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Creation of a formalized model for automated management of operational processes in railway transport by means of an intelligent decision support information system using the fuzzy analytic hierarchy process

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Abstract

The article presents a model for an automated control system (ACS) for operational processes (OP) in railway transport (RT). The proposed model differs from known solutions by integrating methods for processing fuzzy information and predicting reliability. This approach promotes adaptive transportation management. Unlike traditional deterministic models, it takes into account the variability of logistics scenarios, time constraints, and dynamic changes in operational parameters. In combination, the use of fuzzy logic (FL) methods provides a more accurate assessment of the probability of failures and delays during the operation of rolling stock and railway infrastructure. The study also included a list of target functions for the computing core of the intelligent decision support system (IDSS) integrated into the automated control system of the electronic control system. The IDSS module takes into account the coefficient of variation of delays, the level of infrastructure utilization, indicators of resource redistribution, as well as an assessment of the availability of rolling stock, which makes it possible to formalize the optimization of the item instance, taking into account the multi-criteria management at the railway station. The study employs the Fuzzy analytic hierarchy process (Fuzzy AHP) method, which makes it possible to structure the process of selecting criteria and assign their relative priorities. This approach ensures the consistency of expert judgments and enhances the model's robustness to the uncertainty of transport processes.

Keywords: Adaptive control, Automated control, Fuzzy logic, Information systems, Mathematical modeling, Operational processes, Railway transport, Reliability forecasting.

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1. Introduction

Automated management of operational processes (OP) in the railway transport (RT) of the Republic of Kazakhstan (RK) requires the use of fuzzy information processing methods and reliability forecasting. This study proposes a model for OP ACS. The proposed model, unlike known solutions, takes into account time parameters, transport standards, and the multiplicity of logistics scenarios for transporting railway cargo. The relevance of computer-aided automation in transport-related industries is confirmed by research in mechanical engineering, where design systems and integration of software platforms are considered as modern trends [1]. Research in decentralized computer-aided design systems also demonstrates the efficiency of integrated environments such as Trace Mode6 for improving process control and decision-making reliability [2]. As a hypothesis, we believe that this model can serve as the basis for an algorithm used in the Automated System for Operating Processes.

As the analysis of scientific publications [3-5] shows, over the past decade, many studies in the field of automated control of railway transport have focused on developing intelligent algorithms and models for automated control systems. This approach is based on the stochastic nature of transport flows. As well as the specifics of maintaining the technical condition of rolling stock (RS) and railway infrastructure and the load on hub stations [3-11]. As the analysis of the reviewed works showed, classical models of OP management on the railway transport do not sufficiently reflect the specifics of work in conditions when the factors of uncertainty affect. This created the prerequisites for researchers to use the mathematical apparatus of fuzzy logic (FL) to work in conditions of uncertainty, similar approaches relate to the use of FL for reliability forecasting tasks in railway installations [6-12].

In a number of scientific publications, in particular [13-16] the authors proposed mathematical models based on FL for railway transportation management, taking into account time standards, logistical constraints and reliability indicators. However, an analysis of these publications indicates that they primarily focus on either operational time parameters or resource optimization. Based on this, this study does not develop existing methods. However, unlike previous work, we attempt to integrate fuzzy sets, parameters for reliability forecasting, and operational performance analysis in a single model. At the same time, to formalize the selection and ranking of management criteria for operational processes under uncertainty, it is proposed to use the Fuzzy Analytic Hierarchy Process (Fuzzy AHP). Its application makes it possible to account for the subjectivity of expert evaluations, aggregate the opinions of specialists, and derive more justified weighting coefficients for inclusion in the model. Thus, the integration of Fuzzy AHP enhances the capabilities of decision-making systems and increases the reliability of multi-criteria optimization in automated operational process control systems [17]. Similar approaches to integrating multi-criteria decision-making methods and smart technologies into transport management tasks are also discussed in research on electric vehicle infrastructure, where intelligent decision-making systems ensure adaptability and sustainability in conditions of uncertainty [18]. We believe that this approach, combined with automated control systems and intelligent systems, can not only predict potential delays but also enable the development of flexible OP management strategies. Additionally, it can help minimize deviations from OP standards. Comparable approaches of automation and intelligent modeling for increasing efficiency and reliability of technological processes are demonstrated in environmental studies, where sensor networks and modeling are used to optimize the control of high-frequency ozone generators for groundwater purification from heavy metals [19]. The main message of the work is that the use of the FL apparatus will allow the ACS system to adapt to uncertain conditions. Similar approaches to adaptation of transport systems in uncertain environments are also considered in [20]. In addition, the importance of integrating multisensor architectures with artificial intelligence for managing complex and dynamic processes is emphasized in recent reviews of counter-UAV systems, where AI-augmented frameworks provide robustness, adaptability, and reliability under conditions of uncertainty and rapidly changing external threats.

This will ultimately reduce the overall number of risks and failures. At the same time, the efficiency of railway transport will increase. It should be noted that the model proposed in this article develops existing approaches to modeling systems (automatic control systems and decision support systems) for managing railway transport. Similar research areas have been discussed in Pavlovic, et al. [3]; Sirko, et al. [4]; Malykov and Pokrovskaya [5]; Mailybayev, et al. [6]; Akhmedov [7]; Drozdova [8] and Moradi, et al. [9]. However, unlike these studies, we aim to combine the use of neural networks and dependencies for predicting the reliability of the transportation process in a single model. The addition of the Fuzzy AHP method enhances integration and formalizes the multi-criteria decision-making procedure, making the model more robust. The main prerequisite for the development of our model was the fact that the automation of OP management on the railway transport (and not only in the RK, but also in other countries developing the railway transport) faces uncertainties. These uncertainties are associated with dynamic changes in transport flows. Therefore, the use of the FL in conjunction with Fuzzy AHP apparatus, in our opinion, will allow us to model these uncertainties and form adaptive solutions, also to develop a model for automated control of operational processes (OP) on the railway, integrating methods of reliability analysis and forecasting, in order to increase the adaptability of transportation management, minimize time deviations, and optimize transport process scenarios.

2. Materials and Methods

We assume that the ECS is represented as a set of interacting elements. The following elements are adopted: restrictions and standards $S-$ a set of technological standards, including time parameters T of operations; control objects $O-$ a set of RS (locomotives, wagons), characterized by parameters P_o; cargo processing processes $P-$ stages of the technological process (TP) of transportation, characterized by time T_p; reliability indicators $R-$ characteristics of the system, determining the fault-tolerance.

For example, the time standards for operations typical of OP set the permissible boundaries for performing standard technological processes (TP). They can be set as strict (clear) or adaptive (fuzzy). For example, the time it takes to process a car at a station ($T\_process$). We also assume that the standard value is 2-6 hours. Accordingly, the permissible range (fuzzy boundaries) is as follows: fast (0-2 hours); normal (2-6 hours); long (6-12 hours); critically long (>12 hours). Similarly, the parking time at the hub station (T_stop).

The standard value is 1-4 hours. Accordingly, the maximum delay is limited to 6 hours, after which the route is manually or automatically (or a combination of both) revised. The maximum allowable delay in the route (T_max_delay): the norm is no more than 12 hours; the actual limits are as follows: no delay (0–3 hours); minor delay (3–6 hours); significant delay (6–12 hours); critical delay (>12 hours). The empty run coefficient of wagons (K_empty): the target is ≤ 0.4 (40% empty runs). Accordingly, the restrictions are as follows: if the value is >0.5, the routing must be optimized. The acceptable deviation from the plan ($\Delta T\_permissible$) is ±5% of the estimated travel time. If the deviation exceeds 10%, the dispatching system will need to intervene.

The relationship between the restrictions and the standards can be represented as follows:

$$T_{fact} \in \left| T_{norm} - \Delta T_{permis\sin le}, T_{norm} + \Delta T_{permis\sin le} \right|, \tag{1}$$

where $T_{fact} -$ is the actual time of the operation. We assume that each object $o \in O$ has parameters $P_o = \{T_c, T_f, \mu, \sigma\}$, where $T_c -$ the standard processing time, $T_f -$ the actual time, and μ, σ – the mathematical expectation and standard deviation of the operation time are, respectively. Consider the control objects, i.e., for example, a set of RS characterized by their parameters.

We assume that the control objects in the simulated system are cars and locomotives, each of which has its own characteristics that affect the OP. Below are examples of control parameters: car category ($Wagon\_type$) – open wagon, tank car, covered wagon, refrigerated wagon, etc. car owner ($Wagon\_owner$) – owners (railway station, private operator, foreign company, etc.); car technical condition ($Wagon\_condition$). For example, a fuzzy scale is used: excellent (wear <20%); good (20–50%); satisfactory (50–80%); critical (>80%, car requires repair).

Current load of the locomotive ($Loco\_load$). That is, a parameter for assessing the power in % of the permissible limit: low (0–50%); optimal (50–90%); overload (>90%). The RS service factor ($Reliability\_index$), in our model, is calculated by the formula:

$$R = 1 - \frac{N_{failuser}}{N_{total}}, \tag{2}$$

where $N_{failuser} -$ the number of failures per period (accepted in accordance with the technical specifications at the ACS design stage), $N_{total} -$ and the total number of wagons. We assume that a deviation is determined for each stage of transportation $\Delta T_i = T_f - T_c$. If $\Delta T_i > \varepsilon$ (where $\varepsilon -$ the acceptable deviation threshold is exceeded), corrective measures U are taken. Since the time parameters of operations on the railway may vary, a fuzzy set (FS) is formulated for time intervals:

$$\tilde{T} = \left\{ \left(T_i, \mu_i, \sigma_i \right) \middle| T \in T,\ \mu_i - \text{average time}, \quad \sigma_i - \text{standard deviation} \right\}. \qquad (3)$$

Then FS $\tilde{T}$ uses models to predict and correct deviations. Here $\mu_i, \sigma_i -$, the average time and standard deviation are used, respectively. Consider the system as a set of submodels listed below. The model for temporary control of the transport process. Assume that the system consists of a set of wagons moving through stations. A model of temporary control of the transport process. We assume that the system consists of a set of wagons V, moving through the stations S.

For each wagon $v_i \in V$, we introduce a set of time characteristics: For each wagon $t_{\text{arrival time}}\left(v_i, s_j\right) -$ the time of arrival at the station s_j; $t_{\text{departure time}}\left(v_i, s_j\right) -$ the time of departure from the station; s_j; $\Delta T\left(v_i, s_j\right) = T_{departure\ \text{time}}\left(v_i, s_j\right) - T_{arrival\ \text{time}}\left(v_i, s_j\right) -$ and the time of processing the wagon.

The planned (standard) time characteristics are defined by a set of control time points KCT_{ij}, and the deviations are:

$$\Delta T_{ij} = T_{fact}\left(v_i, s_j\right) - T_{plan}\left(v_i, s_j\right). \qquad (4)$$

Next, let's consider a fuzzy model for predicting delays. Let's introduce linguistic variables: $\Delta T_{ij} -$ the delay of a car, expressed in linguistic terms such as minimum, average, or critical; $R\left(v_i\right) -$ the predicted risk of a car delay; $U\left(v_i\right) -$ and the control action of the dispatching system. Then, we assume that there is a fuzzy rule of the form:

$$IF\left(\Delta T_{ij}\ is\ High\right) AND \left(R\left(v_i\right) is\ Critical\right) THEN$$
$$\left(U\left(v_i\right) is\ \mathrm{Im}mediate\ Intervention\right). \qquad (5)$$

We assume that the objective function for minimizing time deviations can be defined by the following expression:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{M} w_{ij} \cdot \left|\Delta T_{ij}\right|, \qquad (6)$$

where $w_{ij} -$ weighting factors for the significance of stations.

For a well-founded selection of weight coefficients, it is advisable to use the Fuzzy AHP method, which makes it possible to structure the hierarchy of criteria and define their relative priorities under conditions of uncertainty. The obtained criterion weights are then used in the calculation of the objective functions (6), (22)-(25). To illustrate the application of the Fuzzy AHP method, let us consider the task of determining the weights of criteria for evaluating operational processes in railway transport. The following criteria were selected: minimization of delays (D), reliability of transportation and rolling stock (R), infrastructure load (L), and redistribution costs (K).

Table 1.
Pairwise comparison matrix (in terms of Triple Fuzzy Number (TFN))

Criteria	**D**	**R**	**L**	**K**
D	(1,1,1)	(1,2,3)	(4,5,6)	(6,7,8)
R	(1/3,1/2,1)	(1,1,1)	(4,5,6)	(6,7,8)
L	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1,1,1)	(1,2,3)
K	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/3,1/2,1)	(1,1,1)

Stages of calculation.
1) Construction of the pairwise comparison matrix using TFN.
Expert evaluations are converted into triangular fuzzy numbers: $\tilde{A}$ = (l, m, u).

$$\tilde{A} = \tilde{a}_{ij} = \begin{pmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) \cdots & (l_{1n}, m_{1n,} u_{1n}) \\ (l_{21,} m_{21}, u_{21}) & (1,1,1) \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n3}) \cdots & (1,1,1) \end{pmatrix} \qquad (7)$$

$$\tilde{a}_{ji} = 1/\tilde{a}_{ij} = (1/l_{ij}, 1/m_{ij}, 1/u_{ij} \qquad (8)$$

2) Determination of the synthetic degree of importance (Chang's method, Extent Analysis)
The synthetic degree for each criterion is calculated as:

$$\widetilde{S_i} = \left(\frac{\sum_{j=1}^{n} l_{ij,}}{\sum_{j=1}^{n}\sum_{j=1}^{m} u_{ij}}, \frac{\sum_{j=1}^{n} m_{ij},}{\sum_{j=1}^{n}\sum_{j=1}^{m} m_{ij}}, \frac{\sum_{j=1}^{n} u_{ij},}{\sum_{j=1}^{n}\sum_{j=1}^{m} l_{ij}}\right), i = \overline{1, n}; \quad (9)$$

3) For each criterion, the minimum degree of preference compared to the others is selected:

$$\left(\widetilde{S_i} \geq \widetilde{S_j} \middle| j = 1, \dots n; j \neq i)\right| = \min V(\widetilde{S_i} \geq \widetilde{S_j}), = 1 \dots n; \quad (10)$$

4) The final weights are subjected to normalization:

$$w_i = \frac{V\left(\widetilde{S_i} \geq \widetilde{S_j} \middle| j = 1, \dots n; j \neq i\right)}{\sum_{i=1}^{n} V\left(\widetilde{S_i} \geq \widetilde{S_j} \middle| j = 1, \dots n; j \neq i\right)} \quad (11)$$

5) Defuzzification method

Each TFN (l,m,u)(l,m,u)(l,m,u) is transformed into a crisp value.

The most frequently employed methods are:

$$X_{max}^{1} = \frac{\mathrm{l + m + u}}{3} \quad (12)$$

where l_i, m_i, u_i — denote the lower, middle, and upper bounds of the triangular number.

6) The maximum value is selected defuzzy = max ($X_{max}^1;\ X_{max}^2;\ X_{max}^3$)

Normalization to the sum of 1.

Table 2.
Final criterion weights.

Criteria	Weight
Minimization of delays (D)	0.4888
Reliability (R)	0.3632
Infrastructure load (L)	0.0914
Redistribution costs (K)	0.0567

The primary priority is the minimization of delays (≈49%).

The second most significant criterion is reliability (≈36%).

Infrastructure load (≈9%) and redistribution costs (≈6%) play a supplementary role.

Thus, Fuzzy AHP confirmed that the system should be focused on time and reliability, while the remaining indicators are to be considered as constraints.

If we abstract from the reliability of the RS and consider only the reliability parameters of transportation, then according to [14] we can use the following expression to determine the probability of timely cargo delivery:

$$P\left(T_{\text{delivery}} \leq T_{notm}\right) = \int_0^{T_{notm}} f\left(T\right)dt, \quad (13)$$

where $f\left(T\right)-$ the distribution density of the delivery time, determined based on retrospective (i.e., previous) data. If we consider reliability as a parameter that determines the system's fault tolerance, we can use the dependencies proposed in Mailybayev, et al. [10]:

RS availability factor ($Availability\ index,\ A$):

$$A = \frac{MTBR}{MTBR + MTTR}, \quad (14)$$

where $MTBR-$ average operating time per failure (Mean Time Between Failures) [6, 14];

$MTTR-$ average recovery time (Mean Time To Repair) [12].

The probability of schedule violations (P_delay) [12]:

$$P_{delay} = \frac{N_{late}}{N_{total}}, \quad (15)$$

where $N_{late}-$ number of trains that were more than 1 hour late $\Delta T\_permissible$.

A similar indicator can be used for wagons. ($Failure\_rate$),

$$\lambda = \frac{N_{failure}}{T_{operating}}, \quad (16)$$

where $T_{operating}-$ total operating time of the vehicle.

The model also included the probability of a railway infrastructure element failing. Mailybayev, et al. [6] and Kyrychenko [12]

($P\_failure$):

$$P_{failure}(t) = 1 - e^{-\lambda t}, \quad (17)$$

where $\lambda -$ failure rate; $t -$ operating time.

Additionally, it is proposed to consider the transportation stability criterion (or the delay variation coefficient):

$$CV_{delay} = \frac{\sigma_{delay}}{\mu_{delay}}, \quad (18)$$

where $\sigma_{delay} -$ standard deviation of delays; $\mu_{delay} -$ the average value of delays.

We believe that in order to model the OP in the framework of our research, it is necessary to determine the key parameters. That is, these parameters can be expressed in terms of fuzzy variables. Moreover, the list of parameters can be specified. And our list in the framework of the article is presented to illustrate the operation of the model and its subsequent algorithmization and software implementation).

The main input parameters considered in the modeling process were as follows:

the time of the car's arrival at the station ($T\_arrival$); the time of the car's processing at the station ($T\_process$); the expected delay in traffic (T_delay); the load on the infrastructure ($Load\_station$); the technical condition of the rolling stock ($Wagon\_condition$); the expected reliability of the forecast ($Prediction\_reliability$); and the weather conditions ($Weather\_conditions$).

Then, it is reasonable to assume that each of these parameters can be represented as a fuzzy variable with linguistic values. That is, a set of fuzzy terms is defined for each parameter:

$T\_arrival \rightarrow$ early, on time, late, critical delay;

$T\_process \rightarrow$ fast, medium, long, abnormally long;

$T\_delay \rightarrow$ no delay, minor, significant, critical;

$Load\_station \rightarrow$ low, medium, high, overload;

$Wagon\_condition \rightarrow$ excellent, good, satisfactory, critical;

$Prediction\_reliability \rightarrow$ high, medium, low

$Weather\_conditions \rightarrow$ good, moderate, bad, extreme

When implementing the developed module for the Automated System for Electronic Processing on the Railway Transport using fuzzy models and reliability forecasting, each value is set using the corresponding membership function. For example, the membership function for the parameter of car processing time $T\_process$ can be described as follows:

$$\mu_{fast}(t) = \begin{cases} 1, & t \leq 20, \\ \frac{40-t}{20}, & 20 < t \leq 40, \\ 0, & t > 40. \end{cases} \quad (19)$$

.

Or, in other words, for the parameter of the processing time of the car $(T\_process)$, the membership functions are introduced (13). This function describes the degree of compliance of the parameter value with certain qualitative categories. In this case, we consider three categories: "fast", "medium", and "slow". The membership function $\mu_{fast}(t)$ determines the degree of membership of the processing time of the car in the "fast" category. It is defined as follows.

If the processing time does not exceed 20 units of time (in general, minutes), then the degree of membership is equal to 1, which means that the processing time fully meets the "fast" category. As the processing time increases from 20 to 40 units of time, the degree of membership decreases linearly to 0, reflecting a decrease in the degree of compliance with this category. For processing times exceeding 40 units of time, the degree of membership is equal to 0, indicating that the processing time does not meet the "fast" category. Similarly, the membership function is defined $\mu_{average}(t)$, see expression (13) for the "medium" category. In this case, the membership degree is equal to 0 for processing times less than 20 units of time or greater than 60 units of time. In the range from 20 to 40 units of time, the membership degree increases linearly from 0 to 1, and in the range from 40 to 60 units of time, it decreases linearly from 1 to 0. In the range from 20 to 40 units of time, the membership degree increases linearly from 0 to 1, and in the range from 40 to 60 units of time, it decreases linearly from 1 to 0.

This allows you to describe a situation where the processing time for a car is in the intermediate range corresponding to the "medium" category. It should be noted that the use of such membership functions allows us to describe the parameters of the OP during modeling. At the same time, we take into account their fuzziness and variability. This, in turn, increases the accuracy of predicting the reliability and efficiency of OP management on the railway. After defining the input parameters and linguistic variables, a fuzzy production model for OP management on the railway is constructed. Below, we provide a fragmentary description of some of the rules used for the ACS module.

If ($T\_arrival$ ="Late") & ($Load\_station$ ="High") That ($T\_process$ ="Quickly").

If ($T\_process$ ="Abnormally long") or (T_delay ="Critical") That ($T\_arrival$ ="Critical delay").

For ease of perception, the rules can be formalized as fuzzy implications:

$$R_i : IF\left(X_1 = A_1\right) AND\left(X_2 = A_2\right)\ THEN\left(Y = B_i\right), \tag{20}$$

where $X_1, X_2 -$ input variables; $A_1, A_2 -$ linguistic values of input variables; $Y -$ output variable, $B_i -$ linguistic value of output variable.

When the input data is received, it is fuzzified, after which the production rules are activated. The values of the output variables are calculated using fuzzy logic methods. Min-Max (Mamdani method) – the minimum degree of membership among the conditions and the maximum value of the result are selected.

The center of mass method is used to defuzzify the output of the system.

Formally, defuzzification is carried out using the following formula: $Y = \dfrac{\sum_i \mu_{B_i}(y) \cdot y_i}{\sum_i \mu_{B_i}(y)},$

where $\mu_{B_i}(y) -$ the degree of affiliation of the outlet to B_i; $y_i -$ the numerical value of the output.

For example, for the parameter we discussed above T_delay, if the fuzzy inference result gave the following membership functions: insignificant (0.2), significant (0.5), and critical (0.3), the numerical result of the delay time would be calculated as the weighted average of the values corresponding to these terms. Similar reasoning is also valid in general for fuzzy electric drive control system. For example, it can be used to predict the probability of delays and identify critical deviations from the schedule. It can also be used to assess the reliability of the software system RS, i.e., to determine the probability of failure.

In addition, the parameter of dynamic resource redistribution was considered. This parameter is important because it helps to optimize traffic on the railway, redirect routes when sections are overloaded. In other words, it allows for flexible regulation of the load on stations (changing the departure time, redistributing wagons), reducing empty runs, and reducing inefficient use of rolling stock. We believe that it is advisable to consider the following key parameters: section load ($Load_{section}$) – low, medium, high, critical; availability of free tracks at stations ($Free_{tracks}$) – many, sufficient, insufficient, none; availability of locomotives ($Available_{locos}$) – sufficient, limited, shortage; predicted delay (P_{delay}) – none, minor, significant, critical; redistribution of the train ($Reallocate_{trains}$) – not required, partial, full.

Table 3 presents a database of fuzzy rules for predicting reliability and resource redistribution in the railway transport sector.

Table 3.
An example of a fuzzy rule base for predicting reliability and resource redistribution in the railway industry (compiled by the author).

№	Conditions (IF...)	Exit (THEN...)
1	2	3
1	$P_{failure} =$ «High» & $Load_{section}$ = «Critical»	$Reallocate_{trains}$ = «Full»
2	P_{delay} = «Critical» & $Free_{tracks}$ = «Missing»	$Reallocate_{trains}$ = «Full»
3	P_{delay} = «Significant» & $Available_{locos}$ = «Deficit»	$Reallocate_{trains}$ = «Partial»
…	…	…

Table 3 adds a variable, according to Pavlovic, et al. [3]; Akhmedov [7]; Mailybayev, et al. [10]; Shinykulova, et al. [13] and d'Ariano, et al. [14]: $Wear_{in\,fra} -$ a dynamic assessment of infrastructure wear and tear, which allows for predicting (forecasting) the need for repairs to railway tracks, stations, locomotives, and other rolling stock, as well as determining the likelihood of infrastructure overload, which can lead to delays and accidents.

In this article, it is assumed that the Fuzzy Logic Controller includes the following main components: input parameters (fuzzy variables that characterize the system's state); a rule base (a system of fuzzy production rules for process control); fuzzification (the transformation of clear input data into fuzzy data); a decision-making mechanism (methods for processing fuzzy data); and defuzzification (the transformation of fuzzy output data into clear control actions).

Time prediction $\hat{T}$ based on previous transportation data is performed using a regression model, as shown in the study [11] or in general:

$$\hat{T}_f = \alpha \cdot T_c + \beta \cdot \mu + \gamma \cdot \delta, \tag{21}$$

where $\alpha, \beta, \gamma -$ regression coefficients determined by empirical analysis (for example, at the stage of drawing up a technical specification (TS) for the design of an automated control system).

The problem of optimizing the transportation schedule is formulated as minimizing the delay function [12]: $\min \sum_{i=1}^{n} \left(T_f^i - T_c^i\right)^2$, taking into account resource constraints and technological regulations.

To account for reliability forecasting, we will add a target function to minimize the probability of transportation schedule violations:

$$\min P_{delay} = \frac{N_{late}}{N_{total}}, \tag{22}$$

where $N_{late} -$ number of trains that were more than late $\Delta T\_permissible$; $N_{total} -$ total number of trains.

The objective function (16) is consistent with the reliability prediction task, as it allows minimizing the share of delays and thereby improving the accuracy of the schedule on the RK Railway. We believe that the model should take into account the factor of maximizing the availability coefficient of wagons and locomotives:

$$\max A = \frac{MTBR}{MTBR + MTTR}, \tag{23}$$

where $MTBR -$ average operating time per failure ; $MTTR -$ average recovery time.

Redistributing rolling stock in a busy railway infrastructure is a costly operation. Accordingly, the number of such adjustments can be minimized:

$$\min \sum_{i=1}^{M} \mathrm{Re}llocate, \tag{24}$$

where $\mathrm{Re}llocate -$ a binary variable that takes the value 1 if the composition needs to be redistributed in the i-th area, and 0 otherwise. Function (18) is consistent with fuzzy control models, as forecasting allows for pre-emptive adjustments to railway traffic routes at high levels of infrastructure utilization and delays. Finally, to ensure the stability of the transportation process, it is advisable to minimize the coefficient of variation of delays:

$$\min CV_{delay} = \frac{\sigma_{delay}}{\mu_{delay}}, \tag{25}$$

where $\sigma_{delay} -$ standard deviation of delays ; $\mu_{delay} -$ the average value of delays.

Thus, the application of fuzzy logic and reliability forecasting methods in combination with Fuzzy AHP provides a comprehensive approach: from modeling fuzzy parameters and production rules to the well-founded selection of objective function weights and the optimization of operational processes in railway transport.

It should be noted that the inclusion of additional target functions (16)-(19) in the proposed mathematical model of automated control of electrical power on the railway is justified from the point of view of comprehensive consideration of factors affecting the reliability and efficiency of the system.

3. Results and Discussion

The implementation of an intelligent decision support system (IDSS) in the automated control system of operational process at the railway station will require an integrated approach to processing and analyzing data obtained from various sources. In general, such integration will be aimed at increasing the adaptability, accuracy of forecasting, and effectiveness of management decisions in conditions of uncertainty and dynamic changes in the operational parameters of railway transport facilities. The basis of such a system is the architecture presented in Figure 1, where the key components are the information data warehouse of the railway technologies, OLAP technologies, big data analysis systems and OLTP operational bases. The system architecture includes the following main components (at the concept level, the scheme may be specified when drawing up a specific TS), see Figure 1.

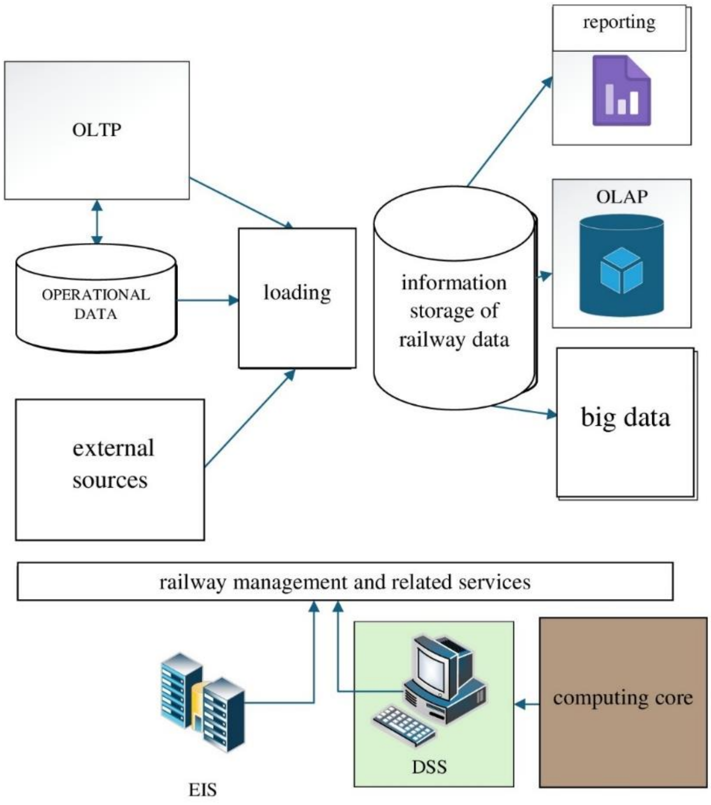

Figure 1.
Architecture of an intelligent DSS in an ACS for managing OP on the railway.

Operational databases (OLTP) and operational data store primary information about railway traffic, infrastructure, schedules, train loadings, and other operational indicators. These data are fed into the information repository through the process of uploading and transforming into formats for further processing. External data sources include information about the state of transport infrastructure, passenger and cargo flows, as well as information from logistics operators and government regulators in the Republic of Kazakhstan.

The Railway Data Warehouse (Data Warehouse) is a central component that provides storage, processing, and integration of data for further analysis and decision-making on issues related to railway energy efficiency OLAP-systems (On-Line Analytical Processing) – allow for multidimensional analysis of performance indicators, identification of patterns, and modeling of alternative scenarios for managing railway energy efficiency. Big Data analysis systems (Big Data Analytics) – provide prediction of the reliability of rolling stock, infrastructure and OP based on FL methods.

Reporting systems – generate analytical and forecast reports for various levels of railway transport management. EIS (Executive Information System) – information systems for senior management providing strategic analytics and forecast models for the management of the Kazakhstan Railway Transport. DSS (Decision Support System) – intelligent algorithms and decision support methods that use FL and forecasting methods. Essentially, this is the computational core of the DSS system, which is based on the model discussed in the article and will be part of the research objectives.

As part of the validation of the proposed model, the criterion weights were calculated using the Fuzzy AHP method.

The obtained values were as follows: minimization of delays – 0.4888, reliability – 0.3632, infrastructure load – 0.0914, redistribution costs – 0.0567. The results indicate that the key priority for operational process management is the reduction of delays, which confirms the necessity of emphasizing time-related parameters in the operation of the IDSS. The second most significant criterion is the reliability of rolling stock and infrastructure, which directly affects schedule predictability and system stability. Infrastructure load and redistribution costs are treated as additional constraints, reflecting their secondary role in decision-making. Thus, the Fuzzy AHP method has made it possible not only to formalize expert judgments but also to integrate them into multi-criteria optimization, thereby strengthening the adaptability and robustness of the proposed model.

4. Conclusion

As a result of the research, the following results were obtained and the following conclusions were drawn. A mathematical model (MM) of automated control of operational processes (OP) in railway transport (RT) has been developed, which differs from known solutions in that it integrates methods of processing fuzzy information and predicting reliability for adaptive transportation management. The proposed model, unlike known solutions, takes into account the multi-variability of logistics scenarios and the dynamic change of operational parameters on the railway transport. The list of target functions for the computational core of the intelligent decision support system integrated into the automated control system has been expanded, which, unlike known solutions, includes not only the minimization of time deviations and the probability of traffic schedule violations, but also the coefficient of delay variation and the level of infrastructure load. In addition, the model employs the Fuzzy AHP method, which ensures the formalization of expert judgments and the determination of weight coefficients in the multi-criteria optimization of operational processes. This has enhanced the model's resilience to uncertainty and aligned the priorities of various indicators (delays, reliability, infrastructure load).

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