ШТУЧНИЙ ІНТЕЛЕКТ У СИСТЕМАХ СТАЛОГО ЕКОНОМІЧНОГО РОЗВИТКУ

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THE USE OF MACHINE LEARNING TO OPTIMISE ENERGY CONSUMPTION IN INDUSTRY 4.0

Industry 4.0 represents a new paradigm in industrial production, based on the integration of cyber-physical systems, the Internet of Things (IoT), big data and artificial intelligence. High energy consumption remains one of the key challenges facing modern manufacturing. It accounts for a significant proportion of costs and has a negative impact on the environment. The application of machine learning (ML) enables the prediction, analysis and optimisation of energy usage in real time, facilitating the transition to energy-efficient, so-called 'smart factories' [1–3].

Machine learning enables the creation of accurate models for forecasting energy consumption based on historical data, weather conditions, equipment characteristics and production processes. Algorithms such as 'random forests', gradient boosting and neural networks (in particular LSTM and CNN) demonstrate high accuracy in forecasting peak loads and detecting anomalies [4; 5]. These models process vast amounts of multidimensional data to identify patterns that traditional statistical methods often fail to account for. For example, hybrid approaches combining singular spectrum analysis with LSTM networks improve the forecasting of extreme values and non-linear behaviour in industrial energy profiles. The integration of ML with IoT enables continuous monitoring and automated decision-making, which is particularly relevant for Industry 4.0, where data is received in real time from sensors [2; 6]. IoT sensors provide high-frequency data streams on equipment operation, environmental factors and process variables, enabling ML models to dynamically adjust parameters and prevent energy wastage.

One promising area is the application of deep learning to manage energy consumption in 'smart buildings' and industrial complexes. Convolutional neural networks (CNNs), combined with the Internet of Things (IoT), analyse consumption data and identify inefficiencies. They then implement ‘demand response’ strategies, achieving forecasting accuracy of up to 88% [1]. Such systems use historical data on energy consumption, weather conditions and building characteristics to ensure real-time optimisation and the detection of anomalies in heating, ventilation and air conditioning systems, lighting and production equipment. In addition, ML is used to optimise production schedules, preventive maintenance and load balancing using renewable energy sources. This not only reduces costs but also contributes to achieving sustainable development goals, for example by reducing CO_2 emissions [7; 8]. In the steel industry, predictive modelling helps to adjust furnace parameters and operating schedules to minimise energy consumption whilst maintaining product quality. Research indicates potential reductions in energy consumption through dynamic adjustments based on fluctuations in demand and energy prices.

Research shows that combining machine learning with digital twins and cyber-physical systems makes it possible to simulate scenarios and optimise business processes at the plant level. Digital twins create virtual copies of physical objects and processes, synchronised with real-time data, allowing engineers to test energy-saving strategies without halting production. In practical examples, machine learning-based approaches reduce downtime and energy consumption by 10-30% through predictive maintenance and process optimization [5; 9]. For example, reinforcement learning and hybrid models support dynamic scheduling and fault detection, leading to reduced downtime and more efficient resource allocation. Ukrainian researchers are focusing on adapting these technologies to national conditions, particularly in the context of integration with ‘smart grids’ and hybrid energy systems, where ML helps to balance variable renewable energy sources and improve the overall resilience of the system in the face of infrastructure challenges [10; 11].

The synergy between Industry 4.0 technologies further enhances these benefits. The Internet of Things (IoT) and big data analytics improve the coordination and visualisation of energy flows, whilst artificial intelligence enables self-regulating equipment and energy-optimised production planning. In smart manufacturing environments, machine learning (ML) supports predictive maintenance, which minimises unplanned downtime; energy-optimised planning, which aligns operations with periods of low energy prices; and anomaly detection, which prevents inefficiencies.

Case studies in the automotive and heavy machinery sectors demonstrate that higher levels of digital maturity lead to closer integration of these tools, resulting in significant improvements in energy efficiency metrics [3]. Furthermore, digital twins facilitate the modelling of various scenarios for entire production lines, helping to identify optimal configurations in terms of energy efficiency and sustainability.

Despite its significant advantages, the implementation of machine learning faces many challenges. These include: data quality and availability, the computational complexity of models (particularly deep learning architectures), cybersecurity risks in connected Internet of Things ecosystems, and the need for skilled professionals capable of developing and maintaining such systems. Integration with legacy equipment in many sectors also creates compatibility issues. Further research should focus on the development of hybrid models (e.g., combining optimisation algorithms with neural networks), explainable AI techniques to build trust in decisions, and the standardisation of frameworks for Industry 4.0 to ensure scalability across different manufacturing contexts [6; 12]. Overcoming these obstacles is essential for wider adoption, particularly in countries with economies in transition and sectors undergoing digital transformation.

Machine learning is thus becoming a key tool for optimising energy consumption in Industry 4.0, ensuring the sector's economic efficiency, environmental sustainability and competitiveness. By enabling real-time, data-driven decision-making, ML not only reduces operational costs but also supports global decarbonisation efforts and the transition to circular and sustainable production systems.

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INTEGRATING BIG DATA, THE INTERNET OF THINGS AND MACHINE LEARNING TO OPTIMISE OPERATIONAL ACTIVITIES IN THE HOSPITALITY AND CATERING SECTORS

The modern hospitality and catering industry faces numerous challenges: increasing competition, changing customer expectations, the need to reduce costs and ensure sustainable development. The integration of Big Data, the Internet of Things (IoT) and machine learning (ML) technologies forms a powerful toolkit for optimising operational processes, improving efficiency and personalising services. These technologies enable the collection, processing and analysis of vast amounts of data in real time, transforming traditional establishments into ‘smart’ venues capable of adapting to dynamic market conditions [1; 2]. The Internet of Things plays a key role in collecting data from sensors installed in hotel rooms, restaurant kitchen equipment, lighting systems, HVAC and inventory. IoT sensors record parameters such as energy consumption, temperature, humidity, food stock levels and guest movement. This