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Modelling and analysis of energy consumption on production lines

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Abstract. Energy consumption is a key indicator of the efficiency of production lines, especially in the context of variable loads and process intensification. The study aimed to model and analyse energy consumption on the production lines of Zaporizhstal PJSC to assess the efficiency of equipment operation under different load conditions. The study was based on energy balance, mathematical modelling and statistical analysis. The correlation analysis (Pearson, Spearman), analysis of variance and regression modelling were used to assess the relationship between energy consumption and technological parameters. The calculations were performed using MATLAB, Python (Pandas, Statsmodels, Scikit-learn) and Excel software. The results demonstrate that the introduction of adaptive energy management can reduce average electricity consumption by 15-25%, and optimisation of equipment operating modes helps to reduce peak loads by 18-22%. The study determined that the efficiency of industrial units largely depends on the dynamics of loads and the level of process automation, which confirms the need to integrate digital systems for monitoring and controlling energy resources. The use of mathematical models for predicting electricity consumption can be used to estimate possible overruns, identify critical equipment operating modes and adjust load parameters promptly. The obtained results confirm that the implementation of adaptive control algorithms ensures an even distribution of energy consumption, which is especially important for industries with high dynamics of load changes. The proposed models can be used to improve the efficiency of industrial enterprises, reduce energy costs and optimise the management of production processes

Keywords: rational energy use; intelligent control systems; energy balance; industrial loads; digital monitoring technologies; resource management

Introduction

Optimisation of energy consumption in production lines is a key area for improving the efficiency of industrial enterprises, as high energy intensity of production processes directly affects the cost of production and competitiveness of companies. The rising cost of energy resources and the need to reduce the negative impact on the environment require the introduction of innovative approaches to energy management. Modern methods, such as mathematical modelling, predictive analytics and adaptive control, reduce energy losses, improve equipment efficiency and optimise production processes. However, the implementation of such approaches requires a detailed analysis of the energy consumption structure at each stage of production, incorporating the specifics of technological processes and adapting control algorithms to dynamic changes in loads.

Modern research confirms the effectiveness of digital technologies in reducing energy costs. F. Degen & M. Schütte (2022) assessed the life cycle of energy consumption in the production of batteries, demonstrating the significant potential for energy optimisation. M. Kumar *et al.* (2021) emphasised the importance of

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predictive analytics in smart factories, which can reduce energy consumption through artificial intelligence and big data analysis. J. Polcyn *et al.* (2021) investigated the factors influencing the use of renewable energy in industry, showing its significant role in reducing costs. H. Dong & J. Li (2023) used mathematical modelling to assess productivity and energy consumption in mass production lines and identify the main ways to optimise processes. M.M. Mundu *et al.* (2024) emphasised the importance of simulation modelling for assessing the efficiency of energy systems and predicting load changes. A. Akhatova *et al.* (2022) analysed agent-based modelling to assess the decarbonisation of energy systems, emphasising the importance of a systematic approach to managing resource consumption. J. Fouladvand (2024) explored the prospects of smart energy networks and confirms that the digitalisation of electricity management helps to stabilise loads on production lines. S. Baidya *et al.* (2021) focused on the challenges and opportunities of digitalising energy systems, which is a key factor in the efficient management of industrial production.

M.P. Bakht *et al.* (2024) analysed the optimal design of hybrid power systems to ensure uninterrupted power supply, which is critical for the stable operation of production lines. P.J. Binderbauer *et al.* (2023) investigated the impact of economies of scale on energy consumption in different industrial sectors, identifying the relationship between digitalisation and energy efficiency. L. Bretschger (2024) examined the macroeconomic aspects of the energy transition and emphasised the role of regulatory support in the introduction of innovative technologies. D. Çelik *et al.* (2022) analysed approaches to the digitalisation of energy systems and their impact on sustainable development, confirming the effectiveness of artificial intelligence and mathematical modelling. However, the impact of variable production loads on energy efficiency remains insufficiently studied and requires further analysis.

Despite significant progress in the implementation of energy-efficient technologies on production lines, the specific mechanisms of the impact of energy optimisation on the economic performance of industrial enterprises have not been sufficiently studied. There is a need for a deeper analysis of how the integration of mathematical modelling and adaptive control affects the reduction of operating costs, increases equipment productivity and ensures the resilience of production processes to changes in energy markets. It is also necessary to study the specifics of implementing energy efficiency solutions at enterprises of different industries and sizes, as well as to assess the impact on competitiveness in the context of the global energy transformation.

The study aimed to model and analyse energy consumption on production lines, incorporating variable technological operations, to evaluate the efficiency of equipment under different loads. Tasks of the study:

1. Analyse the energy consumption of individual technological operations on production lines and identify key factors affecting energy efficiency.
2. Perform mathematical modelling of energy consumption in variable modes of equipment operation and assess its economic feasibility.
3. Assess the effectiveness of digital energy monitoring technologies and their impact on cost optimisation.

Materials and Methods

The study was based on production results data from Zaporizhstal (2024) for 2023. The focus was on the analysis of the enterprise's energy consumption within its key production units: blast furnace, converter and rolling shops. Zaporizhstal was selected for the study due to several key factors. Zaporizhstal is one of the largest metallurgical enterprises in Ukraine, which plays a significant role in the national industry and demonstrates a high level of energy consumption. Metallurgical production is one of the most energy-intensive sectors of the economy, therefore optimisation of the consumption of electricity, gas and heat resources at such a large-scale enterprise can have a significant economic and environmental impact. Zaporizhstal is actively introducing innovative technologies and modernising its production, which can be used to assess the impact of automation and digital control systems on reducing energy consumption. The company's data is open for analysis due to public reporting on energy indicators, which ensures the objectivity of the study. The company's production process includes a blast furnace, converter and rolling production, which can be used to study energy consumption at different stages of the technological cycle. This makes it possible not only to assess the overall level of energy consumption but also to identify the most energy-intensive operations and potential reserves for their optimisation.

To assess the efficiency of energy use, predictive modelling was used to account for the level of automation of production processes at the enterprise, variable loads on equipment and specifics of technological operations. Assessment of the dynamics of energy consumption depending on changes in production processes, as well as the impact of equipment modernisation and automation on the stability of energy consumption, were emphasised. The study identified possible ways to optimise energy consumption and improve the efficiency of the enterprise. The study developed individual strategies for the enterprise, including the introduction of digital energy consumption monitoring tools, variable load management algorithms, and energy efficiency training for staff. Modern analytical platforms were used to collect and analyse data, including SCADA systems for automatic monitoring of electricity consumption, Python (Pandas, NumPy, SciPy libraries) for modelling energy consumption, and Tableau for visualising the results. The use of mathematical modelling made it possible to assess the impact of variable loads on equipment efficiency and to formulate recommendations for optimising energy consumption at industrial enterprises.

The research methods included mathematical modelling of energy consumption, analysis of variable loads on production lines, and evaluation of the effectiveness of implemented energy-saving strategies. Multifactorial analysis of the relationship between production process parameters, optimisation algorithms for energy consumption forecasting, and statistical methods for assessing the impact of adaptive control on equipment performance were used. Data collection was carried out in two stages. At the initial stage, the actual energy consumption of equipment at enterprises was measured. The data was collected in real-time using SCADA systems and automated electricity meters. Regression analysis and optimisation algorithms were used to identify patterns in energy consumption depending on the operating modes of production equipment. Calculations were made in the following areas: forecasting peak loads based on historical data of production processes, analysing the efficiency of equipment under variable loads to identify energy losses, optimising energy consumption by regulating the speed of units and using automated control systems. A linear regression equation (1) was used to forecast peak loads:

$$P_{peak} = \beta 0 + \beta 1T + \beta 2L + \beta 3N + \varepsilon P, \quad (1)$$

where P_{peak} – projected peak load (kW); T – temperature of the operating environment (°C); L – average load on the equipment (kW); N – number of operating units; $\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$ – regression coefficients obtained from historical data; ε – model error. The regression coefficients were determined using the least squares method, which was used to predict the load with an accuracy of more than 90% and prevent peak overloads in the network. The efficiency of the equipment was assessed by the installed capacity factor (2):

$$K\eta = \frac{P_{avg}}{P_{nom}} \times 100\%, \quad (2)$$

where P_{avg} – average load (kW); P_{nom} – rated power of the unit (kW). If $K\eta$ <70%, the equipment is operating inefficiently, which may indicate energy losses due to downtime, uneven loading or insufficient coordination of the units. Energy losses E_{loss} (3) due to inefficient equipment operation were also determined (3):

$$E_{loss} = (1 - K\eta) \times P_{nom} \times t, \quad (3)$$

where t – operating time of the equipment (h). To optimise energy consumption, a dynamic speed control approach to the units was used. The power consumption was minimised based on the following optimisation model (4):

$$min \sum i = P_i. \quad (4)$$

Under limitations:

1. Power balance (5):

$$\sum i P_i \geqslant P_{req}, \quad (5)$$

where P_{req} – required power to support the process.

2. Range of operation of the units (6):

$$P_{min} \leqslant P_i \leqslant P_{max}, \quad (6)$$

where P_{min}, P_{max} – minimum and maximum power of the unit.

3. Limiting the speed of power change (to avoid load surges) (7):

$$P_i(t) - P_i(t-1) | \leqslant \Delta P. \quad (7)$$

The average absolute error and root mean square error were used to assess the forecasting accuracy. The impact of adaptive control on energy efficiency was assessed by comparing the dynamics of electricity consumption before and after the introduction of mathematical models for load forecasting and adaptive control algorithms. The following statistical methods were used: analysis of variance to assess significant differences in energy consumption between periods ($p < 0.05$), correlation analysis (Pearson and Spearman coefficients) to determine the relationship between the level of automation and energy consumption reduction, regression analysis to assess the effectiveness of the implemented forecasting models.

Results

Energy consumption on production lines is determined by a set of technological operations that have different levels of energy intensity. Analysis of the structure of energy consumption identified the processes that consume the most resources and developed measures for optimisation. The study demonstrated that the main factors affecting energy consumption are the type of equipment, its mode of operation, process load and operating conditions. Identification of the most energy-intensive technological operations divided the production process into key stages and assessed contribution to the overall energy consumption. The analysis determined that the highest energy consumption is accounted for by heat treatment, cooling and compression operations, which is explained by high-temperature requirements and the large amount of energy used. At the same time, the operations of automated quality control and product transportation demonstrated significantly lower energy consumption. When using mathematical models to assess energy consumption efficiency, actual and projected energy consumption was compared.

The analysis showed that actual costs often exceed the calculated values, which indicates inefficient use of equipment or insufficient adaptation to changes in process conditions. Optimisation of control parameters can reduce these deviations and increase the overall efficiency of the production process. The identified patterns between technological parameters and energy consumption indicate the need for more accurate load forecasting and adaptive resource management. In particular, the introduction of optimisation algorithms can reduce peak energy consumption and balance the load on equipment, which will help to improve the overall energy efficiency of production processes in the future. Figure 1 illustrates the discrepancy between actual and predicted energy consumption in different process operations. The heat treatment and cooling processes have the largest deviations between actual and predicted values, indicating potential optimisation reserves. Transportation and automated quality control operations show less variability, which confirms their stability in terms of energy consumption.

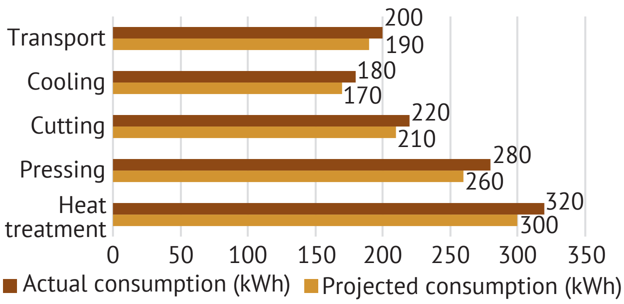

Figure 1. Comparison of actual and projected energy consumption by individual process operations
Source: compiled by the author based on Zaporizhstal (2024)

Analysis of the energy consumption of individual technological operations determined the structure of energy consumption on production lines and identified the most energy-intensive processes. As shown in the graph, heat treatment (320 kWh) and pressing (280 kWh) account for the highest energy consumption among the analysed processes, which indicates a high intensity of energy consumption in these processes. Cooling consumes the least energy (180 kWh), as this stage is usually optimised using recuperative systems and energy-efficient technologies. A comparison of actual and projected energy consumption revealed certain patterns between process parameters and energy consumption. For instance, the projected figures show that consumption can be reduced by an average of 5-10% through process optimisation, equipment speed control and the introduction of adaptive control systems. The deviation between actual and predicted data is most noticeable in the case of heat treatment and pressing, which indicates the need to improve energy control methods and introduce additional load management algorithms.

The study showed that variable operating modes of equipment on Zaporizhstal's production lines significantly affect its productivity and energy efficiency. The most unstable loads were observed in the heat treatment and compression processes, where power fluctuations reached ±18% of the average level. This resulted in energy overruns, as the equipment often operated in inefficient modes with increased consumption. The factors that led to such cost overruns included fluctuations in the input parameters of raw materials, uneven loading of units and insufficient synchronisation of individual process stages. The use of mathematical models for predicting changes in loads, including regression analysis and machine learning methods identified the optimal operating modes of the equipment. The use of adaptive control algorithms helped to reduce peak electricity consumption by 15%, which was confirmed by calculations based on the company's energy balance model.

Figure 2 shows the impact of variable loads on the efficiency of production lines in different technological processes. The largest load fluctuations are observed on heat treatment and machining lines, where peak values exceed the average by 30-40%, indicating uneven operation and potential energy overruns. Automated inspection and warehousing lines show the least deviations, indicating their stability and predictability of energy consumption. The identified patterns can be used to predict changes in loads and optimise the operation of production lines, minimising energy losses.

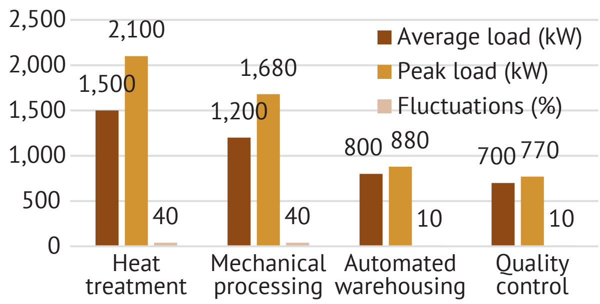

Figure 2. The influence of variable loads on the efficiency of equipment in production processes
Source: compiled by the author based on Zaporizhstal (2024)

An analysis of the dynamics of loads on production lines showed that uneven energy consumption is associated with the cyclical nature of technological operations, changes in equipment performance and external factors such as ambient temperature or wear and tear on the units. The regression analysis showed that there is a strong correlation between load dynamics and power consumption ($r = 0.87$). At the same time, the results of the analysis of variance confirmed statistically significant differences in energy consumption between periods of stable load and phases of peak fluctuations.

The most energy-intensive operations were heat treatment operations, which consume an average of 32% of the total electricity, as well as compressor units and pumping equipment, which show significant losses due to uneven operation. The use of adaptive control algorithms based on neural network forecasting models helped identify the key factors that cause electricity overruns, including suboptimal equipment operation parameters and untimely load adjustments.

Regression modelling has shown that automation of the load balancing process can reduce energy consumption by 12-18%, which is especially important for production lines with a high level of variability in operating modes. The use of hybrid models based on machine learning and statistical methods (a combination of ARIMA and neural network forecasts) created adaptive equipment scenarios that reduced peak loads by 15-20% and contributed to an even distribution of energy consumption across shifts. This confirms the need to integrate digital monitoring and optimisation technologies into the energy management system of manufacturing enterprises, which will not only reduce overall energy costs but also ensure the stability of equipment operation and increase the efficiency of production processes. Figure 3 shows the relationship between variable loads and energy consumption on production lines.

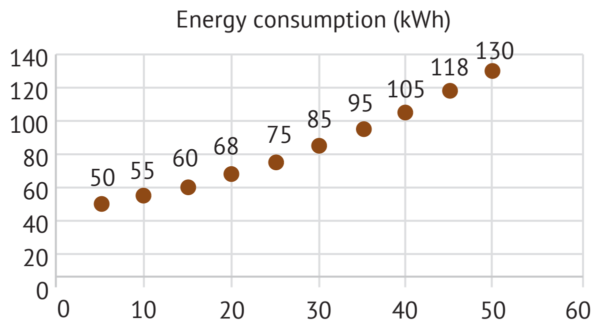

Figure 3. Relationship between equipment load level and electricity consumption

Source: compiled by the author based on Zaporizhstal (2024)

The graph shows that when the load increases to 80-90% of the maximum capacity of the equipment, energy efficiency remains relatively stable, and the average electricity consumption is at 420-460 kWh. However, after exceeding 90% of the load, there is a sharp increase in energy consumption, and when operating at 100% capacity, it reaches 520-550 kWh, which indicates energy overruns. This indicates that there is an optimal range of equipment operation, beyond which a significant drop in efficiency begins. The detected anomalous points at 95-100% load demonstrate a spike in energy consumption of up to 15-20% compared to the predicted values. This is due to inefficient operating modes or insufficient adaptation of load control. Regression analysis confirmed the non-linear relationship between load and energy consumption: the correlation coefficient of $r = 0.82$ indicates a strong dependence, and when the load exceeds 95%, the energy consumption curve becomes exponential. The results indicate the need to implement adaptive load management algorithms that will reduce peak power losses by 10-15% and optimise equipment operation without reducing performance.

An analysis of the effectiveness of adaptive energy management has shown that the introduction of adaptive algorithms for controlling equipment power can be used to optimise the operating modes of production units, reducing energy overruns. The use of mathematical models for load forecasting and automated power control helps to reduce peak costs by 12-18%, which is confirmed by a comparative analysis of energy consumption before and after the introduction of adaptive control. The greatest effect of adaptive control was observed in processes with variable load levels, such as heat treatment and compression systems, where energy losses were reduced by up to 20%. Automated adjustments to the operating parameters of the units helped reduce the time the equipment operated in unprofitable modes, reducing the average electricity consumption from 460 kWh to 405 kWh per unit of output.

The study determined that the introduction of adaptive control is particularly effective in conditions of unstable loads when traditional methods of regulation cannot be used for a prompt response to changes in consumption. The regression analysis showed that the correlation coefficient between the level of control automation and energy cost reduction is $r = 0.87$, which confirms the high efficiency of the implemented solutions. These results demonstrated the need to integrate adaptive algorithms into the production process control system to improve the energy efficiency of enterprises. Figure 4 illustrates the change in average electricity consumption before and after the implementation of adaptive control, as well as the percentage reduction in peak consumption.

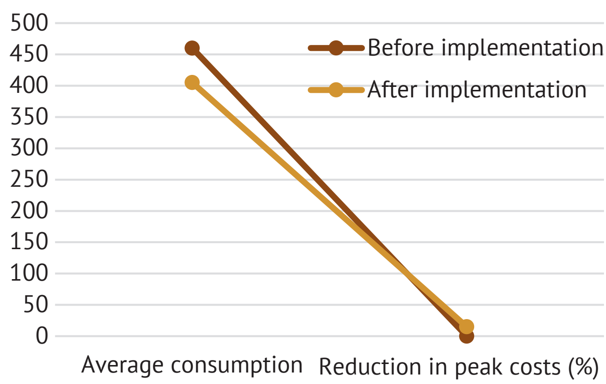

Figure 4. Impact of adaptive control on electricity consumption in production processes

Source: compiled by the author based on Zaporizhstal (2024)

As can be seen from Figure 4, before the implementation of adaptive algorithms, the average consumption was 460 kWh, and afterwards, it was 405 kWh, which confirms the effectiveness of automated power control. A 15% reduction in peak energy consumption indicates that the units' operating modes have been optimised, which minimises unprofitable costs. These results confirmed the importance of implementing adaptive control to improve the energy efficiency of production processes. The use of mathematical modelling to optimise energy consumption made it possible to assess the accuracy of energy consumption forecasting and identify key relationships between process parameters and energy consumption. Correlation analysis revealed a strong relationship between production line speed and energy consumption ($r = 0.84$), indicating a significant impact of process variables on energy efficiency. Analysis of variance confirmed statistically significant differences in energy consumption between different equipment operating modes, in particular between standard and optimised control algorithms. Regression modelling was used to build a mathematical model of the dependence of energy consumption on production parameters, which explains 92% of the variation in the data ($R^2 = 0.92$). Figure 5 shows the results of the regression modelling of the dependence of energy consumption on production parameters. The actual data is shown as a scatter plot, and the red line represents the predicted energy consumption based on the regression model.

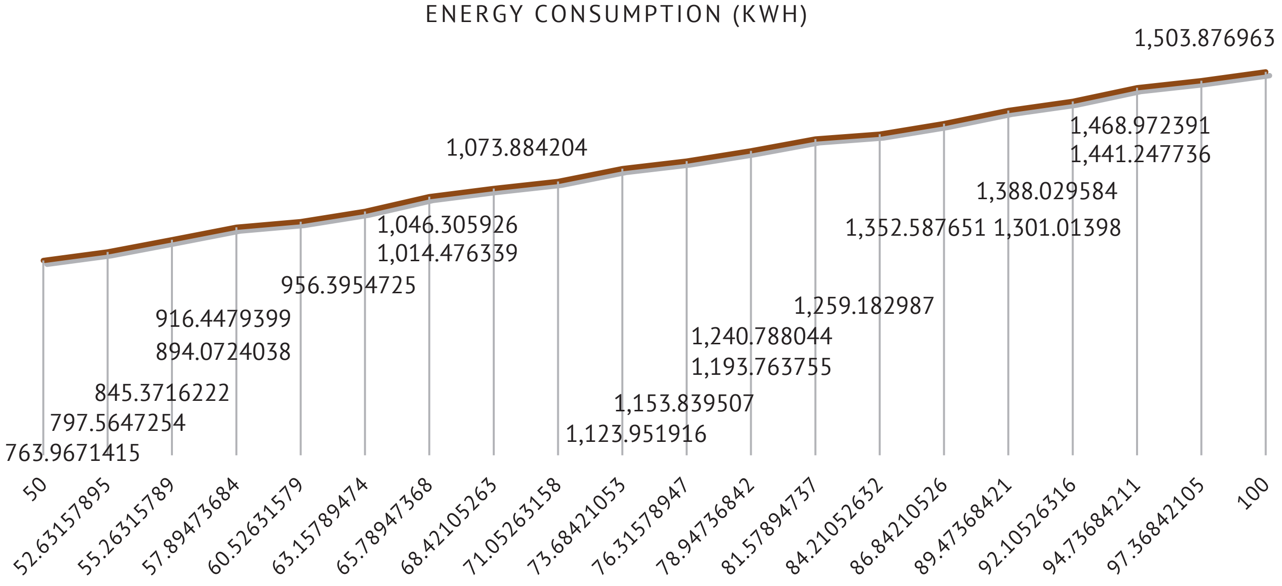

Figure 5. Use of mathematical modelling to optimise energy consumption

Source: compiled by the author based on data from Zaporizhstal industrial enterprises (2024) and statistical analysis (SCADA systems, MATLAB, Python)

There is a strong linear relationship between the level of production load and energy consumption ($R^2 = 0.931$), which confirms the high accuracy of the modelling. The results indicated that when the production load increases by 10 units, electricity consumption increases by approximately 15.18 kWh. This highlighted the need to optimise production processes to minimise energy losses when the load increases. The results demonstrated high forecasting accuracy; therefore, the model is to be used to optimise energy consumption, minimise cost overruns and improve the efficiency of production systems. Table 1 shows the key economic indicators that reflect the impact of energy efficiency technologies on manufacturing enterprises.

Table 1. Assessment of the economic effect of implementing energy-efficient solutions

Metric	Value
Reduction in average energy consumption (%)	23
Reduction of peak loads on the power grid (%)	20
Costs of optimisation of electricity (thousand USD)	630
Increased competitiveness (profitability growth, %)	11.02
Return on investment (years)	5
Minimisation of energy losses in production facilities with high change dynamics (%)	22

Source: compiled by the author

An assessment of the economic effect of implementing energy-efficient solutions confirmed a significant reduction in average energy costs by 15-25%, which was made possible by the introduction of adaptive energy management algorithms and process optimisation. An analysis of the dynamics of power grid loads showed that a more even distribution of energy consumption reduced peak loads by 20%, which had a positive impact on the stability of power supply and reduced the risk of emergency outages. Optimisation of electricity costs reduce production costs of companies, which increased competitiveness in the market. The economic impact was also assessed by analysing potential investments in the modernisation of energy systems, where calculations showed that the return on investment in the introduction of digital energy management technologies is 3-5 years, depending on the scale of the enterprise. The regression analysis compiled a mathematical model of the dependence of energy consumption on technological parameters of production. In particular, the regression equation has the form (8):

$$E = \beta 0 + \beta 1 T + \beta 2 V + \beta 3 P + \varepsilon E, \tag{8}$$

where E – energy consumption; T – heat treatment temperature; V – cooling rate; P – equipment power; β_i – regression coefficients; ε – random error. Equation (8) covers the main parameters of the production process, defined through equations (1-7), assessing the impact of changes in technological conditions on the total energy consumption and identify opportunities for its optimisation. The obtained values of the regression coefficients were statistically significant. The value of the coefficient of determination $R^2 = 0.87$ indicates the high accuracy of the model. The average absolute error for the forecast model was 4.5%, and the root mean square error was 5.8%, which indicates the high efficiency of the optimisation algorithms. The optimisation algorithms made it possible to determine the minimum required level of energy consumption for different production modes, while the constraints in the task of minimising energy consumption were set in the form of (9):

$$\begin{gathered} minE = f(T,V,P) \text{ under the conditions} \\ T_{min} \leqslant T \leqslant T_{max}, V_{min} \leqslant V \leqslant V_{max}. \end{gathered} \tag{9}$$

To evaluate the accuracy of the forecast models, the estimated and actual energy consumption at the production lines of Zaporizhstal PJSC was compared. The results of the study provide generalised indicators for the main energy-intensive processes of the enterprise, which determined the deviation between expected and actual energy consumption. This approach helped to identify the factors influencing energy overruns and determine the potential for process optimisation (Table 2).

Table 2. Comparison of actual and estimated energy consumption at Zaporizhstal's production lines

Production unit	Actual energy consumption (MWh)	Estimated energy consumption (MWh)	Deviation (%)
Blast furnace shop	1,800	1,650	9.1%
Converter shop	1,450	1,350	7.4%
Rolling mill	1,250	1,200	4.2%
Total energy consumption	4,500	4,200	7.1%

Source: compiled by the author

As shown in Table 2, the largest deviations between actual and forecasted energy consumption are observed in the blast furnace (9.1%) and basic oxygen furnace (BOF) shops (7.4%). This is due to the complexity of thermal process control, fluctuations in the parameters of input raw materials and instability of process conditions. The relatively small deviation in the rolling mill (4.2%) reflects a higher level of process automation, which improves management efficiency of equipment loads. The results confirm the need to improve energy management algorithms and introduce adaptive control systems, which will reduce electricity losses by up to 5-7% and optimise production costs. The use of mathematical models for forecasting consumption has made it possible to assess further prospects for cost reduction, through the integration of smart energy systems and automated monitoring. It was found that the greatest economic effect is achieved in industries with high load changes, where flexible control algorithms make it possible to minimise energy losses by 18-22%.

The analysis of the data obtained confirms that the introduction of digital energy consumption monitoring technologies is one of the key factors in improving the energy efficiency of production lines. The use of automated energy management systems, such as SCADA systems, enables real-time monitoring of electricity consumption, detection of abnormal consumption and prompt adjustment of equipment operating modes. Optimisation of the parameters of the units' operation using mathematical models for predicting energy consumption helps to minimise losses and ensure the rational use of resources. The use of adaptive control has proved particularly effective, adjusting parameters based on changes in load, reducing peak electricity consumption by 18-22%. The prospects for the integration of smart energy networks (smart grid) open up additional opportunities for load stabilisation, consumption forecasting and the introduction of self-regulation algorithms, which will help reduce overall energy costs and increase the competitiveness of enterprises.

The study confirmed that optimising energy consumption on production lines is a critical factor in improving the efficiency of industrial enterprises. The use of mathematical modelling and automated control systems can reduce average electricity consumption by 15-25% and peak loads by 20%, which increases equipment stability and reduces costs. Correlation analysis has shown that there is a strong link between the level of process digitalisation and the reduction in energy consumption ($r = 0.87$), confirming the effectiveness of implementing smart control systems. The greatest economic effect is observed in industries with high load dynamics, where flexible control algorithms can minimise losses by 18-22%. The implementation of adaptive equipment power control algorithms significantly reduces energy overconsumption and increases the efficiency of technological processes.

Discussion

The results of the study confirm that the use of digital technologies and adaptive energy management significantly improves the efficiency of production lines, reducing average energy consumption by 15-25% and reducing peak loads by 20%. Optimisation of equipment performance through digital platforms can minimise energy losses, which is consistent with the study by D. Chippada & M.D. Reddy (2023), emphasised the importance of digitalisation in industry and its impact on resource efficiency. Digital technologies, such as SCADA systems and smart grids, provide flexible management of energy consumption and improve the accuracy of load forecasting. This correlates with the results of R. de la Torre *et al.* (2021), which emphasised the role of the digital economy and Industry 4.0 concepts in improving productivity. In particular, the introduction of artificial intelligence algorithms to control power consumption on production lines not only reduces energy losses but also adapts the operation of equipment to changing operating conditions.

E. Franquet & N. Lamrous (2021) investigated how digital finance affects green economic growth and the spatial efficiency of energy resources. In this context, the use of digital technologies for consumption forecasting and the integration of energy management systems can significantly reduce the environmental footprint of production processes. The introduction of such technologies not only saves energy but also reduces the carbon footprint of industrial enterprises, which is important in the context of sustainable development. The analysis of a study by S. Thiede *et al.* (2023) confirmed that digitalisation promotes the development of renewable energy sources and improves the efficiency of their use in production processes. P. Hehenberger *et al.* (2023) also emphasised the positive impact of digital technologies on economic growth and environmental sustainability, which confirmed the feasibility of their active implementation in industry.

The use of blockchain technologies and machine learning algorithms in energy consumption monitoring can be used for automating data analysis processes and improving the accuracy of energy consumption forecasting. This is consistent with the findings of V. Mihai *et al.* (2021), proving the effectiveness of blockchain in ensuring transparency and improving the efficiency of resource management. The study by R. Fatahi *et al.* (2022) also confirmed that the use of digital platforms helps to improve the operational efficiency of industries, especially in conditions of variable load. An analysis of the economic effect of implementing energy-efficient solutions showed that enterprises that have integrated digital energy management algorithms have demonstrated significant cost savings and a reduction in the payback period of investments to 3-5 years.

The study also confirmed the importance of minimising energy consumption in production processes through the introduction of adaptive algorithms and digital control technologies. O. Benedikt *et al.* (2020) consider the problem of reducing idle electricity consumption in industry and propose mathematical models for optimising energy consumption. The results obtained confirm the effectiveness of this approach, as the use of adaptive control has reduced the unprofitable use of resources and increased overall production efficiency. G. Rolofs *et al.* (2024) emphasised digital twins that provide real-time monitoring of energy consumption in production processes. Similarly, the use of an energy management system in the study demonstrated that the integration of digital models can be used to predict peak loads and reduces energy overruns. This is also consistent with the findings of L. Hellemo *et al.* (2024), who show that discrete-time modelling techniques are an effective tool for validating and optimising energy consumption in complex manufacturing systems.

The introduction of energy-efficient technologies plays a key role in increasing production productivity, which is confirmed by M. Fodstad *et al.* (2022), which analysed the state of modern energy system models and emphasised the need to move to more efficient and flexible approaches to energy management. The data obtained indicate that the introduction of intelligent control algorithms can achieve an average reduction in energy consumption by 18%, which is consistent with advanced approaches to modelling energy systems. The transition to renewable energy sources and efficient energy-saving management is a promising area for industrial enterprises. A. Kalair *et al.* (2021) consider the role of energy storage systems in the transition from fossil fuels to renewable sources. Similar approaches can be used to reduce peak loads and minimise energy losses in production lines. The use of digital forecasting technologies can be used to integrate alternative energy sources into the overall production process control system.

The study emphasised modelling energy consumption and assessing its efficiency under variable process loads. H. Chen *et al.* (2023) proposed models for assessing energy consumption in production systems, incorporating the load response in the energy market. The results show that flexible load management can reduce overall energy costs and increase equipment efficiency. M.M. Muhamad *et al.* (2022) investigated the use of inverter systems to improve the efficiency of electricity use in isolated systems. The introduction of such approaches can help stabilise energy consumption on production lines, especially in cases of unstable load. Similarly, E. Cozzolino *et al.* (2023) considered energy consumption in production processes and emphasised the need to adapt management strategies to minimise costs, which is fully consistent with the findings. Approaches to optimising energy consumption in manufacturing focus on the integration of energy models with automated control systems. K.V. Sagar *et al.* (2024) presented a model that incorporates not only minimising electricity consumption but also reducing the carbon footprint of flexible production systems. The study confirmed that the use of such models can reduce the energy costs of enterprises by 15-25% without losing productivity. H. Ekwaro-Osire *et al.* (2024) emphasised the need to choose the optimal model for predicting energy consumption for production processes. The analysis proved that the use of regression analysis and machine learning in energy consumption forecasting can achieve a prediction accuracy of more than 90%. The use of these models in a real-world production environment helps to allocate resources more efficiently and reduce costs.

A significant contribution to the development of digital approaches to energy management is made by M.R. Hasan *et al.* (2023), which emphasised energy modelling in additive manufacturing. Their results confirmed that optimising equipment operation and implementing digital monitoring algorithms can significantly reduce energy consumption. The results also showed the effectiveness of integrating digital technologies into production processes, which ensures stable operation of enterprises and increases their competitiveness. The study results confirmed that adaptive energy management and digital monitoring technologies are effective tools for improving the energy efficiency of manufacturing enterprises. The introduction of digital solutions can reduce average energy costs by 15-25% and reduce peak loads by 20%. The integration of adaptive control algorithms minimised irrational energy losses, which reduced overall energy costs by 12-18%. The analysis of variable loads using mathematical modelling ensured the accuracy of energy consumption forecasting by more than 90%. Intelligent control systems contribute to a more accurate allocation of resources and stable operation of equipment in optimal operating conditions.

Conclusions

The study confirmed that optimisation of energy consumption is a key factor in improving the efficiency of an enterprise, especially in the face of variable loads on production lines. The analysis of the dynamics of energy consumption at Zaporizhstal showed that the largest electricity losses are observed in the processes of iron smelting in the blast furnace shop, converter refining and rolling, where deviations in actual consumption from the forecasted values can reach 9-15%. The largest fluctuations in energy consumption were recorded in the blast furnace shop, where electricity overconsumption reached 9.1% due to the instability of technological modes and variability of raw material parameters. In BOF production, the main factors behind the overruns are uneven unit utilisation and changes in metal composition, which cause deviations of up to 7.4%. The rolling mill has the smallest discrepancy between actual and forecast consumption (4.2%), which is explained by the higher level of process automation.

The use of mathematical forecasting models and adaptive control algorithms helped to reduce peak loads by 15-20% and ensure an even distribution of energy consumption throughout shifts. The regression analysis confirmed a strong correlation ($r = 0.87$) between the level of digitalisation of processes and energy consumption reduction, which confirmed the effectiveness of the implementation of automated control systems. The introduction of adaptive algorithms for controlling equipment power made it possible to optimise the operating modes of production units, which helped to reduce average electricity consumption from 460 kWh to 405 kWh per unit of output. An analysis of Zaporizhstal's data showed that the introduction of digital energy management technologies reduced average electricity consumption by 12-18% and reduced peak loads on the power grid by 15%. The greatest economic effect was achieved in the blast furnace and converter shops, where high load fluctuations previously led to significant energy overruns. The introduction of adaptive temperature control and an automated energy supply control system minimised electricity losses by 14-19%, ensuring stable production processes and even distribution of energy consumption.

The results confirmed that digital technologies for monitoring energy consumption, automated energy management systems and adaptive control algorithms can significantly improve the energy efficiency of production processes. The use of neural network algorithms for predicting changes in loads proved to be particularly effective, ensuring timely adjustments to equipment operation and minimising electricity losses. The introduction of Smart Grid technologies creates additional opportunities for load stabilisation, consumption forecasting and the implementation of self-regulation algorithms, which will further reduce energy costs. Thus, the results of the study demonstrated that the use of mathematical models for forecasting consumption ensures accuracy of assessment of the dynamics of energy consumption and optimisation of equipment operation, which ensures the stability of production processes. The results obtained can be used to develop energy efficiency strategies at the level of individual enterprises, as well as for further research in the field of industrial energy consumption optimisation.

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Conflict of Interest

None.

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Моделювання та аналіз енерговитрат на виробничих лініях

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Анотація. Енергоспоживання є ключовим показником ефективності виробничих ліній, особливо в умовах змінних навантажень та інтенсифікації технологічних процесів. Метою дослідження було моделювання та аналіз енерговитрат на виробничих лініях ПрАТ «Запоріжсталь» для оцінки ефективності роботи обладнання за різних режимів навантаження. Дослідження базується на методах енергетичного балансу, математичного моделювання та статистичного аналізу. Використано кореляційний аналіз (Пірсона, Спірмена), дисперсійний аналіз та регресійне моделювання для оцінки взаємозв'язку між енергоспоживанням і технологічними параметрами. Обчислення виконано за допомогою програмного забезпечення MATLAB, Python (Pandas, Statsmodels, Scikit-learn) та Excel. Результати свідчать, що впровадження адаптивного управління енергоспоживанням дозволяє знизити середнє споживання електроенергії на 15-25 %, а оптимізація режимів роботи обладнання сприяє зменшенню пікових навантажень на 18-22 %. Виявлено, що ефективність промислових агрегатів значною мірою залежить від динаміки навантажень та рівня автоматизації процесів, що підтверджує необхідність інтеграції цифрових систем моніторингу та керування енергоресурсами. Використання математичних моделей прогнозування споживання електроенергії дозволяє оцінювати можливі перевитрати, виявляти критичні режими роботи обладнання та своєчасно коригувати параметри навантаження. Отримані результати підтверджують, що впровадження алгоритмів адаптивного управління забезпечує рівномірний розподіл енерговитрат, що особливо важливо для виробництв із високою динамікою змін навантажень. Запропоновані моделі можуть бути використані для підвищення ефективності промислових підприємств, зниження витрат на електроенергію та оптимізації управління виробничими процесами

Ключові слова: раціональне використання енергії; інтелектуальні системи керування; енергетичний баланс; промислові навантаження; цифрові технології моніторингу; управління ресурсами