Ways to Improve the Efficiency of the Truck's Branded Service System

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Abstract: The article discusses ways to improve the trucks maintenance efficiency. It is shown that only integrated solutions will optimize the activities of the automotive corporation's branded service system (BSS). The best solution in this situation is a decision support system (DSS) with an open architecture. The proposed methodology is aimed at improving the maintenance and repair system while expanding markets. Examples of developed modules applying as part of DSS, such as statistical data analysis and simulation models, are shown.

1 INTRODUCTION

The economy globalization, as well as the rapid development of engineering and technology and increased competition in the markets, have shortened the launch time for new goods. High-tech products require service during the entire life cycle, so should ensure trouble-free operation, which implies the responsibility of the manufacturer to the client. In the automotive industry, this concept is implemented by creating a branded service system (BSS). As a rule, the system includes a network of dealer & service centers (DSC). Regardless of format, such DSC operate in accordance with the manufacturer standards. Two aspects must be considered. The first is the vehicle's maintenances & repair (M&R) systems quality, which should keep the vehicle in working condition. The second is the process quality of providing services to the client - the vehicle owner. This is important because manufacturer competitiveness and brand trust depend on the BSS effectiveness. It is necessary to correctly evaluate the performance services indicators and risks, as well as provide actions that will help to avoid risks or will be needed in risk situations case.

The most common way to ensure accessibility is to create a reserve. These actions can be divided into two directions. The main reserve capacities are formed on the basis of demand forecasting and provide estimated performance. This helps to insure against errors in forecasts and from possible delays in the current orders execution. The second direction of service efficiency increase is realization of the customer-oriented approach. Ensuring customer loyalty should be considered as a prerequisite for achieving the success of the company in the competition (Lovelock et al., 2011).

One way to increase the competitiveness of both the entire BSS and each of the DSCs is to regulate the processes in each of them according to manufacturer reviews. Currently, there are tools for working with big data, so many vehicles manufacturers create tools for collecting and processing large data amounts that connect all production, logistics and service enterprises into a single information space. This allows you to control each vehicle throughout the entire life cycle and helps to optimize all processes. At the same time, it is possible to analyze the work results, compare them with previous periods and give recommendations for further adjustment of the development strategy. To make adequate and justified decisions, Decision Support Systems (DSS) are developed, the main module of which is the intelligent core, which is responsible for obtaining optimal decisions. This approach is especially relevant in situations where

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resources are limited, or in the case of the new vehicle models launch on the market (Buyvol et al., 2019).

2 PROBLEM STATUS: BRANDED SERVICE SYSTEM

2.1 Simulation Models in DSS as a Way to Find Optimal Solutions

Upon entering new markets, vehicle manufacturers create BSS abroad. As a rule, this is a network of DSC authorized in accordance with the manufacturer's standards. In most cases, they organize their activities on the principle of "three S": sale - service - spare parts.

For trucks, this approach is most relevant, since the share of trucks in the total fleets number is rather small, and it is more difficult to organize a maintenance in small workshops than to cars. In addition, the maintenance cost, as well as the complexity of servicing trucks is higher (Makarova et al., 2013; 2015). Decision Support Systems (DSS) contain three main subsystems: 1) module for data collection and storage that comes from internal and external sources (usually this is a data warehouse); 2) module for data processing and analysis - the intellectual core; 3) the user interface, which is necessary for interaction and communication of clients using information flows. This allows you to select data for analysis and parameters that affect the management decision. The DSS conceptual diagram is shown in Fig. 1. Simulation models as part of the intellectual core provide the search for the best solutions in various activity fields of the entire service system and each of its subsystems. Information from a common data warehouse in which data is constantly updated is used to determine model parameters. Updating the parameters allows you to find the best solution in each specific situation.

The main problem here is the quality, completeness and adequacy of statistics' data. Since the reliability of complex technical systems depends on many factors, the analysis quality will depend on the various data groups quality. An incorrect situation interpretation due to incorrect source data can significantly affect the frequency of failures. Because of this, the information quality about the vehicle technical condition at the failure time and the conditions of its operation preceding the failure allows the manufacturer to improve not only the vehicle design, but also the warranty service system. Statistical information is used not only to create a simulation model, but also to verify its adequacy and compliance with the real system (validation and verification). When trucks M&R planning during the warranty period, the information quality problem and model adequacy can become critical (Mikulec et al., 2017, Srinivasana et al., 2016). This is due to the increased failures number in the initial operation period, and the manufacturer must remove the failure consequences in accordance with the warranty service contract. In many cases, it is related to use incomplete or subjective information, which is contained in the complaint acts drawn up when the vehicles owners contact the DCS. To obtain more correct information, data is often used from an intelligent vehicle on-board system. In the research (Meeker et al., 2014), it is shown that various sensors installed on the product can be used to collect information about how, when, at what environmental parameters and under what conditions the product is operated. This approach is suggested in the paper (Last et al., 2010). They state that it is possible to use multi-target algorithm of estimated probability for a probability prediction and a choice of failure time in system of guarantee maintenance. For reliability modeling authors use Weibull's analysis.

2.2 Processes Organization in the Branded Service System

Diagnosing faults in automotive systems is an important stage in M & R, as it affects the duration to complete the work. For fault taxonomy, a fault tree diagram is often used. However, since the system's structure is implicit, the article (James et al., 2018) authors propose digraph modelling method, which uses the graph theory's system approach. The proposed approach contains recommendations for diagnosing the main failures causes. Methodology computerization will help in creating a knowledge base about failures and how to resolve them. Therefore, this approach is especially useful for M & R engineers.

Vehicle Health Management (VHM) often includes real-time monitoring of operating conditions, as well as decision-making on driving, operating, and maintenance based on predicted conditions. The article (Jaw et al., 2004) presents a universal, flexible integration and testing concept for control evaluating, including the accuracy of decision-making, algorithms and models in real time and in closed cycle.

Meckel S. (Meckel et al., 2019) propose methods for extracting knowledge from unstructured and informal materials on Internet forums, offering more effective and targeted actions for diagnostics and maintenance in real time. This is necessary for the synthesis of diagnostic graphs from the created knowledge base for use in vehicle maintenance.

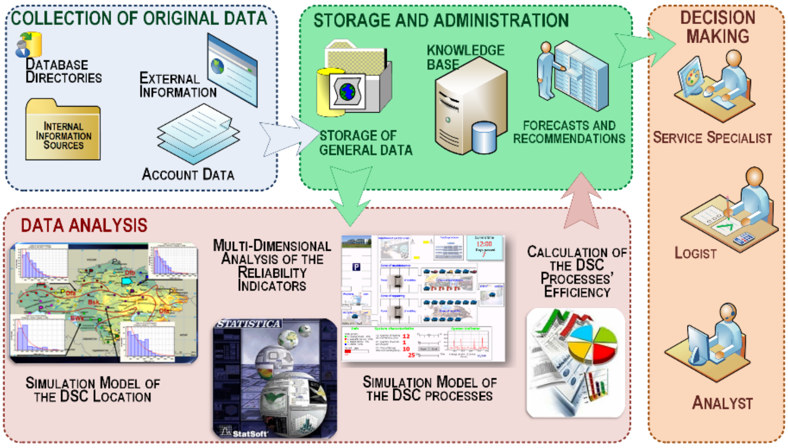

Figure 1: DSS conceptual scheme.

The study (Börger et al., 2019) goal is to reduce the time required for trucks maintenance. It can be done by applying the Lean methodology. The article (Vintr et al., 2003) goal is to find ways to optimize the concept of maintenance for reduce the life cycle cost (LCC) of a vehicle based on operational reliability data. The authors indicate that it is relatively easy to find reserves and achieve significant savings in the vehicle LCC using a simple administrative measure of change in the maintenance frequency.

In order to maintain a high vehicle operability level and the transport system safety as a whole, it is necessary to adhere to a strategy and an appropriate schedule for vehicle maintenance. In the paper (Kamlu et al., 2019), to develop a fuzzy model, a condition-based maintenance strategy is proposed that takes into account various types of uncertainties for individual vehicles, such as, for example, load, mileage and terrain using either wired or wireless data and to failure's predicts.

3 CASE STUDY: THE USE OF MODELING TO SOLVE PROBLEMS OF PROCESS OPTIMIZATION IN THE BSS

3.1 Application of DSS in Strategic Planning in the Corporate Service System

Statistical data in the BSS can be used in the following ways. Firstly, on the data array basis for a certain period, it is possible to establish the main DCS activity parameters (the requests flow intensity or services, the requests number, the average services laboriousness) and use them to perform an optimization experiment and improve processes. Secondly, an analysis of the failure distributions allows us to identify the problems causes and find a way to eliminate them.

Thirdly, the failures flow trend analysis makes it possible to predict the failures number in the prospective periods of DSC activity and improve the spare parts supplies management. The distribution laws parameters analysis consists in comparing the data set characteristics different periods and developing methods for making managerial decisions. In this case, as the optimal distribution in the current period, a distribution law is selected that has the estimates values (variance and mathematical expectation) closest to the real data. Such laws are built for each detail, unit and aggregate in a special DSS software module "Statistical data analysis for DSC".

A change in the distribution law parameters indicates to change in the analysing indicator. For example, if the optimal parameters among the distribution laws in previous periods are the parameters M = 16650 (km) And δ = 177560 (km^2), and as a result of the current data sample analysis, the parameters M =14350 (km) and δ =213430 (km^2), this indicates that the average mileage of the vehicle to failure for investigated vehicle's component has decreased, while the random values spread has increased, which is most likely caused by a quality decrease to this component's manufacturing.

The user interface form of the module "Statistical Data Analysis for DCS" has two tab cards: "Prediction of component failures" and "Monitoring of service parameters" (fig. 2). When you select the "Vehicle mileage statistics" option, a selective two-dimensional data set is formed according to two parameters: "component name" and "vehicle mileage", and then is exported to the Statistica software application.

Based on this set, for a given component, a frequency distribution histogram of the range values is built, after which the distribution law that best describes the resulting array is selected. As Fig. 3 shows the vehicle mileage value distribution laws until the failure of the “ST142-10 starter” component on KAMAZ 4320 truck model, according to data for the 2018 first quarter. The decision-making method consists in choosing the distribution law with the best agreement criterion and comparing this law parameter of with the previous periods parameters. For this, the data is transferred to a special decision-making module developed in MS Excel (Fig. 4), in which compiles a summary table of distribution laws parameters.

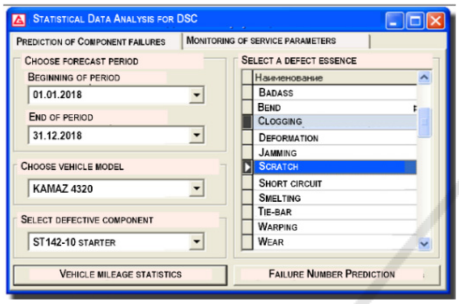

Figure 2: DSS statistical analysis module.

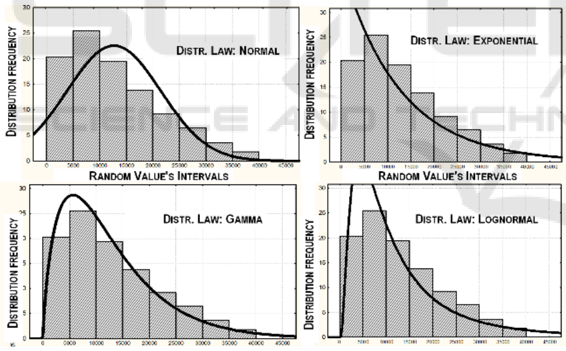

Figure 3: The distribution laws of the mileage to failure.

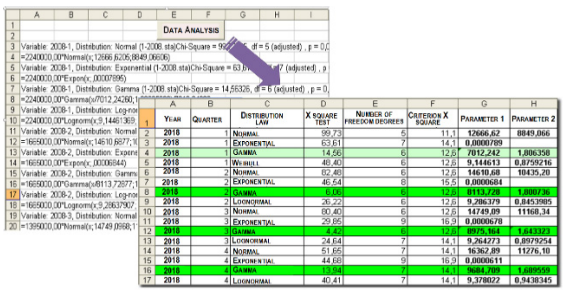

Figure 4: Decision-making module for DCS management.

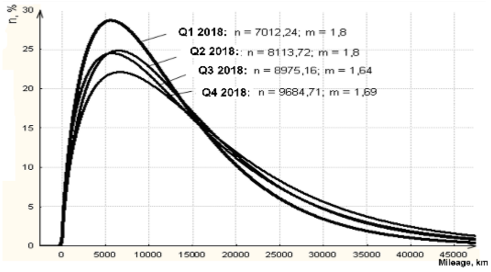

Figure 5: Comparison of gamma-distribution law parameters for the four quarters of 2018.

Thus, it can be seen from the presented example that the random vehicle mileage to defective component failure conform the gamma distribution law, while the law parameters change in the direction optimal for the enterprise (Fig. 5), that is, the shape parameter increases, which affects the mathematical expectation of the random magnitude, and also decreases the scale parameter, affecting the random variable's variance. In the general case, it can be predicted that over time, the gamma distribution law will be transformed into the normal distribution law.

The algorithm for the module “Forecasting the failures number” allows you to create a time series of the replacements number of the defective component for the period specified by the user, which is also exported to the Statistica software, where the model of the seasonal component is selected (additive or multiplicative), and a time series line and an extrapolated trend line with a relative less than 10% error (Fig. 6). The tool “Monitoring service parameters” allows, on the basis of calls to the service center, to determine the DCS activity parameters during the period specified by the user. The data sets corresponding to the selected service parameters are transferred to the Statistica software (Data Science …, 2020), where they are processed statistically. The module window view is shown in Fig. 7.

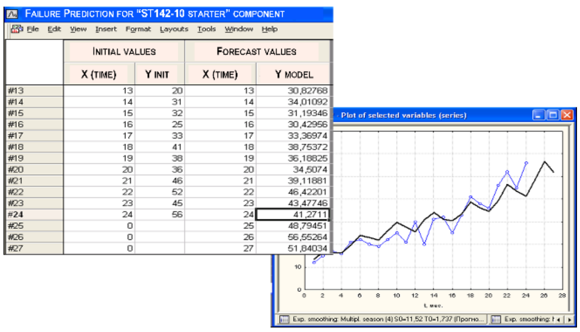

Figure 6: The problem solution to the component failures numbers predicting.

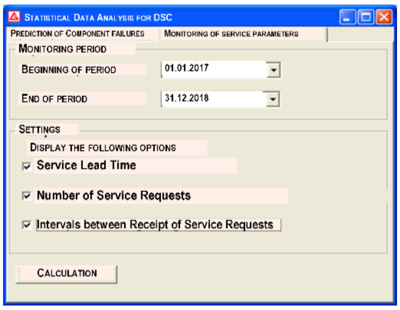

Figure 7: Select service monitoring options.

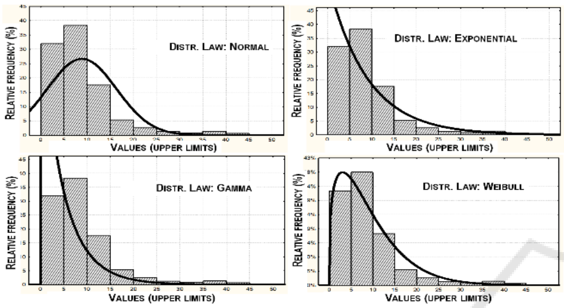

Figure 8: Service Time's Distribution Laws (hours).

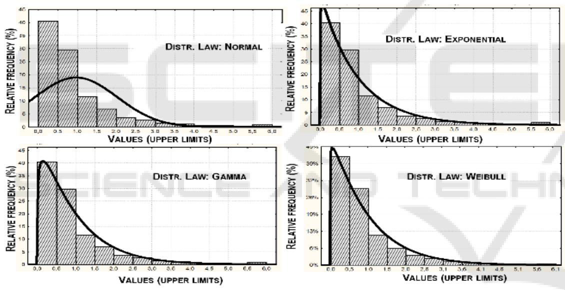

Figure 9: Distribution Laws of interval between request receipt’s (hours).

In fig. 8 shows the distribution laws of the service execution time value in hours (for all database defects). From the above graphs it follows that the Weibull distribution law with the parameters $\alpha = 28.76$ and $\beta = 1.29$ is the most suitable, since it is the only one that has a significance level $p = 0.10125$ that exceeds the specified level $\alpha = 0.1$. Figure 9 shows the distribution law of the random interval value between the service requirements receipt in hours.

From the above graphs it follows that the most suitable is the exponential distribution law with the parameter $\lambda = 1.035$, since it is the only one that has a significance level $p = 0.13401$ that exceeds the specified level $\alpha = 0.1$. The calculations result of the queuing system parameters are used to develop a simulation model and conduct an optimization experiment. The analysis results serve to develop and adjust instructions intended for both service centers and vehicle owners. Compliance with these instructions can improve the vehicle operation reliability.

Constant monitoring of the service system status allows you to increase not only the vehicle reliability, but also the DSC efficiency. If the distribution laws parameters indicate a deterioration in the system state (for example, a decrease in the average vehicle mileage to failure), then the management in the previous step was not rational, and the system needs a control action. In this case, recommendations for the control action are developed on the optimization experiment basis a conducted on a simulation model. In the case when the parameters values of the distribution law indicate an improvement in the parameters of the system functioning, we can conclude that the control in the previous period was rational, that is, adequately by set goals (Khabibullin et al., 2013).

3.2 M & R Processes Simulation in DSC

When new vehicle models appear, it is necessary to evaluate the capabilities of the existing dealer and service network (DSN), which can be done using simulation models. After simulation model creating and checking its adequacy, it can be used for an optimization computer experiment, why allows you to find a control impact in which performance indicators will be optimal for the system under certain external conditions. When creating the model, two approaches were combined: agent modeling (agents - vehicles) and discrete event modeling (service process execution in the DCS). This made it possible to combine the queuing system principles with the stochastic behavior model of separate objects.

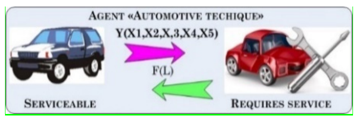

Figure 10: Agent-based model for «vehicle» object.

The agent “vehicle” can be in two states: “serviceable” and “repair required”.
The transition from the first state to the second is determined by the vehicle's failure probability function to mileage. The time to return to working condition (“The average time of fault removal” - Y) is determined by the parameters: the percentage of requests for spare parts directly from the warehouse (X1), the number of workstations in the DSC (X2), the number of workers per workstation (X3), the distribution of

arrivals from the vehicles concentration point in the DSC (X4), the schedule of the DSC (X5) (Fig. 10).

In addition, when generating "vehicle" for each agent, the "type" property is determined (base vehicle, truck tractor, trailer vehicle, dump truck, specialized vehicle), which affects the repair work duration in accordance with the standards. To develop a simulation model, we used the library of discrete event modeling objects (Enterprise Library) in the AnyLogic software application (Borshchev, 2014). Besause trucks in most cases represent corporate fleets, two classes were created during the simulation: Auto (agent class, models one truck) and VCP (models the vehicle concentration place). When the model is started, for each "Auto" agent, the initial mileage value (which then constantly increases by the flowAuxVar value), the maximum vehicle mileage and the mileage to failure are generated. Upon reaching the mileage to failure, the agent state goes from working ("Serviceable") to OutOfOrder ("Repair is required"), a need for M&R is formed, and vehicle is delivered to DSC for services.

After the vehicle is transportation to DSC, the service algorithm corresponding to the created class agent "Service station" is applied to it. So, if all the parking spaces for vehicles awaiting repair are occupied, the service request is rejected and the vehicle leaves the DSC. After the repair station is vacated, the availability necessary spare parts for repair are checked. If there is no necessary spare part, the request arrives at the delay unit simulating the spare parts expectation, after which the request falls into the "deferred repair" block and leaves the service system. To verify the proposed approach adequacy, we chose the Kazakhstan Republic (RK) DSN, which has 16 DSS. This market is actual for KAMAZ in competition with Chinese manufacturers conditions, so improving the efficiency of this BSS segment is important. Since the RK territory has four climatic zones with different operating conditions (Köppen, 2011), the law on the failure distribution was specific for each of them. Criterion function of system management model establishes balance between of manufacturer investments on DSN development and the lost profit from client's loss in view of admissible queue length excess:

$$Z_1 - Z_2 \rightarrow max \quad (1)$$

where Z_1 – benefit of additional clients' service at the taken measures of DSN development,

$$Z_1 = E - KL_{inv} \quad (2)$$

E – average benefit of one served client, rub; KL_{inv}– the difference between quantity of served clients before and after development; Z_2 – costs of investments of DSN development,

$$Z_2 = P + N_{inv} \cdot S_n \quad (3)$$

P – expenses on information support, rub; N_{inv} - number of added DSC in DSN; S_n – cost of additional DSC building rub.

Full system effectiveness is defined by decrease in client's losses that depend on excess of vehicle delay time in BSA in comparison with a specified time on declared works implementation, and also DSC expense minimization depending on equipment and worker's downtimes. The client's losses connected with delivery and vehicles delay in the DSC:

$$\sum_j^R \left[\left(\frac{D^j}{V} + \frac{T^j_{rep}}{X^j_3} + T^j\left(1 - \frac{X^j_1}{100}\right) + T^j_w\right) S_c N^j\right] \rightarrow min \quad (4)$$

where:S_c – the average client's losses due to with vehicle shutdown, rub/hour; N^j – number of vehicles, server in j DSC; D^j –average vehicle transportation distance to the j DSC, km; V – vehicle transportation speed to the DSC, km/h; R – the number of DSC; T^j – standard delivery time on spare parts to j DSC, hours; T^j_{rep} – vehicle repairs average time in j DSC, hours; X^j_3 – number of workers per one station in j DSC; T^j_w –average expectation time in service queue in j DSC, hours; X^j_1 – satisfaction percent for spare parts demands directly from a warehouse in j DSC.

DSC expenses connected with shutdowns:

$$\sum_{j=1}^R \left[\left(S_p \cdot X^j_2 + S_w \cdot X^j_2 \cdot X^j_3\right) \cdot T^j_{pr}\right] \rightarrow min \quad (5)$$

where: S_p – costs associated with stopping one workstation on hour (missed profit), rub/hour; S_w – average salary per hour, rub/hour; T^j_{pr} – average time stopping one workstation in j DSC, hours; X^j_2 –number of workstation in j DSC.

Model's limitations:

1. Limitation on exceeding the investment amount of economic benefits

$$Z_1 > 0 \quad (6)$$

2. Limitation on the maximum investments amount that the manufacturer is ready to invest for progressing for the DSN development:

$$Z_2 > INV \quad (7)$$

3. X^j_{1min}, X^j_{1max} – limitation on the warehouse space size for storage of the minimum and maximum spare parts volume:

4. $$X^j_{1min} \leq X^j_1 \leq X^j_{1max} \quad (8)$$

5. $$\sum_{j=1}^R N^j = \sum_{j=1}^R \sum_{i=1}^P X^{ij}_4 \cdot VCP_i \quad (9)$$

X_4^{ij} – distribution of arrivals from i-place of fleet concentration to j DSC, %,

VCP_i – number of inoperative vehicles in i-place of park concentration.

6. $K_{zagrmin}^{j}, K_{zagrmax}^{j}$ - coefficients of the minimum and maximum admissible workload of workstations in j-DSC.

7. $$K_{zagrmin}^{j} \le \frac{N^j \cdot T_{rep}^{j}}{N_5^j \cdot T_{sm}^{j} \cdot D \cdot X_2^j} \le K_{zagrmax}^{j} \qquad (10)$$

where D – quantity of days in simulated period; T_{rep}^{j} – the average time of vehicle repairs in j- district, hour; T_{sm}^{j} – working shift duration in j- district, hours; X_2^j – number of working shifts in j-district, hours.

8. X_{2nmin}^{j}, X_{2nmax}^{j} – minimum and maximum normative workstations number of j DSC (limit the stations number).

$$X_{2nmin}^{j} \le X_1^j \le X_{2nmax}^{j} \qquad (11)$$

9. X_{3nmin}^{j}, X_{3nmax}^{j} – minimum and maximum workers quantity on workstations in j DSC (limit on the labor resources number).

$$X_{3nmin}^{j} \le X_1^j \le X_{3nmax}^{j} \qquad (12)$$

The model was verified by the tracing method (Sargent, 2011). Since each DSC is a queuing system with a specified number of parallel workstations, to verify the model, the average workload on the workstation was compared with the calculated use coefficient for the selected time period $\rho = (m \cdot t_m)/(n \cdot t_n)$, where m – vehicles quantity being repaired funds, t_m – average repair time of one vehicle, n – quantity of workstations in DSC, t_n – workstation capacity for the considered period (Introduction to …, 2008). During the simulation experiment, data were used on the fleet's species-age structure and the DSC characteristics. As the system's response vector, we used the average time spent by the vehicle in the DSC, belonging to the corresponding format's group, which were obtained as a clustering result. Clustering was carried out according to the estimated parameters by the k-means method based on dendrograms based on project and calculated parameters. The graph of cluster averaging over estimated parameters is shown in Fig. 11.

The developed simulation model's adequacy was evaluated according to the statistical theory of assessment and hypothesis testing, using the following criteria:

1. Dispersions of the model's responses deviations from the average values of systems response. Dispersions comparison was performed to Fisher criterion. The results, presented in Tab. 1, show that in all three clusters $F < F_{kp}$, i.e. the hypothesis of the differences importance between the two variance estimates is rejected.

2. Using the Student t-test, we tested the hypothesis that the average values of each n-component of the Y_n model responses are close to the average values of the n-component of the real system Y'_n responses. For the real system and simulation model, the expected value and dispersion Y'_n, D'_n and Y_n, D_n, were estimated (Tab. 2) (Buyvol et al., 2019). The calculation results show that for all three clusters $t_n < t_{kp}$, i.e. the hypothesis on proximity of the responses average values for model and the system is accepted.

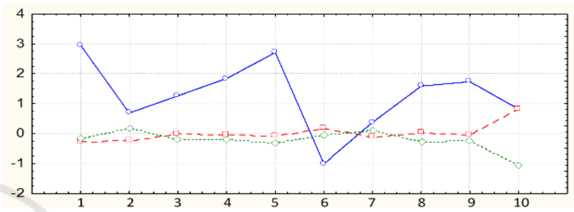

Figure 11: Graph of a clustering averaging by estimated parameters (1 - complaints number; 2 - warranty vehicles number; 3 - services volume; 4 - sold spare parts cost; 5 - sold vehicles cost; 6 - sold vehicles number (units); 7 - operations results for the reporting period (profit/loss); 8 - profitability of sales; 9 - services profitability; 10 - fulfillment of customer service requirements.

Table 1: The results of comparing dispersions according to the Fisher test.

№	system	γ1	D_n	F	F_{kp}
1	Real system	3	2.247	3.68	4.76
	Simulation model	6	0.610		
2	Real system	3	0.868	0.47	8.94
	Simulation model	6	1.864		
3	Real system	3	2.648	1.93	8.94
	Simulation model	6	5.100		

Table 2: The hypothesis verification results using *t*-student test.

№	system	N	Y_n	D_{pn}	t_n	t_{kp}	Δω
1	Real system	4	37.05	1.16	1.409	2.262	0.78
	Simulation model	7	36.75				
2	Real system	4	46.34	1.53	1.80	2.26	1.41
	Simulation model	7	47.00				
3	Real system	4	41.90	4.28	0.21	2.26	1.39
	Simulation model	7	42.48				

4 CONCLUSIONS

Scientific attitude at BSS improvement helps to react to the arising problems at new model vehicles operation quickly, having provided possibility of it constructions improvement. As the executed researches have shown that only system solutions for increasing the vehicle reliability at all life cycle stages will make it possible to increase its safety, as well as to ensure the possibility of trouble-free operation. The decision-support systems for management improvement use will allow to correct the actions, which directed on strategic goal realization at each stage. Statistical data analysis and simulation modelling as the intelligent block main element of DSS will allow selecting the most rational variant for each real condition combination. At the same time, it is necessary to create conditions for initial data timely updating, its operative processing and ready solutions storage.

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