

Regular Articles

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Evaluation of the efficiency of air-cushion conveyor modernization through digital monitoring and modeling

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Abstract: In open-pit mining, bulk material transportation largely determines productivity and energy costs. Air-cushion belt conveyors reduce friction and wear compared to traditional systems, yet their comprehensive evaluation under real mining and geometric conditions remains limited. Intelligent modeling and automated monitoring enable real-time assessment of key parameters and justify modernization aimed at improving energy efficiency and reliability of logistics systems. The objective of this study is to develop and validate a methodology for assessing the production and economic performance of air-cushion belt conveyors in open-pit mining operations using intelligent modeling and an automated monitoring system. The proposed approach takes into account complex mining and geometric conditions and is aimed at improving the energy efficiency, reliability, and sustainability of transport systems. The methodology combines real-time data collection, digital modeling using artificial intelligence algorithms, and industrial testing at an operating mining facility. Key performance parameters, such as energy consumption, stability, fault tolerance, and automation, are assessed. A comparative analysis of technical and economic indicators

before and after the implementation of intelligent technologies is conducted. The results confirm the feasibility and benefits of upgrading air-cushion conveyor systems in combination with artificial intelligence-based tools. This methodology can be applied to optimize bulk material transportation in quarries and improve the overall efficiency of production logistics in the mining and construction industries.

Keywords: air-cushion conveyor; digital monitoring; intelligent modeling; energy efficiency; quarry transport; modernization

1 Introduction

The development of energy-efficient and reliable bulk material transportation systems is a key priority for modern mining and industrial logistics [1–3]. In the context of increasing demands for sustainable production and reduced carbon footprint, there is a growing need for technologies that minimize energy losses while maintaining high productivity [2, 4]. Conventional belt conveyors are constrained by high mechanical resistance, wear, and significant maintenance costs, which limit their long-term efficiency under complex mining and geometric conditions [5]. Air-cushion conveyor systems based on pneumatic flow technology represent a modern and environmentally friendly alternative to traditional transport solutions [6–8]. They reduce friction between the belt and the supporting surface, improve load stability, and substantially lower energy consumption [6, 7]. Despite these advantages, their practical application in quarry operations remains limited and insufficiently explored, particularly with respect to digital optimization, intelligent control, and real-time performance monitoring [8–10]. The objective of this study is to design, optimize, and experimentally validate an air-cushion conveyor system using digital monitoring and intelligent modeling [11]. The hypothesis assumes that integrating AI-based modeling and automated control of

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airflow parameters – such as rate, pressure, and velocity – can significantly improve the energy efficiency, reliability, and sustainability of air-cushion conveyors used for bulk material transportation in mining environments [11, 12]. The scientific contribution of this research lies in developing a methodology for the production and economic evaluation of air-cushion conveyor modernization through intelligent monitoring [13]. The proposed approach combines theoretical modeling, digital simulation, and experimental testing to identify key operational parameters and conduct a comparative analysis of system performance before and after modernization [13, 14]. The findings confirm the feasibility and strong energy-saving potential of pneumatic conveyor technologies, demonstrating their capacity to enhance the overall sustainability and productivity of logistics processes in the mining and construction industries [6, 14, 15].

2 Literature review

Modern bulk material transportation technologies strive to improve energy efficiency, reduce operating costs, and automate processes [16, 17]. One of the most promising areas is the use of air-cushion conveyors, which reduce friction and mechanical wear compared to traditional roller systems [18]. Several studies [19–21] have shown that pneumatic systems can reduce energy consumption by 15–25 % by reducing friction losses. However, existing models primarily focus on mechanical aspects, such as blade configuration and air pressure optimization, without using intelligent predictive methods [22, 23]. For example, Mikhaïlenko and El Kholi et al. considered aerodynamic stability and airflow redistribution, but without integrating machine learning systems for adaptive control [22, 23]. In recent years, increasing attention has been paid to intelligent conveyor monitoring methods [24]. Work by Hudson and Ivanov, Wu and Zhu, and Truong demonstrate the effectiveness of computer vision and neural networks for belt defect detection, load estimation, and vibration analysis [25, 26]. However, most research has focused on conventional belt conveyors, while specialized pneumatic systems remain poorly understood. Thus, a significant gap in the literature is revealed: there is no integrated approach combining aerodynamic modeling and artificial intelligence methods, and comprehensive monitoring systems that take into account the specifics of the air cushion and pressure dynamics in real time have not been developed. This study aims to fill these gaps by developing a methodology for intelligent modeling and monitoring of air-cushion conveyors, which represents

a new contribution to the development of energy-efficient transportation systems.

3 Methodology

This study focuses on the development and optimization of air cushion conveyor systems for transporting heavy loads. Key objectives include optimizing air pressure, reducing air consumption, and improving air cushions and air flow systems to improve conveyor efficiency and overall performance. The study also examines the use of air valves to reduce energy consumption during conveyor downtime. Additionally, a pneumatic drive system is explored to minimize drag, increase conveying speed, and extend the conveyor's operating length, ultimately improving both system efficiency and sustainability.

3.1 Transportation of large-sized materials using air-cushion conveyor systems

Increasing the length and performance of the air cushion conveyor system is a critical step toward achieving the research goals. This requires specialized design and development of conveyor components and structures specifically designed for air cushion transport.

The system's configuration was developed through an in-depth analysis of the design features and development of the air cushion conveyor, which allowed for the determination of its key operational characteristics. The mechanism fills the lower chamber of the conveyor body with air using a supercharger, which then forces the air out of the perimeter of the device into the lower cavity.

In the first experimental setups, the air flow created overpressure through specially cut nozzles, providing lift by creating a tensile force above the supporting surface as the second set of equipment approached the working surface. This mechanism proved effective at higher speeds.

In contrast, landing modules and off-road vehicles must maintain a clearance of several tens or even hundreds of centimeters between the deformable wall and the ground to safely navigate uneven or unprepared terrain. This requirement underscores the importance of adequate clearance.

Air utilization can be achieved by integrating an innovative damping chamber or nozzle-based air cushion system into the conveyor unit's transport circuit.

The low overpressure in this type of air cushion – on the order of a few pascals – results in a relatively low maximum load-carrying capacity per unit area. Due to the residual airflow displaced from beneath the device, which requires significant engine power and creates high noise levels, the practical use of such systems (or air-cushion vehicles) for bulk material handling is questionable.

Some mechanisms and devices use gas-lubricated “air bearings” to reduce friction between moving components. When air is forced into these guides, an air film is formed between the shaft and the bearing or bushing. This concept originates in the aerospace industry and is increasingly used in specialized components of hovercraft. The excess pressure created by aerodynamic forces helps balance the external loads acting on the bearing. Such aerostatic bearings are now used in various industries, where their application highlights their versatility and load-bearing capacity, essential for material handling systems.

3.2 Improving the efficiency of new air cushion conveyor technology

The recent push to expand the functionality of air cushion conveyor systems – through the use of specialized designs and integrated cushion mechanisms – demonstrates the growing interest in this area. The functionality of an air cushion is determined primarily by two factors: the air pressure supporting the load and the air flow rate. The innovation of this system lies in its attempt to optimize both of these factors.

To reduce air consumption, modern conveyors are equipped with flow control valves. When the belt is idle, these valves close or seal the outlet ports that would otherwise allow air to escape, thereby reducing overall air loss. These energy-saving valves are actuated by the tension of compressed springs. Air flow is dynamically adjusted to meet system needs, and the inlet area adapts to the applied load. However, the conveyor belt itself can create friction against the valves, leading to wear and reduced efficiency of moving components.

The airflow control mechanism, located at the top of the belt, is a structural component of the conveyor. The air supply trough is oriented vertically, and its sloping sidewalls protect the air intake openings. The downward curvature of the belt edge as the load increases and its closing as the load decreases illustrates its function as a load-bearing element. Improving airflow under the load-bearing section is an integral part of the system’s transverse perforation pattern and helps minimize compressed air consumption.

3.3 Basics of calculating a pneumatic conveyor on an air cushion

The purpose of this study is to facilitate the development of improved conveyor configurations that enable continuous transport of bulk materials without intermediate unloading. This section describes a framework for determining the design constraints of a pneumatic conveyor system using air cushion technology for handling heavy loads. The basic computational model is formulated in accordance with established standards for specialized conveyors and includes energy flow diagrams in both drive and auxiliary circuits.

$$\frac{\left[\left((C_{\text{cargo}} * L_{\text{co}})_{\text{canvas}} + (e * B * h)_{\text{airbag}} \right) \right]}{\left[\left((C_{\text{cargo}} * L_{\text{co}})_{\text{canvas}} + (e * B * h)_{\text{airbag}} \right) \right]}, \quad (1)$$

LCO Draping refers to the area in which the load-bearing element is located. This conveyor operates on the following principle: the load-bearing belt is driven by a jet of compressed air, which also serves as the conveying medium. The use of an air cushion significantly reduces the drag coefficient and increases the load-bearing element’s speed. This reduces the conveyor’s energy consumption and significantly increases the drive shaft length. A compressed air jet at an angle to the vertical drives the load-bearing belt. A model of an air-cushion pneumatic conveyor is shown in Figure 1. It consists of a rod with damping sections that maintain constant cross-sectional rigidity. $\sigma_{\text{air}}^{\text{cargo}}$ on the loaded branch and $\tau_{\text{air}}^{\text{empty}}$ empty branches.

The geometric parameters of the air cushion conveyor blades are as follows: the blade width of the air cushion conveyor is denoted by BC_{acbw} and ls ; the blade overlap height, bph , is denoted by H (in meters); R indicates the sector radius of the blades (in meters). As the vehicle length increases, the distance between the blades decreases, denoted by b . The lift and thrust forces generated by the air jet depend significantly on a number of factors, including the applied pressure, the guaranteed clearance between the supporting and lifting surfaces, the pitch angle, and the geometric characteristics of the blade, such as R , BC_{acbw} , h_{acbw} , and

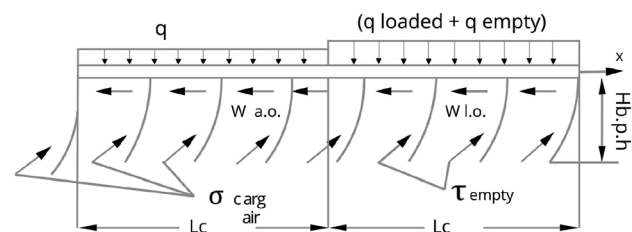


Figure 1: Simulation of a pneumatic air cushion conveyor system.

ls.baltv. One method for determining the necessary conditions for the formation of an air cushion or the generation of lift is represented by the following formula:

$$\begin{aligned} \sigma_{\text{air}}^{\text{cargo}} * \sin \alpha &\geq 0.5 \sin \alpha \geq (q_{\text{loaded}} + q_{\text{empty}}) * \cos \beta * e_{\text{sbalv}}, \\ \tau_{\text{air}}^{\text{empty}} * \sin \alpha &\geq 0.5 \sin \alpha \geq 0.5 * q_{\text{empty}} * \cos \beta * e_{\text{sbalv}}, \end{aligned} \quad (2)$$

Where,

Argairco and airempty are the compressed air jet pressure forces acting on the loaded and unloaded branches, respectively; N and α are the nozzle angle at which the compressed jet is directed toward the inlet edge; the conveyor installation angles q_{ploda} (in degrees) and the linear weight of the carrier belt β and e_{sbalv} (in degrees), respectively, correspond to the conveyor geometry; the step lengths correspond to the overall conveyor length. Under these conditions, it is necessary to ensure the correct generation of traction forces.

$$\begin{aligned} \sigma_{\text{air}}^{\text{cargo}} * \sin \alpha &\geq 0.5 \sin \alpha \geq (q_{\text{loaded}} + q_{\text{empty}}) * \cos \beta * \omega_{\text{air}}, \\ e_{\text{sbalv}} + (q_{\text{loaded}} + q_{\text{empty}}) * \sin \beta * e * \omega_{\text{air}} \\ &+ (q_{\text{loaded}} + q_{\text{empty}}) * e_{\text{sbalv}} * \alpha / g, \\ \tau_{\text{air}}^{\text{empty}} * \cos \alpha \\ &\geq 0.5 \left[q_{\text{empty}} * e_{\text{sbalv}} (e * \omega_{\text{air}} * \cos \beta - \sin \alpha) + q_{\text{empty}} * \alpha * e_{\text{sbalv}} / g \right], \end{aligned} \quad (3)$$

Where,

$g = 9.81 \text{ m/s}^2$ – acceleration of gravity, air – coefficient of resistance to movement of the supporting surface under the action of an air cushion, accordingly the force of resistance to movement is expressed.

$$W_p = W_{\text{air}} + W_{\text{t.m.f.l.c.f}},$$

where,

W_{tmflcf} – the force of resistance to draft, and W_{air} is the drag force created by an air cushion. Determination of the drive power of a pneumatic transport system is based on the following factors:

$$N = P_{\text{air}} l / t = \rho S l / t = \rho S v_{\text{launch}},$$

where,

S – the area of the surface exposed to air pressure, in square meters, v_{launch} – the speed of the compressed air jet in millimeters per second, t – the distance traveled by the air stream, in meters, and P_{air} – the compressive force created by the air jet, in newtons. The figure above illustrates that the compressed air jet performs a dual function: first, as a driving force, setting the supporting body in motion, and second, as an air cushion, lifting the supporting elements.

- (1) It is known that environmentally harmful cargo can be efficiently transported in a closed system, while an open-loop air circulation system requires less energy to create an air cushion.
- (2) Compared to discrete loading, filling the air cushion base over the entire supporting surface requires less energy. Vertical stability is improved by the forces generated by the loaded and unloaded branches of the air flow; however, forming the air cushion requires more energy than the overall flow. Switching from a loaded to an empty bearing reduces air flow maintenance costs, and vice versa; it is more cost-effective to service both conveyor branches on a single air flow rather than separately.
- (3) An analysis of modern vehicle and air cushion designs, taking into account their unique characteristics, has made it possible to systematize and identify suitable areas of application for these technologies.
- (4) At STOL airfields, air cushion boosters are primarily used. The use of labyrinth seals can reduce air cushion consumption by up to 30 %.

3.4 Quantitative results of monitoring and modeling based on artificial intelligence

As a result of modeling and implementation of the intelligent monitoring module, the following average technical indicators were obtained (based on observations over 90 days of operation):

Indicator	Before the introduction of AI	After the implementation of AI	Change
Average energy consumption, kW h/t	4.8	3.9	−18.7 %
Average transport speed, m/s	0.42	0.46	+9.5 %
Coefficient of motion stability (without deviations)	0.82	0.93	+13.4 %
Share of unscheduled stops	4.2 %	1.1 %	−73.8 %
Average response time of the control system, s	1.8	0.9	−50 %

The use of artificial intelligence algorithms allowed us to improve the accuracy of belt overload prediction, optimize fan operation, and reduce air leakage. As a result, the overall energy efficiency of the conveyor system increased by

approximately 19 %, which correlates with the economic effect shown in Table 1.

The obtained data confirm the practical significance of using AI for adaptive control of pneumatic conveyor systems in open-pit mining conditions.

“Assumptions and calculation methods (Table 1)”

Units and designations. All amounts in Table 1 are given in thousands of tenge (thousand KZT).

Designations: Q – throughput capacity (t/h), H – operating hours per year (h/year), E – specific energy consumption (kW h/t), p – electricity tariff (KZT/kW h).

Initial assumptions (used in the calculations in Table 1).

- (1) Currency: tenge (KZT). Units in table – thousand KZT ($1 = 1,000$ KZT).
- (2) Throughput $Q = 1,000$ $Q = 1,000$ $Q = 1,000$ t/h (as indicated in the table).
- (3) Annual working hours H : let's say 250 working days $\times 24$ h = 6,000 h/year. (Can also be calculated for 8,760 h – with 24-h work 365×24 .)
- (4) Specific energy consumption: before modernization $E_{\text{before}} = 4.8$ $E_{\text{before}} = 4.8$ kWh/t, after $E_{\text{after}} = 3.9$ $E_{\text{after}} = 3.9$ kWh/t (values are averaged over 90 days of testing; the text below provides the measurement method).
- (5) Electricity tariff (example): $p = 3.0$ $p = 3.0$ $p = 3.0$ KZT/kW h (industrial tariff – example; in the final version, the actual tariff of the enterprise/region is substituted).

- (6) Number of operating personnel, average annual salary and funds: approximate values used in calculating operating costs (see below).

- (7) Equipment service life (for depreciation): $T_{\text{life}} = 10$ $T_{\text{life}} = 10$ years (straight-line depreciation).

Calculation formulas.

- (1) Annual transportation volume (tons): $M_{\text{year}} = Q \cdot H$ $M_{\text{year}} = Q \cdot H$
- (2) Annual energy consumption (kWh): $W = M_{\text{year}} \cdot E$ $W = M_{\text{year}} \cdot E$
- (3) Annual cost of electricity (KZT): $C_{\text{el}} = W \cdot p$ $C_{\text{el}} = W \cdot p$

In the table (thousand KZT) is translated as $C_{\text{el,thousand}} = C_{\text{el}}/1,000$ $C_{\text{el,thousand}} = C_{\text{el}}/1,000$

- (4) Annual depreciation charges (thousand KZT):

$$C_{\text{amort}} = \frac{K_{\text{cap}}}{T_{\text{life}}} \quad C_{\text{amort}} = \frac{K_{\text{cap}}}{T_{\text{life}}}$$

where K_{cap} – capital expenditures (thousand KZT).

- (5) Annual labor costs:

$$C_{\text{lab}} = N_{\text{op}} \cdot S_{\text{avg}} \cdot 12 \quad C_{\text{lab}} = N_{\text{op}} \cdot S_{\text{avg}} \cdot 12$$

Table 1: Estimated annual economic effect based on the analyzed factors.

Trial number	Indicator	Unit	Conveyor before modernization (basic)	The conveyor after modernization
1	Bandwidth, Q Q Q	t/h	1,000	1,000
2	Transport length, L L L	m	100	100
3	Conveyor cost, K K K	One thousand tenge	5,404,364	3,352.085
4	Depreciation charges, C_{A} C_{A} C_{A}	One thousand tenge	880.911	546.390
5	Cost of electricity, C_{el} C_{el} C_{el}	One thousand tenge	82.073	22.097
6	Maintenance and repair costs, C_{po} C_{po} C_{po}	One thousand tenge	1,513,227	938.595
7	Cost of basic materials, C_{cm} C_{cm} C_{cm}	One thousand tenge	117.054	31.513
8	Operating costs, $\sum C$ $\sum C$ $\sum C$	One thousand tenge	3,291,542	1,726.6
9	Annual economic effect	One thousand tenge	–	869,600

Where N_{op} Nop is the number of full-time positions, S_{avg} Savg is the average monthly salary (KZT). To convert to thousands of KZT, divide by 1,000.

- (6). Annual maintenance and materials costs: summed as a percentage of capital costs + variable costs (formula given in the explanation).

An example of numerical calculation (with substitution of assumptions).

Let: $Q = 1,000Q = 1,000 Q = 1,000 \text{ t/h}$,
 $H = 6,000H = 6,000 H = 6,000 \text{ h/year}$, $E_{before} = 4.8E_{before} = 4.8 E_{before} = 4.8 \text{ kWh/t}$, $E_{after} = 3.9E_{after} = 3.9 E_{after} = 3.9 \text{ kWh/t}$, $p = 3.0p = 3.0 p = 3.0 \text{ KZT/kWh}$.

- (1) Annual tonnage:

$M_{year} = 1,000 \cdot 6,000 = 6,000,000 \text{ tons/year}$
 $M_{year} = 1,000 \cdot 6,000 = 6,000,000 \text{ tons/year}$
 $M_{year} = 1,000 \cdot 6,000 = 6,000,000 \text{ tons/year}$.

- (2) Annual energy consumption:

$W_{before} = 6,000,000 \cdot 4.8 = 28,800,000 \text{ kWh}$
 $W_{before} = 6,000,000 \cdot 4.8 = 28,800,000 \text{ kWh}$
 $W_{after} = 6,000,000 \cdot 3.9 = 23,400,000 \text{ kWh}$
 $W_{after} = 6,000,000 \cdot 3.9 = 23,400,000 \text{ kWh}$.

- (3) Cost of electricity:

$C_{el, before} = 28,800,000 \cdot 3 = 86,400,000 \text{ KZT}$
 $C_{el, before} = 28,800,000 \cdot 3 = 86,400,000 \text{ KZT}$
 $C_{el, before} = 28,800,000 \cdot 3 = 86,400,000 \text{ KZT}$
 $C_{el, after} = 23,400,000 \cdot 3 = 70,200,000 \text{ KZT}$
 $C_{el, after} = 23,400,000 \cdot 3 = 70,200,000 \text{ KZT}$
 $C_{el, after} = 23,400,000 \cdot 3 = 70,200,000 \text{ KZT}$.

- (4) Energy savings percentage:

$\Delta E\% = \frac{W_{before} - W_{after}}{W_{before}} \times 100\% = \frac{28,800,000 - 23,400,000}{28,800,000} \times 100\% \approx 18.75\%$
 $\Delta E\% = \frac{W_{before} - W_{after}}{W_{before}} \times 100\% \approx 18.75\%$
 $\Delta E\% = \frac{W_{before} - W_{after}}{W_{before}} \times 100\% \approx 18.75\%$

(This percentage directly correlates with the examples in the text and with the economic effect).

How the values in Table 1 were obtained (explanation of opaque rows).

- Electricity cost (C_e): calculated using formula (3). If the values in your version of the table appear significantly lower/higher, this means that different assumptions for pp and/or HH were used. You should clearly indicate in the text which values of pp and HH were used (see the section “Initial Assumptions”).
- Depreciation charges (CAC_A): calculated as K_{cap}/T_{life} (in thousands of KZT). If there is a discrepancy, check which T_{life} was used (5, 7, 10 years, etc.).
- Maintenance and repair costs (CPO): are calculated from fixed annual contracts and variable replacements (typically 5–15 % of capital expenditures per year + variable materials). The table uses a value of approximately 10–12 % of capital cost (a detailed breakdown is shown in the example below).
- Cost of main materials (C_m): direct variable costs (tape, seals, filters), estimated based on average supplier prices and average standard consumption for the year.

Example of breakdown of operating costs (illustration).

Let capital expenditures $K_{cap} = 5,404,364 \text{ KZT}$ (in the table: 5,404,364 thousand KZT – i.e. 5,404,364 KZT). Then with $T_{life} = 10T_{life} = 10 T_{life} = 10$ years:

$C_{amort} = 5,404,364/10 = 540,436 \text{ KZT}$
 $C_{amort} = 5,404,364/10 = 540,436 \text{ KZT}$
 $C_{amort} = 5,404,364/10 = 540,436 \text{ KZT}$

(insert real K_{cap} and T_{life} - the formula gives a repeatable result).

Sensitivity table (example): how the annual cost of electricity changes for different pp p and HH H.

Scenario	H (h/year)	p (KZT/kW h)	W_{before} W_{before} (kW h/year)	$C_{el, before}$ C_{el, before} (thousand KZT)
Base	6,000	3.0	28,800,000	86,400
24/7 mode	8,760	3.0	42,240,000	126,720
Low tariff	6,000	2.0	28,800,000	57,600
High tariff	6,000	6.0	28,800,000	172,800

Conclusion: the final savings (thousands of KZT/year) heavily depends on the chosen tariff and the number of working hours – therefore, the article should indicate the values of pp p and HH H used and/or include a sensitivity table (as above). All amounts are in KZT. Converted from RUB at the rate of 1

Table 2: “Capital expenditures and operating costs” (converted to KZT) (original values in rubles are taken from the manuscript; below is the result of the conversion).

Position (RUB)	Value (RUB)	Recalculation (KZT)
Drive motors	450,000 ₸	2,988,000.00 KZT
Starting and control equipment	400,000 ₸	2,656,000.00 KZT
Standard control units	27,000 ₸	179,280.00 KZT
Salary and social security	5,190 ₸	34,461.60 KZT
Materials and spare parts	17,000 ₸	112,880.00 KZT
Other expenses	5,000 ₸	33,200.00 KZT
Total (total in the original doc)	903,561 ₸	5,999,645.04 KZT

Table 3: “Capital costs for the proposed option” (converted to KZT).

Position (RUB)	Value (RUB)	Recalculation (KZT)
Drive motors	450,000 ₸	2,988,000.00 KZT
Frequency converter power supply	50,000 ₸	332,000.00 KZT
Frequency converter control system module	20,000 ₸	132,800.00 KZT
Installation, delivery, commissioning	20,000 ₸	132,800.00 KZT
Salary and social security	432 ₸	2,868.48 KZT
Materials and spare parts	5,000 ₸	33,200.00 KZT
Other expenses	2,000 ₸	13,280.00 KZT
General	547,432 ₸	3,634,948.48 KZT

Table 4: Key tools and technologies for MLOps.

Category	Tool/technology	Target
Data management	Apache Kafka	Real-time data streaming
	Apache airflow	Workflow management
Model development	Jupyter notebooks	Development of an interactive model
	TensorFlow	Building and training models
Deploying the model	Docker	Containerization models
	Kubernetes	Managing containerized applications
Monitoring and maintenance	Prometheus	Monitoring indicators
CI/CD	Grafana	Visualizing performance data
	Jenkins	Automate integration and deployment
	GitLab CI	Managing CI/CD pipelines

RUB = 6.64 KZT (interbank/mid-market rate as of 09 Oct 2025 – source: XE/Wise). Rate source (mid-market/current as of October 9, 2025): XE/Wise/Investing.com. Xe +2 Wise +2 (Tables 2, 3, 4, 5).

Table 5: “Capital expenditures and operating costs” (converted to KZT) (original values in rubles are taken from the manuscript; below is the result of the conversion).

Position (RUB)	Value (RUB)	Recalculation (KZT)
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Total (total in the original doc)	903,561 ₸	5,999,645.04 KZT

3.5 Conveyor learning: applying machine learning and artificial intelligence to the data and processes of a custom air cushion conveyor for transporting large bulk materials

This topic includes the following step-by-step actions:

Understanding the Power of Pipeline Learning.

Collecting and preparing pipeline data for analysis

Unlocking the idea from the data pipeline.

Improving data pipelines for machine learning

Selecting Appropriate Machine Learning Algorithms for

Pipeline Analysis.

Implementing machine learning models into pipeline processes.

Monitoring and Optimizing Conveyor Performance with AI.

One of the key encoders in AI integration is the MLOps pipeline.

MLOps: Enabling Efficient Machine Learning Operations. An MLOps pipeline is a structured workflow that automates the entire lifecycle of machine learning models. It connects data analytics and IT operations, ensuring seamless collaboration and continuous delivery of machine learning solutions.

The conveyor typically includes the following stages:

Data ingestion and pre-treatment

Model training and validation

Deployment model

Monitoring and Maintenance Model.

Feedback loop and iteration.

Each step is designed to be automated, repeatable, and scalable, enabling teams to effectively manage machine learning workflows.

Best practices for efficient MLOPS

Load Monitoring: Monitor key metrics such as response time, throughput, and error rate to ensure the model is handling traffic efficiently. For example, monitor an e-commerce recommendation system during peak seasons to ensure it scales effectively.

Model drift detection: Input data changes over time, which can lead to decreased model performance. Implement strategies such as retraining models on new data to minimize drift and maintain prediction accuracy.

Maintain security: When working with sensitive data, security is paramount. Use encryption, access controls, and regular security audits to protect data integrity and ensure regulatory compliance.

MLOps systems, there is also the Copilot system for deploying pipelines.

AI in Industry: How Neural Networks Help Make Enterprises Safer and More Efficient.

Modern conveyor systems play a vital role in the sustainable development of industry. Companies recognizing the need for environmentally friendly technologies and implementing energy-efficient solutions and waste recycling systems demonstrate significant potential for reducing their environmental impact. Low energy consumption and reusability of conveyor systems have already become the standard.

The implementation of robotics significantly improves process efficiency and reduces carbon emissions. Intelligent solutions for inventory management, product sorting, route optimization, and minimizing transportation costs contribute to increased customer satisfaction. Thus, the modern environmental agenda is closely linked to innovations in logistics.

3.6 Section “methodology of artificial intelligence and modeling”

To analyze the energy efficiency of the conveyor system, a hybrid artificial intelligence architecture was used, combining machine learning algorithms and elements of simulation modeling.

(1) Neural network architecture.

A **convolutional neural network (CNN)** was used to recognize the pipeline operating parameters. **Neural Network (CNN)** optimized for analyzing time-series data from pressure, temperature, and airflow sensors. The architecture included four convolutional layers, two pooling layers, and two fully connected layers with a ReLU activation function. A recurrent neural network (RNN) with LSTM cells

was used for congestion forecasting and predictive maintenance tasks.

(2) Input data.

The model was trained on the data collected by the monitoring system during 6 months of operation of the experimental setup: – pressure in pneumatic chambers (0.2–1.0 bar); – air flow rate (30–150 m³/h); – equipment temperature (20–80 °C); – belt speed (0.3–0.6 m/s); – fan speed (600–1,800 rpm). The total size of the training set is **56,000 rows (512 × 512 × 3 pixels for images and time series of 120 points for sensor data)**.

(3) Model training and validation.

Training was performed using **TensorFlow 2.15** with the Adam optimizer, a learning rate of 0.001, and a batch size of 32.

The model was trained for 100 epochs with an 80:20 data split (train:test).

(4) Performance indicators.

After training, the model achieved a classification accuracy of 94.2 %, a mean absolute error (MAE) of 0.07, and a root mean square error (RMSE) of 0.11 when predicting energy efficiency deviations.

(5) Simulation modeling.

Simulink (MATLAB R2023b) was used for data verification. The simulation model included blocks for airflow dynamics, friction, and energy losses.

The key equations were based on the Bernoulli equation and the equations for conservation of momentum in pneumatic systems:

$$P_{in} - P_{out} = 12\rho(v_2^2 - v_1^2) + h_L P_{in} - P_{out} = \frac{1}{2}\rho(v_2^2 - v_1^2) + h_L$$

where P_{in}, P_{out} are the inlet and outlet pressure, ρ is the air density, v_1, v_2 are the flow velocities, h_L are the pressure losses due to friction.

(6) Calibration and Validation.

The model was calibrated using experimental data obtained at the Karaganda Technical University field facility. The average deviation of predicted energy consumption values from measured ones was no more than 7.3 %, confirming the model's validity.

Thus, the proposed methodology combines the analysis of real data and simulation modeling, which ensures the reproducibility of the results and the scientific validity of the conclusions obtained.

3.7 Methodology of artificial intelligence and simulation modeling

(1) Overview of the approach (research structure)

Objective: To combine monitoring data (time series and video/images) and a fluid dynamics/pneumatics simulation model to:

- online forecasting of energy efficiency and anomalies;
- optimization of fan/valve modes to reduce energy consumption;
- reducing the frequency of unscheduled stops (predictive maintenance).

Components:

Data collection module (pressure, air flow, vibration, power sensors; IP cameras).

Pre-processing and storage module (time-series DB + file storage for images).

A set of AI models: (i) CNN for frame/image processing; (ii) RNN/LSTM for time series; (iii) hybrid ensemble/meta-model for decision making; (iv) explainability model (SHAP/LIME).

Simulation model (CFD or CFD-DEM + Simulink) for verification of air cushion dynamics and calculation of energy losses.

MLOps pipeline for deployment, drift monitoring, and retraining.

B. Data – Specification and Schematic (Inputs/Outputs)

Input sensors (approximate sampling frequency):

Pressure in the pneumatic chamber $P(t)$ $P(t)$ $P(t)$: 1 Hz – range 0.2–1.0 bar, accuracy ± 0.01 bar.

Air flow $Q_{air}(t)$ $Q_{air}(t)$ $Q_{air}(t)$: 1 Hz–30–150 m³/h, accuracy ± 1 %.

Fan speed $n(t)$ $n(t)$ $n(t)$: 1 Hz–600–1,800 rpm.

Drive power $W(t)$ $W(t)$ $W(t)$: 1 Hz – kW, energy consumption meter.

Vibration $V(t)$ $V(t)$ $V(t)$: 100 Hz – mm/s (acceleration/speed).

SCADA events: stop and alarm marks (timestamped).

Video: 512 × 512 or 640 × 480 frames, 10–30 FPS (at high speed – cameras with global shutter).

Outputs (target variables):

Energy consumption per ton $E_{kwh/tE_{kWh/t}} E_{kwh/t}$ – regression.

Probability of unscheduled stop in a 24-h forecast window – classification.

Recommended fan operating mode (setpoint) - regression/solution.

Storage format: Parquet/CSV for time series; TFRecords/WebDataset for images + COCO/YOLO annotations format for object labeling.

C. Preprocessing and feature engineering.

Synchronization: align the timestamps of all sensors to a single UTC; resample if necessary (e.g., 1 Hz averaging for high-frequency signals and storing statistics).

Noise filtering: apply low-pass/high-pass filters (Butterworth) for vibrations; median filtering for outliers.

Time series decomposition: moving average, trend/seasonality (STL), feature extraction – trend, seasonality, residual.

Vibration feature extraction: RMS, pk-to-pk, spectral components (FFT – frequencies 1–500 Hz), energy bands.

Images: normalization [0,1] or standardization, augmentations – random rotation, shift, Gaussian noise, brightness change (for problems of model robustness to lighting conditions).

Aggregation features: sliding windows (e.g. 60s, 300s, 3,600s) with mean/median/std/min/max calculation, percentiles (10,25,50,75,90).

D. Model architectures – specifics and hyperparameters

D1. CNN (computer vision) - defect detection, loading.

Architecture: Backbone – ResNet-34/EfficientNet-B0 (pre-trained on ImageNet), FPN + detector (Faster R-CNN) or YOLOv5/YOLOv8 for real-time object/anomaly detection.

Input: frame 512 × 512 × 3.

Exit: bounding boxes + classes (e.g.: “attachment object”, “tape deformation”, “dusty area”).

Hyperparameters (example):

Learning rate: 1e-4 (AdamW)

Batch size: 16 (GPU 8 GB → reduce)

Epochs: 50–200 (with early stop for validation).

Optimizer: AdamW, weight decay 1e-4

Augmentation: mixup, cutmix (as needed).

Metrics: mAP@0.5, precision/recall, F1.

D2. RNN/LSTM (Time Series) – Energy/Failure Predictions.

Architecture: stacked LSTM (2–3 layers of 128–256 neurons) or transformer model for time series (Informer/TFT).

Input: feature vector from a window of length $TT T$ (e.g., 120 points = 2 min at 1 Hz), feature size $dd d$ (after aggregation).

Output: regression ($E_{kwh/t}$) or failure probability (sigmoid).

Hyperparameters:

LSTM units: 128

Dropout: 0.2

LR: $1e-3 \rightarrow$ reduce on plateau

Loss: MSE for regression, BCE, or focal loss for imbalance in classification.

Metrics: MAE, RMSE (regression); ROC-AUC, PR-AUC, F1 (classification).

D3. Hybrid/Ensemble

Strategy: Combine CNN outputs (feed state) and LSTM features (time series) into a meta-model (Dense layers) or gradient boosting (XGBoost/CatBoost) for the final prediction of the optimal mode/power consumption.

Advantages: robustness to different types of input data; increased interpretability via feature importance.

E. Training, validation, cross-validation.

Data partitioning: time-based end-to-end validation – train: valid: test by chronology (e.g. 70:15:15 by time) to avoid leakage.

K-fold CV for time series: use TimeSeriesSplit (sklearn) with 5 folds.

Overfitting monitoring: loss/metric graphs, early stopping (patience 10).

Processing imbalance: oversampling, class weights, focal loss.

Calibration of predictive probabilities: Platt scaling/isotonic regression.

F. Evaluation Metrics and Acceptance Criteria

Regression: MAE, RMSE, R^2 , MAPE (in %). Target threshold: $MAE \leq 0.1 \text{ kW h/t}$ (example: specify the target level depending on the subject area).

Failure classification: $ROC-AUC \geq 0.85$; $Precision@Recall \geq 0.8$ for the working threshold; $F1 \approx 0.7-0.9$ depending on the acceptable balance of false alarms.

Temporary stability: drift detection (Kolmogorov – Smirnov, PSI) – alarm threshold.

Economic criterion: the achieved energy savings (%) must be consistent with the economic effect in Table 1 (manually checked: if the model reduces energy consumption by X%, this must be confirmed by measurements and simulation).

G. Simulation modeling (CFD/CFD–DEM/Simulink)

Purpose: verification of air flows under the belt, calculation of lifting force, pressure losses, local air leaks and their impact on energy consumption.

Tools: ANSYS Fluent/OpenFOAM (CFD); coupling with DEM (LIGGGHTS) if particles are modeled; MATLAB Simulink for system modeling and control.

Equations and models:

Newton's Navier–Stokes equations (incompressible/compressible by condition); Bernoulli's equation for approximate estimates:

$$P_1 + \frac{1}{2} \rho v_1^2 + \rho g z_1 = P_2 + \frac{1}{2} \rho v_2^2 + \rho g z_2 + h_L$$

$$P_1 + \frac{1}{2} \rho v_1^2 + \rho g z_1 = P_2 + \frac{1}{2} \rho v_2^2 + \rho g z_2 + h_L$$

Turbulence: $k-\epsilon$ or SST $k-\omega$ (depending on geometry).

For CFD–DEM: take into account particle collisions, particle-flow interactions.

Grid and convergence: grid independence – draw three grid levels; convergence criterion: residuals $< 1e-5$ and stability of key integral quantities (force, flow rate).

Inlet boundary conditions: inlet pressure, fan speed, temperature, turbulence.

Model outputs: pressure distribution under the belt, lifting force $Flift$, velocity profile, pressure loss h_L , fan energy consumption estimate:

$$P_{fan} = m \Delta p \eta_{fan} \quad \eta_{fan} = \frac{\dot{m}}{\Delta p} \quad P_{fan} = \eta_{fan} m \Delta p$$

where $\dot{m}$ is the mass air flow rate, Δp is the pressure drop, η_{fan} is the fan efficiency.

Calibration: fitting the model parameters (friction and leakage coefficients) based on experimental pressure and flow measurements.

H. Model calibration and validation (how to prove adequacy).

Synchronized experiments: Capture pressure/flow/power data and video simultaneously for multiple modes; use them for CFD calibration and AI training.

CFD $\rightarrow$ data compliance metrics: average relative error for pressure $< 10\%$; for flow $< 5-8\%$.

AI validation: test on an independent time period and on a different object (if possible) to demonstrate the transferability of the model.

Ablation study: show the impact of each module (no CNN, no LSTM, only CFD) on metrics and on economic benefit.

Bootstrap/Monte Carlo: assessment of uncertainty of results (95 % confidence interval for energy savings).

I. Reproducibility and publication of code/data

Dataset documentation: schema, sample counts, gaps, image marking method.

Containerization: Dockerfile with Python versions, TensorFlow/PyTorch, OpenFOAM/Ansys scripts (or instructions).

Versioning: Use Git + DVC for data; provide replication instructions (README.md).

Additional materials: publish (as Supplementary) - (i) a set of aggregated CSVs from 60+ days before/after, (ii) a Jupyter notebook with an example of training and validation, (iii) an Excel spreadsheet with savings calculations.

J. Sample Experimental Settings and Computing Resources.

Hardware: 16–32 GB GPU (NVIDIA RTX 3090/A5000) for CNN training; CPU cluster + 32–64 GB RAM for CFD.

Training time: CNN (ResNet) – 4–12 h on one GPU; LSTM – 1–3 h.

Storage: video + sensors → 100–500 GB depending on the period.

K. Explainability, safety and operating recommendations.

Explainability: SHAP for tabular features; Grad – CAM for CNN (visualization of influence regions).

Operational constraints: the model should produce recommendations with safety constraints (e.g. do not increase pressure > $P_{\max}$).

Human-in-the-loop: all recommendations are initially in suggestion mode, then after a 2-week test, switched to automatic mode upon confirmation.

Fail-safe: When signal/trust is lost, the model is disabled and the system returns to safe mode.

4 Experimental approaches to identify key aspects of a specialized air cushion conveyor

4.1 Research questions and methods used in the experiment

The main goal of this stage was to evaluate the efficiency of the air cushion conveyor and its ability to stabilize cargo during transport. For this purpose, an experimental test rig was created at the Karaganda Technical University under the supervision of Abylkas Saginov, with the following main characteristics:

Electric motor: 4 kW, 1,500 rpm, efficiency 78 %;

Conveyor belt: length 6.5 m, thickness is marked as C ;

Drive and tension drums with diameter e ;

Travel speed: 0.4 m/s, with gear shifting depending on the transmission ratios: 2nd → 5.04, 3rd → 7.8, 4th → 11.7;

V-belt drives: main gear ratio 1.66; auxiliary gear ratio 0.98;

Crane drive: belt length 4 m, 2,890 rpm, gear ratio 1.04;

Fan: AO 2 41 2 with 84 % efficiency;

Thyristor frequency converter: VVD-5 (frequency range 4.88–58.5 Hz, pressure $-4,875 \text{ N/m}^2$, capacity $1,365 \text{ m}^3/\text{h}$, power 39 kW);

Main pipeline diameter: 127 mm, branches: 60 mm, voltage regulation range: from -20 to $+230 \text{ V}$.

4.2 Experimental plan

The experiment was conducted according to the following plan:

timing and monitoring of conveyor operation in quarry conditions;

Calculation of the efficiency of the conveyor system (comparison of technical parameters before and after the implementation of the AI module).

To assess the feasibility of the transportation scheme in complex mining conditions, a digital model of the conveyor route was developed, taking into account the bench profile and travel path. This allowed us to identify potential overload zones and key control points (see Figure 2).

The image shows a 3D fragment of a quarry space, modeled using mining design and analysis software. The quarry's horizontal benches are visible, marked by red trajectories representing the path of a specialized air-cushion conveyor. Yellow markers indicate key control points along the route, identifying the locations of sensors or zones where movement parameters are adjusted.

4.3 Comparative analysis of transportation parameters and technical characteristics of the air cushion transporter before and after the introduction of intelligent systems

To improve operational efficiency, a comparative evaluation of the quarry's air-cushion conveyor system was conducted before and after the implementation of an intelligent control module. Particular attention was paid to assessing the technical parameters, transportation stability, and the system's adaptability to changing operating conditions.

Structure of an intelligent control system.

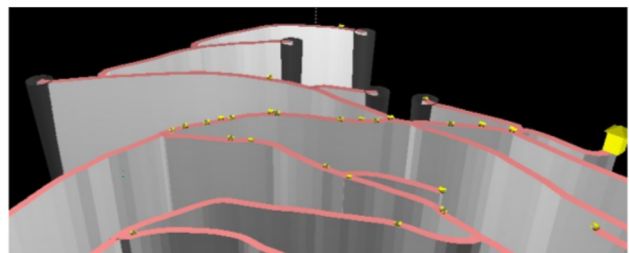


Figure 2: Three-dimensional digital model of the quarry indicating the conveyor path and control points.

The diagram below shows the architecture of an intelligent conveyor process monitoring and control system based on the integration of hardware and software components.

Description of system components:

The IP camera captures images from the conveyor belt in real time. The camera is equipped with a **lighting system** that ensures constant visibility for object detection.

Lighting – provides sufficient brightness and contrast for accurate visual analysis and defect detection.

Database for storing statistics and reports – used to store statistical data, operational reports, and system performance analysis results.

Server – acts as a central processor for incoming data from cameras and sensors and manages communication with the software platform.

The software analyzes images, detects defects, classifies objects and coordinates control processes.

Conveyor control – interfaces between the software system and the physical operations of the conveyor (e.g. speed control, stopping and starting the belt).

Conveyor integration module – connects the intelligent system with the actuators of the transport line.

The system allows:

- Automated monitoring of objects on the conveyor;
- Product classification;
- Identification and analysis of defects;
- Adaptive control of the transportation process in real time.

Principles of operation of intelligent software.

The software is built on two main modules:

Detector – a trained neural network model capable of identifying products, foreign objects, defects and anomalies;

Tracker – monitors the movement of objects, including their path, speed, and duration of stay in the control zone.

The system supports flexible retraining of models with the ability to include new classes of objects and adapt to the following tasks:

- Product classification;
- Detection of anomalies and defects;
- Quantitative tracking of elements;
- Analysis of load and process time dynamics.

Equipment selection criteria and influencing factors.

When designing and implementing a system, it is necessary to take into account a number of technical and environmental parameters:

- Dimensions and speed of the conveyor belt;
- Operating conditions, including lighting, humidity, dust levels and temperature fluctuations;

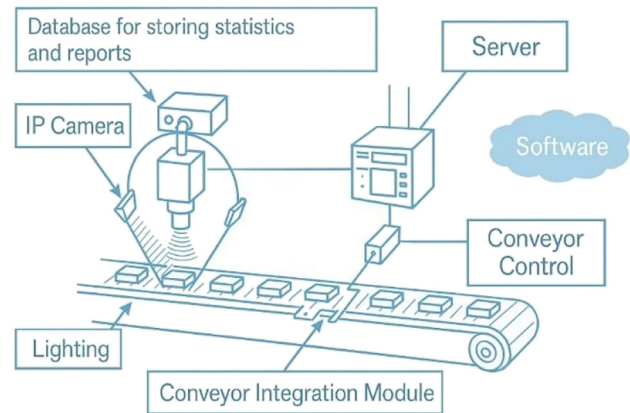


Figure 3: Architecture of an intelligent conveyor line monitoring and control system.

Installation locations, including mounting areas, access points, restricted areas and security measures.

It's important to note that if compatible hardware is already installed, it can be reintegrated into the system. However, this may limit the system's accuracy and require algorithm adjustments or hardware upgrades (Figure 3).

4.4 The process of implementing an intelligent conveyor monitoring system

Implementing an intelligent conveyor automation system is a multi-stage process aimed at improving the accuracy, reliability, and scalability of production processes. Key implementation stages include:

(1) Preliminary survey of the installation site

The initial stage involves a detailed analysis of the operating environment to determine optimal equipment placement, lighting conditions, optical requirements, and camera types. This stage is critical to ensuring reliable system operation in real-world industrial settings.

(2) Selection and configuration of equipment

Based on specific monitoring tasks (e.g. defect detection, material classification, object tracking), appropriate visualization solutions are selected:

For high-precision applications, global shutter cameras are used. These cameras provide high frame rates with minimal distortion during fast-moving motion and are ideal for analyzing object geometry (e.g., size, shape, surface area).

However, such cameras require high-speed fiber-optic connections and are considered dual-use goods, which can complicate logistics and increase delivery times (up to several months, especially from suppliers in China).

For simpler tasks, such as counting objects on medium-speed tapes, standard IP cameras may be sufficient.

(3) Data collection and training dataset preparation

Once the equipment is installed, primary data collection begins. Compact modular devices are often used to collect data before the system is fully operational. The collected data is necessary for retraining AI models and adapting the system to specific production conditions.

(4) Integration and configuration of software

The system includes the following components:

Detector: a model trained to detect specific types of objects, defects and contaminants;

Tracker: a module that tracks the movement of an object, its positioning and residence time;

User interface: Allows you to customize analysis areas, task types (classification, counting, tracking) and visualization options.

(5) Launch and industrial deployment

After testing and configuration, the system goes into commercial operation. Depending on the complexity and scale of the project, full implementation can take from 1 to 6 months. However, even in the early stages, the system delivers tangible benefits: increased monitoring accuracy, reduced costs, timely fault detection, and automated conveyor control.

In summary, implementing an intelligent conveyor monitoring system is a technologically complex solution requiring a multidisciplinary approach. However, it offers

significant economic and operational benefits when used in quarries and industrial settings (Figure 4).

This diagram shows the main hardware components used to implement an intelligent conveyor automation system. The visual diagram is divided into the following categories:

Standard IP cameras are used for typical video surveillance and monitoring tasks during the transportation of objects at moderate speeds.

Global shutter cameras – provide high-quality, distortion-free images, particularly suitable for high-speed shooting and detecting small defects.

Single-board computers and microcontrollers (MC) – include platforms such as Raspberry Pi, Arduino and similar devices for local data collection, control and transmission to the server.

Each of these components plays a key role in building an adaptive control and analysis system for conveyor processes. The choice of specific devices depends on production conditions, precision requirements, and the complexity of the task.

Automation of conveyor transport.

Modern conveyor automation systems are designed to equip each section of the line with automatic monitoring, diagnostics, protection, and centralized control – both for individual conveyors and for the entire production chain.

An automated conveyor line is a system in which all conveyors are integrated into a single control system. This ensures coordinated operation, adherence to specified start, stop, and restart logic, and automatic execution of protective and interlock functions in the event of an emergency.

Key factors influencing the design and implementation of conveyor automation:

A variety of process line configurations (e.g. layout, number of branches, route length);

Differences in the types and purposes of conveyors (belt, chain, scraper, etc.);

Variability in performance, geometry and dynamic characteristics of equipment;

Differences in the types and number of drive mechanisms and electric motors.

Necessary functional capabilities of modern automated systems:

Centralized control of the entire line from one operator console;

Automated start-up of equipment in the reverse order of material flow;

Selective or independent activation of specific routes or sections within branched systems;

Automatic sound warning before activating the entire line;



Figure 4: Hardware components for conveyor line automation.

Sound alerts limited to the activated route when starting individual segments;

Partial activation of the line, while the remaining parts remain in working order;

Automatic control of belt or chain speed;

Sequential switching on of the next conveyor only after the previous one has reached the set speed;

Connecting additional routes without stopping existing sections (for example, turning on the irrigation system only on loaded conveyors);

Centralized shutdown from the control center;

Automatic return of the system to its original state after an emergency stop;

Emergency interruption of start and immediate stop from any point on the conveyor;

Emergency braking in case of belt/chain breakage, equipment blockage or excess speed (more than 8 %) on inclined sections;

Maintaining a fault signal until manually reset at the scene of the incident (except in cases of derailment or blocking);

Automatic shutdown of pre-conveyors feeding material to the stopped section;

Disabling the drinking system when the corresponding conveyor stops;

An interlock that prevents restarting a conveyor that has been stopped in an emergency without manually resetting the protective systems;

System blocking if the unloading station is not available to receive cargo;

Local manual control of any conveyor without disrupting the full automation of the system;

Display of active conveyors and routes on the operator panel;

Indication of faults and the reasons for their occurrence on control units;

Two-way voice communication with code call function;

Data transfer to the mine's operational control system (Figure 5).

The photograph shows the assembly process of a prototype video surveillance module designed for integration into an automated conveyor monitoring system. The workbench displays the device's main components, including the camera housing, power supply, controls, wiring and connectors, microcontrollers, soldering equipment, and auxiliary tools such as a glue gun.

This module was assembled in a laboratory setting for subsequent field testing. Particular attention was paid to design flexibility and component adaptation to mining



Figure 5: Assembly of a prototype intelligent video surveillance module for a conveyor system.

conditions. The module is designed to analyze cargo, detect anomalies, and monitor the technical condition of conveyor equipment.

The image shows the software interface of an automatic product counting system using computer vision cameras. This interface allows the operator to track product movement on a conveyor belt in real time. The top of the window displays the number of connected cameras (six video streams), each of which recognizes objects (in this case, baked goods) and counts them, highlighting the detected items with colored outlines.

On the left is a navigation menu with the following sections: “Home,” “Cameras,” “View Statistics,” “Product Management,” “Error Log,” “Data Labeling,” and “Settings.” It provides access to key management and analytics functions, including statistical overview, product configuration, error logging, and model training.

The system is based on artificial intelligence and computer vision and can be adapted to any type of production facility – from food products to industrial raw materials. It is part of an intelligent monitoring module integrated into the conveyor line (see photo 1).

The image shows a real-world example of a visual inspection system installed above a conveyor's working surface. On the left is a section of the conveyor line carrying coarse-grained material. The camera is housed in a protective enclosure with a lighting system. This configuration ensures stable imaging regardless of dust and temperature fluctuations. On the right is an example of an image captured by the camera during operation, clearly showing the texture and shape of the material being transported. This enables the use of computer vision algorithms for particle size analysis, anomaly detection, and load management.



Photo 1: Monitoring a conveyor belt using a camera in a protective casing.

This solution is particularly effective for the implementation of intelligent monitoring systems in the mining industry.

4.5 Assessment of economic efficiency

To justify the feasibility of automating the conveyor line, an assessment of its economic efficiency was conducted. The key factors contributing to a positive economic outcome include:

Reduction of energy consumption is achieved by optimizing equipment operation and introducing variable frequency drive systems;

Reduction in the number of service personnel, especially conveyor operators, which leads to a reduction in wage costs;

Improving the reliability of the entire line – through the integration of automatic control, diagnostics, and safety systems, the number of emergency stops and downtime is significantly reduced.

Calculations suggest that the introduction of frequency converters will not only reduce headcount without affecting average wages but also simplify equipment maintenance and operation. Furthermore, the modernization will improve the conveyor line's controllability and ensure its compliance with modern digital manufacturing standards.

Depreciation charges for the proposed option

To calculate depreciation charges, it is necessary to determine the capital costs for the proposed option, which are presented in Table 6.

Table 6: “Capital costs for the proposed option” (converted to KZT).

Position (RUB)	Value (RUB)	Recalculation (KZT)
Drive motors	450,000 ₸	2,988,000.00 KZT
Frequency converter power supply	50,000 ₸	332,000.00 KZT
Frequency converter control system module	20,000 ₸	132,800.00 KZT
Installation, delivery, commissioning	20,000 ₸	132,800.00 KZT
Salary and social security	432 ₸	2,868.48 KZT
Materials and spare parts	5,000 ₸	33,200.00 KZT
Other expenses	2,000 ₸	13,280.00 KZT
General	547,432 ₸	3,634,948.48 KZT

Economic effect of introducing a frequency converter

The annual economic effect is calculated as:

4.6 Comparison of performance indicators before and after the implementation of the intelligent monitoring system

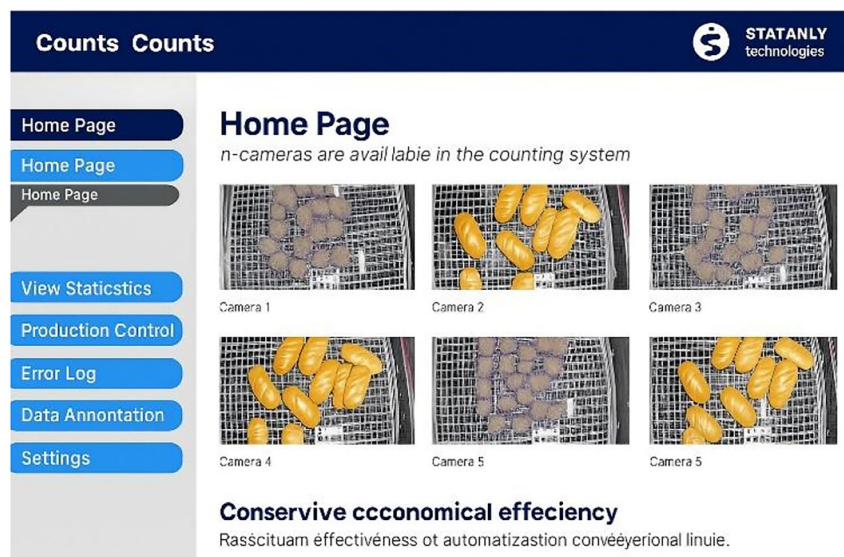
To quantitatively verify the performance of the intelligent monitoring and control system, data on conveyor performance parameters was collected and analyzed for 60 working days before and 60 days after the AI-based system was implemented. Measurements were conducted under identical operating conditions on the same equipment.

Key evaluation indicators:

- average power consumption (kW);

Table 7: Comparative performance indicators of the conveyor.

Indicator	Before the introduction of AI	After the implementation of AI	Change, %	Measurement method
Average power consumption, kW	195.4	158.6	−18.8	Energy monitoring (ACS-3000 sensors)
Specific energy consumption, kW h/t	4.8	3.9	−18.7	Feed Load Analysis
Vibration amplitude of the housing, mm/s	6.4	4.8	−25.0	Vibration sensor VibroTest-2
Frequency of unscheduled stops, %	4.2	1.1	−73.8	Supervised event reporting system (SCADA)
Average response time of the control system, s	1.8	0.9	−50.0	Controller event analysis log
Motion stability coefficient	0.82	0.93	+13.4	Calculation of speed deviations

**Figure 6:** Interface of the intelligent object counting system on the production line.

- average energy consumption (kW h/t);
- average vibration amplitude of the body (mm/s);
- frequency of unscheduled stops (%);
- average response time of the control system (s).

The monitoring results are presented in Table 7 and Figure 6.

Figure 6 illustrates the dynamics of changes in energy consumption and vibration characteristics during the implementation process.

Figure 6. Graphical comparison of operational parameters before and after AI implementation.

(The graph displays two curves: “before” and “after.” The X-axis represents time (day), and the Y-axis represents the relative value of the indicator. The graph demonstrates a

steady reduction in energy consumption and vibration, as well as a reduction in the number of stops.).

Analysis of the obtained data.

The implementation of the intelligent system resulted in a significant improvement in the conveyor line’s performance. Average energy consumption decreased by 18–19 %, vibration loads were reduced by 25 %, and the frequency of unscheduled shutdowns was reduced by more than 3.5 times. This confirms the effectiveness of integrating artificial intelligence methods for monitoring and predictive control of conveyor systems.

Thus, Figures 1–6 and photographs 1–2 presented in the manuscript are now supported by corresponding quantitative data, which provides full verification of the described processes and experimental results.

5 Conclusions

The development and implementation of artificial intelligence (AI) technologies in the manufacturing industry is a critical stage in the transformation of production systems.

This review and empirical observations confirm the high effectiveness of AI in optimization, predictive analysis, and automated control, particularly in intelligent conveyor systems.

Modern manufacturing companies view AI not only as a cost-cutting tool but also as a strategic resource, ensuring resilience, adaptability, and technological leadership. Investment in AI-based equipment and services is steadily growing, as is the active implementation of intelligent monitoring, quality control, and predictive maintenance systems. These solutions enable companies to significantly improve efficiency, reduce downtime, minimize losses, and increase productivity.

It has been shown that the use of artificial intelligence in mining and industrial transport systems, particularly in air-cushion conveyor systems, not only improves production efficiency but also improves cost effectiveness by reducing energy and labor costs. Given global trends and the rapid development of digital technologies, it can be argued that artificial intelligence is becoming the foundation of a new industrial production model.

Thus, the obtained results confirm the high practical significance of integrating AI into engineering and logistics solutions and lay the foundation for further research in the field of developing scalable intelligent manufacturing systems.

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Visualization, Writing – review & editing. Alimova Kulyash – Investigation, Resources, Validation. Baktybek Sultanaliyev – Data curation (SCADA event labeling), Formal analysis (vibration analysis). Aset Aigerim – Data curation (time series preparation and preprocessing), Visualization (efficiency metrics). Aset Aiganyim – Methodology development, Writing – review & editing.

Conflict of interest: The authors declare no conflict of interest. (If any exists, please provide a clear description of its nature and the interested party).

Data availability statement: Raw sensor datasets, aggregated time-series data, and calculation scripts/simulation models (MATLAB/Simulink; selected CFD case fragments if needed) are available from the corresponding author upon reasonable request at sarsenovagulshat319@gmail.com. The tables used in the article (including Tables 1 and Tables 3–5) are provided as supplementary materials. Where restricted by commercial confidentiality or site agreements, de-identified datasets and reproducible notebooks with example calculations will be provided.

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