system, while the distribution of random variables can be determined by the user.

The state graph of the queuing system is shown in Figure-4.

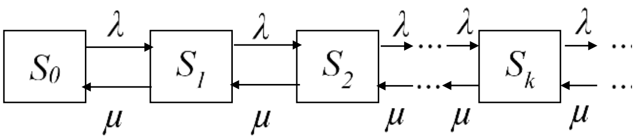

Figure-4. Graph of the state of the car repair unit in the current repair area.

The system can be in several states, passing into each other sequentially with the intensity of the flow of requests λ and the intensity of the flow of services μ: S_0 - the channel is free, S_1 - the channel is busy (serves the request), there is no queue, S_2 - the channel is busy, one request is in the queue, the channel is busy, S_{k-1} requests are in the queue. At the same time, the number of system states is limited by the total number of repair requests at the current modeling step, and the queue size of unprocessed requests incremented to it from the previous step. The simulation step is also equal to one day. The model reads the total number of repair requests from the database and adds to it the number of requests in the queue from the previous day. This value will be the initial number of applications arriving in the repair zone. Existing studies were mainly aimed at optimizing the work schedule of units [22]. The difference between this model and the known ones is the mechanism for leveling a load of units by redistributing requests between them. That is, the request is received each time not for the first unit of n available, but for the one whose average load over the past simulation period is minimal. To do this, the model determines the unit load indicator, after which it sorts them according to the degree of load increase (Eq.1).

$$k_l = \sum_{i=1}^{N_m} D_b / N_m \qquad (1)$$

where k_l - unit load factor; D_b - number of days the unit is in operation; N_m - number of days from simulation start to current step m.

Features of the implementation of the proposed method are shown in Figure-5.

VOL. 18, NO. 5, MARCH 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

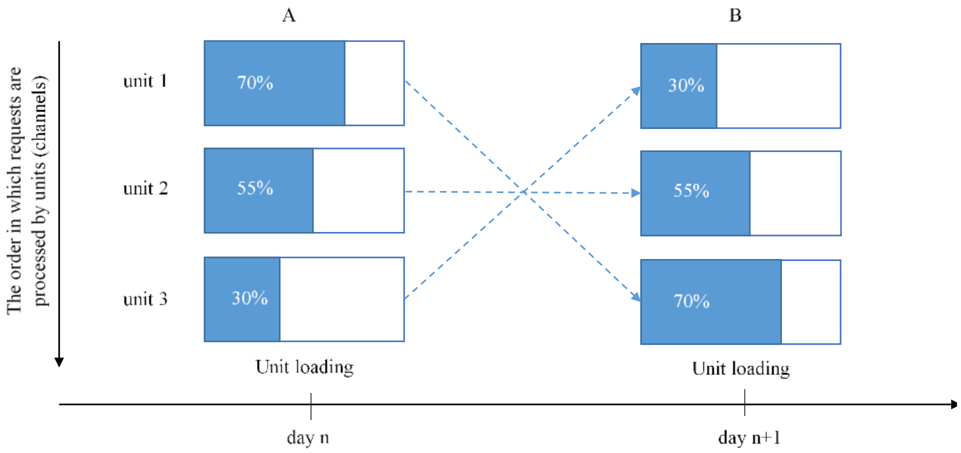

Figure-5. Redistribution of units depending on their average load.

In the example shown, Option A corresponds to the standard queuing method for processing requests by channels. In this case, the load of the first channel is always greater than the load of the subsequent ones, since the algorithm distributes requests sequentially as the channel index increases. In practice, uneven loading of units can be inefficient, as it leads to uneven loading of mechanics, which is associated with subsequent financial and economic problems and dissatisfaction of the staff. Option B is preferable, as it assumes uniform loading of all service channels. Channel 1, loaded by 70%, is determined to have the lowest priority for the receipt of applications in this iteration of the model, the underloaded channel 3 is put in place 1, and channel 2 remains in place. Thus, the next request will be sent not to the already overloaded first channel, but to the underloaded third one.
If at the current modeling step, the number of requests is greater than or equal to one, then the operation of the repair zone is simulated to process each of the incoming requests. The repair area consists of a number of units predetermined by the operator with a given distribution of their productivity. The units are already sorted according to the load average leveling principle presented above. If the unit is free, i.e. its release time is less than the current model time, then the order is assigned to this unit. At the same time, the status of the unit is changed to "busy", a new value of the unit's release time is determined, the counter of serviced requests is updated, and statistical indicators of its functioning are recorded in the database. These steps are performed for all applications. If there are unprocessed requests in the system, and all units are busy, then these requests go to the queue and are added to the requests at the next modeling step. A unit's status changes to "free" when the current model time exceeds its release time. The module returns information on the daily workload of each unit.

The final stage of modeling is the function of determining the load indicators of the repair area when iterating through various options for the number of repair units. To ensure the required accuracy, the simulation is performed for a certain number of cycles, after which the results are averaged and analyzed.

INITIAL DATA FOR MODELING

The simulation model is implemented in the Python programming language using the numpy, pandas, matplotlib, and random modules. The purpose of the simulation was to test the performance of the model and the possibility of optimizing production processes. To perform a specific task, the user can set any values of input variables and distribution laws based on data from the enterprise. In addition, the analytical module of the digital model can make recommendations on the average values of the input parameters based on the processing of primary data. The input data for the simulation are listed below.

Number of simulation cycles: 100
Simulation period: 365 days
Simulation step (model time change): 1 day
Number of vehicles (fleet size): 100 units
Maintenance interval: 12,000 km.
Mathematical expectation of mean time before failures: 4000 km.
The mathematical expectation of the duration of the elimination of failure: 3 days.
Types of failures (large groups): engine, transmission, suspension, electronics, chassis
Vehicle age range: 2005 - 2020
Distribution laws of random variables: daily mileage, time between failures, application service time, vehicle age generation - uniform distribution (random.randint() Python3.10 module).

SIMULATION RESULTS

Based on the results of the simulation, a database of operational indicators of the car fleet is formed, presented in Table-1.

ARPN Journal of Engineering and Applied Sciences

Table-1. Results of modeling data on the operation of the fleet of vehicles for the year.

No	License number	Brand	Model	Year of issue	Mileage since start of operation	Day	Mile age	Accumulated mileage	Mainten ance	Fail ure	Failure type
37	P474TO 72	BMW	7	2013	124467	16	187	2601	0	0	0
37	P474TO 72	BMW	7	2013	124654	17	162	2763	0	1	suspensi on
37	P474TO 72	BMW	7	2013	124816	18	0	2763	0	0	0

The table shows a slice of data for a 2013 BMW 7 car with serial number 37. On January 16, the car drove 187 km. There was no failure. January 17 after 162 km. mileage, the car experiences a running gear failure, after which it was sent to the repair area and was still in it on January 18 (daily mileage = 0, no mileage increment was recorded by the model). The information on the form above should be recorded by the internal services of the trucking company and used to optimize work processes. Currently, the model generates it, but the final version of the digital twin should use data from the analyzed company.

As a result of simulation modeling using the created digital model for a different number of repair units, the following data were obtained: the loading of posts, and the number of applications processed and unprocessed by the units (Table-2).

Table-2. The results of modeling the operation of the system for servicing requests for car repairs for different methods of distributing requests between units.

Number of units	Number of requests for repairs	Number of processed queries	Number of unprocessed queries	Average unit load factor
5	2297	605	1692	0,99
10	2297	1207	1090	0,98
15	2297	1801	496	0,98
20	2297	2295	2	0,93
30	2297	2297	0	0,63

The load factor of units in the implementation of the standard algorithm for assigning requests to units changes on average by 20% ranging from 0.99 for 1 unit to 0.78 for the last 20th. At the same time, the first and all units with a low index (1-14) were loaded to the limit during the entire simulation period (Figure-6 - upper graph), and units with a higher index (15-20) could be idle for some time (Figure-6 - central graph).

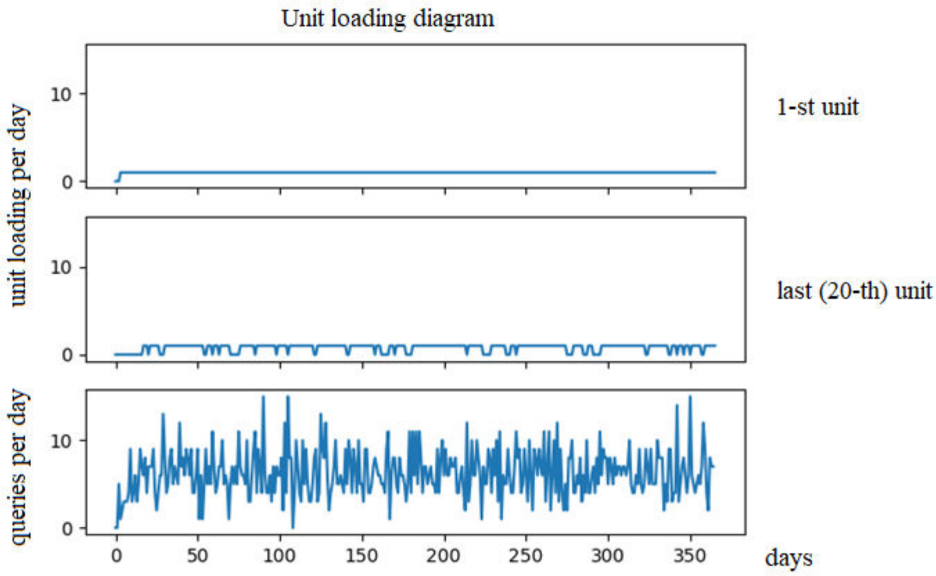

Figure-6. Changing the loading of units with different options for distributing requests between them.

With such a scheme for distributing queries and the number of channels for processing them (units), all queries are processed by the system, but more than 50% of the channels operate at the limit of their capabilities with maximum load. This can lead to a significant queue and denial of service with any change in the intensity of requests entering the system or the distribution of random variables. Obviously, this method seems to be less rational than the channel load balancing method, which makes it possible to reduce the load on the system and prevent channel downtime, thereby increasing its ultimate strength. When using the load leveling algorithm, each channel was loaded on average by 93%. Thus, each channel has a margin, which will allow it to cope with deviations in the input parameters from the predicted ones. The graph of changes in channel loading when using various algorithms for distributing applications between them is shown in Figure-7.

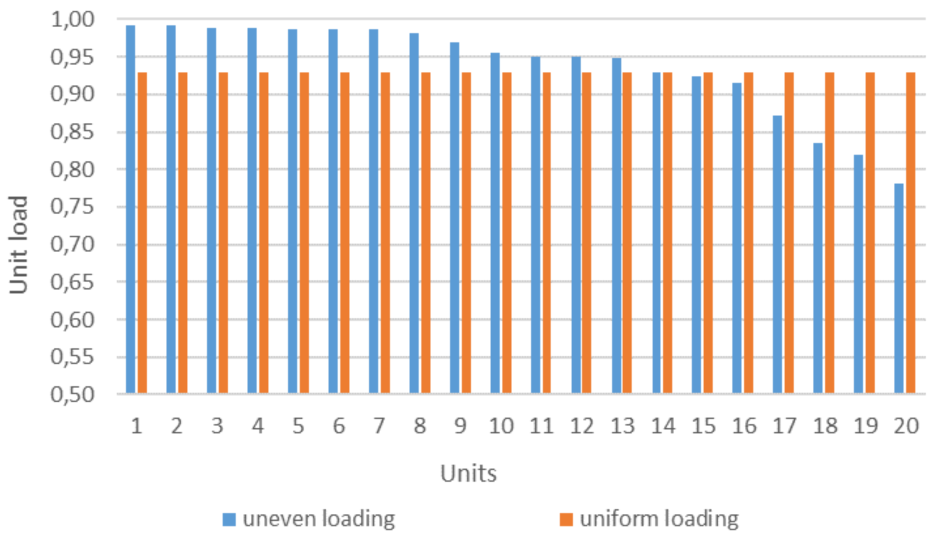

Figure-7. Changing the loading of units with different options for distributing requests between them.

It should be noted that for both options, the final performance indicators of the system: the number of queries received, the number of queries processed, and the average unit load factor - are the same. The problem turns into a standard queuing system optimization problem in order to determine the optimal number of channels [17]. It becomes obvious that in order to efficiently process all incoming queries, the system must have 20 units with an

ARPN Journal of Engineering and Applied Sciences

average load factor of 0.93. This is confirmed by the breaking point of the curve for the degree of unit occupancy in the graph shown in Figure-8.

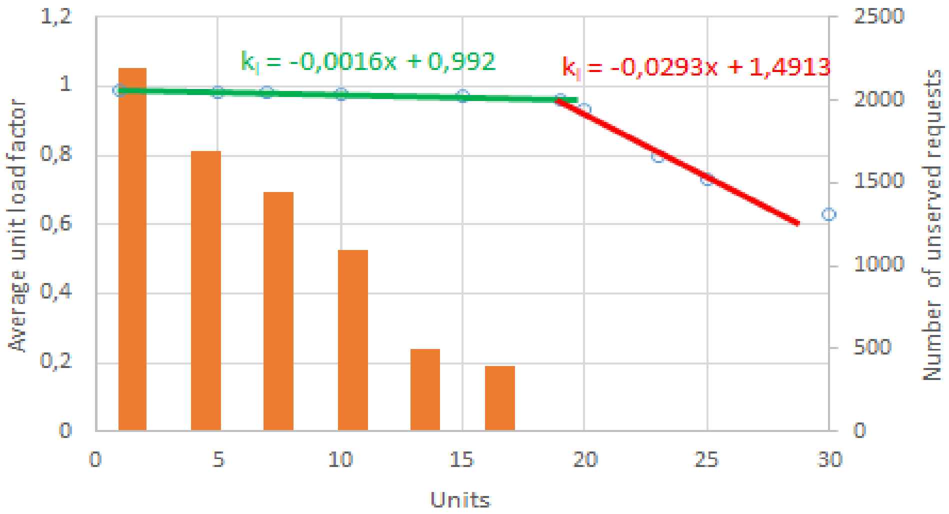

Figure-8. The relation between the loading of units and their amount

It can be approximated by two linear equations (Eq.2 and Eq.3), each of which can be used within certain limits.

$k_l = -0.0016 \cdot X + 0.992$, with X in the interval (1, 20) (2)

$k_l = -0.0293 \cdot X + 1.4913$, with X in the interval (21, 50) (3)

where X is the number of points (units) for car repair.

The value of the approximation reliability R^2 for both models exceeds 0.95.

The practical application of the results presented above can be the search for system parameters for the required level of loading of the repair zone. So, to ensure a given load level of 80%, a company may need 24 units to serve all applications with current indicators λ and μ. The digital model makes it possible to plan the operation of a car service and repair area in this way and to predict the output parameters of the system without resorting to experiments on real production processes.

Optimization using economic indicators is beyond the scope of this study since economic indicators are specific and variable for each company. However, this approach can be used in the final version of the digital model of a company.

WEB APPLICATION

A prototype of the web application: "Automotive Company Digital Twin" was developed using the Django Python framework and Bootstrap 5. It implements the modules already discussed above. The application allows simulating of the operation of cars or downloading the initial data of a real company in the form according to Table-2.

An automobile company connects to the service through the authorization system and gets the opportunity to use the information analytics system for its operating activities. The application has a main page where users can choose an action (Figure-9).

ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

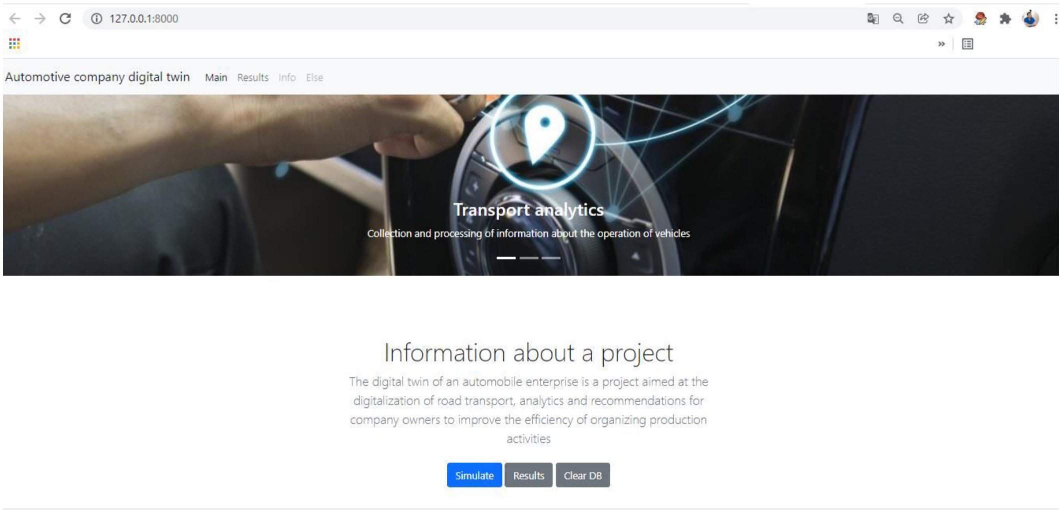

Figure-9. The main page of the developed Web application.

The information obtained by any of these methods is analyzed by the application, after which the user receives a report on the performance indicators of the company and its services, visualization of changes in indicators from the established standard values, as well as recommendations for improving the efficiency of the fleet. They are divided into groups and may include a list of measures to increase the availability of the fleet of vehicles or to reduce unproductive downtime in the area of maintenance and repair of vehicles, etc.

The application can point to a number of indicators and processes that are not working effectively and that should be given increased attention. The system makes it possible to simulate the further work of the company with these parameters and see what it can lead to. This will allow for making the right management decisions.

CONCLUSIONS

In the future, it is planned to expand the capabilities of the application and connect additional modules to it, for example, scenario modeling to determine the rational age of the vehicle fleet; determination of rational parameters of the zone for maintenance and repair of vehicles; evaluating the performance of the commercial and technical department. It will also introduce predictive analytics using deep learning, such as dynamic failure prediction. A decision support system will be implemented based on dynamic analytics of primary information, for example, the system will track vehicle downtime and determine influencing factors.

The developed application can be used by the management of automotive companies and transport departments of large manufacturing companies to make decisions on improving the efficiency of using cars without the need to involve their own analytical department, since the model, based on the patterns embedded in it, makes it possible to identify negative factors and trends and prevent them in a timely manner.

Thus, as a result of the study, the following results were obtained:

a) A digital model of the operation of an automobile company, which includes a simulation model for generating statistical information on the operation of a fleet of vehicles with the possibility of changing input parameters
b) A simulation model of the area for maintenance and current repair of cars, which uses the method of redistributing applications among free areas, taking into account their uniform loading.
c) A method for determining the parameters of the car repair zone, which is able to provide a given level of site loading.
d) Analytical model for determining the optimal number of repair sites, taking into account the minimization of the level of their load and the number of unprocessed requests for repairs
e) The web interface of a digital model of an automobile company with the ability to determine the initial parameters of the simulation, the intellectual analysis of the results obtained, and the prototype of the management decision-making system.

REFERENCES

[1] Abu Bakar E., Isa N. S., Osman S. 2017. Application of theory of planned behavior in the motor vehicle repair and service industry. Safety Science, 98: 70-76, doi: 10.1016/j.ssci.2017.06.001.

[2] Biesinger F., Krass B., Weyrich M. 2019. A survey on the necessity for a digital twin of production in the automotive industry. In: 23rd International Conference on Mechatronics Technology, Salerno, Italy, 23-26 October.

[3] [3] Bouvard K., Tedie H., Lesobre R. 2018. Joint dynamic scheduling of missions and vehicle: value of on-line information vehicle: value of on-line information. IFAC PapersOnLine, 51-24: 837-842, doi: 10.1016/j.ifacol.2018.09.672.

[4] Dobromirov V., Verkhorubov V., Chernyaev I. 2018. Systematizing the factors that determine ways of developing the vehicle maintenance system and providing vehicle safety. Transportation Research Procedia. 36: 114-121.

[5] Elhüseyni M., Ünal A. T. 2021. An integrated heuristic and mathematical modelling method to optimize vehicle maintenance schedule under single dead-end track parking and service level agreement. Computers & Operations Research, 132: 105261, doi: 10.1016/j.cor.2021.105261.

[6] Filák M., Famfulík J., Richtář M. 2021. Ways of comparing the advantages of operating different types of vehicles in the fleet. Transportation Research Procedia. 55: 133-140.

[7] Hedvall K., Dubois A., Lind F. Analysing an activity in context: A case study of the conditions for vehicle maintenance. Industrial Marketing Management, 2016; 58: 69-82, doi 10.1016/j.indmarman.2016.05.016 2016.

[8] Jbili S., Chelbi A., Radhoui M., Kessentini M. 2018. Integrated strategy of vehicle routing and maintenance. Reliability Engineering and System Safety, 170: 202-214, doi: 10.1016/j.ress.2017.09.030.

[9] Kossiakoff A., Sweet W. M., Seymour S. J., Biemer S. M. 2014. Systems engineering. Principles and practice. 2nd ed. John Wiley and Sons.

[10] Liu G., Chen S., Jin H., Liu S. 2021. Optimum opportunistic maintenance schedule incorporating delay time theory with imperfect maintenance. Reliability Engineering and System Safety, 213: 107668, doi: 10.1016/j.ress.2021.107668.

[11] Lu C. C., Yan S., Li H. C., Diabat A., Wang H. T. 2021. Optimal fleet deployment for electric vehicle sharing systems with the consideration of demand uncertainty. Computers & Operations Research, 135: 105437, doi: 10.1016/j.cor.2021.105437.

[12] Lu Y. J., Zhao Z. C., Wei W., Kui Z. Digital twin product lifecycle system dedicated to the constant velocity joint. Computers & Electrical Engineering, 2021; 93, doi: 10.1016/j.compeleceng.2021.107264.

[13] Markudova D., Mishra S., Cagliero L., Vassio L. *et al*. 2021. Preventive maintenance for heterogeneous industrial vehicles with incomplete usage data. Computers in Industry, 130: 103468, doi: 10.1016/j.compind.2021.103468.

[14] Militao A. M., Tirachini A. 2021. Optimal fleet size for a shared demand-responsive transport system with human-driven vs automated vehicles: a total cost minimization approach. Transportation Research Part A, 151: 52-80, doi: 10.1016/j.tra.2021.07.004.

[15] Monteiro Tavares C. M., Szpytko J. 2016. Vehicles emerging technologies from maintenance perspective. IFAC-PapersOnLine, 49-28: 067-072, doi: 10.1016/j.ifacol.2016.11.012.

[16] Parameshwaran R., Srinivasan P. S. S., Punniyamoorthy M., Charunyanath S. T., Ashwin C. 2009. Integrating fuzzy analytical hierarchy process and data envelopment analysis for performance management in automobile repair shops. European journal of industrial engineering, 3(4): 450-467, doi: 10.1504/EJIE.2009.027037.

[17] Prytz R., Nowaczyk S., Rögnvaldsson T., Byttner S. 2015. Predicting the need for vehicle compressor repairs using maintenance records and logged vehicle data. Engineering Applications of Artificial Intelligence, 41: 139-150, doi: 10.1016/j.engappai.2015.02.009.

[18] Rajesh P. K., Manikandan N., Ramshankar C. S., Vishwanathan T., Sathishkumar C. Digital twin of an automotive brake pad for predictive maintenance. In: 2nd International Conference On Recent Trends In Advanced Computing Icrtac -Disrup - Tiv Innovation, Chennai, India, 11-12 November, 2019; Vol.165, pp. 18-24, doi: 10.1016/j.procs.2020.01.061.

[19] Rokhforoz P., Fink O. 2022. Maintenance scheduling of manufacturing systems based on optimal price of the network. Reliability Engineering and System Safety, 217: 108088, doi: 10.1016/j.ress.2021.108088.

[20] Semykina A., Zagorodnii N., Novikov I., Novikov A. Main directions of improving the maintenance and repair of vehicle units in the Far North. Transportation Research Procedia, 2021; 57: 611–616.

[21] Shivasankaran N., Senthil Kumar P., Nallakumarasamy G., Venkatesh Raja K. 2012. Repair shop sheduling with parallel operators and multiple constraints using simulated annealing. International Journal of Computational Intelligence Systems, 6(2): 223-233, doi: 10.1080/18756891.2013.768434.

[22] Tautenhahn T. 1994. Scheduling unit-time open shops with deadlines. Operations research, 42(1): 189-192, doi: 10.1287/opre.42.1.189.

[23] Vujanovic´ D., Momcˇilovic´ V., Bojovic´ N., Papic V. 2012. Evaluation of vehicle fleet maintenance management indicators by application of DEMATEL and ANP. Expert Systems with Applications, 39: 10552-10563, doi: 10.1016/j.eswa.2012.02.159.

[24] Wang J., Lai X., Zhang S., Wang W. M., Chen J. 2020. Predicting customer absence for automobile 4S shops: a lifestyle perspective. Engineering Applications of Artifical Intelligence, 89, doi: 10.1016/j.engappai.2019.103405.

[25] Wang Y., Limmer S., Nguyen D. V., Olhofer M., Bäck T., Emmerich M. 2021. Optimizing the maintenance schedule for a vehicle fleet: a simulation based case study. Engineering Optimization, 53, doi: 10.1080/0305215X.2021.1919888.

[26] Wang Y., Limmer S., Olhofer M., Emmerich M., Bäck T. 2021. Automatic preference based multi-objective evolutionary algorithm on vehicle fleet maintenance scheduling optimization. Swarm and Evolutionary Computation, 65: 100933, doi: 10.1016/j.swevo.2021.100933.