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Fuzzy energy management strategies for energy harvesting IoT nodes based on a digital twin concept

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ABSTRACT

This study presents a cloud-assisted energy management strategy for energy harvesting Internet-of-Things (IoT) nodes, using a novel digital twin (DT) concept for dynamic optimization of IoT node behavior. The system is built upon a fuzzy-rule-based controller optimized through a differential evolution (DE) algorithm. DE is particularly well-suited for this application, as it is capable of optimizing the controller without requiring gradient information, allowing it to efficiently navigate the complex, nonlinear characteristics of IoT energy management problems. The optimization process tunes nine key fuzzy input coefficients to create an energy-efficient control strategy. The DT concept serves as a virtual replica of the physical IoT node, continuously synchronizing real-time data from sensors and other internal parameters, including energy harvesting rates and component health. Through this real-time feedback loop, the DT enables predictive adjustments to the control system, increasing the longevity and reliability of the IoT devices in harsh and changing environments. Compared to traditional energy management strategies, the proposed method improves energy utilization by 11%, leveraging four years of solar data collected from multiple geographical locations. Moreover, the system achieves a 12% increase in successful transmissions, ensuring greater data availability in the cloud while minimizing device failures and optimizing the use of available energy. The DT concept allows the system to simulate and predict IoT node behavior under various conditions, continuously refining the energy management strategy. This ensures not only optimal energy efficiency but also accounts for component degradation over time, offering long-term adaptability and minimizing the need for manual intervention. Thus, the synergy between the DT concept and DE optimization offers a powerful, scalable solution for managing energy-constrained IoT networks, surpassing conventional expert-designed strategies in both adaptability and performance.

1. Introduction

The Internet-of-Things (IoT) provides many options for interconnecting a range of sensory devices which collect and transmit data in real time. In environmental monitoring, the use of IoT sensors equipped with energy harvesting technology [1,2] predominates because the regular maintenance required due to the depletion of the power sources is eliminated [3]. The application of energy management technologies opens up many research challenges, for example the selection of suitable energy sources or the development of dynamic energy management strategies to eliminate sensor outages and maximize useful operation [4]. Solar radiation [5], heat [6], wind [7], vibrations [8] and radio frequencies [9] provide suitable energy sources, each with different availability characteristics through their specific stochastic natures [10]. Designing appropriate energy management strategies is therefore crucial to effective operation of IoT nodes used for environmental monitoring [11].

The Digital Twin (DT) concept has emerged as a transformative technology, enabling dynamic optimization and real-time monitoring for systems such as IoT devices. A DT acts as a virtual replica of a physical asset, continuously synchronizing with real-time data to mirror the behavior and condition of its counterpart. This bidirectional data flow allows the DT to simulate, predict, and optimize the performance of the physical system throughout its lifecycle. In the context of energy-harvesting IoT nodes, the DT can analyze sensor data and system parameters to develop adaptive energy management strategies, even for aging components like supercapacitors or solar panels [12,13]. By leveraging cloud-based computational power, the DT framework allows for complex optimization processes to be executed remotely without burdening the energy-constrained IoT nodes [14]. This synergy

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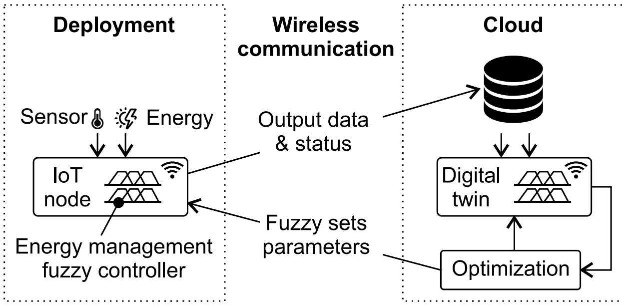

Fig. 1. Sensor DT concept for IoT-based energy harvesting devices: an optimal energy management strategy based on up-to-date, real data is located in a cloud.

between physical devices and their digital counterparts unlocks new potential for improving energy efficiency, maintaining performance, and ensuring longevity, especially in environments where energy resources are limited.

Fig. 1 illustrates the concept explored in this study, highlighting the integration of energy management and fuzzy logic control in IoT sensors. An IoT sensor is initially deployed with a default energy management strategy (default fuzzy set parameters), which is later adapted to varying operational conditions. The sensor collects data during regular operation and is powered by an energy harvesting subsystem. Simultaneously, it monitors internal states, such as input energy flow, state of energy storage (SoES), energy conversion efficiency, and the decrease in supercapacitor maximum capacity. These parameters, along with input energy data, are transmitted via an up-link communications channel to a cloud platform, where all data is stored. A DT implemented in the cloud uses the transmitted data to model the deployed IoT node's physical behavior. Computationally intensive optimization processes, including fine-tuning the fuzzy controller parameters, are conducted in the cloud to evaluate the device's field operation and determine an optimal energy management strategy. The optimized parameters and strategies are then transmitted back to the IoT node via a down-link communications channel. The fuzzy logic controller is implemented directly within the IoT node for real-time decision-making. Simultaneously, the DT includes a replica of the fuzzy controller, facilitating comprehensive analysis and parameter tuning in the cloud.

In the context of optimizing multi-objective problems, a many of approaches are available. Among these, evolutionary algorithms stand out for their capability to provide optimal solutions in energy management optimization which is well established research area [1]. This prowess stems from their inherent ability to function without rigid assumptions about the application domain. Specifically, the employment of Differential Evolution (DE) [15], a widely-utilized meta-heuristic, is a notable highlight of this contribution. One of the advantages of DE lies in its independence from the requirement of problem differentiability for gradient calculation. Given the nature of energy management strategies for IoT harvesting nodes, which defy conventional mathematical expressions, the application of DE becomes particularly pertinent. This approach opens up avenues for the evolution of optimal strategies grounded in diverse rule-based controllers, a facet that holds immense promise in this complex domain.

Based on a review of related works, the current study offers the following novel contributions:

- A cloud-based DT motivated approach of dynamic energy management strategies for energy harvesting IoT devices.
- An effective method of transmitting energy management parameters, fully aligned with low data transmission IoT communication standards, to a target device.
- A general framework for optimizing parameterized components (supercapacitors, solar cells, etc.) in IoT sensor nodes for effective future hardware design.

The paper is organized as follows: Section 2 presents related works, Section 3 describes the hardware model, input datasets, controller algorithms and performed experiments; Section 4 presents the experimental results obtained from training and testing processes; Section 5 discusses the results of the experiment in the context of the study's body of knowledge; Section 6 summarizes the paper's research and outlines possible future work.

2. Related works

Energy management controllers based on machine learning can be implemented at IoT nodes through a range of methods.

Table 1 lists related studies which have investigated machine learning methods applied in energy management scenarios and provides a comparison of these methods to the proposed DT concept. The use of machine learning techniques for energy management in IoT sensors powered by solar panels has led to advancements in optimizing energy consumption and enhancing operational efficiency. These methods are particularly important for maintaining the perpetual operation of sensors in energy-scarce environments. The literature highlights various approaches, categorized mainly into reinforcement learning and fuzzy logic systems.

Under the Reinforcement Learning (RL) category, several methods have been proposed. For instance, in the application of monitoring vital signs in the human body, [16] introduced a deep reinforcement learning-based duty cycle (DRDC) method. This approach controls the sensor activity at the base station using a Deep Q-Network (DQN), optimizing the duty cycle based on the sensed data's rate of change and the energy available. However, the sensor nodes themselves do not implement an energy management strategy, relying instead on the base station for control.

In the domain of battery-less wireless sensor networks, [17] proposed a reinforcement learning-based energy management controller that remotely manages the duty cycle. The controller operates at the server level, and the sensor node lacks its own energy management capabilities, making it fully dependent on external control . Similarly, [18] introduced a Q-learning-based wake-up scheduling mechanism for power-aware IoT devices. This method dynamically adjusts the control parameters to estimate future values of the energy supply, ensuring that the duty cycle adapts to the anticipated energy availability.

In the Fuzzy Logic and Neuro-Fuzzy Systems category, more advanced methods have been developed. [19] designed a dual battery management system using an adaptive neuro-fuzzy inference system (ANFIS). This system aims to extend the sensor node's lifespan by reducing battery degradation. The ANFIS model, however, is trained offline and does not update with new data during operation, limiting its adaptability.

Another fuzzy logic application is the dynamic duty cycle adaptation proposed by [20]. This approach uses fuzzy Q-learning for energy-neutral operation of wireless sensor nodes (WSNs). In contrast to other models, the learning process occurs at the node level, making it independent of cloud-based control. For flood and environmental monitoring, [21] proposed a method involving adaptive sampling of sensors using a fuzzy logic controller. However, the fuzzy sets are manually designed by experts, and no optimization process is integrated, restricting the adaptability of the system.

Finally, [22] introduced a more complex approach by combining fuzzy logic with differential evolution. In this method, the fuzzy controller is optimized offline using evolutionary algorithms to manage the dynamic duty cycling of environmentally powered wireless sensors. While this approach enhances efficiency, the transmission of the optimized control parameters presents challenges due to the offline learning process.

Table 2 provides a comparison of the related studies with the proposed approach. The individual studies are compared according

Table 1
State-of-the-art: Application areas and energy management methods applied in IoT sensors powered from solar panels, classified by machine learning approach.

Application	Energy management method	Machine learning approach	Comparison to DT concept
Reinforcement Learning			
Monitoring vital signs in the human body [16]	Sensor control at the base station	Deep reinforcement learning	Sensors are controlled over wireless communications. No energy management strategy for the sensor node.
Energy management in battery-less, wireless sensor networks [17]	Remote duty cycle management	Reinforcement learning	Energy management controller is fully implemented at the server level. The node has no controller.
Power-aware mobile monitoring IoT devices [18]	Wake-up scheduling	Q-learning	Control parameters are modified spontaneously. Energy is managed by estimating future values.
Fuzzy Logic and Neuro-Fuzzy Systems			
Dual battery wireless sensor networks [19]	Node lifespan extended by decreasing battery degradation	Adaptive neuro-fuzzy inference system	Model is trained offline. No updates according to new data.
Dynamic duty cycle adaptation for energy-neutral operation [20]	Adjustment of the duty cycle	Fuzzy Q-learning	Learning process performed at the node. No cloud-assisted control strategy.
Monitoring floods and the environment [21]	Adaptive sampling of sensors	Fuzzy logic controller	Fuzzy logic controller is not optimized; only expertly designed fuzzy sets are used.
Monitoring environmental parameters [22]	Dynamic duty cycling	Fuzzy controller optimized with differential evolution	Evolved controllers use offline learning. Controller parameters are not easy to transmit.

Table 2
Comparison of state-of-the-art methods to the proposed approach.

Author	Dynamic energy management	Machine learning	Online learned model	Cloud DT
Mohammadi et al. [16]	×	✓	×	×
Ahn et al. [17]	✓	✓	✓	×
Prauzek et al. [18,22]	✓	✓	×	×
Bathre et al. [19]	×	✓	×	×
Hsu et al. [20]	✓	✓	✓	×
Yazid et al. [21]	✓	✓	×	×
Presented approach	✓	✓	✓	✓

to their application of a dynamic energy management strategy, cloud DT, and machine learning process and type (e.g., the model is trained online or offline). The authors examined current studies on DT usage in the IoT area. However, none of the studies focused on applying a DT framework for developing energy management strategies. To the best of our knowledge, none of the previous papers considers this aspect, leaving a gap that the proposed approach aims to address. All of the related studies applied specific machine learning methods, such as reinforcement learning or fuzzy logic controllers combined with neural networks, to control energy management at the IoT node. While these studies implemented reinforcement learning and fuzzy Q-learning techniques as on-site online learning processes (which can also be pre-learned offline), only the proposed approach incorporates a cloud-based DT to optimize sensor parameters deployed in the field. The authors consider this idea novel.

3. Methods and data

This section describes the IoT sensor DT based concept, the study's hardware IoT model, the parameters applied to the simulation framework, and the historical environmental data collected from four locations in the Czech Republic. Details of the energy management controller, which is based on fuzzy sets and static duty-cycle controls, and the experimental methodology are also given.

3.1. IoT sensor DT concept

Ideal DT describes all aspects digitally of existing or future product. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its DT [23]. Generally, it is not possible to involve all aspects and create a perfect virtual copy of physical device. It is therefore always necessary to make certain simplifications, but these simplifications must not affect the desired functionality [24]. This digital information would be a "twin" of the information that was embedded within the physical system itself and be linked with that physical system through the entire lifecycle of the system [23].

In the area of IoT nodes, a dual challenge persists: preserving the energy efficiency of deployed physical sensor nodes while meeting user service demands [25]. This pursuit is complemented by a need for conceptual clarity concerning virtual sensors, encompassing their benefits and a hierarchical delineation spanning pure sensor virtualization to dynamic cooperative sensing [26]. Addressing the burgeoning landscape of IoT devices in smart homes, a solution emerges in the form of virtual sensors, offering a means to curtail device proliferation while sustaining functionality [27].

Table 3 presents the DT features and their alignment with the proposed solution. The table outlines ten fundamental attributes of the DT concept, elucidating the interconnection between digital and physical entities. Furthermore, these attributes encapsulate supplementary notions congruent with Industry 4.0 principles. The authors' objective is to seamlessly transpose these attributes into the area of IoT nodes and energy management strategies challenge. Presently, this endeavor incorporates a substantial portion of DT features, albeit at varying degrees of integration. Naturally, there exists potential for further enhancement, encompassing the complete implementation of all features or the expansion of the existing integration.

A key capability of the DT is its ability to answer "what if" scenarios. In our case, this can be applied to explore different hardware configurations and deployment conditions for IoT nodes. The DT allows

Table 3
DT features and compliance with proposed solution.

DT feature	IoT sensor paradigm impact	Currently integrated	Possible future extension
Real-time Representation	Real-time IoT node status monitoring and supervision.	Supercapacitor diagnostics, temperature measurement, state of charge, power consumption parameters.	Other components monitoring, e.g. sensors or DC/DC converters.
Data Integration	IoT node status monitoring and logging. IoT nodes behavior can be optimized based on historical trend.	Collection of solar radiation data, extension of a training data set in order to update an energy management model.	Integration of other energy harvesting techniques, such as thermal, wind, RF, etc.
Interaction and Simulation	Allows to simulate the IoT node energy management strategy in various conditions.	Various energy management strategies could be tested and the optimal one is selected.	–
Monitoring and Diagnostics	Monitoring of IoT node status and remote diagnostic.	Collecting IoT nodes status parameters.	Reactive and predictive maintenance could be performed on collected data.
Predictive Analysis	Predictive analysis based on IoT node status observations.	–	Predictive analysis of IoT node behavior and predict problems based on previous statuses.
Virtual Environment for Innovation	Possibility to design energy management solutions in virtual space.	The optimization process proposes new strategies based on the collected statuses.	–
Communication and Collaboration	Enables an open platform for designing energy management strategies.	–	Open software platform could be developed.
Scalability	It is possible use data from various sensors and locations.	–	Data from a sensor cloud can be processed and used to design new strategies.
Security and Data Protection	IoT sensors use networks that already implement security as the standard. Cloud solutions are also fully compliant with this requirement.	Already integrated as standard for cloud platforms and LPWANs.	–
Lifecycle Coverage	Design of the optimal energy management solution and its adaptability during deployment.	Design, implementation, and deployment optimization.	Maintenance and disposal.

the hardware model to simulate and evaluate the performance of various energy management strategies under specific conditions. This predictive analysis could provide insights into how different configurations and environments affect energy efficiency, enabling proactive adaptation of energy management strategies for the specific hardware in question.

3.2. Hardware model and data

The model is based on the hardware of an IoT node which measures environmental parameters with external sensors and is powered with ambient energy collected with an energy harvesting subsystem and solar panel. All obtained parameters are derived from the operation in which the device is capable of harvesting energy, measuring desired variables, storing data, and transmitting data via the LoRaWAN Semtech module.

Fig. 2 shows a block diagram of an environmental IoT node hardware model. To harvest energy, this model contains a single solar cell with an area of $1.08\,\mathrm{cm}^2$. The solar panel's efficiency is 21%. Total incoming energy is reduced by 50% due to the solar panel's position and energy loss from the sensor casing. The reduction constant was chosen for a worst-case deployment scenario. Harvested energy is stored by a DC/DC boost-topology converter with an average efficiency of 50% into a supercapacitor with a maximum capacity of 60 J. The efficiency of the buck/boost converter from the supercapacitor to the load is estimated at 60%. An ARM Cortex-M0+ based microcontroller provides computing power and controls the IoT node, and a LoRaWAN communications module transmits data via upload and download communications channels. The results from practical experiments indicated that the energy required for transmission was

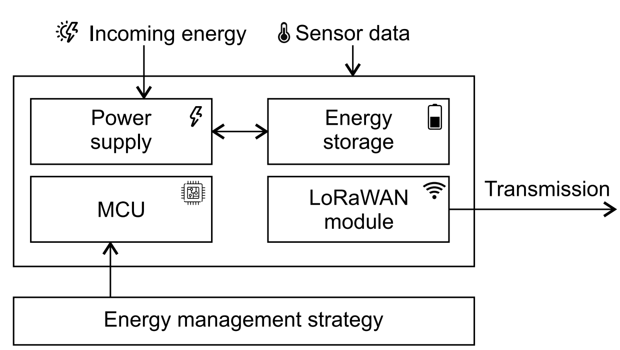

Fig. 2. General model of an environmental IoT node and its energy management control strategy for harvested ambient energy.

260 mJ for two measurement samples and 320 mJ for 14 measurement samples. The estimated energy required for memory operation was 11 μJ, and sleep consumption was 16 mJ every 10 min, corresponding to the standard measurement period configuration.

Table 4 describes the evaluation criteria essential of the IoT node energy management strategy. When the system depletes the energy stored in the supercapacitor, a Device Failure (DF) indicator is incremented. If the system does not have enough energy to transmit data when a transmission period is initiated, a Transmission Failure (TF) event is logged. The Unused Energy (UE) value represents the energy not harvested because the energy storage is full. If a node completes a scheduled data transmission correctly, the Transmission Count (TC) indicator is incremented. The model's memory buffer is limited to 434

Table 4
Evaluation criteria for an energy management strategy.

Criteria	Unit	Description
Device Fails (DF)	(–)	Number of device failures due to lack of energy.
Transmission Fails (TF)	(–)	Number of failures for planned transmissions not performed because of lack of energy.
Unused Energy (UE)	(J)	Sum of harvested energy not used or stored.
Transmission Count (TC)	(–)	Number of successful transmissions.
Lost Data (LD)	(–)	Number of lost measurements.
Average SoES (AS)	(J)	Average values of SoES during operation.

Table 5
Environmental data description and locations.

ID	Name	Latitude	Longitude	Altitude
L1	Mosnov	49.6918°	18.1126°	252.8 m
L2	Churanov	49.0683°	13.615°	1117.8 m
L3	Tusimice	50.3765°	13.3279°	322.4 m
L4	Brno Turany	49.153°	16.6888°	241 m

samples, which corresponds to three days of data. When the buffer is full and data storage is required, the last sample is overwritten and the Lost Data (LD) indicator logs this action. The node SoES is monitored in each cycle; the Average SoES (AS) indicator is calculated as the arithmetic average of all values in each monitoring cycle.

To simulate incoming energy, the experiment used four years of solar radiation data collected at 10-min intervals from 2016 to 2019 at four locations in the Czech Republic (Table 5). The four deployment sites were selected for their varying geographic properties and altitudes. The locations include lowlands and mountainous areas with respect to north/south and west/east positions. The data were obtained from the Czech Hydrometeorological Institute as a paid service.

3.3. Energy management controllers

The current study used energy management controllers to configure subsequent transmission periods and dynamic duty-cycling for communications channel activity. This setup is able to dynamically control power consumption for reliable operation and maximum use of available energy. This section describes the fuzzy-based approach and the static controller used for fixed-period transmission intervals.

3.3.1. Fuzzy controller

The primary motivation for using a fuzzy controller in this study is its ease of implementation, particularly in computationally constrained IoT nodes. Energy-harvesting IoT devices, which often operate with limited processing power and energy resources, benefit from the lightweight, rule-based approach of fuzzy logic. Unlike more complex control methods like reinforcement learning or neural networks, which require significant computational resources, fuzzy controllers can be implemented with minimal overhead. Their simple structure allows for offline design and efficient execution on low-power microcontrollers. Additionally, the use of fuzzy controllers minimizes the communication overhead, a crucial factor in IoT systems reliant on low-power wireless technologies. Instead of transmitting large datasets or model updates, the parameters of fuzzy sets can be represented by a small set of constants. This makes the transmission of updates highly efficient.

The fuzzy controller is based on a Mamdani fuzzy interference system and driven by four inputs obtained from an IoT node's internal states and data received from a cloud. The output is the estimated next transmission interval (T_{next}) for optimized dynamic IoT communications and effective use of harvested energy.

Fig. 3 illustrates the configurations for the input and output fuzzy sets. The SoES input represents a range normalized current state of charge in three fuzzy sets (Low, Mid, High). DayLight (DL) is the estimated time between sunrise and sunset, normalized according to the shortest and the longest days at the particular location. EnergyOutlook (EO) represents the estimated incoming energy for the next 24 h and is

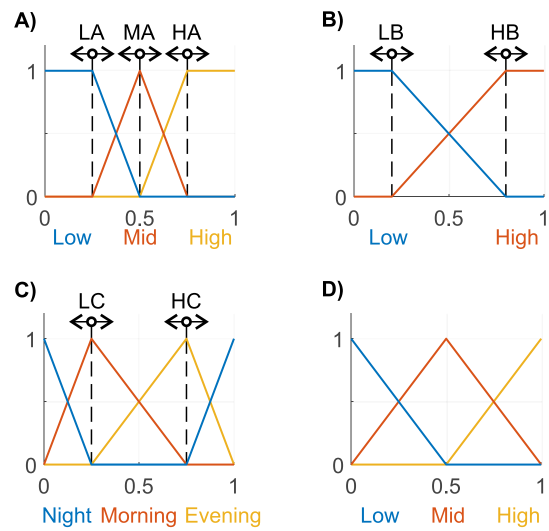

Fig. 3. Implemented fuzzy set types with dynamic configurations for specific inputs and outputs: **(A)** State of Energy Storage (SoES); **(B)** DayLight (DL) and EnergyOutlook (EO); **(C)** DayPhase (DP); **(D)** Next transmission interval (T_{next}) output.

updated at intervals corresponding to data transmissions, simulating a real-world cloud-based energy prediction system. EO is normalized to the maximum possible incoming energy within floating 24-h windows throughout the year, specific to the target location. The 24-h horizon is selected to capture the daily weather cycle, ensuring that predictions can be made at any time of day. If the prediction window were not a multiple of 24 h, different parts of the day (either daytime or nighttime) would dominate depending on the time of the prediction. While predictions can be updated as frequently as every 10 min, they always forecast the energy for the following 24-h period. DayPhase (DP) input is designed to control the strategy throughout the day when the fuzzy sets are distributed across a 24-h interval (Night, Morning, Evening). The output is divided into three equidistant fuzzy sets representing the time of the next transmission. The T_{next} period is calculated from the inverted value of the fuzzy output, limited to a maximum period of 24 h.

Optimizing the positions of fuzzy sets is a crucial feature of the DT. Without any knowledge of the deployment location, DT enables the discovery of an optimal controller solely based on previous historical data. The designed solution facilitates the dynamic adjustment of input fuzzy set positions in four principal directions. The input fuzzy sets for the SoES define three main states: minimal energy for reliable IoT node functionality, very high charge, and the middle area. Optimizing these fuzzy sets enables the optimal configuration of the supercapacitor with respect to deployment location and hardware configuration as follows: the IoT node should avoid deep discharges and overcharging, maintaining an optimal charge range. The optimization of DL using two fuzzy sets allows the identification of zones with low and high energy income, enabling the appropriate selection of strategies for T_{next}. EO optimization helps identify positions of minimal and maximal energy, which could become available in the near future. Lastly, the optimization of DP permits the adjustment of orientation throughout

Table 6
Expert input fuzzy set parameter settings.

Name	Expert parameters
StateOfEnergyStorage	LA = 0.25; MA = 0.5; HA = 0.75
DayLight	LB = 0.2; HB = 0.8
EnergyOutlook	LB = 0; HB = 1
DayPhase	LC = 0.25; HC = 0.75

the day based on sunrise and sunset. This adjustment is significant as even within a specific timezone, these values may vary across different locations.

The input fuzzy sets were configured according to the specific settings in Table 6. The table contains the estimated expert point positions for the reference fuzzy solution. With optimization, however, these changed. The expert setting was used as a default reference to evaluate the results obtained from optimization.

Table 7 lists the fuzzy rules. These rules were designed by an expert according to three main goals. First, the system must prevent device failure by setting a low T_{next} when the SoES is low. The IoT node inspects the SoES and schedules operation in the evening and at night according to the available energy. Finally, when the node has sufficient energy in the morning or the energy outlook is high, operation is scheduled to make use of the available energy.

3.3.2. Static period approaches

The current study applied six static period control methods to obtain baseline results for experimental evaluation. These controllers operated with a T_{next} period fixed to 10, 30, 60, 120, 720 and 1440 min.

Table 8 lists the figures obtained for parameters at four locations (L1–L4), with fixed duty cycle (DC) energy management strategies executed over four years. The results clearly indicate that the high-performance 10-min controller achieved the most completed transmissions and used the maximum possible harvested energy, but it also produced the most device and transmission failures. By contrast, the low-performance 1440-min controller did not use energy effectively and achieved low transmission performance, but it also had the lowest failure rate. The controllers for 30 to 720 min indicate a trade-off between transmission success and device failure.

3.4. Experiment

The energy management of IoT nodes presents a complex optimization problem. These nodes must balance the need for consistent data transmission and the limited energy available from environmental sources, such as solar panels, while avoiding device failures due to power shortages. The goal is to minimize energy consumption while maximizing operational time and data availability. In this section, we formalize this energy management problem, declare its NP-hard nature, and justify the necessity of using meta-heuristic algorithms, such as DE, for solving this optimization problem.

The core objective of energy management for IoT nodes can be expressed as a multi-objective optimization problem, where the system must:

1. Maximize data transmission frequency to ensure timely sensor updates to the cloud.
2. Minimize energy consumption by optimizing the duty cycle and transmission intervals.
3. Minimize the probability of device failures, which occur when the energy storage, such as a supercapacitor, is depleted during critical operation times.

The cost function (CF) definition reflects defined objectives and it is defined as Eq. (1).

$$CF = \sqrt{(c \cdot NDF)^2 + NOCH^2}, \tag{1}$$

where CF is the cost function value, NDF is the number of device failures normalized to simulation steps, and NOCH is the number of overcharges normalized to simulation steps. Generally, the parameters reach significantly different values and therefore a coefficient c is added into the CS equation in order to create trade-off between NDF and NOCH. In this experiment, c is set to 20 to prefer lower device failure events.

The optimization objective depends on the desired behavior of the IoT node. Naturally, reliability is crucial, and therefore the number of device failures (NDF) should be minimal, ideally zero, in the best case. However, minimizing the NDF can lead to a conservative strategy where the minimum number of transmissions would be chosen. To achieve the maximum transmission count, the parameter of overcharge needs to be considered. Generally, if the management strategy is intended to prevent overcharges, it should prioritize energy usage for transmissions.

The complexity of solving the energy management problem stems from its multi-objective nature, the stochastic availability of energy sources, and the nonlinear behavior of IoT node components. In this case, the problem resembles classical scheduling problems, such as the “knapsack problem” or “job shop scheduling”, both of which are known to be NP-hard. In the energy management scenario, the system must decide when and how often to activate data transmissions (analogous to job scheduling) given the constraints of available energy, which fluctuates based on environmental factors like solar radiation. These fluctuations make the problem dynamic and nonlinear, further complicating the search for optimal solutions.

Meta-heuristic algorithms, such as DE, offer several advantages:

- Adaptability to Nonlinear Problems: DE and similar algorithms do not require the problem to be differentiable or convex, allowing them to handle the complex, nonlinear objective function described above.
- Exploration of Large Solution Spaces: Meta-heuristics explore a wide range of potential solutions through mechanisms such as mutation and crossover, which enable them to avoid local minima and converge towards near-optimal solutions.
- Robustness to Uncertainty: DE is particularly suited to dynamic problems with uncertain inputs, such as fluctuating energy availability from environmental sources. This adaptability makes it highly effective for energy management tasks in IoT nodes.

In the case of this study, DE is applied to optimize the configuration of a fuzzy-rule-based energy management controller. The fuzzy controller adjusts the duty cycle and transmission intervals dynamically based on input parameters such as the SoES, daylight availability, and energy outlook. These parameters are optimized by DE to minimize energy consumption while ensuring sufficient data transmission frequency and preventing device failures. The meta-heuristic approach, specifically DE, provides a powerful solution for addressing the NP-hard problem of energy management in IoT systems. Its ability to navigate complex, nonlinear solution spaces and adapt to uncertain environmental conditions makes it indispensable for optimizing energy use in dynamic, real-world scenarios.

Designed in Matlab, the experiment provided a simulation with 10 min granularity of the parameters from the hardware model described in Section 3.2 and the control strategy parameters described in Section 3.3. The granularity of the simulation was selected according to the used solar radiation data which are obtained with 10 min interval.

Fig. 4 illustrates the overall experiment. During the training phase, three years of input data were used as input for optimization. The optimization loop evolves three types of controller base in the hardware model evaluated with the cost function. The energy management controller parameters are optimized according to the following procedure: A with 1-year data, B with 2-year data, and C with 3-year data. The concept behind the testing phase is in sequential testing of controllers when they are ready to use. The input data contained a 4-year interval

Table 7
List of expert fuzzy rules.

```
IF  SoES=L                                 THEN Tnext=L
IF  SoES=M  AND DL=L              AND  EO=H  THEN Tnext=M
IF  SoES=M  AND DL=H  AND  DP=Mo             THEN Tnext=H
IF  SoES=M  AND DL=H  AND  DP=Ev  AND  EO=L  THEN Tnext=L
IF  SoES=M  AND DL=H  AND  DP=Ev  AND  EO=H  THEN Tnext=M
IF  SoES=M  AND DL=H  AND  DP=Ni  AND  EO=L  THEN Tnext=M
IF  SoES=M  AND DL=H  AND  DP=Ni  AND  EO=H  THEN Tnext=H
IF  SoES=H  AND DL=L  AND  DP=Ev  AND  EO=L  THEN Tnext=L
IF  SoES=H  AND DL=L  AND  DP=Ev  AND  EO=H  THEN Tnext=M
IF  SoES=H  AND DL=L  AND  DP=Mo  AND  EO=L  THEN Tnext=M
IF  SoES=H  AND DL=L  AND  DP=Mo  AND  EO=H  THEN Tnext=H
IF  SoES=H  AND DL=L  AND  DP=Ni  AND  EO=L  THEN Tnext=L
IF  SoES=H  AND DL=L  AND  DP=Ni  AND  EO=H  THEN Tnext=M
IF  SoES=H  AND DL=H                         THEN Tnext=H
-----------------------------------------------------------------------------------
Fuzzy sets:
Low(L), Mid (M), High (H),
Morning (Mo), Evening (Ev), Night (Ni)
```

Table 8
Reference results for static solution parameters.

	DC (min)	DF (–)	TF (–)	UE (kJ)	TC (–)	LD (–)	AS (J)	OCH (–)
L1	10	16 095	475	35.9	116 789	9453	28.5	22 792
	30	8210	228	63.3	53 640	7906	37.7	36 032
	60	3703	105	78.3	30 955	6268	44.7	46 928
	120	1652	31	87.6	16 799	2519	50.9	56 258
	720	1314	27	88.0	2811	3031	50.8	57 612
	1440	630	39	88.5	1408	4205	52.9	59 290
L2	10	12 817	477	33.0	121 756	8724	29.9	22 277
	30	5338	190	61.0	57 252	7284	39.9	37 102
	60	1831	83	77.5	32 002	4799	47.4	49 996
	120	321	14	87.3	17 235	1529	52.9	59 821
	720	245	16	87.6	2877	1714	52.9	61 493
	1440	146	17	88.2	1441	1903	53.1	61 788
L3	10	14 544	475	34.6	118 888	13 612	28.7	22 277
	30	7372	242	63.5	52 852	12 680	38.1	37 102
	60	4428	145	78.8	29 708	10 355	44.1	49 996
	120	2264	58	87.6	16 252	5179	49.4	59 821
	720	1488	68	87.9	2722	6626	49.3	61 493
	1440	1021	70	88.4	1370	6873	51.2	61 788
L4	10	13 862	443	37.9	124 172	11 060	29.6	24 374
	30	6955	218	68.3	54 751	8342	39.1	39 149
	60	3563	110	84.0	30 978	6039	45.5	50 732
	120	918	39	93.3	16 779	3489	51.2	59 693
	720	564	44	93.6	2802	4129	51.1	61 032
	1440	305	44	94.2	1410	4168	53.1	62 650

DC — Duty Cycle, TF — Transmission Failures, UE — Unused Energy , TC — Transmission Count, LD — Lost Data, AS — Average SoES, OCH, Overcharge count.

when testing commenced with a non-optimized expert design energy management controller N. After a 1-year testing interval, the *N* controller was replaced with controller A, which was trained on the first year of data and was therefore ready to use at this point. This process is repeated at the end of years 2 and 3, when controllers B and C are applied. The experiment was designed to test the hypothesis that the IoT node controlled with the strategy trained on past situations should perform better than the non-optimized fuzzy controller approach.

The optimization process significantly relies on both the refreshness of data, which ensures real-time representation of environmental conditions, and the reliability of data integration. Data refreshness ensures that the IoT nodes operate based on the most up-to-date information, allowing for timely adaptations in energy management strategies. However, frequent updates can consume more power and bandwidth, necessitating a balanced approach. By leveraging historical trends, we designed the system to refresh energy management parameters periodically (e.g., annually), capturing seasonal variations without overburdening the nodes with continuous updates. Furthermore, the reliability of data integration plays a crucial role in ensuring that all relevant energy inputs and hardware status information are accurately reflected in the optimization process. This balance between refreshness and reliability enables the system to optimize energy consumption while maintaining stable device operations over extended periods.

Table 9
Differential evolution parameters.

Population size	Generations	Iterations	Parameter count
10	1000	50	9

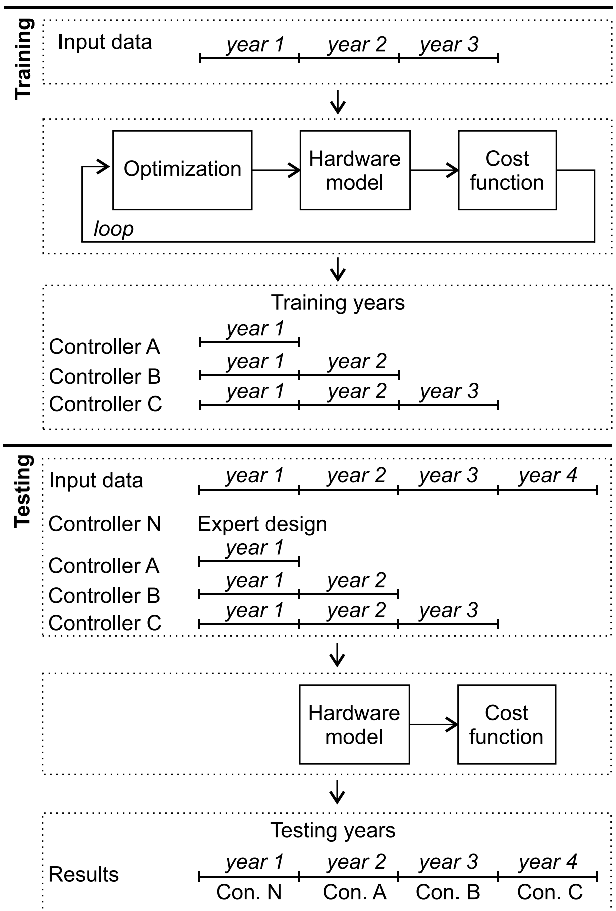

Fig. 4. Training and testing process: Controllers A, B and C are trained with 1, 2 and 3-year horizons. Testing is done by sequentially applying a trained controller to future data.

The controller parameters are optimized using a Differential Evolution (DE) algorithm. Table 9 provides the configuration for the DE optimization process. The DE procedure optimizes the nine fuzzy controller input parameters listed in Table 6. The population was set to 10 as a sufficient number to solve a low-dimensional problem. The generation number was experimentally estimated at 1000 by determining when optimization does not produce a better result at a higher generation count. The configuration presented here for population size and generation number should perform well with reasonable computational costs. Because DE has a stochastic nature, the experiment was repeated 50 times and evaluated according to the calculated arithmetic average.

4. Results

This section summarizes the results of the experiments, first evaluating the training process and then discussing the results from the test data set to evaluate experiment's hypothesis stated in Section 3.4.

4.1. Training process

The aim of the training process is to find the best fitting fuzzy controller configurations to train the data sets. As mentioned in Section 3.4, the optimization process used training data sets of different lengths to evolve three different energy management controllers.

Table 10 lists the cost function values after the evolution process for the four locations and provides a comparison with the expertly designed fuzzy controllers tested on the same training data sets with 1 to 3-year horizons (N_{1-3}). It is clear that the evolved controllers perform with low CF values, and therefore optimal functionality can be expected in all examined cases. The overall performance of the expertly designed and optimized controllers also strongly depended on the deployment location, therefore the location results cannot be cross evaluated.

Table 10
Average cost function values for the training process.

	N_1	A	N_2	B	N_3	C
L1	0.1764	0.1041	0.1430	0.1049	0.1786	0.1312
L2	0.1221	0.0830	0.1266	0.0916	0.1333	0.0990
L3	0.2078	0.1089	0.1453	0.1058	0.1663	0.1202
L4	0.1779	0.1141	0.1623	0.1133	0.1789	0.1200

The locations and training horizons can be examined according to the input fuzzy set configurations. Table 11 summarizes the median values of the input fuzzy sets from 50 optimization cycles and provides a comparison to the expertly designed values. The optimized parameters exceeded the expertly designed values for each location's energy management controller behavior. The parameters also depended on the training horizon. The optimization process preferred a more aggressive policy with the fuzzy input sets for SoES and shifted all the parameters to lower values. This configuration used more energy than the expertly designed configuration when the controller considered *High* and *Medium* SoES at a larger scale. This also affected the *Low* fuzzy set and minimized it in all cases. Significant changes can be seen in the DL input data set, which represents time of day and seasons. Optimization extended the *High* fuzzy set to select the greater part of the year which corresponded to a solar energy harvesting character. A phenomena can also be observed at locations L1 and L4, where a three-year training horizon contained significantly different values from a shorter horizon. This behavior was due to regional weather conditions reflected in the first two years of historical data not having a similar character to the rest of the data. The daytime controller configuration was modified with the optimized DP parameters. The optimized parameters placed greater importance on the night fuzzy set, and therefore the controller had to be configured according to the time remaining before daylight and the availability of solar radiation. L1 and L4 experienced the same phenomena as with the DL parameter. The optimization process also introduced significant changes to the position of the EO fuzzy sets. *Low* and *High* fuzzy sets were placed nearer to each other and shifted to lower values. This suggested that the future incoming energy in an approximate range of 20% to 30% was sufficient for an aggressive transmission policy.

4.2. Testing process

The aim of the testing process is to evaluate the optimized energy management controllers sequentially on the training data as they were evolved.

Table 12 provides a comparison of the non-optimized and optimized energy management controller performance in the testing process described in Section 3.4. The parameters for the optimized controller are calculated as the arithmetical average of 50 evolved solutions. The results indicate that the optimized fuzzy energy management used significantly more available energy than the expertly designed controller. This behavior is also related to the number of transmissions, which were more than with the expertly designed controller. The greater transmission frequency resulted in up-to-date data being available in a cloud, which was the intended target behavior. Another benefit over the expertly designed controller was more efficient energy use and a resulting lower AS and lower amount of OCHs. The optimized energy management strategy for data transmission preferred optimized energy use over the elimination of sporadic device failures, which would produce greater data loss and TFs. Data loss at locations L2 and L4 increased, whereas at locations L1 and L3 it decreased. This behavior

Table 11
Median values of input fuzzy sets for each location after training optimization.

		StateOfEnergyStorage			DayLight		EnergyOutlook		DayPhase	
		LA	MA	HA	LB	HB	LB	HB	LC	HC
Expert design		0.25	0.50	0.75	0.20	0.80	0.00	1.00	0.25	0.75
L1	Controller A	0.06	0.42	0.52	0.44	0.47	0.14	0.24	0.31	1.00
	Controller B	0.10	0.42	0.58	0.44	0.55	0.15	0.25	0.34	0.98
	Controller C	0.15	0.42	0.56	0.11	0.44	0.20	0.29	0.27	0.33
L2	Controller A	0.09	0.33	0.71	0.01	0.24	0.15	0.32	0.42	0.54
	Controller B	0.08	0.34	0.69	0.02	0.40	0.14	0.28	0.42	0.52
	Controller C	0.07	0.36	0.69	0.06	0.33	0.13	0.27	0.42	0.47
L3	Controller A	0.14	0.46	0.65	0.15	0.28	0.23	0.31	0.22	0.49
	Controller B	0.10	0.36	0.57	0.16	0.23	0.21	0.36	0.33	0.47
	Controller C	0.10	0.32	0.50	0.17	0.23	0.19	0.36	0.27	0.32
L4	Controller A	0.10	0.34	0.52	0.32	0.45	0.09	0.34	0.29	0.88
	Controller B	0.09	0.35	0.51	0.30	0.45	0.11	0.26	0.27	1.00
	Controller C	0.08	0.31	0.62	0.12	0.24	0.13	0.34	0.34	0.36

Table 12
Comparison of the average parameters for non-optimized and optimized controllers obtained with the testing procedure at various locations.

	Non-optimized expert controller							
	CF (–)	DF (–)	TF (–)	EU (kJ)	TC (–)	LD (–)	AS (J)	OCH (–)
L1	0.1698	1148	63	42.9	101 243	6673	36.7	27 357
L2	0.1334	355	47	40.2	106 451	3539	38.4	27 147
L3	0.1931	1512	101	41.8	103 299	9543	36.2	27 137
L4	0.1674	979	64	45.9	107 078	5874	37.6	29 282
	Optimized controller							
	CF (–)	DF (–)	TF (–)	EU (kJ)	TC (–)	LD (–)	AS (J)	OCH (–)
L1	0.1666	1260	56	37.6	110 888	5646	35.6	24 312
L2	0.1188	589	54	32.5	121 296	4200	33.5	21 968
L3	0.1850	1539	90	36.0	113 922	8695	34.4	23 769
L4	0.1530	1005	68	38.8	120 373	5976	34.8	25 070

CF — Cost Function, TF — Transmission Fails, EU — Energy Unused, TC — Transmission Count, LD — Lost Data, AS — Average SoES, OCH — Overcharge count.

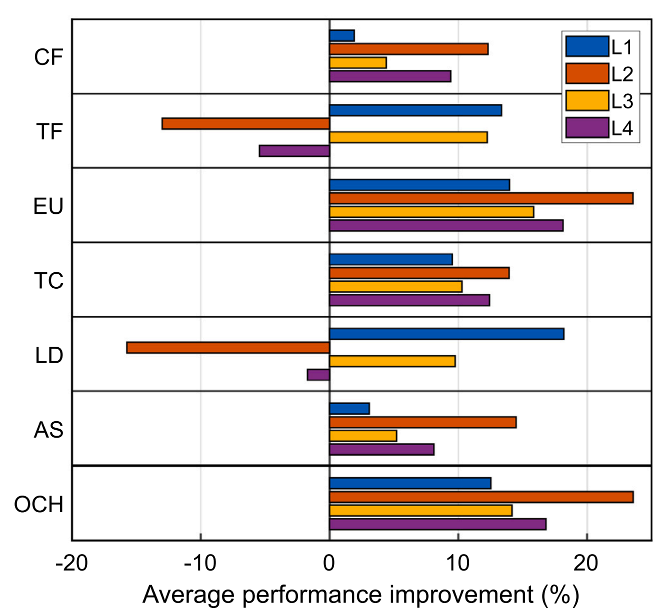

Fig. 5. Performance ratio of optimized fuzzy controller and expert fuzzy controller: CF — Cost Function TF — Transmission Failures, UE — Unused Energy, TC — Transmission Count, LD — Lost Data, AS — Average SoES, OCH — Overcharge count.

can be compensated for with coefficient c (see Eq. (1)).

Fig. 5 shows the improvement in performance of the evaluation parameters. The graph indicates the percentage improvement in the optimized controller parameters at the four locations compared to the expert design. Energy use showed the highest improvement in performance, where the optimized solutions made use of up to 24% more of the available energy than the expertly designed controller. More effective energy use increased the number of data transmissions by up to 14%. The graph also indicates decreased performance in the communication parameters (TF and LD), however only one location exhibits a not negligible deterioration, which could be attributed to specific climatic conditions in different years.

Fig. 6 provides a comparison of the behaviors over time for the reference algorithms and optimized fuzzy controllers, showing graphs for two static controllers, an expertly designed fuzzy controller and an optimized fuzzy controller over one month in both winter and summer. The graphs indicate the two undesirable states of device failure and overcharging.

Fig. 6A depicts the behavior in winter. The 10-min static controller transmitted data in each step, being very energy consuming and leading to frequent device failures. The 1440-min static controller, however, transmitted data only once per day, leading to frequent overcharging. Compared to the static configurations, the expertly designed controller solved both undesirable states, balancing reliable operation and frequent transmissions to effectively eliminate device failures and overcharging. The optimized fuzzy controller demonstrated behavior similar to the expertly designed controller, but it was more successful in avoiding overcharging. The optimized fuzzy controller was also able to use harvested energy more effectively, indicated by an average SoES of 18%, which is lower than the expertly designed controller.

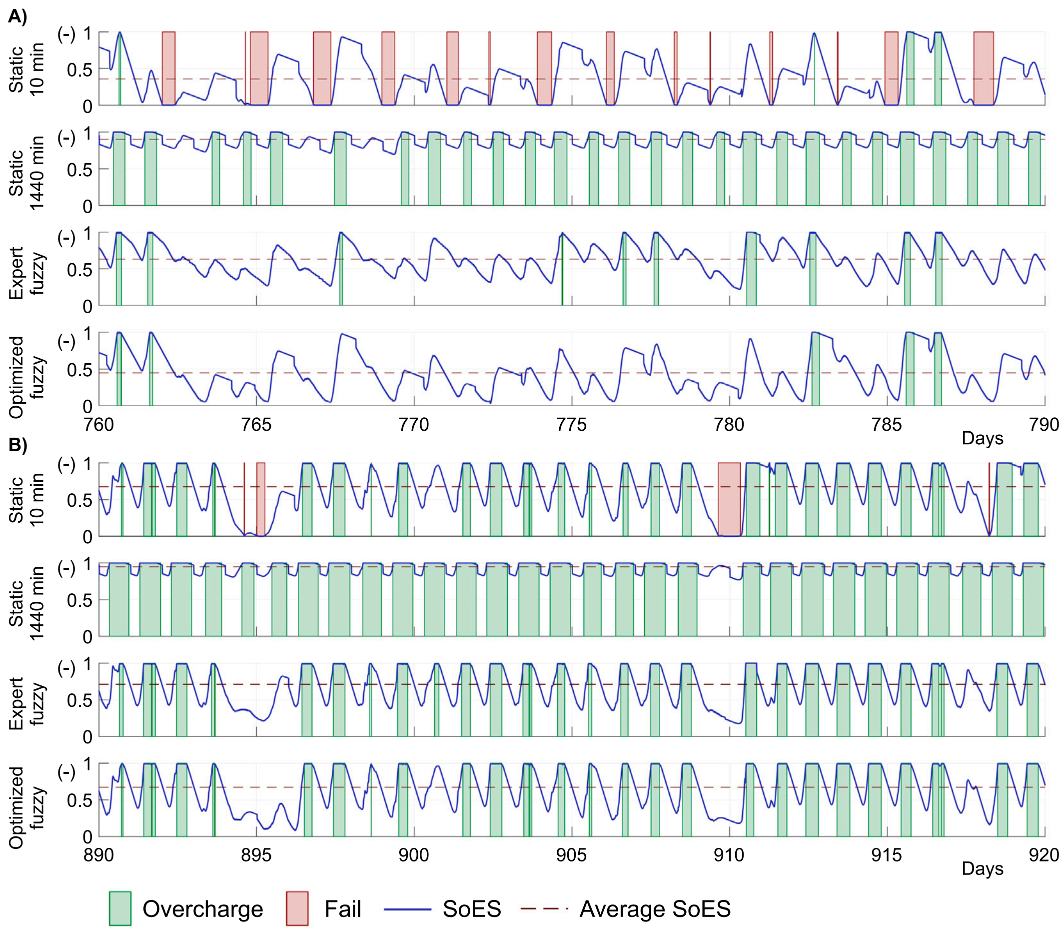

Fig. 6. Comparison of behaviors over time for selected reference algorithms and optimized fuzzy controllers: **(A)** Winter. **(B)** Summer.

Fig. 6B depicts the behavior in summer. The 10-min static controller had episodes of failure even when the amount of incoming energy was high. Overcharging was caused by very high amounts of incoming energy which were not able to be consumed, even though the controller transmitted data at very short intervals. The 1440-min static controller consumed much less of the incoming energy because of its very low duty cycle (one transmission per day), and thus overcharging occurred frequently. The expertly designed fuzzy controller eliminated failures and overcharging. The optimized controller demonstrated similar behavior, but it eliminated several cases of overcharging and thereby used energy more effectively. The optimized fuzzy controller also produced the lowest average SoES (67%), lower than the average SoES of both the expertly designed fuzzy controller (71%) and 10-min static controller (68%).

4.3. Results summary

The results demonstrate the effectiveness of the optimized fuzzy controller compared to static period approaches and the expert-designed fuzzy logic controller. The DE-optimized fuzzy controller consistently performed better in terms of energy efficiency and transmission frequency across all deployment locations. By dynamically adjusting the transmission intervals based on real-time conditions, the controller was able to use up to 24% more of the available energy compared to static controllers, resulting in more frequent data transmissions and fewer device failures.

In terms of overall system performance, the optimized controller maintained an efficient balance between energy consumption and transmission success. Although the controller occasionally experienced slightly higher transmission failures and lost data compared to the expert-designed controller, these issues were offset by the significant improvements in energy use and transmission frequency. These results highlight the potential of a cloud-based DE optimization process for adaptive energy management in IoT nodes, ensuring long-term reliability and efficiency in energy harvesting environments.

5. Discussion

The study discusses several topics in relation to the use of a DT sensor to determine and apply dynamic energy management strategies to IoT energy harvesting devices. A model is described for optimizing performance in a cloud and subsequently transmitting optimized parameters to IoT device hardware. Individual cloud-assisted optimization methods and their features are detailed, and cost optimizations for hardware components are suggested.

IoT devices commonly employ Low-Power Wide-Area Network (LPWAN) technologies as primary communications channels. These technologies operate with low power constraints which impose strict limits on data stream transmissions. The development of edge computing or data compression methods to reduce data volume in the up-link and down-link channels is therefore very challenging and critical to effective operation. The current study proposes an approach which is fully aligned with LPWAN principles in which energy management updates include only nine coefficients which modify the positions of input fuzzy sets. In relation to specific LPWAN technologies (LoRaWAN, SigFox etc.), this approach can use a data-limited down-link communications channel window. This feature solves the disadvantages of state-of-the-art methods such as neural networks or modified reinforcement learning, which commonly must transmit all the extensive look-up tables generated by the training process.

IoT devices deployed in the field are frequently exposed to environmental or industrial conditions which cause mechanical damage, decrease the energy harvesting module's efficiency or degrade electronic components. The proposed DT for sensors enables models to be updated based on the actual hardware component state provided by diagnostic data uploaded to a cloud. This approach allows a DT to be customized according to the deployment conditions. The DT concept thereby provides more accurate energy management strategies for the particular deployed IoT sensor.

The general concept behind DTs for sensors enables the possibility to customize IoT node configurations, for example in the supercapacitor, solar cell area, data storage or DC/DC converter, to achieve the best possible performance at the target location. This approach creates a general framework for appropriately selecting electronic components with the most suitable technologies, optimal parameters and cost effectiveness. Using data from the future deployment area, it is also possible to estimate the amount of incoming energy and the data transmission rates to customize IoT nodes already at the design and production level.

The frequency of modeling and adaptation in the DT must carefully balance the energy consumption of IoT nodes with the benefits of optimization. While cloud-based optimization processes may be computationally intensive, they do not impact the energy consumption of the IoT node, where low-power operation is crucial. Our approach, using a fuzzy logic controller that requires only nine parameters to adjust the energy management strategy, is fully compliant with LPWAN standards. This allows the DT to transmit minimal data for optimization updates, reducing the energy cost of data transmission. By running the optimization in the cloud, the IoT nodes can benefit from optimized energy management strategies without the need for high-frequency transmissions, thereby ensuring efficient energy use and maintaining low power consumption at the node level.

The authors provide the best solution as possible, however, there are possible limitations. At first, in case of high variability used electronic parts parameters, it may cause inaccuracy between a real device and a DT due to technology limits of diagnostics. Another possible limitation is that this research uses one specific energy harvester and LoRaWAN module. In the future, there is a need for additional research that evaluate another IoT node architecture, energy harvester and transmission module. The limitation of the usage a DT is also possible misleading optimization results. Any optimization procedure is no able to ensure valid results that represents global maximum. This situation did not appears during this research, however it cannot be ruled out. Finally, in the best case the DT should be identical to real device, it is generally not possible and always the behavior has certain differences. The aim of the research is to develop a DT, which will provide results close as possible to real life product.

The authors present the most optimal solution attainable; however, certain limitations are recognized. Primarily, when dealing with high variability in the parameters of electronic components used, discrepancies between an actual device and its DT may arise due to the technological constraints of diagnostics. Another potential constraint lies in the use of a specific energy harvester and LoRaWAN module within this study. Subsequent research is warranted to explore alternative IoT node architectures, energy harvesters, and transmission modules. Furthermore, the utilization of a DT may potentially lead to misleading optimization outcomes. No optimization procedure can guarantee definitive results that accurately represent the global maximum. While such a scenario did not manifest in this study, its occurrence cannot be entirely discounted. Ultimately, while the aspiration is for the DT to mirror the real device in the best-case scenario, achieving complete parity is generally unfeasible, and deviations in behavior are inevitable. The objective of this research is to establish a DT capable of furnishing results that closely approximate real-world product performance.

It is generally expected that certain deviations between the model's behavior and its real-world deployment may occur. These deviations can result in a slight departure from the optimal behavior of the controller. A more detailed analysis reveals the specific impacts of such deviations on individual inputs of the fuzzy controller. For instance, inaccuracies in the SoES setting might slightly affect the boundary for deep discharge, increasing the risk of node depletion, or lead to overcharging, resulting in a marginally inefficient use of energy. Similarly, inaccuracies in DL estimation can lead to imperfect predictions of daylight duration, impacting energy harvesting planning. Deviations in DP configuration may cause inefficiencies, particularly during sunrise and sunset transitions, when the node switches between day and night modes. Additionally, errors in EO predictions can result in suboptimal forecasting of future energy availability, leading to further deviations from the controller's optimal behavior. It is anticipated that these deviations from the model will remain minor and will not degrade the controller's performance to a level inferior to the default, non-optimized configuration.

6. Conclusions and future work

This article introduced a DT concept for sensors. The concept can be applied to develop energy management strategies for deployment to IoT energy harvesting devices. This simulation based study investigated the behaviors of hardware models and consumption coefficients obtained by experimental measurements. The results section analyzed the data from four deployment locations in the Czech Republic, but the presented principles can be assumed to be transferable to any location in the world. The DT concept could also be applied to energy harvesting sources other than solar panels (e.g., thermoelectric generators, wind turbines, radio frequency energy harvesters, etc.).

The discussion section provided a brief outline of options for future work and addressing research challenges. Future work could involve formalizing a set of parameters for remote diagnostics at the IoT node deployment site. Parameters in advanced electronic components (e.g., supercapacitors, solar panels, etc.) could also provide adjustments to the DT model's behavior and indicate actual device statuses more accurately. This research area could also develop a concept for an evolving sensor DT approach. Another area for research would be creating a framework for collecting deployment experiences to aid in producing optimal hardware designs. Optimal IoT nodes such as these could be effective both for balancing the costs and technical aspects of sensors for compatibility with the DT concept.

CRediT authorship contribution statement

Michal Prauzek: Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Data curation. **Karolina Gaiova:** Writing – original draft, Resources. **Tereza Kucova:** Writing – review & editing, Writing – original draft, Resources. **Jaromir Konecny:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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