





Article

Indirect Fuel Rationing for a Special Self-Propelled Rolling Stock

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Abstract: A method of indirect rationing of diesel fuel for special self-propelled rolling stock is presented, based on the identification of actual fuel consumption and controlled operating modes. Based on the results of test trips using automated accounting systems for operating modes and fuel consumption, the method allows us to assess reasonable volumes of fuel consumption in a specific section of the railway infrastructure. We show how the methods of identifying actual fuel consumption and operating modes can establish consumption rates of special self-propelled rolling stock without the use of automated fuel metering. The identification method is based on solving a multifactorial equation, the coefficients of which are determined in a program with statistical functions. To eliminate multicollinearity problems, the use of cluster analysis methods is proposed. Unlike traditional calculation methods, the method allows for the determination of the norming indicators in conditions of incomplete and partially incorrect data. The study was conducted using data on fuel consumption of special self-propelled rolling stock at a particular railway range and the relevant regulatory documents provided by Russian Railways. The results were obtained by applying the method to special self-propelled rolling stock used in the electrification and railway track departments of Russian Railways. The proposed method allows for simulation of the indicator of normalized fuel consumption with an accuracy not worse than 96%. Based on the obtained model of normalized fuel consumption, the method and parameters for identifying abnormal and unauthorized fuel overconsumption are shown. The criteria for identifying abnormal fuel overconsumption using the normalized standard deviation function were determined.

Keywords: diesel fuel consumption; special self-propelled rolling stock; predicted fuel consumption; self-propelled rolling stock functioning modes; identification method; simulation accuracy; factors of cluster analysis



Citation: Mitrofanov, A.; Ivaschenko, A.; Avsievich, A.; Avsievich, V.; Golovnin, O. Indirect Fuel Rationing for a Special Self-Propelled Rolling Stock. *Energies* **2022**, *15*, 836. <https://doi.org/10.3390/en15030836>

Academic Editor: Attilio Converti

Received: 13 October 2021

Accepted: 21 January 2022

Published: 24 January 2022

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1. Introduction

Modern large railway companies utilize a wide range of special self-propelled rolling stock (SSRS), which is designed to perform various activities of maintenance and repair of the infrastructure, such as the railway track, the catenary network, etc. By design, SSRS is a motorized wagon with a diesel engine, in which special equipment is installed. Through the use of SSRS on the railways, various types of jobs are carried out in the maintenance and repair of railway infrastructure.

The most common types of work include delivery of workers and goods to repair sites, lifting and laying of goods, installation of railway supports, lifting of personnel to adjust and repair the contact network, and a number of other activities [1,2]. Most of the work on the repair and modernization of railway tracks in Russia is carried out by SSRS

of the loading transport motor locomotive type MLT-6 (or motorized carriage loading transport MLT-6). For work on the repair and modernization of the contact network, a diesel mounting rail of the automotive diesel mounting (ADM-1) type is used.

In addition to these SSRS types, more than 30 other types can be used to perform work on the railway infrastructure. The amount of fuel consumed by SSRS is one of the key indicators when assessing the efficiency, productivity, profitability, and environmental friendliness of the railway company.

For the task of assessing the efficiency of SSRS fuel use by the Russian Railways transport company, it is customary to compare actual and standard fuel consumption. In this case, the absolute standard value of fuel consumption is calculated based on the duration of the SSRS operation in various modes and the values of the corresponding coefficients. These coefficients represent specific fuel consumption and are set for different types of SSRS and diesel engines, and, in general, are stochastic values. Actual fuel consumption is measured either by SSRS standard measuring instruments or by additional electronic fuel consumption meters.

The experience of operating SSRS at Russian Railways landfills shows a significant discrepancy between the actual and normative values of fuel consumption. Such discrepancy may be related to differences in the path profile of SSRS sections of travel, the mass of goods carried, the technical condition of the diesel installation, or unauthorized fuel discharge. However, the main problem is the accurate identification of standard fuel consumption, which may be due to the lack of control over the actual time of SSRS operating modes and the dynamic nature of unit flow ratios.

As a rule, only the total operating time and mileage of SSRS are regularly recorded. In this regard, the estimation of normalized consumption is carried out either by the total operating time of the SSRS or with errors due to the uncertainty of the modes. Thus, it becomes relevant to develop methods for indirect identification and adaptation of standard fuel consumption of SSRS.

The study was conducted by Samara State Transport University using SSRS fuel consumption data at a railway test site and relevant regulatory documents provided by Russian Railways.

2. State of the Art

To date, directions for improving the efficiency of fuel consumption have been widely considered in the scientific literature.

Basic approaches to improving fuel efficiency should include the development of basic requirements for the purpose and primary standards of SSRS and other railway rolling stock, including locomotives and railway engines. However, the specific application conditions of SSRS, as well as the operational features, give rise to special requirements regarding maintenance, management, and control. These features motivate the introduction of modern innovations [3].

SSRS maintenance and management have high potential for improvement. As a criterion, the level of safety of rolling stock and infrastructure is determined through the use of various methods and tools to improve the performance of various subsystems [4]. New models of maintenance and repair of rolling stock dynamically optimize management decisions throughout the life cycle [5]. The main problems of diagnosing and eliminating rolling stock breakdowns, using models and methods of data analysis and simulation modeling, have been studied [6].

Improving energy efficiency is one of the key tasks of the operation of railway rolling stock. Within this framework, models have been developed to assess fuel economy for classes of trains transporting various goods [7]. Reduced power consumption and travel time can be achieved through innovative operating modes and optimized solutions, including schedule adjustments [8]. The issue of energy management in transport, which ensures the reduction in economic and environmental losses [9,10], has been considered.

As a subsystem of energy efficiency improvement, optimization of the power supply system for locomotives and diesel internal combustion engines is considered. Various innovative solutions for modernizing the design and operating modes can significantly increase power and fuel efficiency [11–13].

Numerous studies have been devoted to reducing emissions and fuel consumption [14–17]. To solve environmental issues, modern modeling and data analysis technologies are used, as well as systems that can provide automated decision support in the field of alternative fuels [18,19]. Simulation of environmental parameters has become an effective tool to help develop and evaluate vehicle technologies and help predict fuel consumption and vehicle emissions [20].

One popular solution considers the modernization of diesel engines by introducing new types of fuel [21–25]. The resulting dual-fuel or multi-fuel engines require new control systems that involve a stack of modern microcomputing and control technologies [26–29].

Solving the problem of monitoring and managing fuel consumption includes work on developing new methods for rationing diesel fuel consumption [30,31]. These methods provide high accuracy in monitoring and regulating diesel fuel in almost any range of operation, which determines the efficiency of operation.

There are several approaches to monitoring the efficiency of diesel fuel consumption. The first and most highly developed approach is the introduction of hardware and software for monitoring and rationing fuel supplies at stationary vehicle refueling facilities [32].

Another significant direction in the assessment of fuel efficiency is monitoring the dynamics of the technical condition of railway rolling stock, for example, with regard to changes in the condition and layout of engines. The regulation of operating modes is used as a method of reducing fuel consumption. A common regulation method is to turn off some cylinders of a diesel engine during operation [33,34]. With this method of increasing efficiency, fuel consumption can be reduced by 4–30%.

As a subsystem, it is possible to consider the monitoring of environmental indicators as a criterion for fuel efficiency, including for SSRS engines. The operational and emission characteristics of an engine running on both diesel fuel and gas mixtures are investigated in [35–37].

Special attention in this area is given to monitoring efficiency and environmental emissions when using hydrogen in diesel engines. Increased efficiency by 30% has been reported [38]. The development of rationing diesel fuel consumption in railway transport, including SSRS [39,40], expands upon the known materials and publications. This paper discusses ways to improve the quality of standardization of diesel fuel consumption when equipping rolling stock with automated fuel consumption accounting systems, as well as when SSRS is equipped only with standard equipment and there is incomplete data on the operating modes.

3. Motivation

The motivation for improving the rationing of SSRS diesel fuel consumption is to solve the problem of improving fuel efficiency, including by reducing deviations between actual fuel consumption and standard values. In an earlier study [39], the authors presented the results of fuel consumption and rationing for SSRS type MLT-6, which is used in the economy of the track in conditions of equipment with its automation system and sensor equipment for fuel consumption of the KVARTA type.

This equipment was developed by PJSC Electromechanics (Penza, Russia) [41], and according to the developer it allows data on fuel consumption to be obtained with a minimum error of 0.67%, reduced fuel consumption rates, monitoring of compliance with regulations, and prevention of overconsumption and fuel spills.

KVARTA fuel consumption sensor equipment is installed on board SSRS to identify fuel consumption, which increases its reliability and ensures the compatibility of SSRS refueling volumes with the volume of fuel purchases for the company's warehouses by energy management methods.

However, an accurate assessment of actual fuel consumption directly on board SSRS does not guarantee any saving of fuel. Fuel saving can be generated in terms of significant actual costs, but also with higher rates of expenditure.

Therefore, the conditions for the organization of real fuel economy are as follows:

- Identification of fuel consumption standards based on what they bring to actual fuel consumption justified for the performance of work.
- Monitoring of actual fuel consumption with adjustment of significant deviations from the normative values, including unauthorized discharge of residues or excess fuel from SSRS tanks.
- Control of actual fuel consumption in SSRS modes according to the criterion of “not exceeding” the identified consumption rates.

So, the purchase of fuel at unreasonably inflated rates creates a surplus in the warehouse. In addition, the use of inflated regulatory values leads to the accumulation of excess fuel in the SSRS tanks, which can provoke unauthorized discharge of fuel by SSRS personnel.

Thus, the rationing of fuel consumption is aimed at solving the problem of fuel economy. For a transport company like JSC Russian Railways, with significant numbers and types of SSRS equipped only with standard equipment for fuel consumption metering, a significant effect on fuel economy will be achieved when using the following:

- The results of SSRS test trips equipped with automated accounting systems for operating modes and fuel consumption.
- Correct procedures for monitoring and storing indicators of fuel consumption in databases.
- Accurate methods of rationing fuel consumption based on identifying fuel consumption according to the results of SSRS tests and operational trips.

The structure of the KVARTA complex, suitable for organizing test trips, is shown in Figure 1. The principal difference in the equipment is the use of accurate float sensors at the level and density of the liquid with built-in temperature sensors. This technical solution provides an accurate direct measurement of fuel density and its specific gravity, with an absolute error in measuring the fuel level in the tank of ± 1 mm and an error in measuring the density of $\pm 2\text{kg/m}^3$.

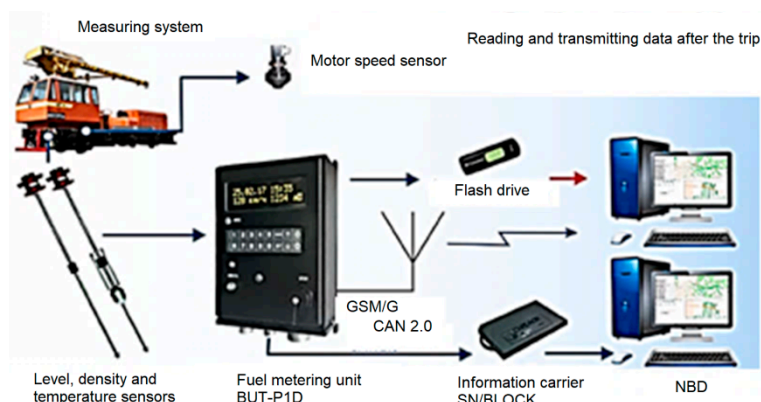


Figure 1. Structure of KVARTA complex.

As an example of using the results of SSRS test trips equipped with automated accounting systems for operating modes and fuel consumption, we consider the data obtained in 2016 at a JSC Russian Railways polygon.

Table 1 presents a portion of the initial data obtained in an assessment of the fuel consumption efficiency of an SSRS type MLT-6 with KVARTA sensor equipment. Figure 2 shows graphs of actual and normalized fuel consumption, as well as SSRS mileage over

trips. It is evident from the graph and table that in individual journeys, the discrepancy between actual and standard fuel consumption values can be as high as 135%.

Table 1. Data on actual and regulatory fuel consumption of SSRS MLT-6 in 2016.

Date	Run (km)	FC(Fact) (kg)	FC(Norma) (kg)	Saving (–)/ Overspending (+) (kg)	ABS (Fact-Norma)/Norm (%)
1 August 2016	90.9	36.0	40.5	–4.5	12.5%
3 August 2016	58.7	34.0	51.3	–17.3	50.9%
4 August 2016	93.5	32.0	56.5	–24.5	76.6%
5 August 2016	3.3	24.0	33.7	–9.7	40.4%
8 August 2016	1.9	4.0	9.4	–5.4	135.0%
...
28 September 2016	156.0	74.0	83	–9	12.2%
29 September 2016	196.6	71.0	76.4	–5.4	7.6%
Mean	88.8	39.9	51.3	–11.4	27.9%
Std. deviation	68.8	23.3	26.0	9.0	15.5%
Coef. variation	77.5%	58.4%	50.6%	–78.7%	55.5%
Max	238.2	96.0	112.1	9.0	66.7%
Min	0.8	0.6	0.5	–36.1	6.0%

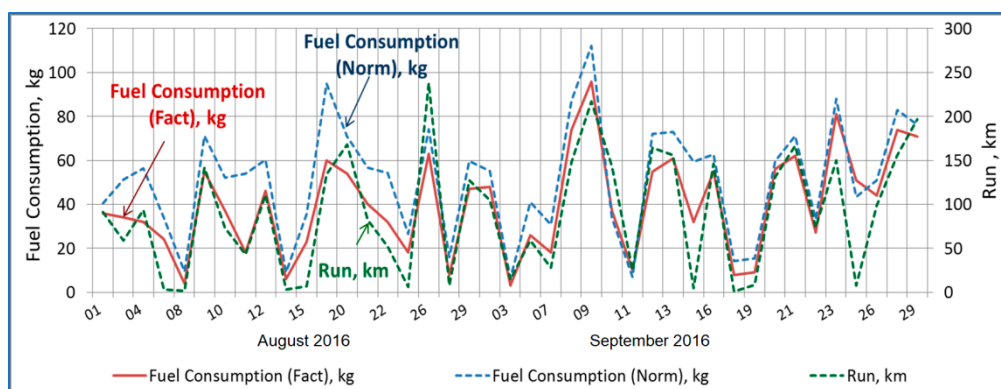


Figure 2. MLT-6 operating modes and fuel consumption in 2016.

In general, during the experimental period from 1 August 2016 to 29 September 2016, 27 trips were made. During that time, the average actual fuel consumption, FC(Fact), was 39.9 kg per trip with a norm, FC(Norma), of 51.3 kg per trip. Thus, the excess of the norm was 11.4 kg on average, which is 27.9% of the actual consumption. The maximum range between the actual and standard flow rate for individual trips can be up to 135%.

The average distance of the SSRS trip to the repair sites was 88.8 km, with a standard deviation of 68.8 km. The normalized coefficient of standard deviation (coefficient of variation = standard deviation/mean) for all factors ranges from 50% to 78%. Because this indicator exceeds 33%, it allows us to characterize all analyzed processes as variable and heterogeneous.

As an example of using SSRS test trips of another type, the results of an assessment of the fuel consumption efficiency of another type of SSRS, ADM-1, were analyzed. ADM-1 is used in the electrification and power supply of JSC Russian Railways and differs significantly from type MLT-6 in its functioning (Figure 3). A study of the fuel consumption process of SSRS type ADM-1 was carried out in the same period (1 August 2016 to 29 September 2016). ADM-1 was also equipped with the KVARITA system (Figure 1). Figure 2 shows graphs of actual and normalized fuel consumption, as well as SSRS mileage over trips.

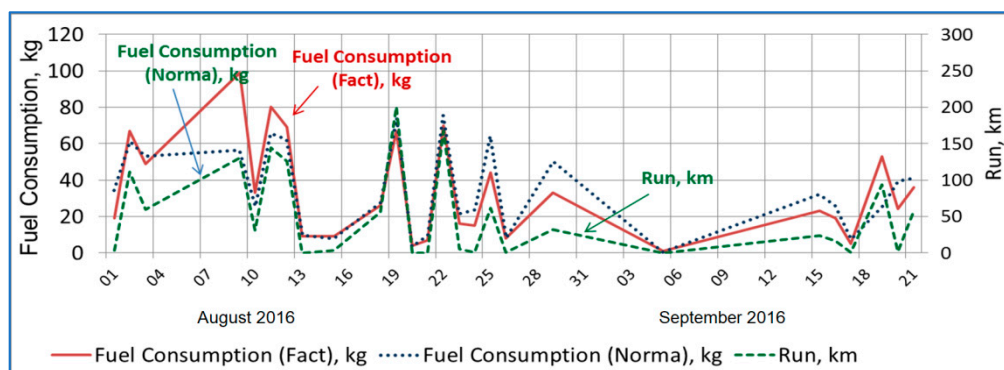


Figure 3. ADM-1 operating modes and fuel consumption in 2016.

It can be seen from Figure 2 and Table 1 that, on some trips, the discrepancy between actual and standard fuel consumption can be as high as 75%. In general, during the experimental period from 1 August 2016 to 29 September 2016, 25 trips were carried out. At the same time, the average actual fuel consumption was 34 kg per trip and the norm was 34.83 kg per trip. Thus, the average excess of the norm was no more than -0.8 kg, which does not exceed -2.3% of actual consumption. However, the maximum span between actual and normalized fuel consumption can be up to 150%. The average duration of the trip to places of repair was 51 km, with a standard deviation of 60.6 km. All values of the normalized coefficient of variation exceed 80%, which characterizes all processes as significantly variable and heterogeneous.

The fuel consumption figures shown in Tables 1 and 2 can be a benchmark for estimating the consumption of SSRS with standard equipment. However, these experiments did not consider the impact of SSRS operating modes on fuel consumption patterns, which must be considered to improve the quality of rationing.

Table 2. Data on actual and regulatory fuel consumption of SSRS ADM-1 in 2016.

Date	Run (km)	FC(Fact) (kg)	FC(Norma) (kg)	Saving (-)/ Overspending (+) (kg)	ABS (Fact- Norma)/Norm (%)
1 August 2016	3.8	19	34.3	-15.3	44.6%
2 August 2016	110.9	67	61.1	5.9	9.7%
3 August 2016	59.3	49	53	-4	7.5%
9 August 2016	130.4	99	56.3	42.7	75.8%
10 August 2016	31.0	33	25.6	7.4	28.9%
...
20 September 2016	1.6	24	39.3	-15.3	38.9%
21 September 2016	57.9	36	41	-5	12.2%
Mean	51.0	34.0	34.8	-0.8	2.3%
Std. deviation	60.6	27.3	23.5	13.4	33.4%
Coef. variation	118.9%	80.2%	67.5%	-1762.8%	106.1%
Max	200.3	99.0	75.5	42.7	150%
Min	0.0	0.8	0.4	-20.3	0.0%

The conclusion regarding the significant variability and heterogeneity of fuel consumption for ADM-1 and MLT-6 requires the development of an adaptive rationing system. This system will need to set reasonable standard levels of fuel consumption in conditions of incomplete data and monitor significant deviations in actual costs for SSRS with standard equipment.

Therefore, the results shown here motivate further research to improve the methods of normalizing fuel consumption on SSRS of various types based on multi-factor accounting of controlled modes of operation.

4. Method

With the modern system of documented fuel accounting for the SSRS of JSC Russian Railways, the actual and normative modes of SSRS operation are taken into account and recorded, which are measured in hours, as follows: H_{tot} —hours in total mode; H_{wm} —hours in working mode; H_{im} —hours in idling mode; H_{trm} —hours in transport mode. The SSRS factor Run is recorded in kilometers (km), and the actual fuel consumption, FC(Fact), is recorded in kilograms (kg).

Moreover, during the monitoring, there must be a balance of the time of implementation of SSRS operating modes for each trip, that is:

$$H_{tot} = H_{wm} + H_{im} + H_{trm}. \quad (1)$$

At the same time, the traditional calculation of the standard level of fuel consumption, B_j^N , is performed according to the following well-known formula:

$$B_j^N = b_{wm} \cdot H_{wm} + b_{im} \cdot H_{im} + b_{trm} \cdot H_{trm}, \quad (2)$$

where b_{wm} , b_{im} , and b_{trm} are the coefficients for SSRS hourly operation in controlled modes, representing specific fuel consumption in kg/h. Their value is calculated as the ratio of the absolute volume of fuel consumption per trip, j , to the time of SSRS operation in the corresponding mode.

It is clear that the SSRS database does not have operating mode values H_{wm} , H_{im} , and H_{trm} on trip j , which reduces the reliability of the assessment of the normative level of fuel consumption. Finding the solution to the problem is possible by developing methods of statistical analysis and identification, as proposed in [39,40]. One advantage of these methods is the possibility of using a wider range of factors in addition to B_j^N , H_{wm} , H_{im} , and H_{trm} ; for example, Run factor, temperature, or environmental performance.

In the proposed methodology, the fuel consumption rate indicator B_j^N is formed on the basis of monitoring the actual fuel consumption, B_j^F , during the SSRS trips.

Digitalization of the values of m operating factors, Xe , is carried out, which affects the level of actual fuel consumption, B_j^F . The equation that links actual fuel consumption to operational factors is presented in general terms, as follows:

$$B_j^F = A(Xe_1, Xe_2, \dots, Xe_i, \dots, Xe_m) + \zeta, \quad (3)$$

where the A operator is the relationship between operational factors, Xe , and actual fuel consumption, B_j^F , and ζ is the stochastic component, which is determined by the presence of an influence on fuel consumption by unaccounted operational factors.

After the stage of identifying the nature and parameters of the operator of relationship A and monitoring the values of the selected operational factors, Xe , it is possible to calculate the values of fuel consumption rate, B_j^N , based on the following expression:

$$B_j^N = A(Xe_1, Xe_2, \dots, Xe_i, \dots, Xe_m) + \zeta. \quad (4)$$

A significant advantage of the identification methodology for assessing the rate of fuel consumption in comparison with the methods currently used by Russian Railways is the ability to configure the interconnection operator A for a specific type of rolling stock, type of job, and infrastructure facility.

In order to improve the adequacy of the identified operator A , it is possible to use both linear and nonlinear types of operators.

With a linear nature of the relationship between operator A and factors Xe , Equation (2) is expedient to represent in the form of a regression equation, as follows:

$$B_j^N = a_0 + b_1 \cdot Xe_1 + b_2 \cdot Xe_2 + \dots + b_i \cdot Xe_i + \dots + b_m \cdot Xe_m + \zeta, \quad (5)$$

where a_0 is a free term of the regression equation, and $b_1, b_2, \dots, b_i, \dots, b_m$ are parameters for operational indicators, representing fuel consumption.

Accuracy is estimated by the average absolute error by mean absolute percentage error (MAPE) assessment when comparing model B_j^N and actual consumption standards B_j^F using 100% diesel.

The solution of an equation in the form of (3) can be found by constructing multifactor models based on software tools with statistical functions [42–44]. As an example of the work of the methodology, a real database of eight factors (X1, X2, . . . , X8), characterizing the operation of the technical system based on 40 data measurements, was selected. The goal was to build a predictive model, Predict (X1), of the actual values of factor X1 based on the relationship with seven other “explanatory” factors—X2, X3, . . . , X8.

The problem is considered solved when the coefficients of Expression (3) are determined: a_0 (intercept) and b_2, b_3, \dots, b_8 are the coefficients of Equation (5) (see Table 3).

After identifying these coefficients, a multifactorial equation in the form of (3) can be constructed, as follows:

$$X1 = 22.8634 + 0.1871 \cdot X2 + 8.93456 \cdot X3 - 12.0377 \cdot X4 + 2.9747 \cdot X5 + 1.0832 \cdot X7 + 0.5792 \cdot X8 \tag{6}$$

Table 3. Results of search for coefficients of six-factor equation by a program with statistical functions.

	Beta	Beta Std. Err	B	B Std Err.	t(34)	p-Value
Intercept			22.8634	6.075533	3.76319	0.000635
X2	0.334625	0.101032	0.1871	0.056498	3.31206	0.002203
X3	0.673119	0.080782	8.9455	1.073562	8.332251	0
X4	−0.181588	0.115385	−12.0377	7.649059	−1.57375	0.124715
X5	0.114232	0.107335	2.9747	2.795108	1.06425	0.294715
X7	0.081041	0.107542	1.0832	1.437419	0.75358	0.456291
X8	0.087434	0.069990	0.5792	0.463652	1.24925	0.220107

In the above example, the X6 factor was excluded due to incorrect data recording. According to the equation, a graphical implementation of the model can be built: Predict (X1). The obtained indicators of the Predict (X1) model are considered adequate if the multiplier coefficient of the R2 model is greater than 0.80, or the Fisher–Snedekor coefficient (F) exceeds the table value of FT. So, with an experimental 20 measurements of 8 factors and with a level of significance of $p = 0.05$ for the identification results, the critical value is $FT = 2.55$. With an experimental 20 measurements of 2 factors, the critical value is $FT = 3.49$.

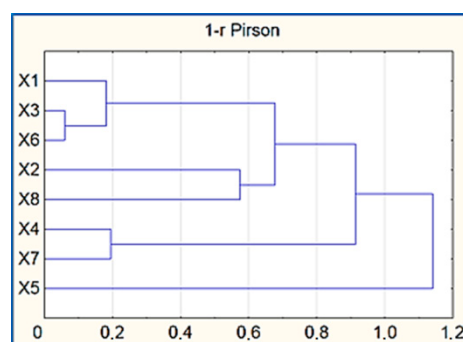
The parameters of the X1* model (Figure 4) indicate a high level of adequacy since they obtained a high correlation coefficient ($R = 0.936$), a high determination coefficient ($R^2 = 0.875$), a high corrected determination coefficient (adjusted $R^2 = 0.853$), a high Fisher criterion level ($F = 39.816$), and a low standard error level (std. error of estimate = 8.95).

A program with statistical functions was used to determine the significant factors, X2 and X3 (highlighted in red). These factors correspond to a p-value close to zero. Values of factors X4, X5, . . . X7, X8 with a high p-value of can be excluded without significantly affecting the accuracy of the model.

To improve the adequacy of the model, factors with the property of multicollinearity must be excluded from an equation of type (3). The higher the multicollinearity, the less reliable the results of multiple regression [42–44]. In these works, it is recommended to search for and exclude multicollinear factors when using correlation analysis (see Table 4). The authors propose to use cluster analysis (see Figure 4) [39,40] to solve this problem.

Table 4. Correlation analysis: matrix of pairwise correlation coefficients.

	X1	X2	X3	X4	X5	X6	X7	X8
X1	1.00	0.67	0.82	0.22	0.05	0.86	0.15	0.51
X2	0.67	1.00	0.32	0.09	-0.14	0.51	0.15	0.42
X3	0.82	0.32	1.00	0.40	0.20	0.94	0.20	0.38
X4	0.22	0.09	0.40	1.00	0	0.51	0.81	0.15
X5	0.05	-0.14	0.20	0	1.00	0.06	0	0.09
X6	0.86	0.51	0.94	0.51	0.06	1.00	0.33	0.42
X7	0.15	0.15	0.20	0.81	0	0.33	1.00	0.13
X8	0.51	0.42	0.38	0.15	0.09	0.42	0.13	1.00

**Figure 4.** Results of statistical processing of eight factors (X1, X2, . . . , X8) in the form of a dendrogram of the relationship of factors.

The method of selecting factors in an equation of type (3) should take into account a number of elements, as follows:

- The correlation between the simulated X1 factor and other explanatory factors, for example, X2, . . . , X8, should be higher than the interfactorial relationship.
- The correlation between explanatory factors X2, . . . , X8 should be no more than 0.7.
- With a high interfactorial relationship, factors with a lower correlation coefficient are selected.

For the selection of factors, it is convenient to use a matrix of pairwise correlation coefficients (Table 4) and a dendrogram, built based on the results of cluster analysis and presented in Figure 4.

In the dendrogram, the clustering of factors is carried out according to the principle of complete connections, and it is used as a metric of the distances between factors (Pearson's r).

The dendrogram indicates the levels of relationships of factors according to the difference between the unit and the correlation coefficient (Pearson's r) in graphical form. The levels of relationship between X1, X2, . . . , X8 are depicted on the horizontal axis according to the indicated criterion. All factors X1, X2, . . . , X8 are combined into groups/clusters. So, the combination of factors X4 and X7 in a cluster at the level of 0.2 corresponds to their correlation at the level of $R = (1 - 0.2) = 0.8$.

The relationship between factors X3 and X6 at a level of less than 0.1 corresponds to correlation coefficient $R = (1 - 0.06) = 0.94$. A relationship on the horizontal axis at a level of 1 corresponds to 0 correlation, i.e., $R = 0$. A relationship on the horizontal axis above, for example, a level of 1.2 corresponds to $R = (1 - 1.2) = -0.2$, that is, a negative correlation. According to the rules for building a model of factor X1 from the dendrogram in Figure 4, it is advisable to choose from the cluster of X3 and X6 only factor X3, with the lowest correlation coefficient (0.82). From the second cluster of factors X2 and X8, with a relationship at the level of $R = 0.51 - 0.67$, X8 = 0.51 is chosen, and so on.

As a result of factor selection, a two-factor equation in the form of (3) is formed from significant factors X2 and X3, with the coefficients presented in Figure 5 and Table 5. The two-factor model also has high adequacy: correlation coefficient ($R = 0.925$), determination

coefficient ($R^2 = 0.856$), and corrected determination coefficient (adjusted $R^2 = 0.848$). However, there is a significant increase in the Fisher criterion ($F = 113.19$).

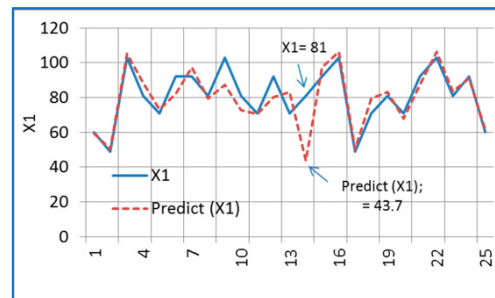


Figure 5. Results of calculations: actual values of factor X1 and its simulated values Predict(X1).

Table 5. Coefficients of two-factor equation.

	Beta	Beta Std. Err.	B	B Std. Err.	t(34)	p-Value
Intercept			18.33154	4.507495	4.06690	0.000231
X2	0.455196	0.064962	0.25455	0.036327	7.00709	0
X3	0.672298	0.064962	8.93456	0.863321	10.34906	0

As a result of substitution of coefficient B from Table 5, a model of factor X1* equation is obtained in the form of Equation (3):

$$X1^* = 18.33154 + 0.25455 \cdot X2 + 8.93456 \cdot X3. \quad (7)$$

Substitution in the resulting equation of the values of X2 and X3 at different times (or in different experimental trips) will allow model implementation of X1* for comparison with the actual X1. Figure 5 shows the joint implementation of the actual values of factor X1 and its simulated X1* values, denoted as Predict (X1). Mean absolute percentage error (MAPE) characterizes the accuracy of the constructed Predict (X1), relative to the actual implementation of X1. The allowable value of MAPE assessment is 10–15%, and the MAPE value for the example is 11%, which indicates sufficient accuracy of the constructed model.

The Predict (X1) model value graph takes into account the dynamics of all controlled and significant factors. Due to this property, this particular model can be considered as a generalized normalized implementation of fuel consumption. This model can be used to compare the actual values to assess fuel efficiency. Significant deviations from this implementation of actual costs can be considered as unauthorized fuel consumption or drain.

The construction of Predict (X1) made it possible to record an excess of the actual value of X1 = 81 by more than 100% of its normalized value (43.7) at time 14. This can be interpreted as an abnormal overconsumption and possibly an unauthorized drain of fuel. Therefore, the above technique can be used to establish standard values for fuel consumption of different types of SSRS under different operating conditions, as well as to identify abnormal overconsumption of fuel.

5. Results

5.1. SSRS ADM-1 Fuel Rationing Results

Based on the above method for rationing identification, an analysis of the results of monitoring the fuel consumption modes of ADM-1 was carried out at a branch of JSC Russian Railways in 2019. The analysis was based on the results of 44 trips for the 3-month period from 1 April 2019 to 29 June 2019 (see Table 6). The previously mentioned parameters of SSRS operating modes were used: FC(Fact), Run, and H_{tot} , H_{wm} , H_{im} , and H_{trm} .

Statistical analysis of the data presented in Table 6 and Figure 6 shows that in 2019, ADM-1, the specified type of SSRS, was characterized by significant fuel consumption. For

ADM-1, the average diesel fuel consumption per trip was 65.8 kg, the standard deviation was 31.4 kg, and the coefficient of variation was 47.7%. The average mileage per trip was 67.1 km with a standard deviation of 47.4 km. The coefficient of variation was 70.7%. The average duration per trip was 6.8 hours with a standard deviation of 2.4 hours, which produces a coefficient of variation of 35.7%.

Table 6. Data on actual and regulatory fuel consumption of SSRS ADM-1 in 2019.

Date	Run (km)	H_{tot} (h)	H_{wm} (h)	H_{im} (h)	H_{trm} (h)	FC(Fact) (kg)
23 April 2019	66	8	4	4	0	76
26 April 2019	108	8	5	3	0	83
29 April 2019	87	9	5	4	0	89
30 April 2019	23	8	3	5	0	69
...
25 June 2019	107	7	0	0	0	63
27 June 2019	107	6	0	0	0	57
28 June 2019	3	3	0	0	0	25
Mean	67.1	6.8	4.5	3.7		65.8
Std. deviation	47.4	2.4	1.5	1.2		31.4
Coef. variation	70.7%	35.7%	33.7%	33.7%		47.7%
Max	194.0	12.0	6.0	6.0		176.0
Min	0.7	0.4	0.0	0.0		0.5

The variability fuel consumption is evidenced by an average for ADM-1 in 2019 of 65.8 kg per trip, while in 2016 it was only 34 kg. Actual mileage in 2019 was 67.1 km, as opposed to 51 km in 2016. The normalized standard deviation for actual fuel consumption in 2019 was 47.7%, compared with 106.1% in 2016. It was found that when filling out database forms in automated control systems of the NBD type (Figure 1) on a personal computer, there may be errors in data input and interpretation. The actual values of the factors are most fully filled: H_{tot} , FC(Fact), and Run.

However, due to a number of organizational or technical problems, the factor data (H_{wm} , H_{im} , and H_{trm}) may be partially absent.

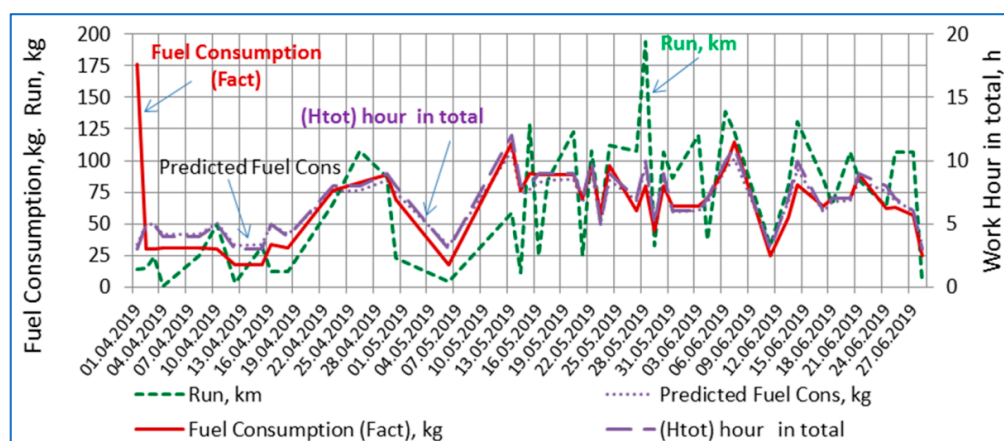


Figure 6. ADM-1 operating modes and fuel consumption in 2019.

The visual analysis of a fuel consumption graph indicates the presence of abnormal excesses of fuel consumption over statistically stable values, for example, on 1 April 2019. In this case, the values of factors H_{tot} and Run SSRS at such times are in normal ranges.

To build the normalized values of fuel consumption according to the presented methodology, based on Table 6, a dendrogram was built (see Figure 7), where the following factors were used: FC(Fact), Run, H_{tot} , H_{wm} , and H_{im} . H_{trm} was excluded from the original data, so it was not used in the dendrogram.

Based on the type of dendrogram, it can be expected that the factor that will have the greatest effect in the model on FC(Fact) is factor H_{tot} , since the correlation coefficient between them is high at $R = (1 - 0.05) = 0.85$.

As a result of calculations for a program with statistical functions, the values of the B coefficients were determined with four explanatory factors: Run, H_{tot} , H_{wm} , and H_{im} .

Indicators of the solution option indicate high adequacy of the compiled 4-factor model (see Tables 7 and 8), based on high values of the correlation coefficient ($R = 0.929$), coefficient of determination ($R^2 = 0.968$), corrected determination coefficient (adjusted $R^2 = 0.938$), high Fisher criterion ($F = 113.88$), and low standard error (5.8723).

However, in this variant, the free part of the equation (Intercept) and the Run factor were insignificant. These factors in Equation (3) can be used for analysis but cannot be used for prediction problems.

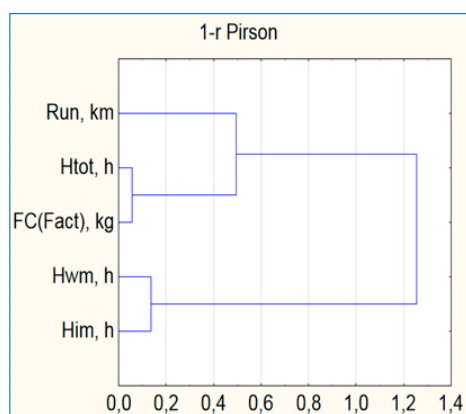


Figure 7. Results of construction of statistical indicators of SSRS type ADM-1: dendrogram of relationship of factors under study.

Table 7. Indicators of primary construction of four-factor equation.

	Beta	Beta Std. Err.	B	B Std. Err.	t(34)	p-Value
Intercept			0.45105	3.7167	0.12136	0.904218
Run (km)	-0.02017	0.067249	-0.01009	0.033632	-0.29993	0.766301
H_{tot} (h)	0.898698	0.066183	9.23942	0.680419	13.57902	0
H_{wm} (h)	0.431198	0.095342	3.92286	0.867383	4.52264	0.000089
H_{im} (h)	-0.30163	0.106922	-3.36296	1.192101	-2.82104	0.008408

Table 8. Optimized two-factor equation.

	Beta	Beta Std. Err.	B	B Std. Err.	t(34)	p-Value
Intercept			0.404305	4.154952	0.09731	0.92309
H_{tot} (h)	0.87637	0.054674	9.009876	0.562102	16.02891	0
H_{wm} (h)	0.180593	0.054674	1.642964	0.497405	3.30307	0.00236

A more adequate model for the rationing tasks for the sample used is obtained using two factors, H_{tot} and H_{wm} .

The adequacy of the model also remained high. The coefficient of multiple correlation was $R = 0.957$, and the value of the Fisher criterion increased significantly ($F = 177$).

To predict the level of fuel consumption and establish an adequate level of fuel rationing for this sample the most significant factor was H_{tot} . The paired Beta correlation coefficient with the forecast model was $R = 0.1805$, and the coefficient of the equation was $b = 1.6429$. A less significant factor was H_{wm} . The paired Beta correlation coefficient with the forecast model was $R = 0.1805$, the coefficient of the equation $b = 1.6429$.

Figure 8a illustrates the results of constructing a graphical view of a two-factor model of ADM-1 fuel consumption. At the top of the graph there is a regression equation that allows us to plot the fuel consumption value plane. From the nature of the constructed plane, it can be seen that significant changes in the output indicator depend mainly on the change in the indicator of the total operating time H_{tot} and, practically, do not depend on the operating (working) mode H_{wm} .

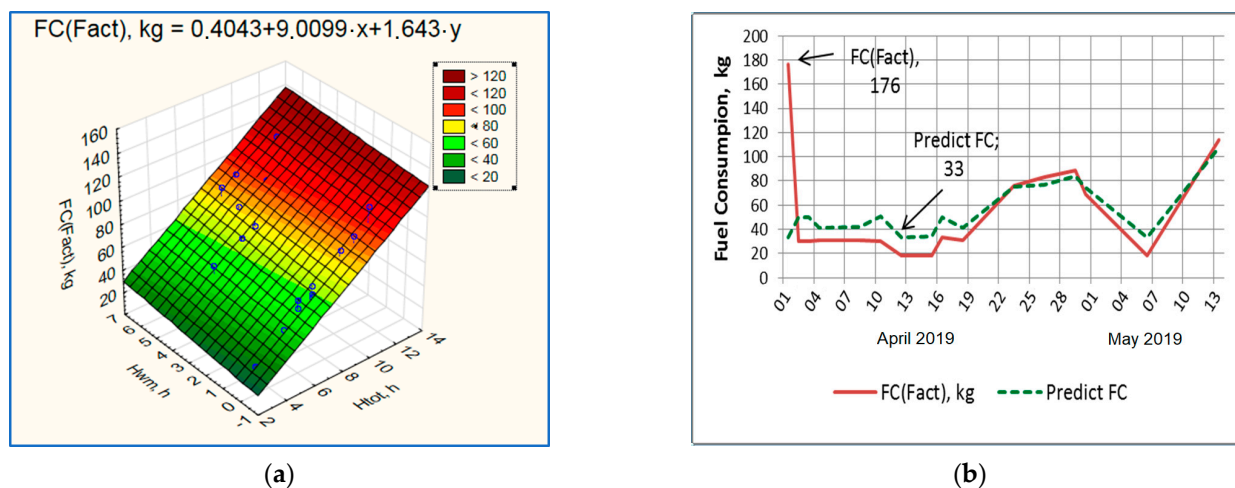


Figure 8. Graph of SSRS indicators of type ADM-1: (a) two-factor model, H_{tot} and H_{wm} ; (b) FC(fact) and model-predicted FC.

Figure 8b shows parts of the overall graph: actual FC(Fact) and model-predicted FC for the period from 1 April 2020 to 13 May 2019. The accuracy of modeling, according to the MAPE criterion, was assessed as high, at 6.9%. Comparing the values of actual and model graphs, for example, for 1 April 2019, allows us to identify an abnormal actual overconsumption of fuel and further find out its cause, including unauthorized fuel draining.

The low degree of adequacy of the ADM-1 diesel fuel rationing model is primarily determined by the lack of data on the time of the operating modes, including operating (working) time, H_{wm} , idle time, H_{im} , and transport time, H_{trm} .

Further improvement of the model can be carried out based on accurate electronic measurement of actual fuel consumption FC(Fact) and correct filling of databases or reporting on the normal operating modes of SSRS: H_{tot} , H_{wm} , H_{im} , and H_{trm} .

In addition, the model can be improved by including other factors, such as Run SSRS to the place of work, the mass of transported goods, the speed of movement, the environmental temperature, equipment wear, the skill of personnel, and other measurable factors that can affect fuel consumption.

5.2. Results of Standardization of SSRS Fuel of MLT-6

Based on the above method of identifying rationing, an analysis of the results of monitoring the fuel consumption modes of SSRS type MLT-6 at a branch of JSC Russian Railways in 2019 was also analyzed. The analysis was based on the results of 62 trips over 3 months from 1 April 2019 to 29 June 2019 (see Table 9). As parameters of the modes of SSRS operation, the factors previously mentioned for ADM-1 were used: FC(Fact), Run, H_{tot} , H_{wm} , H_{im} , and H_{trm} .

Statistical analysis of the data shows that in 2019, MLT-6, the specified type of SSRS, was characterized by significant fuel consumption. For the MLT-6 car, the average consumption of diesel fuel per trip was 89.5 kg, the standard deviation was 47 kg, and the coefficient of variation was 53%. The average mileage per trip was 69.53 km with a standard deviation of 52.4 km. The coefficient of variation was 75.3%. The average duration per

trip was 8.2 hours with a standard deviation of 2.5 hours, which produces a coefficient of variation of 30%.

Table 9. Data on actual and regulatory fuel consumption of SSRS MLT-6 in 2019.

Date	Run (km)	H_{tot} (h)	H_{wm} (h)	H_{im} (h)	H_{trm} (h)	FC(Fact) (kg)
1 April 2019	50	9	6	1	2	92
2 April 2019	100	10	6	1	3	103
3 April 2019	30	8	6	1	1	81
4 April 2019	150	11	7	1	3	114
...
26 June 2019	250	9	4	1	4	92
29 June 2019	15	6	5	1	0	60
Mean	69.53	8.18	5.18	1.00	1.67	89.45
Std. deviation	52.4	2.5	1.6	0.3	1.0	47.0
Coef. variation	75.3%	30.5	31%	33%	60%	53%
Max	250	18	7	2	4	302
Min	0	2	0	0	0	12

The variability of fuel is evidenced by an average of 89.45 kg per trip in 2019, while in 2016 it was only 39.9 kg. Actual mileage in 2019 was 69.53 km, compared with 88.8 km in 2016. The normalized standard deviation for actual fuel consumption in 2019 was 55.5%, compared with 77.5% in 2016.

We note that filling out database forms for transmission to the automated control system of NBD type (see Figure 9) for SSRS type MLT-6 is more correct than for ADM-1. The actual values of the variables are most fully populated: H_{tot} , FC(Fact), and Run.

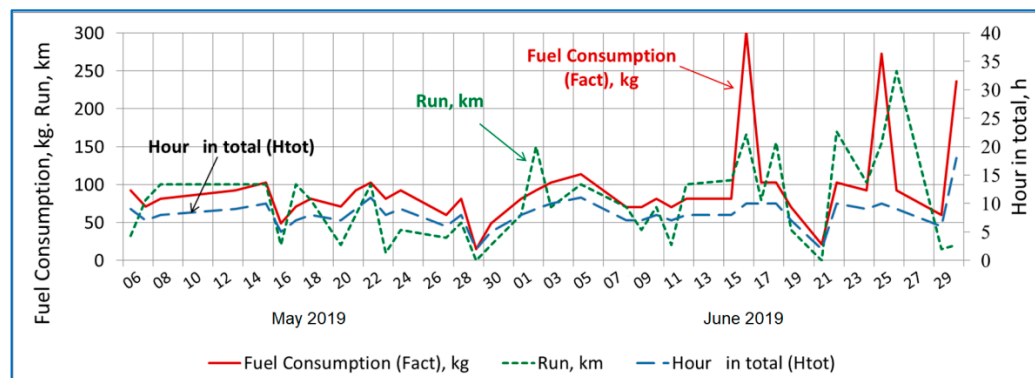


Figure 9. Fuel values and modes of MLT-6 in 2019.

In MLT-6-related databases and reports on organizational or technical problems, factor indicators H_{wm} , H_{im} , and H_{trm} can be filled in formally and do not reflect the actual performance of SSRS operating modes.

This paper made a comparative analysis of indicators and modes of fuel consumption for types of SSRS in 2019—ADM-1 and MLT-6. The average diesel fuel consumption for an MLT-6 trip in 2019 was 89.45 kg, which is 36% higher than ADM-1 (65.8 kg). The span between maximum and minimum values of MLT-6 (290 kg) was 67% higher than that of ADM-1 (175 kg).

The average mileage per trip was almost the same, at 67–68 km.

Differences in the statistical data from the actual performance indicators in modes H_{tot} , H_{wm} , and H_{im} are as follows: ADM-1: 6.8, 4.5, and 3.7 and MLT-6: 8.2, 5.2, and 1.0., respectively.

Thus, the total operating time of MLT-6 is only 20.6% longer than that of ADM-1, and this cannot explain the 36% difference in fuel consumption. Moreover, the fuel consumption of MLT-6 is higher than that of ADM-1 in conditions of the same established consumption

rates, with the same type of diesel power plant, YaMZ-238, produced by the Yaroslavl Machine-Building Plant (Yaroslavl, Russia).

The variation coefficients of the modes of operation of both types of SSRS are approximately the same, at 33%.

For SSRS types ADM-1 and MLT-6, the research established average specific actual fuel consumption, which was calculated from actual consumption for FC(Fact) trips and the total operating time of SSRS, H_{tot} . These values were 9.7 and 10.9 kg/h and the coefficients of variation of the actual specific flow rate were 15.7 and 6.5% for ADM-1 and MLT-6, respectively.

An investigation of SSRS work databases showed that the components of total uptime H_{tot} in modes H_{wm} , H_{im} , and H_{trm} in databases and documentation (route sheets) are entered irregularly and with distortions. More errors are observed in the databases for ADM-1. This may distort the adequacy of the fuel consumption rationing model.

It has been established that the adequacy of the fuel consumption rationing model can be influenced by the non-stationarity property of the fuel consumption process over time or on trips. Figure 10 shows that fuel consumption is non-stationary in nature for the periods of the experiment. This non-stationarity follows from the difference in statistical indicators in different periods of the experiment. Table 10 presents the FC(Fact 1) indicators for the period from 6 May 2019 to 10 June 2019 and the FC(Fact 2) indicators for the period from 10 June 2019 to 29 June 2019.

Table 10. Fuel consumption characteristics of SSRS MLT-6 in 2019.

INDEX	FC(Fact 1) (kg)	FC(Fact 2) (kg)
Mean	80.4	120.4
Std. deviation	22.5	84.9
Coef. variation	28.05%	70.51%
Max	114	302
Min	12	21

A dendrogram was constructed to build a model of fuel consumption rationing for the entire period of the experiment, from 6 May 2019 to 29 August 2019 (see Figure 10).

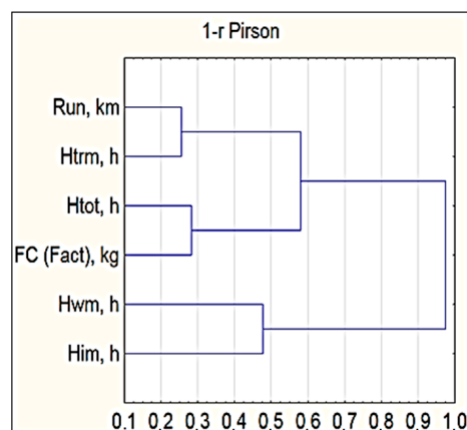


Figure 10. Results of construction of statistical indicators of SSRS type MLT-6 for entire study period in the form of a dendrogram of relationship of factors.

From the type of factor connections in the dendrogram, it can be expected that will have the greatest effect on the FC(Fact) model (as well as for AMD-1). The value of the correlation coefficient between these factors is the highest, at about $R = (1 - 0.3) = 0.7$. The next most related to the FC(Fact) model is Run, or H_{trm} . The correlation coefficient of this cluster with FC(Fact) is a weak relationship, $R = (1 - 0.6) = 0.4$. The relationship of FC(Fact) with the cluster of H_{im} and H_{trm} factors is close to zero.

Calculating the coefficients of an equation in the form of (3) with the five factors in the model (Run, H_{tot} , H_{wm} , H_{im} , H_{trm}) showed that the adequacy of the model is at the lowest permissible level. This is indicated by a low value close to the limit of the coefficient of determination (adjusted $R^2 = 0.503$) and, accordingly, a low multiplier correlation coefficient ($R = 0.737$).

In addition, the value of the F criterion was just over 13, which is higher than the critical value, but an order of magnitude lower than that for the ADM-1 type SSRS model.

The coefficients of the multifactor B equation with four factors (Run, H_{wm} , H_{im} , H_{trm}) are insignificant. This follows from their p-values, which are higher than the permissible value of $p < 0.005$ at 0.17–0.68.

In addition, the low values of the Beta pair correlation coefficients of these factors at the -0.068 and 0.223 indicate a low degree of influence of the factors on the FC(Fact) model.

The most significant coefficient of the Beta pair correlation is the coefficient of H_{tot} equal to 0.6158 . The presence of insignificant factors in the solution requires further optimization of the model.

Tables 11 and 12 show options for optimizing the equation by excluding insignificant factors— H_{wm} , H_{im} , H_{trm} . However, there was no significant improvement in the degree of adequacy: the adjusted R^2 value improved to 0.521 , the multiplier correlation coefficient remained at the level of 0.733 , and the value of the Fisher criterion was 34.27 .

Table 11. Indicators of primary construction of five-factor equation.

	Beta	Beta Std. Err.	B	B Std. Err.	t(34)	p-Value
Intercept			−16.062	17.44132	−0.920914	0.361046
Run, km	0.223059	0.163805	0.2001	0.14694	1.361735	0.178735
H_{tot} , h	0.615885	0.139593	11.7157	2.65541	4.412016	0.000047
H_{wm} , h	0.07774	0.149578	2.1816	4.19749	0.519729	0.605301
H_{im} , h	−0.075170	0.108360	−10.4507	15.06513	−0.693703	0.490736
H_{trm} , h	−0.068884	0.166171	−3.0648	7.39326	−0.414533	0.680067

Table 12. Optimized two-factor equation.

	Beta	Beta Std. Err.	B	B Std. Err.	t(34)	p-Value
Intercept			−19.8874	14.43721	−1.37751	0.173558
H_{tot} , h	0.173903	0.101107	0.1560	0.0907	1.71999	0.090676
H_{wm} , h	0.633153	0.101107	12.0442	1.92331	6.26221	0

Based on the studies conducted, it was assumed that the reason for the insufficient adequacy of the FC(Fact) model was the non-stationarity of implementation in different periods of the experiment, which was presumably associated with an unreasonable and/or unauthorized increase in fuel consumption, for example, on 16 June 2019 and 25 June 2019. Figure 11a shows a graphical view of a two-factor model of ADM-1 fuel consumption. At the top of the graph is the regression equation that allows us to plot the fuel consumption value plane. From the nature of the constructed plane, it can be seen that significant changes in the output indicator depend mainly on changes in the total operating time H_{tot} and do not depend much on the operating (working) mode H_{wm} .

The accuracy of modeling according to the MAPE criterion is good at about 15%. Such accuracy is sufficient to identify and compare graphs of actual and model predicted fuel consumption.

Figure 11b shows part of the overall graph of actual FC(Fact) and model-predicted FC fuel consumption for the period 10 June 2019 to 30 June 2019. For example, the actual fuel consumption on 16 June 2019 of 302 kg is adjusted by the model value on the graph, which is 127 kg. Thus, an abnormal overconsumption of fuel by 130% of the standard can be identified.

Based on the deviations from normative costs for SSRS of type ADM-1 and MLT-6, a collapsing criterion for classifying deviations as abnormal and non-normative is proposed. With this criterion, K_a , it is proposed to use the excess of the current actual value of fuel consumption, $SFC = (FC(\text{Fact})/H_{tot})$, over the level of the established standardized fuel consumption, $SPC = (\text{Predict } FC/H_{tot})$, increased by the standard deviation at the time of assessment, as follows:

$$K_a = (SFC - SPC) > \text{Std. Deviation } (SFC(\text{Fact})) \quad (8)$$

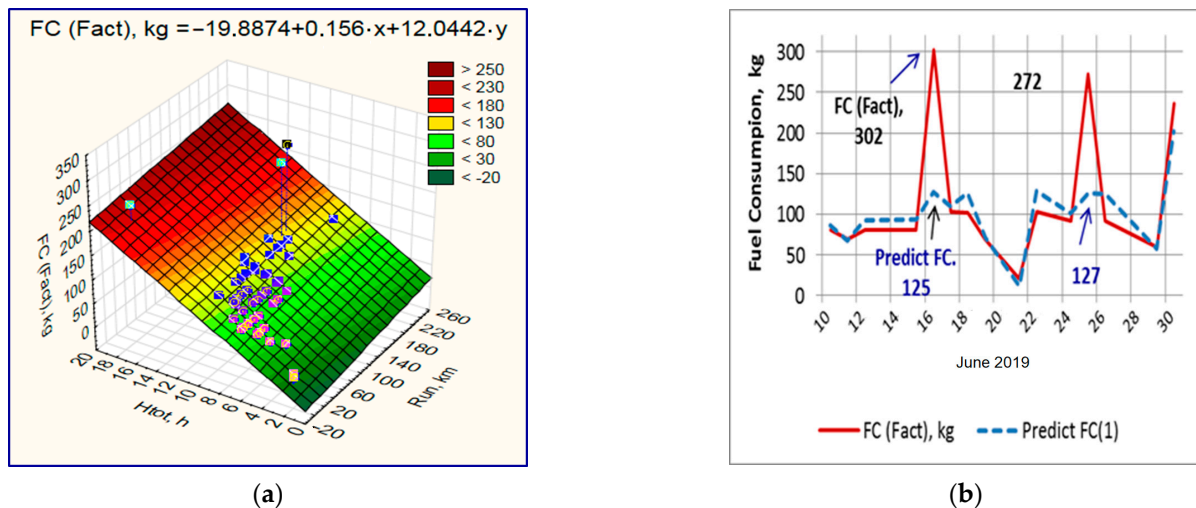


Figure 11. Construction of SSRS indicators of MLT-6 type: (a) two-factor model with factors H_{tot} and Run; (b) actual FC(Fact) implementation and normalized implementation based on model-predicted FC simulation results.

Therefore, according to the calculations for SSRS types ADM-1 and MLT-6, the actual fuel consumption was 9.7 and 10.9 kg/h and the coefficients of variation were 15.7% and 6.5%, respectively. At the same time, the boundary levels for detecting abnormal deviations FC(Fact), calculated through the coefficient of variation are $(9.7 + 9.7 \cdot 15.7\%) = 11.2$ kg/h (ADM-1) and $(10.9 + 10.9 \cdot 6.5\%) = 11.6$ kg/h (MLT-6).

The calculations carried out according to the above methodology for the period from 6 May 2019 to 10 June 2019 for the implementation of FC(Fact 1) (see Table 6) show the possibility of building an adequate five-factor model of fuel consumption using H_{tot} , H_{wm} , H_{im} , H_{trm} , and Run modes with high rates: $R = 0.992$, $R^2 = 0.984$, adjusted $R^2 = 0.983$, F criterion = 2415, standard error = 2.984.

In this case, the error of model construction is determined by a MAPE score of 3.8%. Thus, the use of the considered identification method with the correct choice of SSRS operating modes, for example, cluster analysis, allow us to build models of fuel consumption rationing with an accuracy not worse than 96%.

6. Conclusions

The rationing of fuel consumption is aimed at solving the problem of fuel economy. For a transport company with significant numbers and types of SSRS, equipped only with standard equipment for metering fuel consumption, a significant effect on fuel economy is achieved when using the results of SSRS test trips equipped with automated accounting systems for operating modes and fuel consumption, correct procedures for monitoring and storing indicators of fuel consumption in databases, accurate methods of regulating fuel consumption based on identification with operating modes, and data on fuel consumption from test and operational trips.

Experimentally proven methods of multifactor identification using data of regulated modes of SSRS operation (hours in total mode, hours in working mode, hours in idling

mode, hours in transport, Run) allow us to simulate normalized fuel consumption with an accuracy of not worse than 96% even in conditions of incomplete data.

The model of normalized fuel consumption built by the identification methods makes it possible to determine volumes and periods of abnormal fuel overconsumption. To do this, it is advisable to establish a certain tolerance, for example, the amount of standard deviation from the established normalized fuel consumption. For example, if the total rates for SSRS of the ADM-1 and MLT-6 types were set at 9.7 and 10.9 kg/h, respectively, and the coefficients of variation of the consumption rates were 15.7% and 6.5%, respectively, then the tolerance value that would be considered anomalous regarding consumption would be determined as follows: $(9.7 + 9.7 \cdot 15.7\%) = 11.2$ kg/h (ADM-1) and $(10.9 + 10.9 \cdot 6.5\%) = 11.6$ kg/h (MLT-6).

Indirect fuel rationing for special self-propelled rolling stock can be of significant methodological and practical importance for transport companies that operate SSRS with traditional fuel consumption meters. The lack of means or technology in these devices to monitor the actual operating modes of SSRS can lead to incorrect assessment of fuel consumption standards and adversely affect fuel economy.

Author Contributions: Conceptualization, A.I.; Formal analysis, A.A. and O.G.; Investigation, O.G.; Methodology, A.M.; Project administration, A.M.; Software, V.A.; Validation, A.A. and V.A.; Writing—review & editing, A.I. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Russian Railways, grant number 121031700033-5, “Legal regulation and technical basis for the use of gas engine fuel in transport”, software development was supported by RFBR, according to the research project No. 20-08-00797.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors express gratitude to Andrey Peshkov and Pavel Karpov for the support and participation in the project “Legal regulation and technical basis for the use of gas engine fuel in transport”, as a result of which it was possible to do this research.

Conflicts of Interest: The authors declare no conflict of interest.

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