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Simulation modelling of sampling and replacement of coal suppliers for thermal power plants

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ABSTRACT

This paper embarks to the persistent suboptimal coal quality issues experienced in thermal power plants that hinder operational efficiency and sustainability. The research is divided into three main segments: formulation of a transport problem, creation of a coal supplier selection model, and construction of a MATLAB Simulink® simulation for detecting and refusing low-grade coal. The proposed supplier selection model, important for thermal power plants, considers factors such as potential transport delays and the necessity of reserve refueling to prevent fuel shortages. This model is expected to decrease fuel shortages and enhance the reliability and efficiency of thermal power plants. Additionally, a coal quality detection model has been developed using a sampling approach based on the Cochran formula, aiming to increase defect detection accuracy, thus reducing the likelihood of utilizing poor-quality coal. The model's unique feature is its dynamic adjustment of coal sample selection based on combustion results, enabling real-time response to coal quality inconsistencies. Upon detecting poor-quality coal, the power plants promptly switch to an alternate supplier, minimizing operational disruptions. The validity of the models was confirmed via simulation on various examples.

Keywords: Thermal power plants; coal quality; supplier selection; Cochran sampling formula; quality control; automatic control system; energy production sustainability; transportation delays.

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INTRODUCTION

Coal-fired power plants are vital in meeting global electricity needs, with their efficiency and lifespan largely depending on coal quality and the wear resistance of their boilers' heat transfer surfaces. A previously developed fuzzy control system [1] successfully managed this wear resistance by controlling the coal quality and balancing steam coal flows. However, it didn't address logistic issues affecting coal quality, such as transportation and storage.

This study emphasizes the overlooked aspect of coal quality control – the possibility of a disparity between the coal's declared and actual quality, and additional logistical issues like delivery delays and network congestion, which can cause quality fluctuations and affect grid capacity maintenance. To tackle these issues, was introduced a logistics-integrated coal quality control system for coal-fired plants, aimed at enhancing the fuzzy control system by including logistics considerations and early detection of inconsistent abrasive values from unreliable suppliers. This provides a holistic solution addressing transportation delays, coal shortages, and other similar challenges.

LITERATURE REVIEW

Supplier selection in thermal power plants is a crucial aspect of ensuring continuous power generation. Multiple factors need to be considered, including quality, price, and reliability [2]. Traditionally, coal suppliers were selected based on price and availability. However, research in the field has suggested the inclusion of additional criteria, such as sustainability and coal quality [3, 4].

Regarding the quality control of coal, research has been directed towards controlling the wear resistance of heat exchange surfaces by controlling the quality of coal [1]. The problem of low-quality coal has been addressed in various ways. For instance, coal quality is controlled using various techniques such as floatation [5, 6], [7, 8] and fuel rearrangement control considering burnup [9, 10]. It is imperative to continuously monitor the quality of the coal supplied to thermal power plants as the quality of coal significantly impacts the efficiency of power plants [11].

For supplier selection, the application of fuzzy multiple criteria decision-making (MCDM) techniques has been proposed [12]. Multiple criteria decision-making provides a systematic approach to decision-making when various criteria are involved, especially in complex environments. Fuzzy logic, introduced by Zadeh [13], allows for considering uncertainties and imprecision in the decision-making process. This has also been adopted for supply chain management [12], [14]. Moreover, simulation techniques have been suggested for optimizing various aspects of thermal power plants. For instance, the MATLAB®/Simulink platform has been used for real-time control in various applications [15], [16, 17]. Additionally, simulation has been employed for optimizing coal transportation [18, 19], [20]. These models have proved useful in minimizing costs and optimizing the supply chain [21].

Finally, to obtain representative data for these models, appropriate sample sizes must be calculated [22]. Sampling is a critical aspect of the quality control process. The Cochran formula is a commonly used method for determining the required sample size for a study [23, 24].

THE PURPOSE OF THE ARTICLE

The existing methods in thermal power plants currently fall short in effectively managing transportation delays and efficiently dealing with potential fuel shortages. Additionally, the existing sampling models fail to offer sufficient adaptability in the face of identified defects, and necessitate a gradual reduction in the sampling step until a defect emerges. Furthermore, despite the extensive use of simulation models in numerous aspects of thermal power plant operations, they have not yet been employed for the specific purpose of detecting and rejecting inferior quality coal.

The primary objective of this paper is to establish an adaptive, comprehensive framework that refines the coal supplier selection process, while addressing the aforementioned challenges. This entails the development of an advanced sampling model grounded in the Cochran formula, batch purchase planning as well as a simulation model specifically designed for the detection and rejection of substandard coal (It is assumed that the decision-making algorithms for the formation of a supply batch will be considered as in Fig. 1). These innovative models, built on the basis of adaptive methodologies, are designed to account for factors such as transportation delays and reserve replenishment strategies. These inclusions aim to drastically diminish the prevalence of fuel shortages.

The broader purpose of this research, however, extends beyond model development. By integrating these models into a cohesive system, this study aims to fortify the quality control mechanisms within thermal power plants. This fortified system is anticipated not only to improve the overall operation and reliability of the plants but also to optimize energy sustainability. In essence, this paper strives to enhance the efficiency of thermal power plants by revolutionizing how they handle coal quality, from supplier selection through to combustion.

MAIN PART. METHODOLOGY AND APPROACH

To optimize the coal quality control system for coal-fired power plants, several operational and logistical parameters had to be considered. A train of 30-40 cars, each carrying 30 tons of coal, was considered. Given that the power plant consumes approximately 25'084 tons of coal per day, it would need to receive about 24 trains daily. If there are four different suppliers, each of them will have to deliver 6 railcars per day.

According to the Ministry of Energy of Ukraine, ideally, state-owned power plants should have a guaranteed coal reserve of 150.5 thousand tons, enough for six days of operation without replenishment. So, the challenge is to keep these reserves at the required level.

A scenario is considered where there are four suppliers (three by rail and one by sea). If one of them supplies low-quality coal, it was decided to increase the volumes from the other suppliers by 30 %. However, the issue of delivery time must be taken into account.

If we take as an example the average time for the full transportation of coal from South Africa to Ukraine (in particular, to a power plant), it usually takes about 60 calendar days (Fig. 2). Thus, any adjustments made due to poor quality coal from one supplier will have a significant time delay.

For the problem, we took railroad connections within Ukraine from suppliers to the power plant with different distances: B1 (233 km), B2 (411 km), B3 (1'300 km) to the power plant. If we take into account the average speed of mineral railcars of 160 km/day, the delivery time will be 1.4; 2.6; and 8.1 days, respectively.

The following notations are used in the following tables:

– d - day counter;

– R - amount of reserve stock replenishment, thousand tons;

– B (1, 2, 3,*) - supply volumes from the respective supplier per day, thousand tons;

– md - total coal output per day, thousand tons;

– Ds - receiving railroad trains per day together;

– Dw - receiving railroad cars per day together.

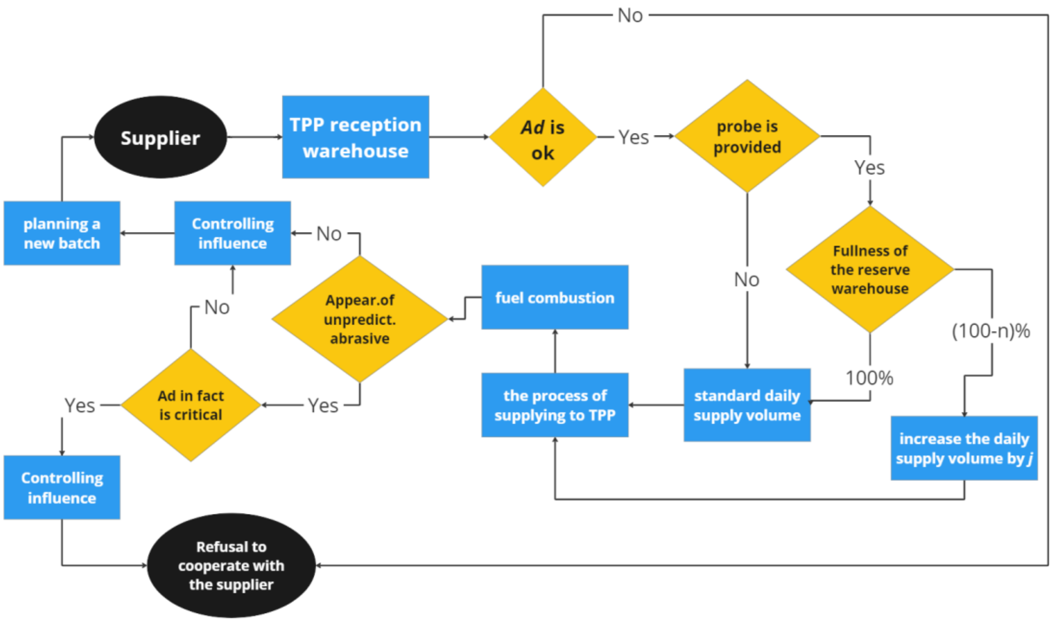

Fig. 1. **Basic algorithmic scheme of decision-making on fuel supply formation**
Source: **compiled by the authors**

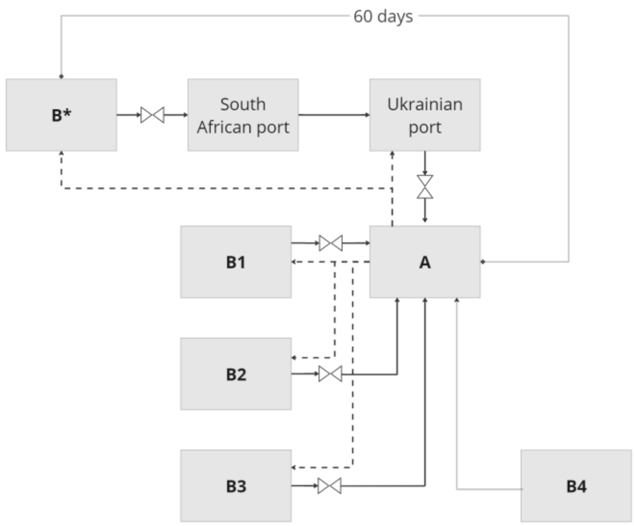

Fig. 2. **Scheme of logistics information links supplier – thermal power plant**
Source: **compiled by the authors**

In an ideal scenario, each supplier delivers coal in a balanced manner, as shown in Table 1. However, when one supplier is unable to provide the plant with the required quality and the plant refuses to cooperate further, there is a need to immediately increase the volume of supplies from other suppliers. This strategy will be rational only for suppliers with fast transit times (not by sea). Suppliers closer to the power plant can provide larger volumes. It is also assumed that supplies can be resumed with a new supplier within two weeks, reducing the volume of increased supplies only when the reserve stock is fully replenished.

Table. 1. **"Perfect" coal supplying**

d	md	R	Dw	Ds
1	25.2	150	840	24
2	25.2	150.2	840	24
3	25.2	150.4	840	24
4	25.2	150.6	840	24
5	25.2	150.8	840	24
6	25.2	151	840	24

Source: **compiled by the authors**

These parameters help to form a logistics model for maintaining a stable supply of high-quality coal for power plants. Integrating these logistical considerations into the existing fuzzy control system is the basis of the proposed logistics-integrated coal quality management system. This system aims to ensure optimal operation of power plants by not only controlling coal quality, but also effectively managing the logistical problems associated with coal supply and storage.

Subsequently, the dynamics of changes in supply volumes from shipments B1, B2, B3, as well as possible changes in the situation when one of the suppliers is absent, were analyzed.

In the first case, when supplier B1 is absent (table 2), we see that the total volume of cars per day decreases, but then increases due to an increase in supply from B2 by 60 % and B3 by 50 %. This allows us to maintain a stable supply until a new shipper arrives. The initial volume is restored on the 18th day, when the reserve is 151.45 thousand tons.

Table. 2. **Rejection of the supplier B1**

d	B1	B2	B3	B*	md	R	Dw	Ds
1	0	6.3	6.3	6.3	18.9	151.2	630	18
2	0	6.3	6.3	6.3	18.9	145.1	630	18
3	0	10.08	6.3	6.3	22.68	139	756	21
4	0	10.08	6.3	6.3	22.68	136.68	756	21
5	0	10.08	6.3	6.3	22.68	134.36	756	21
6	0	10.08	6.3	6.3	22.68	132.04	756	21
7	0	10.08	6.3	6.3	22.68	129.72	756	21
8	0	10.08	6.3	6.3	22.68	127.4	756	21
9	0	10.08	9.45	6.3	25.83	125.08	861	24
10	0	10.08	9.45	6.3	25.83	125.91	861	24
11	0	10.08	9.45	6.3	25.83	126.74	861	24
12	0	10.08	9.45	6.3	25.83	127.57	861	24
13	0	10.08	9.45	6.3	25.83	128.4	861	24
14	0	10.08	9.45	6.3	25.83	129.23	861	24
15	**6.3**	**10.08**	**9.45**	**6.3**	32.13	130.06	1071	30
16	6.3	10.08	9.45	6.3	32.13	137.19	1071	30
17	6.3	10.08	9.45	6.3	32.13	144.32	1071	30
18	6.3	6.3	6.3	6.3	25.2	151.45	840	24.3

Source: **compiled by the authors**

By analogy, we also analyzed the change in supply volumes in the case of absences B2 and B3. In the case of B2's absence, the volume of cars from B1 increases by 60 % and from B3 by 50 %. This compensates for the lack of supply from B2 until the new supplier enters the system. The initial volume is also restored on the 18th day, but with a larger reserve of 151.9 thousand tons. In case of failure of supplier B3, the volumes from B1 increase by 60% and from B2 by 50 %. The initial supply volume is restored on day 16, when the reserve is 151.9 thousand tons. This demonstrates that if one of the railroad suppliers refuses to supply, the others can compensate for the loss, but it takes time and affects the overall reserve.

The case of refusal from supplier B* (sea) should be considered and evaluated separately, namely, two options for solving the problem: finding an alternative supplier by rail (table 3) and by sea (table 4).

In this case, the situation becomes more complicated, but it is still possible to increase volumes from other shippers: the supply from B1 increases by 40 %, from B2 by 40 %, and from B3 by 40 %. The initial supply volume is restored on day 17, when the reserve is 157.24 thousand tons.

However, in the case of loss of B* sea supply, when it is possible to find an alternative supplier exclusively with sea delivery, the situation becomes even more complicated. Studies show that it can take up to 62 days to attract a new supplier with the ability to provide delivery by sea. This time should be reduced to 17 days, if possible, if the search for a new supplier is conducted, in particular, by rail.

Table. 3. **Rejection of the B* supplier, provided that an alternative supplier is found by rail within 2 weeks**

d	B1	B2	B3	B*	md	R	Dw	Ds
1	6.3	6.3	6.3	0	18.9	154	630	18
2	6.3	6.3	6.3	0	18.9	147.9	630	18
3	8.8	6.3	6.3	0	21.4	141.8	714	20
4	8.8	8.8	6.3	0	23.9	138.3	798	22
5	8.8	8.8	6.3	0	23.9	137.2	798	22
6	8.8	8.8	6.3	0	23.9	136.1	798	22
7	8.8	8.8	6.3	0	23.9	135.1	798	22
8	8.8	8.8	6.3	0	23.9	134	798	22
9	8.8	8.8	8.8	0	26.5	133	882	24
10	8.8	8.8	8.8	0	26.5	134.4	882	24
11	8.8	8.8	8.8	0	26.5	135.9	882	24
12	8.8	8.8	8.8	0	26.5	137.3	882	24
13	8.8	8.8	8.8	0	26.5	138.8	882	24
14	8.8	8.8	8.8	0	26.5	140.3	882	24
15	**8.8**	**8.8**	**8.8**	**6**	32.8	141.7	1092	30
16	8.8	8.8	8.8	6	32.8	149.5	1092	30
17	6.3	6.3	6.3	6	25.2	157.2	840	24

Source: **compiled by the authors**

In Fig. 3, it is shown how the amount of reserve fuel in the warehouse would change if the above scenarios were followed in turn, with the goal of restoring the reserve stocks as soon as possible. As soon as the stocks are restored, the next supplier is rejected in turn.

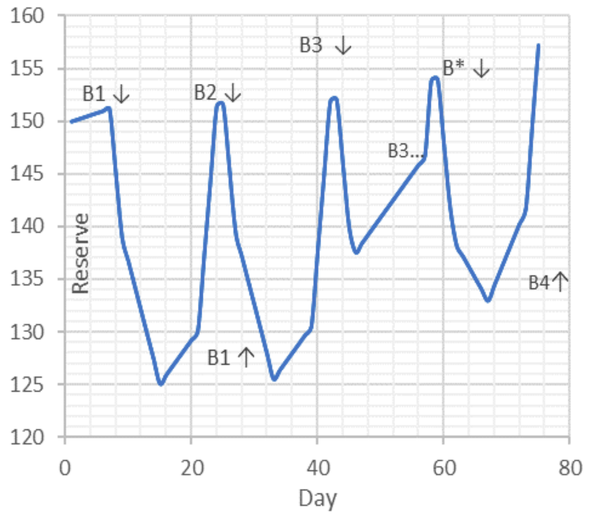

Fig. 3. **Dynamics of changes in reserve warehouse volumes in case of refusal from each supplier in turn**
Source: **compiled by the authors**

Similarly, in Fig. 4 also shows how long this process of reserve restoration will take if the power plant takes the hard way and waits for deliveries from a new shipper by sea.

This research has shown the importance of flexibility in supply management. The ability to quickly change the amount of supply from different suppliers and look for alternatives in case of loss can be critical for a business.

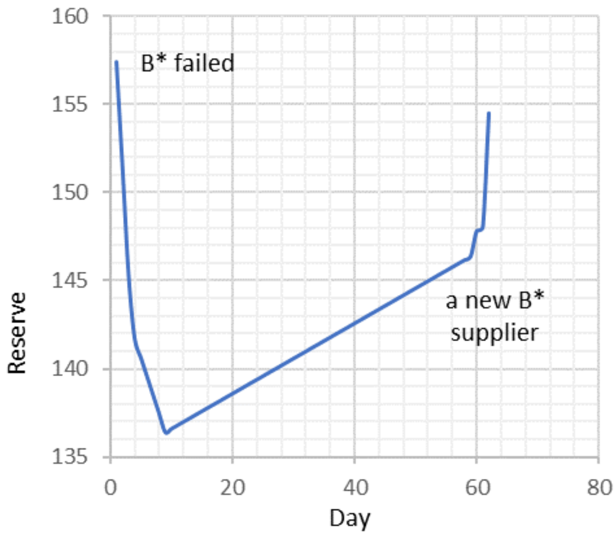

Fig. 4. **Chart of changes in coal reserves in the case shown in Table 4**
***Source:* compiled by the authors**

Table. 4. **Rejection of the B* supplier, provided that an alternative supplier is found by sea within 60 days**

d	B1	B2	B3	B*	md	R	Dw	Ds
1	6.3	6.3	6.3	0	18.9	157.44	630	18
2	6.3	6.3	6.3	0	18.9	151.34	630	18
3	8.82	6.3	6.3	0	21.42	145.24	714	20
4	8.82	8.82	6.3	0	23.94	141.66	798	22
5	8.82	8.82	6.3	0	23.94	140.6	798	22
6	8.82	8.82	6.3	0	23.94	139.54	798	22
7	8.82	8.82	6.3	0	23.94	138.48	798	22
8	8.82	8.82	6.3	0	23.94	137.42	798	23
9	8.82	8.82	7.56	0	25.2	136.36	840	23
10	8.82	8.82	7.56	0	25.2	136.56	840	23
11	8.82	8.82	7.56	0	25.2	136.76	840	23
12	8.82	8.82	7.56	0	25.2	136.96	840	23
…	…	…	…	…	…	…	…	…
60	8.82	8.82	7.56	0	25.2	147.82	840	23
61	**8.82**	**8.82**	**7.56**	**6.3**	31.5	148.02	1050	29
62	6.3	6.3	6.3	6.3	25.2	154.52	840	24

***Source:* compiled by the authors**

To further manage supply, it is recommended to implement a simple method to optimize supply volumes from different suppliers. This method can help determine the optimal supply volumes, considering various constraints and risks.

Table. 5. **Experimental results**

Supplier	New supplier	B1 ↑	B2 ↑	B3 ↑	Reserves recovery day
B1	Railroad	-	60 %	50 %	18
B2	Railroad	60 %	-	50 %	18
B3	Railroad	60 %	50 %	-	16
B*	Railroad	40 %	40%	40%	17
B*	Sea	40 %	40 %	20 %	62

***Source:* compiled by the authors**

All of this points to the importance of using a systematic approach to supply management, including qualitative analysis and planning, inventory optimization, and the constant search and evaluation of alternative supply channels.

For logistics planning, it's summarized the results of the experiment in Table 5.

COAL QUALITY CONTROL AND IMPACT ON ELECTRICITY PRODUCTION

Coal quality control is vital for efficient power generation and can be affected by factors like coal type, power requirements, and equipment efficiency. When coal quality dips, control over its storage increases.

This system ensures daily quality management through multiple strategies:

– Inspection methods: If defects are found or the coal quality is deemed unsatisfactory, the inspection methods may need refinement, such as implementing more precise analysis methods.

– Supplier changes: If coal quality fails to meet standards, consider switching suppliers and use backup fuel until the new supply is adequate. Additional checks with potential suppliers can help choose the one providing the best quality coal.

Regular monitoring and managing of coal quality is crucial to meet requirements and customer demands. The inspection frequency of railcars, determined by specific conditions and quality management policies, may need to increase until coal quality issues are resolved. For determining optimal inspection percentage of gas-coal with a maximum ash content of 15 % at Ukrainian thermal power plants (TPPs), statistical analysis of coal quality is needed, where the Cochran formula can be useful [23], and it's shown in (1):

$$n_r = \frac{N \cdot X}{(X + N - 1)}, \quad (1)$$

and *X*:

$$X = \frac{Z^2 \cdot p \cdot (1 - p)}{MOE^2}, \quad (2)$$

where n_r is sample size; N is the size of the general population; X is sample size (calculated before the finite population correction (FPC) factor); Z is the critical value of the normal distribution at $\alpha/2$ (for example, for a confidence level of 95 %, α is 0.05, and the critical value is 1.96); MOE is marginal error (for example, 0.05 for ±5 %); p is the expected probability of low-quality fuel slipping through.

It is important to note that the sample size formula was adjusted for a finite population. Nevertheless, this formula (2) assumes that the population is almost infinite or very large. In real life, given the limited population (840 freight cars per day), it is recommended to use the finite population correction (FPC), which reduces the sample size.

The finite population correction (FPC) is determined by the formula (3):

$$FPC = \sqrt{\frac{(N - X)}{(N - 1)}}. \quad (3)$$

Consider the following parameters:

– desired error: 4 % (average value between the standard 3 %, 5 %);

– confidence level: 92.5 % (average value between the standard 90 %, 95 %);

– total number of cars (total): 840;

– it is assumed that defects will be present in 5% of all railcars.

The recommended initial sample size for inspection is 85 cars, or about 10 % of total cars, examining every 10th car. If ineffective, the proportion of expected defective cars is increased to 15 %, with a new sample size of 190 cars, or roughly 20 % of the total, checking every 5th car. If defective fuel still enters the system, the expected defective share increases to 50 %, and the sample size goes up to 470 cars, about 40 % of the total, inspecting every 2nd car. If ineffective, the final resort is inspecting every car until faulty fuel is found. This system was simulated for validation.

MODELLING OF A COAL QUALITY CONTROL SYSTEM FOR A THERMAL POWER PLANT

In the example, the plant typically receives coal from three suppliers, chosen based on price, delivery speed, and quality. All deliveries arrive simultaneously and are mixed in the TPP's warehouse. Normally, the TPP processes 840 railcars of coal per day, with regular quality checks on every tenth car. If substandard coal is detected that supplier is dropped, and its volume replaced by trusted shippers and a new supplier. The daily railcar number then increases to a maximum of 1092 until reserve stock recovers to offset costs of reserve fuel use and supplier refusal losses. The plant also has a fuzzy system to identify low-quality coal during combustion [1], which, if triggered, increases inspection frequency. The challenge was to model this situation and develop an automated controller. The existing system was then revised and adapted (Fig. 5). For modelling, the interactive MATLAB® tool, Simulink® (LICENSING 110721904 – MathWorks Trial – Oct 22, 2022) was used [16, 17].

The key blocks of this subsystem are as follows:

– “Variable Transport Delay” takes into account the transport delay when taking a sample.

– “UpdateSelectWagon” is a function that acts as a system controller and determines the sample for the current situation.

– Flow opening level of combustion” is the percentage of the fuel flow that is accounted for by combustion (a feedback signal from a fuzzy controller that distributes fuel proportionally to the following areas: reserve replenishment, furnace, enrichment, fuel refusal and reserve consumption).

According to previous studies, if no more than half of the flow is fed into the furnace, it means that the coal is of poor quality.

The Grand Controller subsystem is a fuzzy logic-based control device that distributes the flow of all coal from the warehouse in 4 directions: furnace, reserve replenishment, enrichment, refusal to burn and reserve use.

Currently, the main interest for detailed study is the subsystem “Acceptance, control and unloading of fuel”. The subsystem will look like the one shown in Fig. 6.

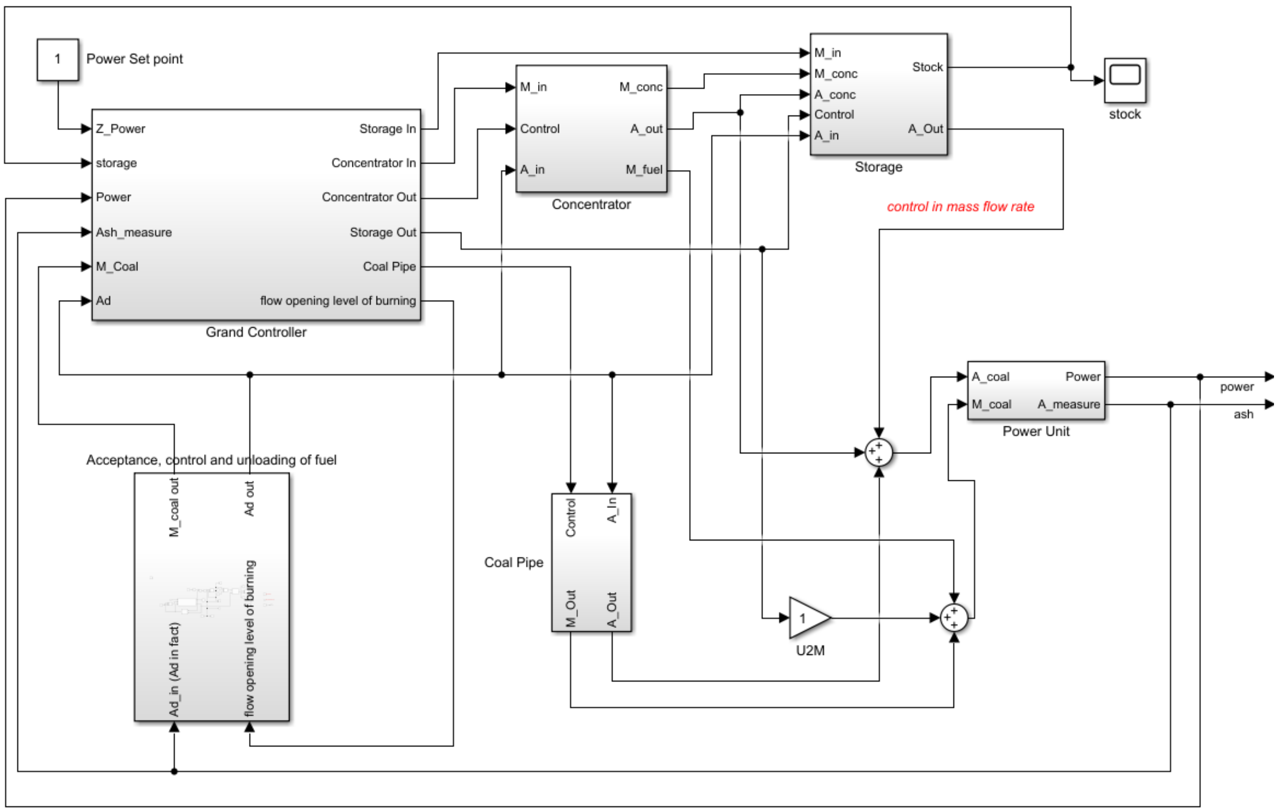

Fig. 5. **Chart of regulation and operation of the thermal power plant**
Source: **compiled by the authors**

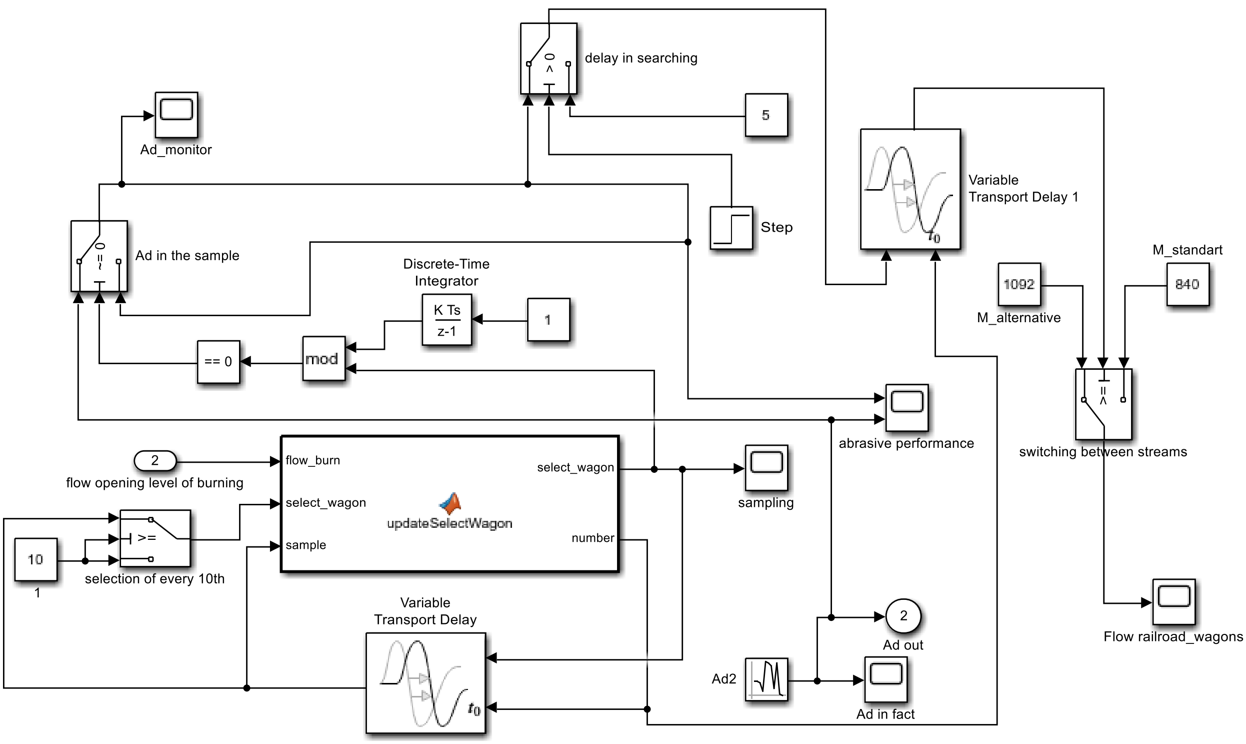

Fig. 6. **Scheme for regulating coal intake and sampling at the warehouse**
Source: **compiled by the authors**

In this case, the regulating function is performed by the “updateSelectWagon” function, which is programmed as follows:

```
function [select_wagon, number] =
updateSelectWagon(flow_burn, select_wagon,
sample)
    if flow_burn <= 0.5
        select_wagon = ceil(select_wagon / 2);
    else
        select_wagon = 10;
    end
    number = 1;
while sample >= 10
        sample = ceil(sample / 2);
        number = number + 1;
    end
end
```

When the coal quality control system identifies a drop in coal quality, the algorithm optimizes the sampling frequency, gradually reducing it until the source of the problem is identified.

If the corresponding source of poor coal quality is identified, the system makes a number of strategic decisions: it refuses from the poor-quality supplier, activates the use of reserve resources, increases the number of railcars coming from reliable shippers, and introduces additional suppliers to compensate for the costs of reserve resources as efficiently as possible.

ANALYSIS OF *Ad* DYNAMICS AND RESPONSE OF THE SYSTEM IN DIFFERENT SCENARIOS

In this section of the article is considered the main examples for testing the correctness of the system: 1) *Ad* is steadily increasing from perfect to poor quality; 2) the *Ad* value does not meet the required default conditions; 3) *Ad* is within the default range; 4) and a control test was performed with completely random *Ad* values.

Subsequently, each point was considered in detailЖ.

1) In Fig. 7 is shown the dynamics of *Ad* growth in the range of 0-30 % over 100 time units. A significant feature is the detection of the moment at 70 s when the coal quality *Ad* ceases to meet the requirements. In this case, the system begins to implement a progressive quality control strategy, reducing the sampling step to every 5th, then every 2nd, and finally every 1st car, which means checking every car.

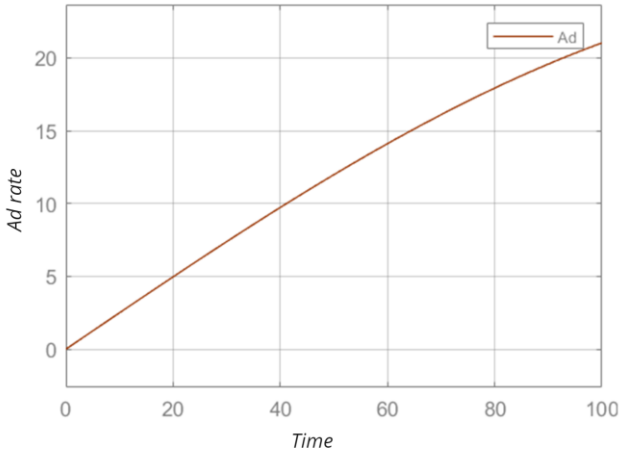

Fig. 7. **Gradual change of *Ad* from 0 % to 30 %**
Source: **compiled by the authors**

Fig. 8 demonstrates how the system detects the quality of *Ad* coal, taking into account sampling and transportation delay. It is important to note that the moment at 70s when the quality ceases to meet the requirements coincides with the transition to more frequent and detailed inspection of each car.

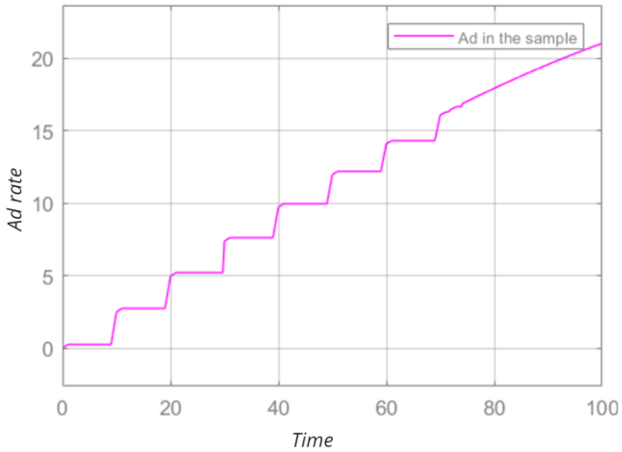

Fig. 8. ***Ad* indicator – at the time of taking a fuel sample for quality**
Source: **compiled by the authors**

Fig. 9 shows the strategic change after 70 s, when the system switches to an alternative flow after the supplier failure. This includes an increase in supply volumes in order to compensate for the reserve costs and ensure sufficient fuel.

2) The case with a large default *Ad* (in the range of 20-40 %) was considered separately. In this scenario, the system sets a sampling step of 1, which means that each car needs to be checked until a defect is detected.

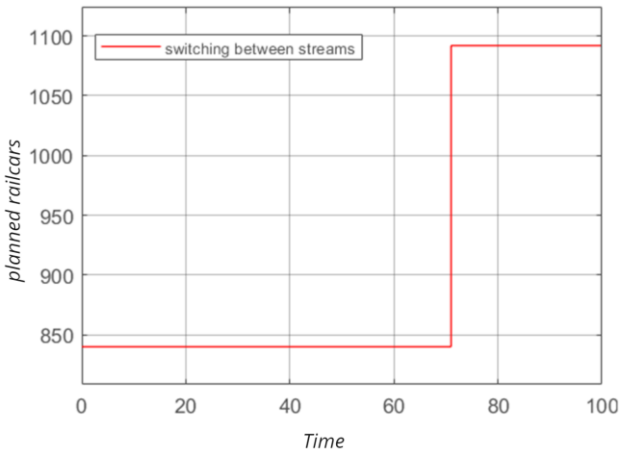

Fig. 9. **Selecting the number of railcars per day signal**
Source: **compiled by the authors**

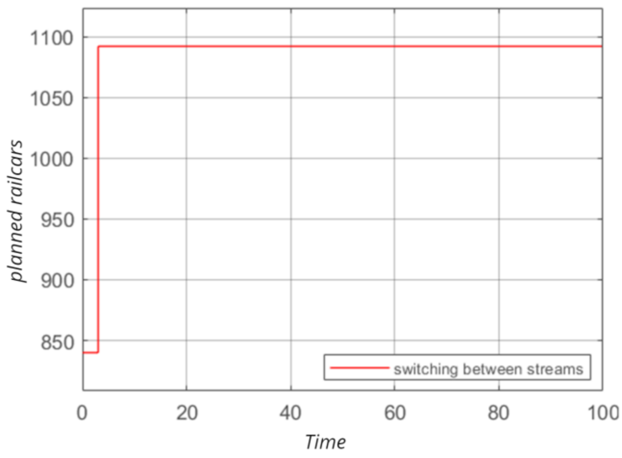

Fig. 10. **Selecting the number of railcars per day signal for *Ad* is 20-40 %**
Source: **compiled by the authors**

Fig. 10 shows how the system switches to an alternative flow shortly after a particular abrasive is detected and the supplier is abandoned. This change involves increasing the supply volume to compensate for the reserve costs and prevent fuel shortages. In this case, the system detects the quality of coal *Ad* during sampling, where the graph will completely coincide with the *Ad* values at each moment of time, confirming that a sample was taken from each container.

3) Subsequently, the system behavior was experimented with a low *Ad* default scenario (0-15 %).

Fig. 11 illustrates the dynamics of *Ad* over 100-time units in the range from 0 % to 15 % (randomly). For this quality, the controller sets the sampling step to 10 (standard), i.e. every tenth car is checked for undesirable effects on the control system.

In Fig. 12, is shown how the system detects *Ad* given the sampling and transportation delay. The value of *Ad* coincides with the value of *Ad* only at those points of the graph at which the sample is taken (every 10th). In this case, the railcar intake at the TPP remains at 840 cars per day until a negative impact on the system is detected.

4) To make sure that the system is operating efficiently, a completely random scenario of changing *Ad*.

Fig. 13 shows the dynamics of a random *Ad* that varies from 0 % to 30 % over 100-time units. In this scenario, the controller continuously adjusts the sampling depending on the detected abrasiveness (Fig. 14 and Fig. 15) and choosing numbers of railcars daily (Fig. 16). For example, at 0 s of the simulation runtime, the actual *Ad* is 19 %, which caused the sampling step to be reduced to 1 and forced the system to switch to signal 1092 due to a 4 s delays associated with sample analysis.

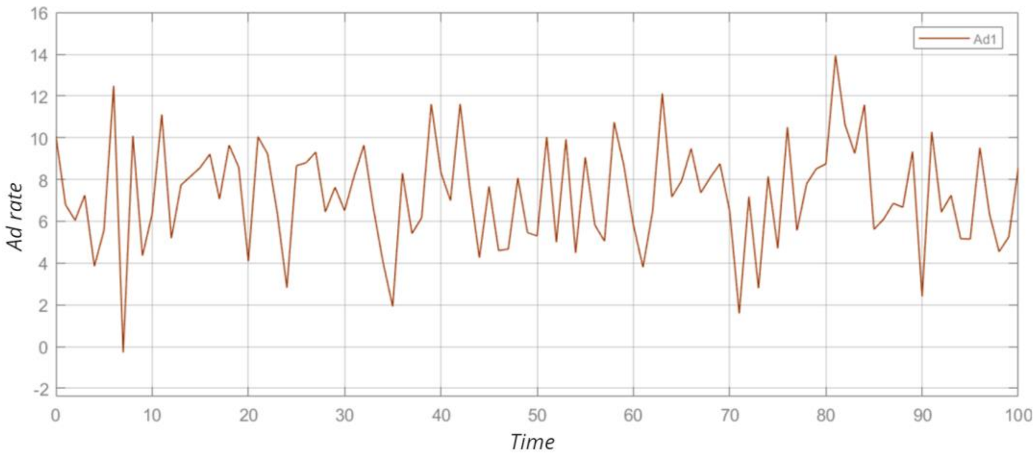

Fig. 11. **Random change of *Ad* in the range of 0-15 %**
Source: **compiled by the authors**

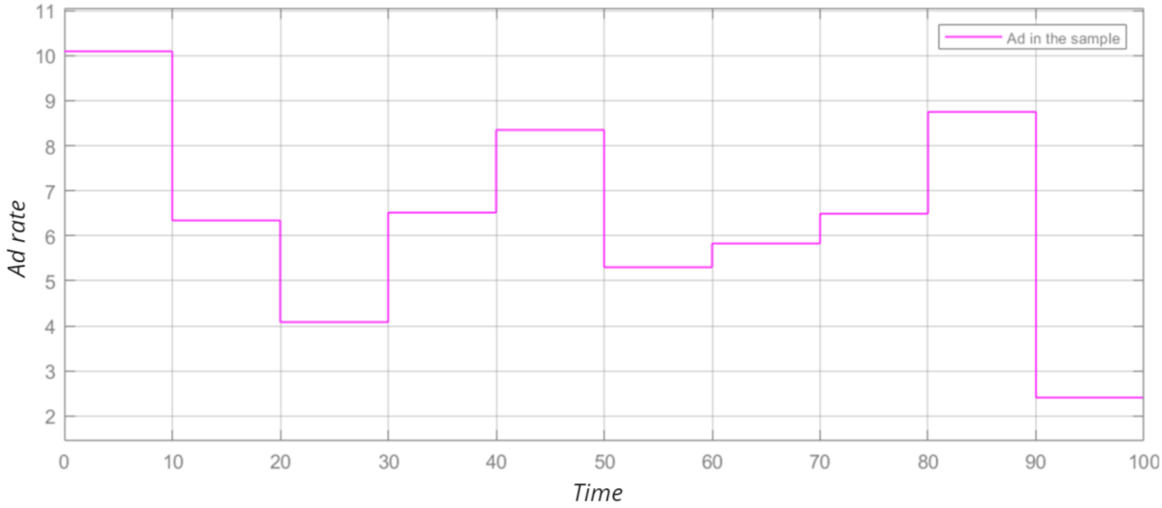

Fig. 12. ***Ad*** **rate at the time of fuel quality sampling**
Source: **compiled by the authors**

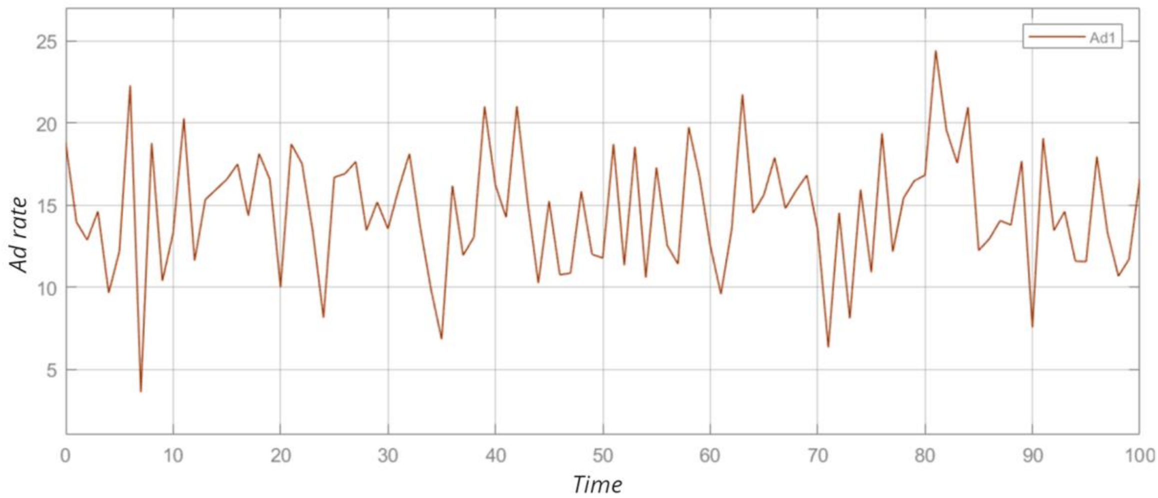

Fig. 13. **Random change of** ***Ad*** **in the range of 0-30 %**
Source: **compiled by the authors**

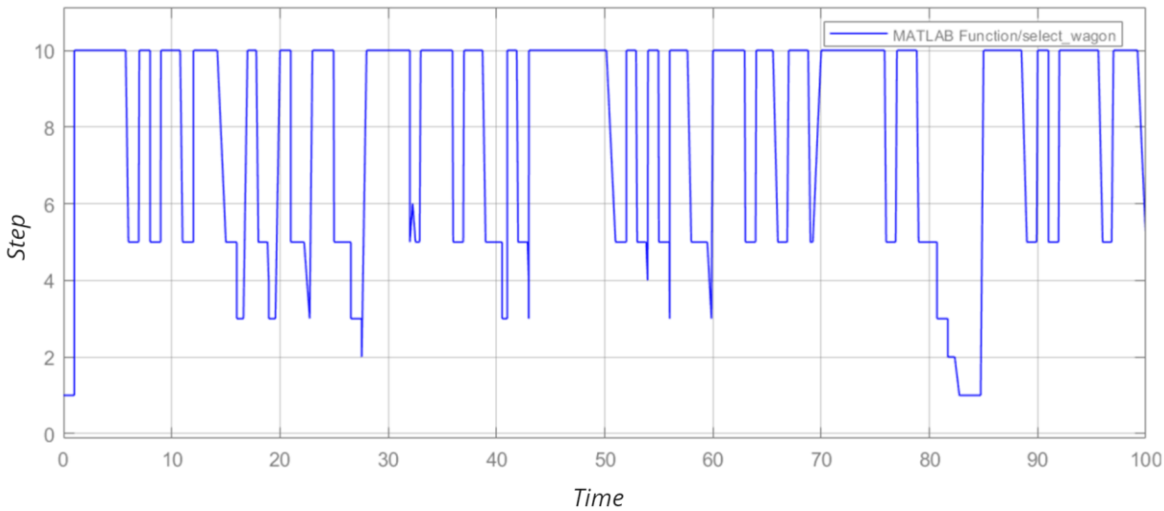

Fig. 14. **The step of selecting a railcar for inspection under the condition of random** ***Ad***
Source: **compiled by the authors**

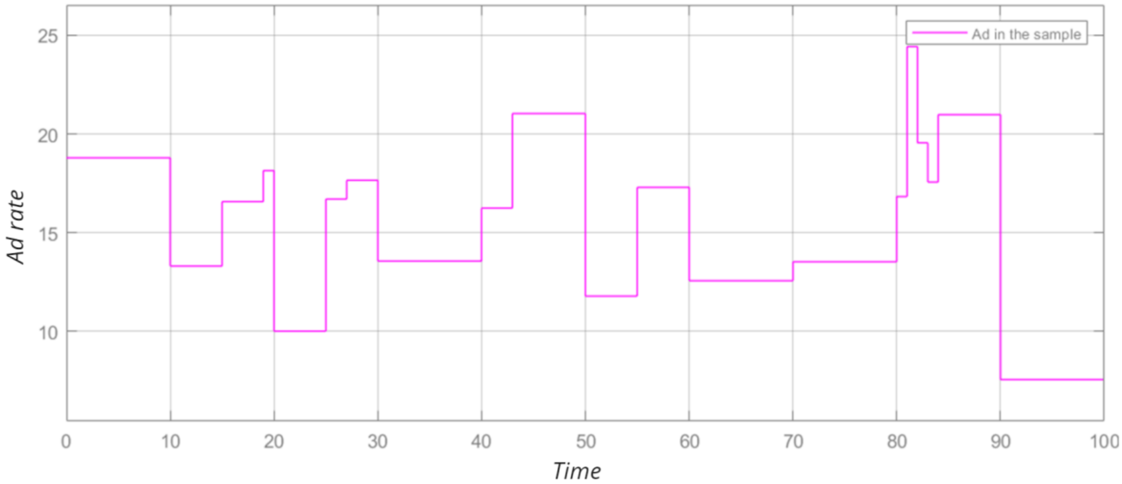

Fig. 15. ***Ad*** **indicator – at the time of taking a fuel sample for quality**
Source: **compiled by the authors**

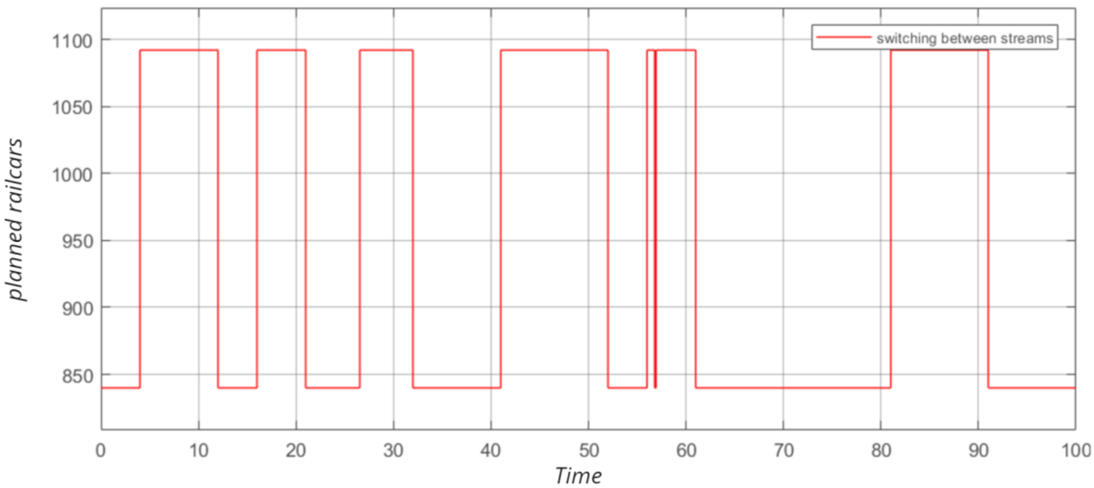

Fig. 16. **Selecting the number of railcars per day signal**
Source: **compiled by the authors**

Another good example can be seen at 10 s of simulation operation, when the actual abrasiveness is 12 % (satisfactory quality), the sampling step at this time interval is every 10 cars, considering the transport delay, signal 840 returns for 52 s. Also, the system's performance is demonstrated from 78 s to 84.5 s, when the actual *Ad* becomes 15.5 %, which causes a sampling step of 79 s – every 5th car. After the abrasive coal slips into the furnace again, between 81 s and 82 s, the sampling step is set to every 2nd car, and between 82 s and 83 s – every first car. At 83 s, the actual *Ad* = 17.5 %, the sampling also revealed *Ad* = 17.5 %, and the signaled number of cars per day is 1092.

CONCLUSIONS

This article-initiated a thorough, comprehensive study of the complex mechanisms underlying the coal preparation and quality control process. The study focused on the abrasiveness parameter *Ad*, which is critical to understanding coal quality and condition. Delving deeper into the dynamics of this parameter, the study examined the multiple circumstances under which it can change and, accordingly, how the regulatory system responds to these changes promptly and effectively.

This study emphasizes an important observation: coal quality is not static, but rather can change over time and under different environmental conditions. These changes, while they may be subtle, have a significant impact on the regulatory process. In anticipation of these changes, the regulatory system has been designed to be flexible and adaptive. It changes the sample size for railcar inspections in response to the collected data on coal abrasiveness. This is an elegant feedback loop that directly links the condition of the coal to the inspection strategy.

Through detailed analysis, it was found that the sampling frequency can be adapted very easily. It depends on the condition of the coal and can vary from checking every single car to rarely checking every tenth car. This finding demonstrates the flexibility and adaptability of the system, emphasizing its reliability in ensuring quality control.

In addition to the above observations, the study revealed another important functionality of the system – its ability to redirect cars to an alternative flow in cases where coal quality drops to an unacceptable level. This strategic mechanism not only mitigates the potential financial consequences of poor coal quality, but also ensures the supply of the necessary fuel. This demonstrates the foresight and resilience of a regulatory system designed to withstand challenges and maintain operational efficiency.

The results of this study emphasize the indispensable role of continuous monitoring and adaptive management in the coal supply chain. In an industry as dynamic as the coal industry, these strategies are essential to maintain a balance between operational efficiency and quality control. The findings of this analysis can be a valuable resource for making informed decisions in the management and operation of the coal industry.

This study provides a lens through which to understand the complex interplay of variables involved in coal processing and offers recommendations to ensure that the coal produced meets the highest quality standards, making it suitable for further use. Finally, further research should pay more attention to the logistics component of the system, possibly using dynamic programming for transport nodes and optimizing supply processes.

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Імітаційне моделювання відбору проб та заміни постачальників вугілля на теплові електростанції

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АНОТАЦІЯ

Робота присвячена постійним проблемам неоптимальної якості вугілля на теплових електростанціях, які перешкоджають підвищенню операційної ефективності та стійкості. Дослідження поділяється на три основні сегменти: формулювання транспортної задачі, створення моделі вибору постачальника вугілля та побудова симуляції в MATLAB Simulink® для виявлення та відбраковування низькосортного вугілля. Запропонована модель вибору постачальника, важлива для теплових електростанцій, враховує такі фактори, як потенційні транспортні затримки та необхідність резервного заправлення для запобігання дефіциту палива. Очікується, що ця модель зменшить дефіцит палива та підвищить надійність і ефективність роботи теплових електростанцій. Крім того, була розроблена модель визначення якості вугілля з використанням вибіркового підходу на основі формули Кокрана, що має на меті підвищити точність виявлення дефектів і, таким чином, зменшити ймовірність використання неякісного вугілля. Унікальною особливістю моделі є динамічне коригування відбору проб вугілля на основі результатів спалювання, що дозволяє в режимі реального часу реагувати на невідповідності якості вугілля. При виявленні неякісного вугілля електростанції оперативно переходять на альтернативного постачальника, мінімізуючи перебої в роботі. Достовірність моделей була підтверджена шляхом симуляції на різних прикладах.

Ключові слова: Теплові електростанції; якість вугілля; вибір постачальника; формула відбору проб Кокрана; контроль якості; автоматична система управління; сталість виробництва енергії; затримки при транспортуванні

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