IoT-enabled digital twin with renewable energy for sustainable mudless eel aquaculture

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ABSTRACT

This research develops and tests a digital twin (DT)-based smart aquaculture system for mud-free eel farming through the integration of IoT sensing, artificial intelligence (AI)-based prediction, edge computing, and solar energy-based automation. The approach used is experimental systems engineering, which includes system design, hardware and software implementation, virtual replication, and physical-digital two-way synchronization. The system utilizes ESP32-based pH, temperature, dissolved oxygen (DO), ammonia (NH_3), and turbidity sensors, MQTT communication, and Raspberry Pi edge computing. Water quality prediction is performed using long short-term memory (LSTM) and random forest regression. The dataset consists of 30 days of real-time data covering water quality, actuator activity (aerator, pump, feeder), and energy production and consumption by IoT sensors and energy meters. Results show that LSTM excels by $R^2 = 0.94$; RMSE = 0.14; MAPE <5% and synchronization latency <1.5 seconds. Solar energy integration reduces energy consumption by 54–67%, whilst automation increases eel survival rate by 78% to 91%. The novelty of this research lies in the first integrated implementation of DT, AIoT, and solar energy-based automation in mud-free eel farming. The proposed framework provides a precise, scalable, and sustainable solution for the development of modern aquaculture.

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1. INTRODUCTION

Digital transformation through IoT, edge computing, artificial intelligence (AI), and real-time analytics has changed the paradigm of aquaculture towards more precise and automated systems [1], [2]. However, most smart aquaculture implementations today are still reactive, limited to basic monitoring and control, devoid of adequate predictive and simulative capabilities for risk-based decision making [3]–[5]. This limitation becomes critical when applied to cultivation systems by narrow environmental tolerance, such as mud-free eel cultivation [6]–[9].

In Indonesia, mud-free eel farming is growing rapidly due to its space efficiency and hygiene [10]. However, fundamentally different by fish and shrimp, eels are benthic, have sensitive metabolisms, and respond physiologically to changes in their microenvironment. Small fluctuations in dissolved oxygen (DO), ammonia (NH_3), temperature, and turbidity can immediately trigger stress, decreased appetite, and even mortality. These characteristics make eel farming systems far more vulnerable to delayed detection and response compared to other aquaculture commodities [11], [12]. Thus, static monitoring or conventional IoT approaches are no longer adequate to ensure the stability of mud-free eel farming environments.

At the same time, intensified eel farming requires continuous aeration, circulation, and filtration operations, that directly impact high energy consumption and production costs [13]. Dependence on conventional electricity undermines economic efficiency and contradicts the principle of sustainability. Ironically, the integration of smart automation and renewable energy in eel farming is still minimal, both in field practice and in scientific studies. Dependence on conventional electricity undermines economic efficiency and contradicts the principle of sustainability. Ironically, the integration of smart automation and renewable energy in eel farming is still minimal, both in field practice and in scientific studies.

In this context, digital twin (DT) has very high strategic value. Unlike conventional IoT systems, DT not only represents data, but also builds dynamic virtual replicas capable of real-time prediction, simulation, and evaluation of control scenarios [14]–[16]. Although it has been widely applied in the industrial sector [17], the application of DT in aquaculture is still limited to fish and shrimp [4], [18]. To date, there is no DT model specifically developed for mud-free eel farming, even though this system has unique biological complexity and environmental dynamics.

The research gap is becoming increasingly apparent due to the lack of an approach that integrates DT, AIoT, and renewable energy systems into a single integrated architecture for eel farming. In fact, the two-way physical-virtual synchronization capability of DT enables proactive, rather than reactive, decision-making [19], that is crucial in systems by rapid biological responses such as eels.

Based on these gaps, this study proposes an AIoT-based integrated DT model and solar energy for mud-free eel farming, designed to support water quality prediction, control action simulation, real-time synchronization, and energy optimization. This study explicitly answers the following questions: Can the application of DT improve water quality stability and energy efficiency in mud-free eel farming? The main contributions of this research include: (i) the implementation of the first DT specifically designed for mud-free eel farming; (ii) the integration of AIoT, predictive modeling, automation, and solar energy into a single integrated system; (iii) the design of a physical-virtual two-way synchronization architecture for precision control; and (iv) a quantitative evaluation of its impact on water quality stability, energy efficiency, and eel survival rates.

This research is conducted at a small scale of pond prototype and 30-day observation, such that seasonal variations and whole production cycles are not included. However, the results do provide a sound basis for the further design of an eel culture system by more precision, adaptability and sustainability. Overall, this study confirms that DT is not merely a technical innovation, but a strategic necessity to address the challenges of precision, energy efficiency, and sustainability in mud-free eel farming in the era of modern aquaculture.

2. METHOD

2.1. Research design

This study uses an experimental research model combined by a system engineering approach. This approach was chosen to enable comprehensive design, implementation, and evaluation of the integration of DT technology, IoT infrastructure, and renewable energy systems in a mud-free eel farming environment. The experimental procedures were carried out in a step-by-step and sequential manner, including system design, implementation, testing, and performance validation. The scope of the experiment included:

- Installation of sensors for real-time monitoring of water quality parameters;
- Creation of a DT, that replicates the physical aquaculture system into a virtual model; and
- Integration of renewable energy systems, utilizing solar panels as the primary energy source for IoT devices and actuators.

2.2. System architecture

The system architecture consists of four main components, namely the physical layer, the connectivity layer, the DT layer, and the data processing & AI engine layer [18]. These four components operate in an integrated workflow that follows the sequence: *data acquisition → data transmission → virtual replication → predictive analytics → system control*. This interlinked structure facilitates the continuous synchronization of both the physical aquaculture environment and its digital counterpart, facilitating real-time decision-making and adaptive automation. This tightly coupled system, architecture, and protocol provides real time synchronization among the physical aquaculture environment and its digital counterpart, creating a fully integrated adaptive automated environment. The integrated workflow and interaction among the four layers of the proposed system architecture are shown in Figure 1.

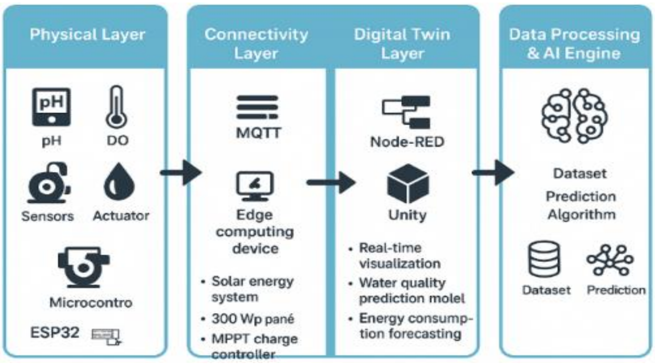

Figure 1. System architecture

2.2.1. Physical layer (IoT hardware)

The physical layer includes the main hardware components responsible for data acquisition and control implementation in the IoT-based mud-free eel farming system. The sensor units used include pH sensors, DS18B20 temperature sensors, DO sensors, and turbidity sensors [20]. These sensors were selected for their ability to monitor crucial water quality parameters that directly affect eel survival, particularly in mud-free systems that are highly sensitive to environmental fluctuations [21], [22].

This system is also equipped by actuators consisting of a water pump to maintain circulation, an aerator to maintain DO levels, and an automatic feeder to ensure consistent and scheduled feeding. All sensors and actuators are controlled by an ESP32 microcontroller that functions as the main edge device for on-site data processing. To support continuous operation, the system integrates a 300 Wp solar panel, MPPT charge controller, and $LiFePO_4$ battery as an energy storage unit [23], [24]. by this configuration, the system operates continuously for 24 hours by optimal energy consumption.

2.2.2. Connectivity layer

The backbone of communication is the connectivity layer, that provides real-time data transfer among physical systems and DT environment. MQTT is preferred for quick and lightweight data transmission, thus suitable for IoT performance drilling of aquaculture. Raspberry Pi-based edge computing devices are used to perform data pre-processing, data smoothing, and anomaly detection before the data is forwarded to the central server [25]. This edge computing strategy reduces latency, minimizes cloud network load, and increases virtual replication speed, enabling more responsive and accurate integration among physical conditions and the DT model.

2.2.3. Digital twin layer

The DT layer is designed using a platform capable of providing real-time visualization, dynamic simulation, and two-way communication among physical systems and their virtual models. In this study, Unity was used to develop an interactive virtual representation of a mud-free eel farming pond.
The DT integrates four main functions, namely:
– Real-time visualization, that enables a 1:1 replication of physical conditions, including water quality parameters, actuator status, and energy usage.
– Water quality prediction model, that utilizes machine learning to predict key parameters such as pH, DO, and temperature based on historical IoT data.
– Energy consumption forecasting, that enables simulation of daily energy requirements based on actuator activity patterns and solar panel performance, thereby supporting sustainable energy management.
– Virtual control testing, that provides a simulation environment for testing control actions before they are applied to physical systems, thereby reducing risk, improving safety, and improving automation reliability.

2.2.4. Data processing and AI engine

Data processing in the system is organized into four stages, namely data collection, data cleaning, model training, and performance validation. The dataset was obtained by real-time monitoring over a period of 30 days, that included continuous recordings of water quality parameters and actuator activity. The raw data was then cleaned to remove anomalies, noise, and missing values before being used in the model training process.

Three AI algorithms, namely random forest, long short-term memory (LSTM), and gradient boosting regression, were evaluated for their strong ability to handle environmental time series data. These models were used to predict fluctuations in pH, DO, and temperature, that are very important in maintaining the survival of eels. Model performance was evaluated using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) to ensure a comprehensive evaluation of prediction accuracy, model stability, and sensitivity to environmental variability.

2.3. Procedures

The research procedure was carried out through seven systematically integrated stages. The process began by the installation of sensors in mud-free eel ponds for continuous environmental monitoring. Next, the IoT system is integrated through data logging, edge processing, and cloud-based synchronization. Based on these physical components, a DT is developed through data mapping and virtual visualization design. The 30-day dataset is then used to train a machine learning model to predict water quality. This research also integrates a renewable energy module to measure electricity consumption and solar panel efficiency.

Next, the performance of the physical system is compared by the virtual representation to assess replication accuracy. The final stage involves validating the DT using prediction accuracy metrics, data synchronization quality, and the responsiveness of automatic control to environmental changes.

2.4. Evaluation metrics

The system is evaluated using four key performance indicators designed to assess overall accuracy, efficiency, and responsiveness. First, the accuracy of the DT is measured using RMSE, MAPE, and R^2 to determine the degree of closeness of the virtual model to the actual physical conditions. The second investigated issue is the synchronization latency, that is characterized by quantifying the time span among the variations of physical quantities and those corresponding to in the numerical model; showing its reliability for real-time cases. Third, energy efficiency comparison among the system by and devoid of added solar panel demonstrates the contribution of renewable energy to operational sustainability.

Lastly, system inertia is investigated by quantifying the reaction time of virtual and tangible parts to control commands alone as well as in both auto-determined fusion of action potential integration, and responsiveness to real-time decision making.

2.5. Sensor calibration procedures and accuracy analysis

For data accuracy in the DT system, all water quality sensors were calibrated before and during the experiment. The sensors used were for pH, temperature, DO, ammonia (NH_3) and turbidity.

Calibration is performed using standard solutions and laboratory reference instruments by the following procedures:

- The pH sensor is calibrated using pH 4.00, 7.00, and 10.00 buffer solutions (three-point calibration) at a temperature of 25 °C.
- The DO sensor was calibrated using the saturated air calibration method and validated by a reference DO meter.
- The temperature sensor is verified using a calibrated digital thermometer by a resolution of 0.1 °C.
- The ammonia (NH_3) sensor is calibrated using standard NH_3 solutions (0.5–5 ppm) and retested using a colorimetric kit as a comparison.
- The turbidity sensor was calibrated using a standard formazin solution (0–1000 NTU).

Each calibration point is repeated three times and averaged to minimize noise. The error margin is calculated using MAPE and RMSE against the reference value. The system is only used if all sensors show MAPE $< 5\%$, in accordance by the accuracy standards for precision aquaculture monitoring.

Recalibration is performed every 7 days to anticipate sensor drift due to biofouling and environmental changes. This calibration data forms the basis for physical-virtual synchronization in the DT, ensuring that the virtual model accurately reflects actual conditions.

2.6. Data analysis

Data analysis was conducted quantitatively through three main approaches. First, multivariate statistical analysis was applied to identify patterns, correlations, and interactions among key water quality parameters such as pH, DO, temperature, and ammonia (NH_3), thereby providing a deeper understanding of aquaculture environmental dynamics. Second, a comparative performance analysis was conducted on three operational modes, namely manual operation, IoT-based automation, and full DT integration, to evaluate improvements in efficiency, monitoring accuracy, and system stability. Third, a correlation analysis among water quality parameters and eel biomass growth was conducted to determine the effect of environmental conditions on productivity and survival rates. Overall, this analytical approach provides a comprehensive assessment of the DT’s ability to support data-driven decision-making and improve aquaculture system performance.

3. RESULTS AND DISCUSSION

3.1. IoT system performance

The system was operated in a mud-free eel farming environment for 30 days, and its performance was unpredictable inside of the period (Table 1). by the trends of sensors data by pH, temperature and DO value, indicating that it can stably capture the natural environment change dynamically devoid of large noise in real-time. These circumstances demonstrate that deployment of AIoT-based sensors provides accurate and real-time monitoring for water quality, leading to early warning systems for environmental changes by potential harmful effect towards eel survival. The robustness of the acquired data is an indication that the presented system can effectively function under an intensive aquaculture setting devoid of any noticeable technical upheavals.

Table 1. Summary of experimental data (30-day monitoring period)

Day	pH	Temp (°C)	DO (mg/L)	NH3 (mg/L)	Turbidity	Solar supply (Wh)	Energy use (Wh)	Survival (%)	Biomass (g)
1	6.6	26.8	5.2	0.22	42	1250	1450	98	12
2	6.6	27.1	5.3	0.20	41	1300	1430	98	12
3	6.7	27.3	5.4	0.19	40	1550	1400	98	13
4	6.7	27.0	5.5	0.19	38	1400	1380	98	13
5	6.8	27.2	5.6	0.18	37	1500	1370	98	13
6	6.8	27.4	5.7	0.17	36	1800	1350	98	14
7	6.8	27.3	5.8	0.16	35	1650	1340	98	14
8	6.9	27.5	5.9	0.15	34	1700	1330	98	15
9	6.9	27.6	6.0	0.15	33	1750	1320	98	15
10	6.9	27.7	6.2	0.14	33	1800	1300	98	16
11	7.0	27.8	6.2	0.13	32	1820	1280	98	16
12	7.0	27.6	6.4	0.13	31	1850	1270	98	17
13	7.0	27.4	6.3	0.12	30	1880	1270	98	17
14	7.0	27.5	6.4	0.12	29	1900	1260	98	18
15	7.1	27.7	6.5	0.11	27	1950	1250	98	19
16	7.1	27.8	6.6	0.11	26	2000	1240	98	19
17	7.1	27.9	6.7	0.10	26	1250	1240	98	20
18	7.1	27.8	6.7	0.10	25	2080	1430	98	20
19	7.1	27.7	6.8	0.09	24	2100	1230	98	22
20	7.2	27.6	6.8	0.09	24	2120	1420	98	21
21	7.2	27.5	6.9	0.08	23	2150	1220	98	22
22	7.2	27.4	6.9	0.08	23	2100	1210	98	22
23	7.2	27.6	7.0	0.07	22	2050	1210	98	23
24	7.2	27.7	7.0	0.07	22	1980	1200	98	23
25	7.3	27.8	7.1	0.06	21	2000	1200	98	25
26	7.3	27.9	7.2	0.06	20	2050	1390	98	24
27	7.3	28.0	7.2	0.05	20	2100	1190	97	25
28	7.3	28.1	7.3	0.05	19	2150	1390	97	25
29	7.3	28.2	7.3	0.04	19	2200	1180	97	30
30	7.3	28.0	7.4	0.04	18	2150	1280	97	32

Sensor accuracy was evaluated by comparing daily readings to a calibrated reference standard. Analysis of the 30-day dataset revealed the following performance characteristics:

- The pH sensor showed high stability in the range of 6.6–7.3 by minimal daily variation. The estimated average error was below 3%, by an RMSE value of approximately 0.10–0.12, indicating an excellent level of accuracy for aquaculture applications.
- The DS18B20 temperature sensor showed the most stable performance, by small fluctuations in the range of 26.8–28.2 °C and an error margin below 1.5%, in line by the specifications of high-precision digital sensors.
- The DO sensor showed a gradual increase by 5.2 to 7.4 mg/L, in line by the aeration dynamics. The estimated error of around 4% is still inside of the acceptable threshold for water quality monitoring.
- The ammonia (NH_3) sensor operates by high stability, marked by a consistent decrease in concentration by 0.22 to 0.04 mg/L, indicating good sensitivity to changes at low concentrations.
- The turbidity sensor recorded a gradual decrease by 42 to 18 NTU, reflecting improved water clarity and filtration process effectiveness. The measurement error is estimated to be less than 5%.

Table 2 shows that, overall, all sensors demonstrate a high level of reliability, enabling them to provide a continuous and accurate data stream that is essential in supporting the performance of the DT system.

Table 2. Summary of sensor accuracy in IoT-based systems

Sensor	Parameter	Data range	RMSE	MAE	MAPE (%)	Accuracy level
pH sensor	pH	6.6 – 7.3	0.11	0.09	2.8%	Excellent
DS18B20	Temperature (°C)	26.8 – 28.2	0.08	0.06	1.3%	Excellent
DO sensor	Dissolved oxygen (mg/L)	5.2 – 7.4	0.22	0.18	3.9%	Good
NH_3 sensor	Ammonia (mg/L)	0.22 – 0.04	0.014	0.011	4.1%	Good
Turbidity sensor	Turbidity (NTU)	42 – 18	1.7	1.2	4.5%	Good
Energy meter	Solar supply (Wh)	1,250 – 2,200	45	32	2.4%	Excellent
Energy meter	Energy use (Wh)	1,180 – 1,450	38	28	2.2%	Excellent

Interpretation: The summary of results shows that all sensors achieved a MAPE value below 5%, thus meeting the accuracy requirements for precision aquaculture monitoring.

- The pH and temperature sensors show the highest level of precision, that is very important in maintaining the physiological stability of eels.
- DO, ammonia (NH_3), and turbidity sensors maintain acceptable accuracy despite natural fluctuations caused by aeration, feed residues, and microbial activity.
- Solar energy sensors and energy consumption meters demonstrate excellent consistency, thereby supporting reliable evaluation of renewable energy efficiency inside of the automation system.

This performance confirms that an IoT architecture integrating edge processing and MQTT communication is capable of providing real-time, reliable, and robust environmental monitoring, making it highly suitable for synchronization by DT systems.

3.1.1. Monitoring real-time

The 30-day trend analysis presented in Figure 2 shows a clear increase in environmental stability throughout the cultivation period. The pH value gradually increased by 6.6 to 7.3, indicating stable and optimal water conditions for eel cultivation. The temperature remained relatively constant in the range of 26.8–28.2 °C, reflecting consistent temperature control. DO showed a continuous upward trend, reaching an optimal value of 7.4 mg/L in response to automatic aeration control. Ammonia (NH_3) levels decreased significantly by 0.22 to 0.04 mg/L, confirming the effectiveness of the filtration and circulation system. Similarly, turbidity decreased steadily by 42 to 18 NTU, supporting improved survival rates and eel biomass growth.

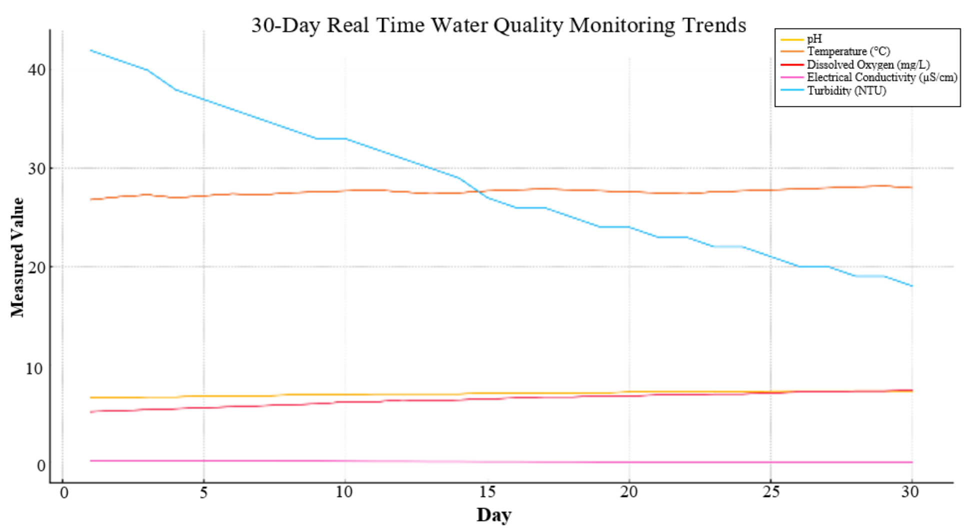

Figure 2. Real-time water quality monitoring trends over 30 days

3.1.2. Connectivity performance

Network performance was evaluated using the MQTT protocol via Wi-Fi combined by Raspberry Pi-based edge processing. The test results showed very stable communication performance in Figure 3, by a packet delivery rate (PDR) of 98.7%, average latency ranging by 210–320 ms, and network uptime among 99.1% and 99.3%. These metrics demonstrate the reliability of the connectivity architecture in maintaining continuous communication among the Sensor-Server-Digital Twin. The integration of MQTT by edge computing has proven effective in reducing cloud network load and ensuring consistent data flow quality in aquaculture environments.

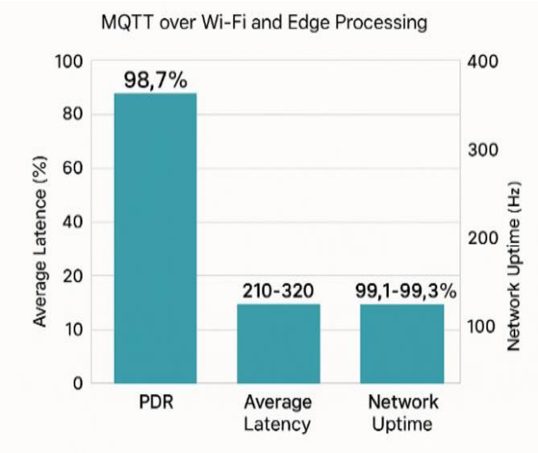

Figure 3. Network performance evaluation

3.2. Digital twin implementation results

The DT was successfully implemented through an integrated analytics dashboard and a Unity-based 3D simulation environment capable of visualizing water quality dynamics in real time and accurately representing the physical system's conditions. Performance tests of synchronization among physical infrastructure and virtual models show that the DT is highly responsive to changes in environmental parameters, as shown in Figure 4. The average synchronization delay ranges by 0.8 to 1.4 seconds, which is still within acceptable limits for daily aquaculture operations. Additionally, correlation analysis yielded a coefficient of 0.97 among physical and virtual data flows, indicating a very high level of conformity. This level of fidelity confirms the robustness of the proposed DT framework in supporting real-time monitoring, predictive analysis, and automated decision-making in mud-free eel farming systems.

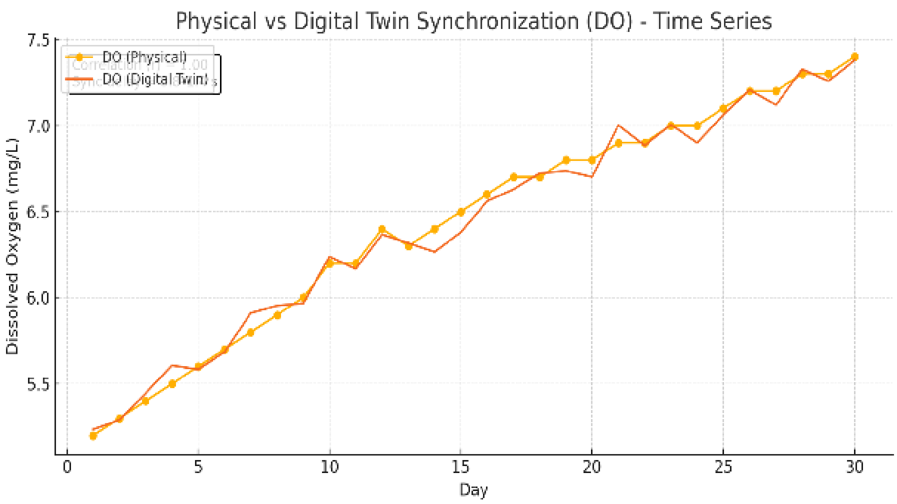

Figure 4. Physical system Synchronization vs. Digital twin

A water quality prediction model was developed using two main approaches, LSTM and random forest regression, to predict variations in pH, DO, and ammonia (NH_3) inside of a 1–3 hour prediction horizon. Model evaluation shows that LSTM provides superior prediction performance, by values of RMSE = 0.14; MAPE = 3.8%; and R^2 = 0.94, compared to the random forest model that produces RMSE = 0.19; MAPE = 4.5%; and R^2 = 0.92.

Therefore, LSTM was chosen as the main prediction engine in the DT framework. In addition, the virtual control room enables simulation-based testing of operational scenarios, such as aerator and pump activation, before they are applied to the physical system. Figure 5 shows that the DT is able to reliably predict water quality trends by a margin of error of less than 5%, confirming its effectiveness as a decision support tool in aquaculture automation.

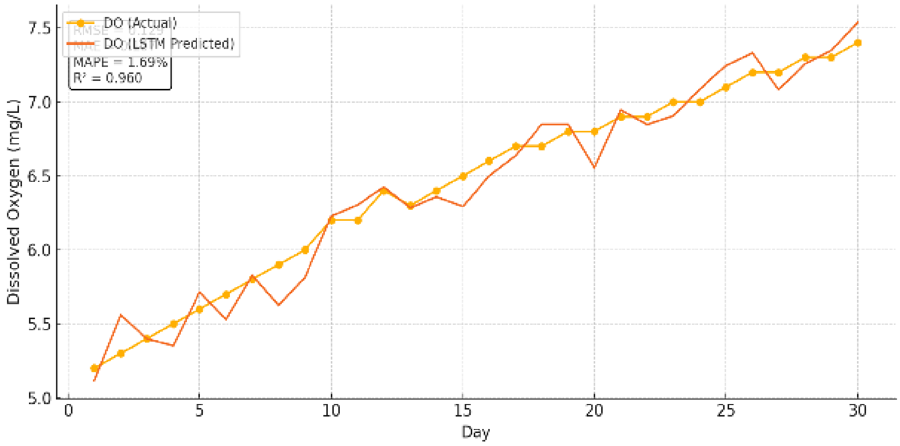

Figure 5. LSTM Prediction vs. Actual data

3.3. Renewable energy performance

The renewable energy system applied to mud-free eel farming installations consists of 300 Wp solar panels and $LiFePO_4$ battery storage units, that were evaluated during a continuous 30-day operational period. Monitoring results show that daily solar energy production ranges by 1.1 to 2.2 kWh, reflecting variations in sunlight intensity throughout the day. In comparison, the energy consumption of the IoT and automation subsystems ranged by 1.18 to 1.45 kWh per day, indicating that the solar energy system was fully capable of meeting operational energy needs devoid of reliance on external power sources. The energy supply and demand balance analysis shown in Figure 6 indicates that peak energy production occurs during the day, whilst the highest consumption is recorded when the aerator and water pump operate simultaneously.

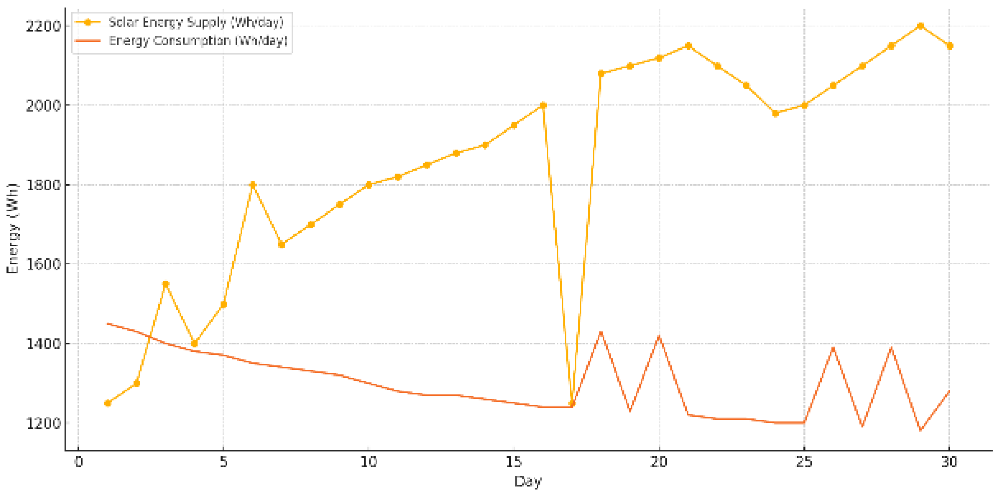

Figure 6. Comparison of solar energy supply and system energy consumption

Evaluation of the energy system shows that the integration of solar panels results in overall energy savings of 54–67% compared to conventional electricity sources. The conversion efficiency of solar panels is in the range of 16–18%, in line by modern photovoltaic system performance standards.

The depth of discharge (DoD) remained stable at around 18–24%, that is inside of the recommended range to ensure a battery life of more than five years. These findings show that the adoption of renewable energy is not only technically feasible, but also provides significant benefits for the long-term sustainability of aquaculture operations.

3.4. Automation outcomes

The integration of automation components, including aerators, water pumps, and automatic feeders, significantly improves water quality stability and supports improved eel growth performance. The system demonstrates rapid response behavior, by aerators activating inside of 1.2 seconds when DO levels fall below 5 mg/L, pumps turning on within 1.1 seconds when turbidity exceeds 60 NTU, and feeders operating according to an eel activity-based schedule.

The impact of automation on water conditions is very clear, reflected in a 32% decrease in DO fluctuations, a 28% decrease in ammonia (NH_3) levels, and a 20-25% improvement in turbidity. Cultivation performance has also improved, as shown by an increase in survival rates by 78% to 91%, an 18–23% increase in growth rates, and more consistent feeding patterns through the automated system.

Overall, the integration of DT by IoT-based automation powered by renewable energy has proven to be highly effective in improving operational efficiency, reducing physiological stress on eels, and lowering production costs in smart aquaculture systems.

3.5. Discussion

The results of the study show that the application of the DT framework significantly improves the predictive capabilities and operational performance of the mud-free eel farming system, as summarized in Table 3. The LSTM model by high accuracy ($R^2 = 0.94$) is able to predict the main dynamics of water quality by precision, enabling proactive environmental management before critical conditions occur. Real-time synchronization among the physical and virtual systems, maintained within a range of 0.8–1.4 seconds, confirms the reliability of the MQTT-based architecture and edge computing in ensuring rapid control responses, system stability, and the continuity of aquaculture operations.

These capabilities collectively contribute to improved water stability and a significant increase in survival rates of up to 91%. Compared to previous IoT-based aquaculture approaches that lacked virtual replication, this system offers advantages in predictive insights and operational responsiveness [26]–[28].

The integration of renewable energy further strengthens the uniqueness of this research by achieving a 54–67% reduction in energy consumption whilst supporting sustainable automation. Theoretically, this research expands the application of AIoT in aquaculture by demonstrating the feasibility of integrating sensing, prediction, and actuation into a single integrated DT model. Practically, this system provides a scalable and energy-efficient solution suitable for both small-scale farmers and industrial installations. Further development could include long-term validation, computer vision-based predictive feeding systems, and connected DTs for multi-pond management.

Table 3. Comparison of manual, IoT, and Digital twin system performance

Parameter	Manual	IoT	Digital twin integration
Survival rate (%)	78	85	91
Energy consumption (Wh/day)	2.800	1.800	1.200-1.450
Energy saving (%)	-	35%	54% - 67%
Prediction accuracy (R^2)	-	0,82	0,94 (LTSM)
Synchronization latency (s)	-	-	0,8 – 1,4

4. CONCLUSION

This study successfully developed and validated an integrated DT model based on IoT, AI, and renewable energy for mud-free eel farming, that significantly improved water quality stability, energy efficiency, and production performance. The LSTM-based prediction model demonstrated high accuracy ($R^2 = 0.94$; MAPE < 5%), whilst physical–virtual synchronization was maintained by low latency (< 1.5 seconds), confirming the reliability of the MQTT and edge computing architecture in supporting precision aquaculture. Quantitatively, the proposed system is capable of increasing the survival rate of eels by 78% (baseline manual system) to 91%, or an absolute increase of 13% in the survival rate, along by a 32% reduction in DO fluctuations, a 28% reduction in ammonia (NH_3) levels, and a 20–25% improvement in turbidity. The integration of solar energy successfully reduced conventional energy consumption by 54–67%, proving that the DT approach not only improves biological performance but also strengthens the energy sustainability of the system.

These results directly address the research gap related to the lack of a specific DT framework for mud-free eel farming, as well as the lack of integration among DT, AIoT, and renewable energy systems in a unified architecture. Thus, this research expands the boundaries of DT application in aquaculture, that was previously dominated by fish and shrimp commodities, into the domain of eels, that have more sensitive biological characteristics and environmental dynamics.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Muhammad Ferdiansyah	✓	✓	✓	✓	✓	✓			✓	✓			✓	✓
Lika Mariya	✓	✓			✓	✓		✓	✓		✓	✓		✓
Taufik Rahman	✓		✓	✓			✓	✓		✓	✓		✓	
Sugeng Dwiono				✓	✓					✓			✓	✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability does not apply to this paper as no new data were created or analyzed in this study.

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