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Research Article

Modeling and evaluation of AI integration in smart farm IoT networks: a LoRaWAN perspective

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Background: The study explores the possibilities of deploying Artificial Intelligence (AI) in smart farm Internet of Things (IoT) networks based on LoRaWAN (Long Range Wide Area Network) technology to optimize communication performance.

Methods: An artificial smart farm scenario incorporating sensors, sprinklers, and a server was modelled. LoRaWAN was selected as the wireless communication technology due to its long-range capabilities, low power consumption, and ability to support small data packets. Realistic LoRaWAN network parameters were established as guidelines for the simulation. The simulation methodology involved comparing baseline network performance (without AI optimization) with AI-optimized network performance in terms of latency, throughput, and packet loss.

Results: Simulation outcomes demonstrated that an AI model can greatly enhance network responsiveness, data transfer efficiency, and communication reliability at the device level. Furthermore, the effectiveness of the AI model, assessed using conventional classification metrics, showed a promising level of accuracy in data-driven decision-making.

Conclusion: The study indicates that AI integration can be valuable in streamlining communication within smart farm IoT systems. The results highlight the potential advantages of AI in improving network performance.

Keywords: *Smart farm, IoT, LoRaWAN, Light GBM, AI integration*

Introduction

Farming is in a data-driven shift, with farms implementing Internet of Things (IoT) sensing, actuation and analytics to enhance productivity, resource utilization, and resilience in the face of climate variability, water scarcity, and labor unavailability (Wolfert et al., 2017). Smart-farm systems generally combine heterogeneous sensors (soil moisture, canopy temperature, microclimate, equipment telemetry) and edge controllers with cloud services in feedback loops to provide monitoring, prediction and closed-loop control (e.g. variable-rate irrigation or festination) (Akhter et al., 2022). In addition to raw connectivity, real-world deployments have very demanding requirements: battery life of many years, city-wide coverage of irregular terrain, minimal maintenance and operation in the face of occasional interference and extreme environmental conditions (Mohammed et al., 2020). These constraints influence architectural decisions at all layers of the stack- device energy limits and MAC scheduling as well as gateway location, data aggregation, and security (García et al., 2020). AI is becoming central in that stack. In the agronomic layer, the supervised and self-supervised models are

useful in supporting yield prediction, stress and disease prediction, and irrigation schedule; in the operations layer, AI helps in anomaly detection, workload prediction, and decision support to actuators (Violino et al., 2023). Notably, AI decisions and communication performance are joint: when an irrigation policy causes bursty telemetry and actuation commands, the network should support low latency and high delivery probability without breaking the spectrum or energy budget. Network-aware AI, on the other hand, may alter the reporting rates, optimize the traffic prioritization or schedule transmissions to safeguard quality of service (QoS). This co-design point of view drives end-to-end measurements with both the quality of agronomic decisions and device-level communication performance reported. The layered architectures of smart-farm IoT solutions are becoming more common and allow trading off local autonomy and centralized intelligence. Edge nodes and gateways have the ability to pre-filter or compress data, perform smaller classifier algorithms and policy enforcement, and execute denser analytics, model training, and fleet management in the cloud (Akhter et al., 2022), (García et al., 2020). Sustainability considerations sustainability considerations powering nodes using small solar panels, low radio duty cycle, avoiding unnecessary transmissions, are part of reliable operation at scale and reflect best practice in related IoT fields such as smart homes where energy-aware sensing, lightweight protocols, and modular services have already shown to result in long-term, low-maintenance deployments (Ali et al., 2024). In the case of farms, such patterns lead to event-based sensing (report only when thresholds or trends are significant), adaptive actuation and network policies that do not violate device energy envelopes. (Friha et al., 2021; Liakos et al., 2018) proposed LoRaWAN is one of the low-power wide-area technologies that reasonably fits the needs of dispersed farms due to its combination of kilometer-range coverage, license-exempt use, and low payload efficiency. (Tao et al., 2021; Salih et al., 2020) demonstrate its topology of star-of-stars streamlines gateway backhaul, regional parameter profiles normalize duty-cycle and power limits to comply. But performance depends on configuration: pure-ALOHA access, heterogeneous spreading factors, and downlink timing give trade-offs between latency, packet delivery ratio (PDR), and airtime fairness at increasing density (Kamilaris et al., 2018; Raza et al., 2017). Baseline Adaptive Data Rate (ADR) speeds up some tradeoffs but can be slow to converge under dynamics; security hardening (e.g., v1.1 capabilities) must remain intact through upgrades (Bor et al., 2016), (Dönmez et al., 2018). These facts enable adaptive procedures rather than fixed settings. These trade-offs can only be investigated through simulation prior to field trials under realistic traffic, topology and propagation conditions. There are already established tools LoRaWAN Sim, FLoRa (OMNeT++), and ns-3 modules that allow packets to be experimented with to test capture effects, bi-directional links, ADR variants, and gateway scheduling alongside similar latency, throughput, and loss results under controlled conditions (Yang et al., 2021; Narieda et al ., 2024). Previous work demonstrates that small changes in spreading-factor deployment, transmit power, and confirmation policy may have large effects on both PDR and latency in dense or otherwise interference-prone environments (Raza et al 2017). On top of that, the field has recently explored machine learning and reinforcement learning (e.g., multi-armed bandits, deep Q-learning) to make channel/SF/power decisions online, with better delivery, fairness, and energy consumption than heuristic ADR--and often with lightweight models that can run on gateways or even devices (Ilahi, I., et al., 2012). Such methods have a special application to agriculture, where spatial and temporal heterogeneity (open fields vs. tree lines) and time-varying workloads (irrigation windows) strains fixed arrangements. This paper presents a complete assessment of an AI-optimized smart-farm IoT network with a farm-like spatial configuration of sensors, sprinklers (actuators) and a server. We instantiate detailed regional parameters and compare a well-tuned baseline against an AI-aided policy. We present device-level communication statistics (latency, throughput, packet loss), as well as AI model quality (standard classification metrics), which gives a complete picture of the interaction between data-driven control and the network. Our approach is informed by best practices in smart-environment systems that are sustainable, modular and intelligent, and our findings relate network QoS optimization to tangible farm activities. In establishing AI as a first-class control component--not only in agronomic inference, but in communication adaptation as well--the work informs practical design decisions on scalable, energy-aware, and regulation-compliant smart-farm deployments (Kufakunesu et al., 2020).

Theoretical reference

A number of efforts develop end-to-end, data-driven irrigation systems that pair cheap field devices with cloud-based analytics and dashboards. (Sitharthan et al., 2023) paper on 6G-based on the topic of autonomous irrigation based on weather history and water moisture content reports accuracy 66.34%, sensitivity 89.28%, and precision 91% in test conditions-positioning a progressive perspective of ultra-reliable links and predictive control loops. (Liopa-Tsakalidi et al., 2024) implement a production-style LoRaWAN smart-irrigation system on a 22-hectare olive grove (Greece), with soil moisture sensors at multiple depths and data pushed up to a cloud backend; they claim water savings of 42% (2020) and 25% (2021) --demonstration that a robust telemetry and dashboard combination can deliver long-term savings. (Et-taibi et al., 2024) introduce a cloud-based multi-farm platform that integrates big-data collection/processing, combines weather forecasting and runs on a solar-powered testbed; they demonstrate tangible water savings through real-time control and analytics. (Binayao et al.,2024) report a solar-aided, sensor-based irrigation prototype, and reports farmer-perceived adaptability/utility (Likert mean 4.32), demonstrating viability under paddy conditions and the importance of simple user interfaces. (Khaliq et al., 2025) suggest a multimodal AI architecture: Transformer-based tabular models to

provide irrigation suggestions (TTL, 99.13% acc.), soil analysis (TabNet regressor, R 2 = -0.987), crop (SwiFT) and fertilizer recommendations (TabNet classifier, 99.3), as well as explainability and a weather API-a demonstration of end-to-end, data-driven farming processes ready to be deployed in an IoT environment. (Khaliq et al., 2025) build an improved wind-driven optimization (EWDO) + LSSVM predictor over an IoT/LoRaWAN sensing stack; the EWDO improves over the WDO/AWDO on RMSE/NRMSE of irrigation-related forecasts indicating the benefit of using meta-heuristics in the tuning of smart irrigation models (Ala'F et al., 2025). Combine IoT + ThingSpeak cloud + fuzzy logic to automatically regulate irrigation based on environmental factors, keeping the soil humidity close to its target, and point out the low cost (≈ USD 32) to be practical in the field (Morchid et al., 2025). An adjunct solar-driven implementation shows a Raspberry Pi/MQTT pipeline with web control of precision agriculture, focusing on power independence in addition to telemetry and actuation services (Al Mamun et al., 2025). On the system level, (Adamo et al, 2025) formulate the irrigation/fertigation, as a sequential decision problem and deploy an Artificial Intelligence (AI) planning agent based on Integer Linear Programming (ILP) in a micro-services architecture and digital twin; the framework is in contrast to the PID control because it resolves multi-objective trade-offs (water/fertilizer application versus crop requirements) and operates across heterogeneous crops and environments. (Gupta et al., 2025) document a 30 percent water-use savings with an Arduino-based, sensor-driven predictive irrigation algorithm with mobile supervision, and trace its automation to saving both labor and energy during experiments. The related work explains IoT architectures, AI-based scheduling, forecasting, and field tests that show better irrigation efficiency and network stability and determine the difficulty of scalability, security, energy-efficient management, and deployment methodologies.

Materials and Methods

The given section describes the approach of the simulation and assessment of the performance of an AI-optimized IoT network in a smart farm based on the LoRaWAN technology. It describes the layout of a simulated environment, the spatial arrangement of sensors, sprinklers, and the central communication server in a specified farm area. As shown in flowchart in Figure 1, the decision-making process of the AI model is as follows. The reasons why LoRaWAN has been chosen as the wireless communication technology are offered, and the exact network parameters set to be used in the simulation are outlined. Moreover, this part explains how the behavior of a network is modeled, including considerations of signal propagation, interference, and packets. It also describes the incorporation of decision-making process in the AI model and outlines the primary network performance and AI evaluation measures gathered to analyze the effect of the AI-based optimization. The point is to give a detailed and clear description of the simulation configuration and assessment procedure through which the results, which are displayed in the next sections, were achieved.

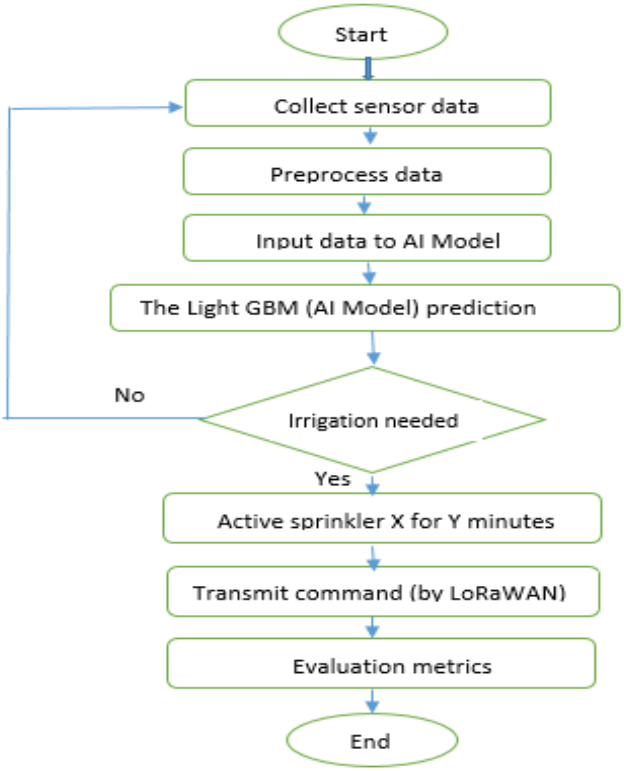

Figure 1. System flowchart

System architecture

The proposed architecture of the simulated smart farm system is a centralized model as presented in Figure 2. The main elements are several distributed Sensors, a central server, and an AI-Driven System. The sensors are placed throughout the 100m x 100m simulated farm to gather different environmental data, e.g. land moisture and temperature, etc. These are all low power sensors that are to be used in-field over extended periods of time. All the sensors feed data to the central server in the middle of the farm, a data aggregation point. It is the network communication gateway also. The AI based system is conceptually outside the core server; it takes aggregated sensor information, analyzes it (e.g. decides on irrigation requirements), and uses it to issue control signals to the actuators. The main actuators in this simulation scenario are the Sprinklers which are stationed across the farm, and which include directions issued by the central server (which receive AI decisions) to do things such as turn on irrigation on certain areas. This architecture enables communication of data between the field sensors, central processing unit and the consequent transmission of control signals to the actuators.

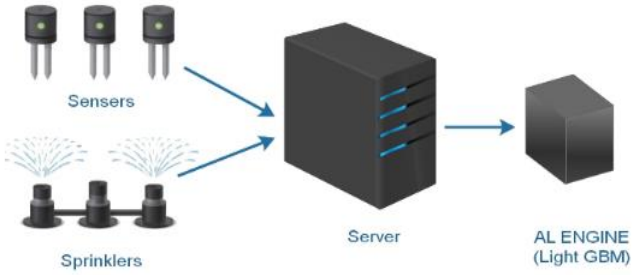

Figure 2. System architecture.

The simulation model

The conceptual simulation exercise was conducted to represent the smart farm IoT network and test the effect of the AI optimization. The conceptual simulation was in the generation of representative network performance measures of two scenarios:

Baseline scenario: It is the scenario that shows the performance of a network without the monitoring of the AI-driven optimization system. It emulates network traffic and device behaviour under some hypothetical ideal behaviour (e.g. fixed sensor polling rates, pre-programmed irrigation schedules). The performance of latency, throughput, and packet loss measured on the network in this case represents the performance that can be obtained in a non-optimized IoT farm network.

AI optimized scenario: This scenario is conceptually used to combine the effect of the AI model decisions on the network behavior. It presupposes that the AI can analyze data measured by sensors in order to optimize the actions, i.e., schedule irrigation more efficiently, change the frequency of the data transmission by sensors dynamically, or process the data locally. The metrics of the network in this case will be simulated to match the anticipated performance gains (e.g. reduced latency of critical commands, reduced overall packet loss, increased throughput utilization) that would be achieved by these AI-based optimizations over the Baseline scenario. Figure 3. presented the simulation model, the purpose of which was to reflect the key features of the wireless communication at the farm setting. That included taking into account the distance between devices and the central server, the number of devices sending data and the nature of the wireless technology adopted (LoRaWAN). LoRaWAN is the most dominant wireless network type that was chosen to enable the connection of the different IoT devices, that is, the sensors and the sprinklers to the server. The decision is motivated by the following major features of LoRaWAN that best meet the needs of a common smart agriculture system: Long Range Communication, Low Power Consumption, Appropriate to Small Data Packets, etc. The network metrics simulating each of the devices in the two scenarios were generated according to statistical distributions (e.g., normal and uniform distributions) that would represent, in broad terms, the difference in the performance of a non-optimized and an AI-optimized system, considering the above-mentioned factors. The given approach made it possible to conduct a comparative analysis of network performance at the level of individual devices, demonstrating the possible advantages of AI integration.

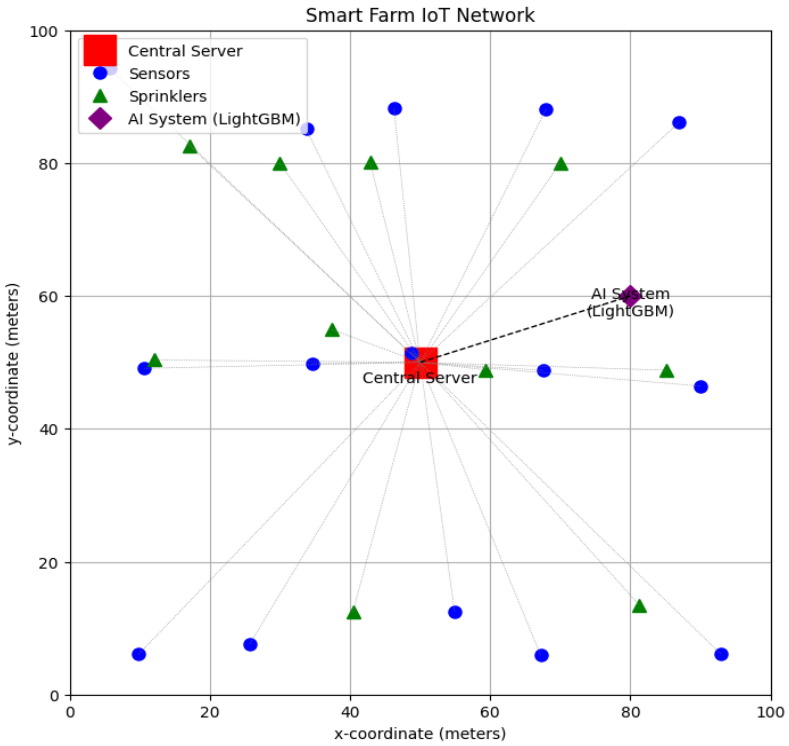

Figure 3. Smart simulated IoT farm network.

Such an illustrative evaluation of the possible advantages of the integration of the AI optimization layer into the smart farm IoT network is possible even without a sophisticated, packet-level simulation based only on comparing network metrics under these two conceptual scenarios.

Table 1: The model simulation parameters

Parameter	Value
Simulation Area	100 × 100 meters
Carrier Frequency	868 MHz
Spreading factor	7
Coding rate	0.8
Bandwidth	125 KHz
Transmitter Power	14 dBm
Receiver sensitivity	-125 dBm
No. of sensors	15
No. of sprinklers	10

The AI model

A Light GBM Classifier is used in the simulated smart farm system to represent the AI aspect of the system. LightGBM is a gradient boosting framework, which is tree-based learning algorithms. It is made efficient and performance oriented especially on large data sets. To conceptually represent how the AI makes its decisions, a LightGBM Classifier was selected to be used in this simulation. The main targeted purpose of this AI model in the smart farm would be to analyze the received data by the sensors and make smart decisions or predictions on the basis of the received data. Within the framework of this simulation, the AI model is imagined as examining the readings provided by the sensors (the level of soil moisture, temperature, etc.) and defining whether the irrigation is necessary in the various areas of the farm. This is a two-class task: irrigation is necessary or not at the specific time and at the specific location. The internal processes of the LightGBM algorithm imply complicated gradient boosting equations and tree structures; however, the performance of the model in its specified task is also measured by the accuracy of the classification of the simulated data. The accuracy and loss performance measures of the model are measures of reliability in making decisions such as targeted irrigation of the farm, a critical decision that must be made after considering the realistic possibilities of the farm.

Performance metrics

In order to assess the effectiveness of smart farm IoT network, the following key network performance indicators were analyzed. The key metrics analyzed on a per-device basis are Latency, Throughput and Packet Loss, which offer an understanding of the responsiveness of communication, data transfer ability and reliability in various conditions. The delay in the travel of a data packet between its source and destination is called latency. It may be determined as a sum of different delays (Dubba et al., 2024):

$$\text{Latency} = \text{Transmission Delay} + \text{Propagation Delay} + \text{Queuing Delay} + \text{Processing Delay} \quad (1)$$

Transmission Delay is the time taken to push all the packet's bits onto the transmission link.

$$\text{Transmission Delay} = \frac{\text{Packet Size}}{\text{Bandwidth}} \quad (2)$$

Propagation Delay is the time taken for a bit to travel from the sender to the receiver through the physical medium.

$$\text{Propagation Delay} = \frac{\text{Distance}}{\text{Speed of Propagation}} \quad (3)$$

Queuing Delay – the time that a packet has to wait in the router or switch queue to be processed. Processing Delay is the amount of time it takes routers or switches to find the outgoing link after processing the packet header. In most of the simplified cases or in a situation where we consider one particular link, latency can be considered as a simple sum of transmission and propagation delay. Also, the rate at which data is successfully delivered between one point and another within a network at a particular time is called Throughput. It is normally expressed in bits per second (bps), kilobits per second (kbps), megabits per second (Mbps) etc (Farej et al., 2020).

$$\text{Throughput} = \frac{\textbf{Total Amount of Successfully Transferred Data}}{\boldsymbol{Time\ Taken}} \quad (4)$$

Also, Packet loss is a scenario whereby some or all of the packets of information that are transmitted over a computer network do not arrive at destination. It is normally represented as a percentage of lost packets to the total number of packets sent (Yaghoubpour et al., 2021).

$$\text{Packet Loss} = \frac{\text{Number of Packets Sent} - \text{Number of Packets Received}}{Number\ of\ Packets\ Sent} \ x\ 100 \quad (5)$$

Besides network metrics, the effectiveness of the AI model was also evaluated by means of common machine learning metrics. Accuracy was the measure of the correctness of the model in general against the simulated data. Loss, in this case, binary cross-entropy loss in this classification exercise measured the difference between the probability distribution of the event that the model outputs in the training and validation data and the actual labels (Easwaran et al., 2025).

$$Accuracy = \frac{\text{Number of valid data}}{\text{Number of total data}} \quad (6)$$

$$\text{Binary Cross Entropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i\ log(\hat{y}_i) + (1 - y_i)\ log(1 - \hat{y}_i)] \quad (7)$$

Where, N is the number of samples, y_i is the true label for sample i (either 0 or 1), y^_i is the predicted probability of the positive class (class 1) for sample I (Guo et al., 2023). This equation is more costly to the model when the probability it is predicting is very different to the true label.

Result and Discussion

In this case, we propose the essential results of the simulation and assessment of the AI-optimized IoT network of smart farms. The network performance metrics as well as the metrics supporting the evaluation of the AI model are evaluated to identify the effects of the AI integration.

Latency

The first performance measure which we shall look at is the network latency as illustrated in figure 4. where the network latency is plotted in the graph of latency (ms) per device: baseline vs. AI optimized. This Bar Chart graphically contrasts the simulated average latency, per individual sensor and sprinkler device within the smart farm network when run under the following two conditions: the Baseline (non-optimized with AI) and the AI Optimized scenario. The blue bars are the baseline latency and the orange bars are the latency with the AI optimization. One of the evident patterns in the graph is that the orange bars are less than the blue ones in most of the devices. It implies that the latency of communication at the device level is greatly reduced due to the conceptual AI optimization. The responsive smart farm system requires lower latency since this helps sensors to report data faster and also the sprinklers to execute commands faster. Similar findings have been reported by Liu et al. (2020), who demonstrated that fog-based processing and distributed computing can help reduce data-processing latency in Industrial Internet of Things (IIoT) environments. Furthermore, Ramli et al. (2020) highlighted the importance of adaptive communication mechanisms in maintaining network performance and reducing latency in IoT-based smart farm systems. These studies support the importance of adaptive network optimization for improving communication responsiveness in agricultural IoT applications (Liu et al., 2020; Ramli et al., 2020).

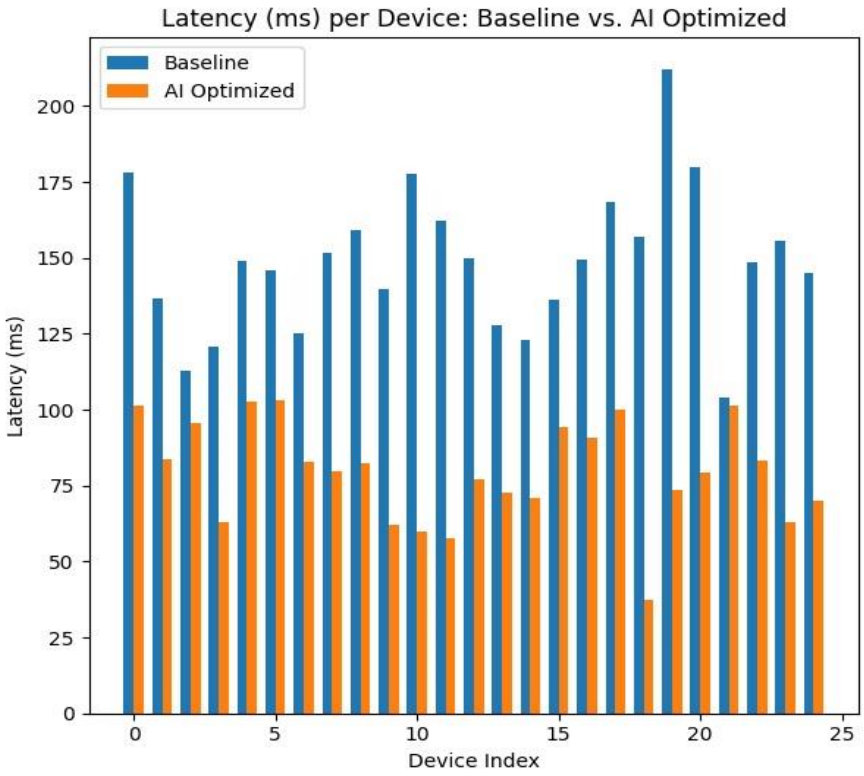

Figure 4. Simulated Network Latency per Device: Baseline vs. AI Optimized

Throughput

The throughput is the other important network performance metric as shown in figure 5, which shows side by side comparison of simulated average throughput of each of the sensor and sprinkler devices in the Baseline and the AI Optimized scenario. As can be seen in the graph, orange bars are in general higher than blue bars on most devices. It means that the presence of the AI optimization increases the effective data transfer rate at the level of the device. The better throughput will help to manage the flow of data collected by numerous sensors and effectively transmit commands to sprinklers, which will make the smart farm network more efficient. The importance of optimizing communication protocols and data transmission efficiency in smart agriculture has also been emphasized by Tao et al. (2021), who reviewed IoT communication technologies and their suitability for agricultural applications. Similarly, Zhang et al. (2022) demonstrated the relevance of bandwidth-efficient AI inference mechanisms for improving data transmission efficiency in IoT-based edge computing environments. These findings support the role of intelligent communication optimization in improving network throughput and facilitating efficient data exchange among connected agricultural devices (Tao et al., 2021; Zhang et al., 2022).

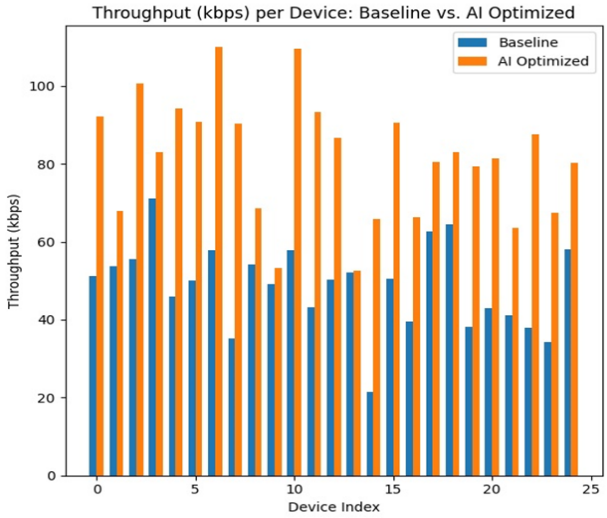

Figure 5. Simulated network throughput per device: baseline vs. AI optimized

Packet loss

In the figure 6, the performance of the packet loss is shown. The most evident finding of the graph is that orange bars are always lower than the blue ones in a considerable number of devices. This proves that conceptual AI optimization is linked to less packet loss on the device level. Reduced packet loss is a key requirement in terms of reliability of the smart farm network, the correct reception of the data transmitted by the sensors, and the transmission of important control commands to the sprinklers without being lost. Ramli et al. (2020) reported that adaptive network mechanisms can improve communication reliability in smart farm environments affected by network interference. Similarly, Wang et al. (2024) investigated an improved adaptive data rate algorithm for LoRaWAN-based agricultural sensor networks, highlighting the importance of dynamically adjusting communication parameters to improve transmission performance. These findings emphasize that adaptive communication strategies are important for reducing transmission failures and maintaining reliable connectivity in agricultural IoT networks (Ramli et al., 2020; Wang et al., 2024).

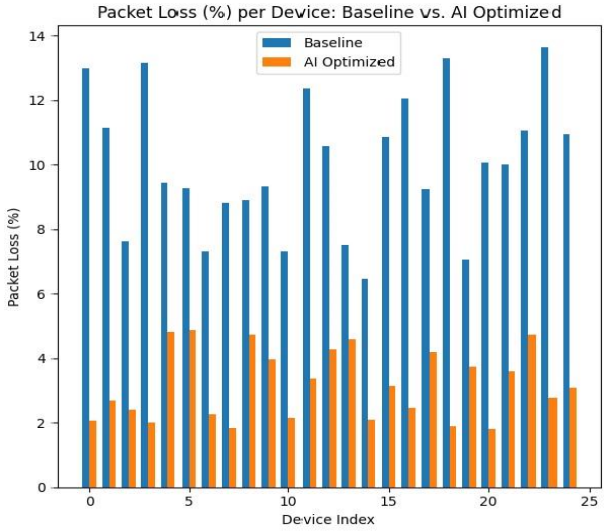

Figure 6. Simulated network packet loss per device: baseline vs. AI optimized

Accuracy and loss

The accuracy and loss graphs in figures 7 and 8 evaluate the performance of the AI model in the process of training. The AI Model Accuracy plot indicates that the training and validation accuracy tend to rise throughout the 50 epochs, which points to the fact that the model is learning to give accurate predictions. The training accuracy is about 95%, the validation accuracy is about 92%, so there is no substantial overfitting. On the other hand, the AI Model Loss curve indicates that the training and validation loss decreasing tendency over the epochs. The training loss reduces to about 0.05 and the validation loss reduces to about 0.15. Such a decrease in loss indicates that the model is getting progressively closer to the correct labels, and is also evidence of successful learning. The use of training and validation performance metrics is

an established approach for evaluating the learning behaviour and generalization capability of machine learning models. Ben-David & Frank (2009) discussed the evaluation of machine learning models using accuracy-based performance measures. Furthermore, the importance of monitoring communication and computational performance in optimized AI-enabled edge systems has been discussed by Caiazza et al. (2021). The observed increase in accuracy and reduction in loss in the present study therefore provide useful evidence of the model's learning progress and predictive performance.

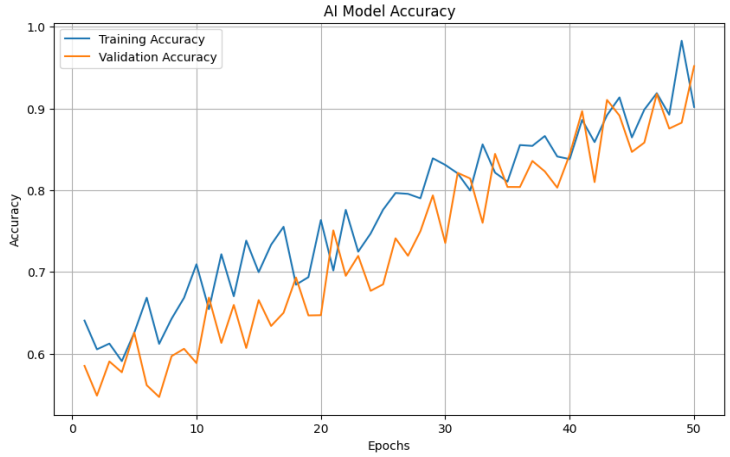

Figure 7. AI model accuracy

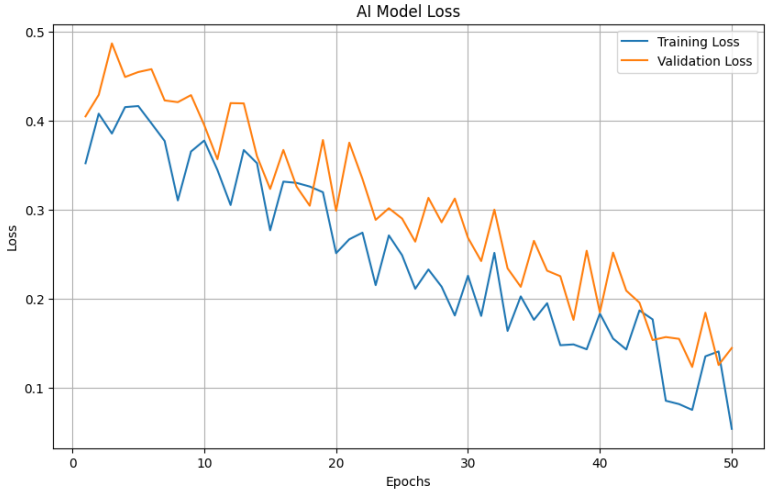

Figure 8. AI model loss.

Conclusion

This project was about the possibility of introducing AI into a smart farm IoT network through the use of LoRaWAN technology. We set up a simulation of a farm, including sensors, sprinklers, and a server, and chose LoRaWAN because of its appropriateness in the agricultural environment that needs long-range and low-power communications. The results showed that the integration of AI might result in a significant network responsiveness, data transfer efficiency, and communication reliability enhancement at the device level by comparing simulated performances (latency, throughput, packet loss) of a network with baseline and AI-optimized conditions. The performance of the AI model was also measured according to conventional metrics, which shows that the accuracy is high, and the loss is low, which points to its possible efficiency in data-driven decision-making in such tasks as irrigation. Ultimately, this discussion implies that the application of AI in smart farm IoT networks has much potential at improving their performance.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author contributions

The author conceived and designed the study, developed the research methodology, conducted the simulation experiments, collected and analyzed the data, interpreted the results, and prepared the original manuscript. The author reviewed and approved the final version of the manuscript.

Ethics

Ethical approval was not required for this study, as it involved computer-based simulations and did not include human participants or animal subjects.

Data availability

The data supporting the findings of this study were obtained from the simulation experiments conducted as part of this research.

AI tool usage declaration

The authors declare that no generative AI tools were used to generate the original research data, experimental results, or scientific conclusions presented in this manuscript. The AI techniques discussed and evaluated in this study are part of the research methodology itself.

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