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ADAPTIVE IOT-BASED LOGISTICS SYSTEM WITH EDGE INTELLIGENCE AND SECURE INTEROPERABILITY LAYER

The article examines an approach to building an adaptive logistics system based on IoT using Edge Computing, AI Layers, and an interoperability Integration Layer. A multi-layer architecture is proposed that covers the full data processing cycle – from sensor data collection to decision-making and integration with enterprise systems, with a focus on reducing latency and improving adaptability. The study analyzes key architectural layers: IoT, Edge, AI, Integration, and Security. Edge Computing enables data processing near sources, reducing central load and supporting real-time responses, while the AI Layer provides predictive analytics, anomaly detection, and route optimization. The Integration Layer ensures data unification, normalization, and integration via standardized APIs, as well as interaction with ERP, WMS, and TMS systems. The security model is based on encryption, authentication, and the zero-trust concept, ensuring data integrity, confidentiality, and availability. The results show that integrating IoT, Edge Computing, and AI improves performance, scalability, and reliability of logistics systems while reducing operational costs and supporting intelligent logistics development.

Keywords: IoT, Edge Computing, AI, logistics systems, route optimization.

1. Introduction. Modern logistics are evolving with IoT, AI, and Edge Computing. Increasing data volumes, faster response requirements, and higher transparency demand adaptive, scalable solutions, as traditional centralized systems cannot provide sufficient performance or flexibility. IoT enables real-time cargo monitoring, vehicle tracking, and automation but introduces challenges in data processing, reliability, interoperability, and security. Integrating IoT with Edge and AI supports distributed processing and decision-making, while Middleware coordinates heterogeneous components and the Security layer ensures protection and resilience, making a unified architecture a critical scientific and practical goal.

2. Problem Statement. The purpose of this work is to develop an adaptive multi-level IoT-based logistics architecture integrating Edge Computing, an AI decision-making module, a Integration Layer, and a comprehensive security model for real-time data collection, processing, and utilization. The objectives are to reduce data processing latency, optimize resources, improve forecasting accuracy and system adaptability, and ensure secure interaction between heterogeneous components and enterprise systems (ERP, WMS, TMS). The work also formalizes data processing across architectural levels, identifies key functional components, and justifies their interaction within a unified intelligent system.

3. Analysis of Recent Research. Recent studies highlight the evolution of IoT from simple tools to integrated ecosystems combining blockchain, AI, and 5G, enhancing transparency and security in logistics [1]. Research also explores frameworks for autonomous supply chains and the role of generative AI in strategic management [2], with growing emphasis on resilience, cybersecurity, and real-time monitoring [3]. In warehousing, IoT and AI enable intelligent monitoring and distribution systems with high efficiency and robustness [4]. Maritime logistics focuses on large-scale data collection and standardization for management optimization [5]. Decentralized solutions using blockchain and smart contracts (e.g., Hyperledger Fabric) reduce dependence on central control by automating operations from sensor data [6]. Implementing Industry 4.0 requires readiness assessment across IT infrastructure and sustainability dimensions [7]. Scaling IoT solutions faces cost and cybersecurity challenges, addressed via cloud computing and big data [8]. IoT-based simulation models aid the design of smart cold chains [9], and adaptive optimization using sensor data can extend product shelf life by up to 18% through real-time temperature control [10].

4. Main Results. The proposed multi-level architecture provides a complete data processing cycle in logistics, from IoT data collection to intelligent analysis and integration with corporate systems, while addressing security requirements. Interaction between IoT, Edge, AI, Integration, and Security layers forms an adaptive, scalable system capable of efficient operation in dynamic logistics environments.

The *IoT layer* collects and transmits data from the physical environment, monitoring cargo conditions (temperature, humidity, vibrations), tracking vehicles and assets via GPS, and enabling automated identification with RFID. Data are sent via lightweight protocols like MQTT and CoAP, ensuring energy-efficient, low-latency communication and a continuous flow for further processing.

The *Edge layer* processes data near the sources, reducing latency and central load. It filters, aggregates, and analyzes data locally, enabling rapid responses to critical events and seamless transfer of processed information to higher layers. This improves system performance, reliability, and autonomy.

The *AI layer* provides intelligent processing and decision support using machine learning and analytics. It performs forecasting, anomaly detection, route and resource optimization, delay prediction, cargo risk assessment, and adaptive planning. By integrating prior-layer data, it generates actionable decisions that enhance system efficiency, flexibility, and adaptability.

The *Integration layer* coordinates interactions among system components and external platforms, unifying and normalizing data, providing standardized API access, supporting asynchronous messaging, orchestrating processes, and integrating with ERP, WMS, and TMS. It ensures interoperability, scalability, and flexibility, acting as a central element in IoT-enabled logistics system.

The *Security layer* protects data and system components at all stages through encryption, authentication, authorization, access control, and anomaly detection. Applying zero-trust principles, it verifies every request, ensuring system integrity, confidentiality, and reliability.

The architecture's structure and component relationships are best illustrated in a block diagram, clearly showing data flows, processing logic, and layer interactions.

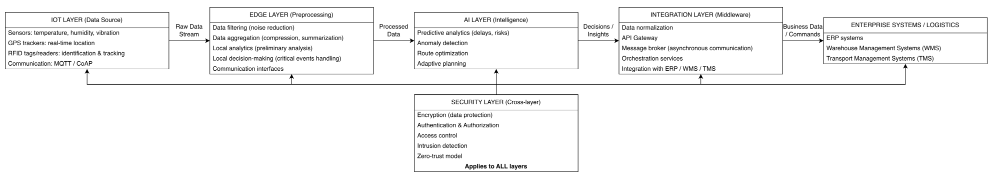

Figure 1. Multi-level architecture of an IoT system for logistics with integration and security.

Data flows from IoT sensors to the AI and Integration layers, with security enforced at every stage. The IoT layer collects and prepares data for Edge and AI processing, ensuring continuous, reliable streams for cargo monitoring and vehicle tracking [11] using heterogeneous sensors and energy-efficient protocols [12]. GPS trackers, temperature sensors, and RFID devices provide comprehensive logistics information.

GPS trackers continuously report real-time geolocation of vehicles, cargo, and containers, supporting route monitoring, speed and delivery time assessment, and overall logistics performance analysis [13]. This enhances supply chain transparency and enables prompt response to route deviations or delays.

To calculate the distance between two geographical points determined by GPS trackers, the haversine formula is used [14]:

$$d = 2 \cdot R \cdot \arcsin \sqrt{\sin^2 \frac{(\varphi_2 - \varphi_1)}{2} + \cos(\varphi_1) \cdot \cos(\varphi_2) \sin^2 \left(\frac{\lambda_2 - \lambda_1}{2} \right)} \qquad (1)$$

where d – distance between two points, R – Earth's radius, φ_1, φ_2 – latitudes, λ_1, λ_2 – longitudes.

Temperature sensors monitor sensitive cargo, while RFID automates tracking and inventory management. Lightweight protocols like MQTT and CoAP ensure efficient, low-latency communication. The IoT Data Acquisition layer provides continuous, standardized data from GPS, sensors, and RFID, supporting reliable monitoring, analytics, and logistics management.

The *Edge layer* processes data near the source, reducing *latency* and *central* load. It filters noise, removes errors or redundancies, and aggregates data before sending it to the cloud or corporate systems. This enables real-time operational decisions, crucial for logistics events like route changes or cargo issues [15]. System latency can be expressed as the sum of delays across processing stages:

$$L_{total} = L_{IoT} + L_{edge} + L_{cloud} \tag{2}$$

where L_{total} – total system latency, L_{IoT} – latency at the IoT level, L_{edge} – latency at the Edge level, L_{cloud} – latency in cloud processing.

Edge nodes analyze data locally, sending only aggregated or anomalous values, reducing network load and boosting autonomy. Edge Computing ensures performance, reliability, and real-time logistics support. The *AI Layer* processes IoT and Edge data into actionable insights for forecasting, optimization, and responses. Predictive analytics uses historical and current data [16], including delivery times, delays, and cargo risks, via machine learning models for real-time supply chain decisions.

For example, delivery time prediction can be performed using a linear regression model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n, \tag{3}$$

where y – predicted value (e.g., delivery time), β_0 – constant (bias), β_n – model coefficient, x_n – input values (distance, traffic, weather condition, etc.).

The *AI Layer* identifies anomalies in IoT and Edge data, such as temperature spikes, unusual routes, or delays, using machine learning and statistical methods, triggering alerts or adaptive responses to enhance safety and reliability. It also performs *route optimization*, calculating efficient paths based on delivery time, vehicle load, traffic, weather, and cargo risks using genetic, nearest-neighbor, graph-based, or ML algorithms. Integration with GPS and IoT data enables dynamic adjustments, reducing delivery time, cutting costs, and improving overall logistics efficiency.

The proposed block diagram illustrates the internal structure of the AI Layer and the sequence of data processing from IoT and Edge layers. Data first undergo predictive analytics (forecasting delivery time, risk assessment, resource planning), then pass through anomaly detection (identifying deviations), and finally reach route optimization, where optimal routes are calculated based on current system conditions.

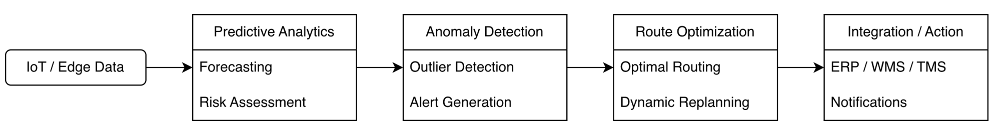

Figure 2. Block diagram of the AI Layer (Decision Engine).

The block enables real-time decision-making: data are transformed into predictions, anomalies detected, and optimal actions suggested. Results go to the Integration layer for ERP, WMS, or TMS synchronization and to the Security layer for protection.

The *Middleware coordinates* IoT, Edge, and AI flows with corporate systems, standardizing and managing data via APIs. The API Gateway routes requests, enforces authentication, monitors usage, and supports scalability, simplifying communication across all layers. Data Normalization unifies heterogeneous inputs, removing inconsistencies and duplicates for accurate higher-level processing [17].

For data unification, *min-max normalization* is used:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

where x' – normalized value, x – original value, $x_{\min}$ – minimum value in the dataset, $x_{\max}$ – maximum value in the dataset.

Data Normalization standardizes formats (e.g., °C, WGS84, timestamps), aggregates similar inputs, corrects errors, and prepares data for seamless use with the API Gateway and corporate systems (ERP, WMS, TMS). This creates a unified, clean data stream, improving analytics, decision-making, and subsystem interaction. Middleware integration applies IoT, Edge, and AI outputs to logistics operations: ERP manages resources and orders, WMS handles warehouse and inventory control, and TMS supports transportation planning, tracking, and cost optimization. This integration turns data flows into actionable management, enhancing efficiency, transparency, and adaptability.

The *Security layer* safeguards data and system stability across all IoT levels, ensuring integrity, confidentiality, and availability. It uses encryption (e.g., TLS) for transmission and storage, *authentication* and *authorization* for role-based access, and a *zero-trust model* that verifies every request [18]. In summary, combining these mechanisms provides comprehensive protection, system trust, reliability, scalability, and readiness for deployment.

For a better understanding of the architecture, it is useful to consider typical system operation scenarios. These scenarios illustrate the sequence of data processing, interaction between architectural layers, and transformation of information from acquisition to actionable decisions. At the first stage **«sensor → data»**, IoT devices collect primary data. Sensors monitor parameters like temperature, humidity, and geolocation, converting them to digital form with metadata (device ID, timestamps) and sending them to the system. Data pass from sensors to the communication module, preparing them for transmission to the next layer.

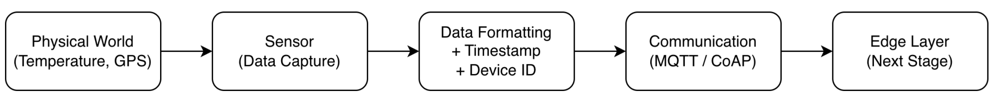

Figure 3. Scenario of primary data flow formation at the IoT level.

At this stage, a structured, processable data stream is formed, reflecting the current state of logistics objects. In the second stage **«edge → processing»**, IoT data are sent to the Edge layer for preliminary processing: filtering, aggregation, and local analysis reduce volume, remove noise, and extract relevant information. Critical deviations can trigger independent Edge responses, lowering latency and enhancing system autonomy.

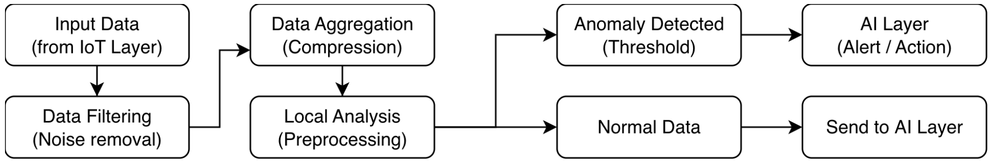

Figure 4. Scenario of preliminary data processing at the Edge level.

The Edge layer serves as an intelligent intermediary between IoT and AI, providing real-time processing, reduced latency, and local responses to critical events.

In the third stage **«AI → decision»**, processed data reach the AI Layer (Decision Engine) for analysis and real-time decision-making. Data pass through predictive analytics, anomaly detection, and route optimization, with deviations prompting adjusted decisions or alternative actions, ensuring system adaptability and resilience.

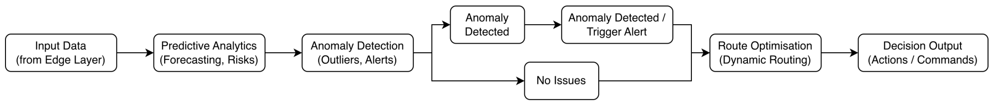

Figure 5. Scenario of data processing at the AI level and decision-making.

Thus, the AI layer serves as the central decision-making component, enabling adaptive management of logistics processes based on predictive analytics, anomaly detection, and route optimization. At the final stage **«system → action»**, AI decisions are transmitted via the Integration layer to ERP, WMS, and TMS systems, triggering route changes, order updates, notifications, or automatic execution of operations.

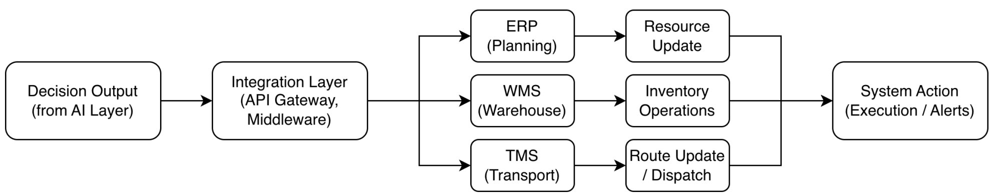

Figure 6. Scenario of implementing decisions in a logistics system.

Thus, at this stage, a full transition from analytics to action occurs: the system automatically or semi-automatically executes management decisions, improving efficiency, responsiveness, and coordination of logistics processes.

The proposed multi-level IoT architecture enhances efficiency, flexibility, and reliability in logistics. Combining IoT, Edge Computing, AI, and Middleware provides the foundation for next-generation logistics systems.

The system offers *high adaptability*, with the AI Layer and real-time processing enabling rapid responses to delays, route changes, or transport condition violations. Edge Computing ensures fast data processing and low latency, supporting real-time logistics decisions. Costs are reduced through route optimization, efficient resource use, process automation, and minimized data transmission. The modular architecture and Integration Layer allow easy scaling from local networks to global supply chains. Together, these features create an logistics system that enhances efficiency, reliability, and competitiveness in the digital economy.

5. Conclusions and prospects for further research. The results demonstrate that IoT enhances transparency, automation, and logistics efficiency, though issues like latency, central resource overload, and security remain. The proposed architecture mitigates these with distributed processing, Edge Computing, and intelligent analytics. Its main contribution is a unified adaptive system integrating IoT, Edge, and AI, improving performance, resource efficiency, and decision-making. Middleware and the Security Model ensure interoperability and protection. Future work includes digital twins for real-time modeling, autonomous logistics, federated learning, and energy-efficient IoT solutions, with real-world implementation needed to assess effectiveness and refine the system.

Conflict of Interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data Availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Contributions of authors

R. Ya. Zhovtani – conceptualization, data preparation, formal analysis, writing – original design, scientific supervision; A. M. Chorniy – methodology, project administration, writing (reviewing and editing); P. V. Yavorskyi – research, resources, visualization; O. M. Zymomrya – translation design, text typesetting validation; Yu. M. Tsipino – validation, software.

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Жовтані Р. Я., Чорній А. М., Яворський П. В., Зимомря О. М., Ціпіньо Ю. М. Адаптивна логістична система на основі IoT з периферійним інтелектом та захищеним шаром взаємної сумісності.

У статті розглядається підхід до побудови адаптивної логістичної системи на основі Інтернету речей (IoT) з використанням периферійних обчислень (Edge Computing), модулів штучного інтелекту (AI) та проміжного програмного забезпечення для забезпечення взаємодії. Пропонується багаторівнева архітектура, яка охоплює повний цикл обробки даних – від збору даних з датчиків до прийняття рішень та інтеграції з корпоративними системами, з акцентом на скороченні затримки та підвищенні адаптивності. У дослідженні аналізуються ключові архітектурні рівні: IoT, Edge, AI, інтеграція та безпека. Edge Computing дозволяє обробляти дані поблизу джерел, зменшуючи навантаження на центральні сервери та забезпечуючи реагування в режимі реального часу, тоді як модуль AI забезпечує прогнозну аналітику, виявлення аномалій та оптимізацію маршрутів. Рівень проміжного програмного забезпечення забезпечує уніфікацію, нормалізацію та інтеграцію даних через стандартизовані API, а також взаємодію з системами ERP, WMS та TMS. Модель безпеки базується на шифруванні, автентифікації та концепції «нульової довіри», забезпечуючи цілісність, конфіденційність та доступність даних. Результати показують, що інтеграція IoT, Edge Computing та AI покращує продуктивність, масштабованість та надійність логістичних систем, одночасно зменшуючи операційні витрати та підтримуючи розвиток інтелектуальної логістики.

Ключові слова: IoT, Edge Computing, штучний інтелект, логістичні системи, прогнозна аналітика, оптимізація маршрутів, кібербезпека.

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