Fuzzy Controlled Wavelet-Based Edge Computing Method for Energy-Harvesting IoT Sensors

Jaromir Konecny, *Member, IEEE*, Michal Prauzek, *Senior Member, IEEE*, and Monika Borova

***Abstract*—The study presents a novel edge computing (EC) method based on a discrete wavelet transform (DWT) and fuzzy logic controller suitable for application with energy harvesting Internet of Things (IoT) sensors. The authors propose a new solution to address information latency in an IoT device when compressed data with high-information density are transmitted to the cloud with high priority or detailed information is added to the cloud when the energy state in the IoT device is sufficient. The solution potentially delivers a completely lossless scenario for low-power sensors, a significant benefit that state-of-the-art methods do not provide. This article describes the hardware model for an IoT device, input and predicted energy data, and a methodology for designing the parameters of DWT and fuzzy logic controllers. The results of the study indicate that the proposed EC method achieved full data transmission in contrast to the reference solution which had the worst case parameters of maximum outage and penalties caused by delayed data. The average delay in uploading approximate data was 0.51 days with the proposed fuzzy controller EC method compared to reference methods, which have an average delay of at least 0.91 days. The results also highlighted the importance of the tradeoff between information latency and reliable functionality. The results are discussed in terms of an innovative approach which features an IoT sensor that maximizes its own energy consumption according to the data measured from specific parameters.**

***Index Terms*—Data compression, edge computing (EC), energy harvesting, information latency, Internet of Things (IoT), wavelet transform.**

I. Introduction

The significance of edge computing (EC) methods in the Internet of Things (IoT) is growing, especially in relation to transmission capacity limitations in low-power wide area network (LPWAN) technology. Modern IoT devices that harvest energy can be improved by adapting data transmission according to the importance of the data and the energy available in the transmitting device. The study extends an experiment which compared neural networks and wavelet-based EC methods presented at the 2022 IEEE Symposium Series on Computational Intelligence and describes the application of wavelet compression methods developed for an energy harvesting device driven by a fuzzy logic controller [1]. This article discusses the achieved data accuracy and suitability of wavelet-based EC for adaptive operation in a model which uses four years of historical data.

The motivation for the study is developing an EC method which is effective in managing the low capacity of a transmission channel, limited computational resources in IoT sensors, and variability of incoming harvested energy. The study presents a design for a computationally lightweight solution which addresses these energy constraints and transmission channel limitations. This novel solution ensures maximum data availability in the cloud with acceptable data loss and is capable of refining cloud data after an acceptable delay. The IoT sensor is also capable of prioritizing the transmission of nondetailed data and subsequently enhancing these data with details according to importance and the quantity of available energy.

The main objectives of the study include identifying the functional parameters, for example energy consumption and performance, in an IoT sensor which is powered by a thermoelectric generator (TEG) energy harvesting device and describing and measuring the transmission channel capacity and power consumption to model the sensor's data transmission requirements. The objectives further involve selecting a suitable compression method with the ability to vary compression level and designing a control algorithm that enables adjustment of the compression level with minimal information loss while ensuring early transmission of approximated data. Finally, the study evaluates the proposed solution using an environmental data set and discusses its features and deployment possibilities.

The principle of the wavelet-based EC method is illustrated in Fig. 1. An IoT device uses sensors to measure parameters in its environment and applies wavelet compression to decompose the data obtained. Data decomposed into both approximate and detailed coefficients are stored in memory alongside compression quality information measured according to Goodness-of-Fit (GoF). A fuzzy controller selects the data for transmission to the cloud. The fuzzy controller inputs are based on node energy state, predicted energy data for future energy harvesting, and data volume stored after compression according to GoF. The aim of this approach is to first transmit approximate coefficients with high-information density when the IoT device is low on energy; detailed coefficients are then later transmitted according to their informational value when

Manuscript received 27 October 2022; revised 7 June 2023; accepted 3 July 2023. Date of publication 6 July 2023; date of current version 24 October 2023. This work was supported in part by the "Development of Algorithms and Systems for Control, Measurement and Safety Applications IX" of the Student Grant System, VSB-TU Ostrava under Project SP2023/009; in part by the "Development of a System for Monitoring and Evaluation of Selected Risk Factors of Physical Workload in the Context of Industry 4.0" of the Technology Agency of the Czech Republic under Project FW03010194; and in part by the European Union's Horizon 2020 Research and Innovation Programme under Grant 856670. *(Corresponding author: Michal Prauzek.)*

The authors are with the Department of Cybernetics and Biomedical Engineering, VSB–Technical University of Ostrava, 708 00 Ostrava, Czech Republic (e-mail: monika.borova@vsb.cz; jaromir.konecny@vsb.cz; michal.prauzek@vsb.cz).

Digital Object Identifier 10.1109/JIOT.2023.3292915

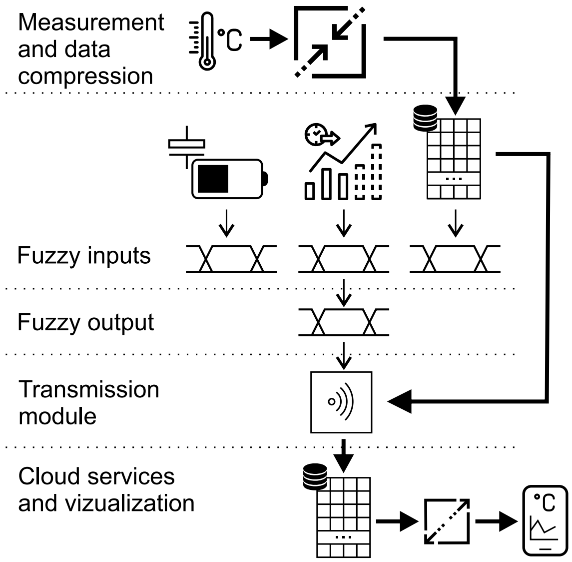

Fig. 1. Principle of the wavelet-based EC method: input data are compressed to wavelet coefficients which contain various information densities. The fuzzy controller drives a transmission module which selects data according to specific criteria for transmission to the cloud.

the device has sufficient energy or the possibility arises to obtain a fresh supply of energy in the near future.

The proposed approach introduces an EC method that prioritizes data with high-information density over insignificant details, thus introducing information latency. Unlike state-of-the-art methods, it combines an adaptive compression rate with a follow-up data update when sufficient energy is harvested by the IoT device and thus attempts to minimize information loss. The application is not domain specific since it employs a discrete wavelet transform (DWT) and does not depend on supervised learning or location-specific parameters. It is therefore versatile and can be applied in various domains. The proposed approach is also suitable for resource-limited embedded IoT devices since the DWT can be efficiently processed using hardware instructions executed in modern microcontrollers.

The novelty and the contribution of this article is summarized below.

1) This article presents the design principles for a compression method which permits changes in the compression level while maintaining a deterministic output. The design also allows gradual refinement of the measured data in the cloud.
2) This article proposes a data priority engine which enables the selection of appropriate data clusters while checking the immediacy and importance of the data.
3) This article introduces the concept of a rule-based controller suitable for embedded devices. This controller permits transmission control which supports the dynamic nature of harvested energy.

This article is organized into seven sections. Section I introduces the motivation, core objectives, and novelty of the present study. Section II summarizes the state-of-the-art related works. Section III provides details of the proposed novel EC method, data decomposition, data priority engine, fuzzy logic controller, and data transmission module. Section IV describes the experiment and its hardware model, input data, and predicted energy data set, along with evaluation criteria. Section V reports the results of the experiment, discussing both the time domain and data availability. Section VI discusses and evaluates the results within the context of the study's novel contribution. Finally, Section VII concludes this article and outlines potential future work.

TABLE I
OVERVIEW OF EC METHODS SUITABLE FOR LOW-POWER IoT DEVICES

EC method	Related studies
Mathematical transforms	• Comparison of mother wavelets in DWTs applied in the IoT [6], [7] • Combination of algorithms: Huffman coding and discrete cosine transforms [8] • Online compression without the need for historical data [9] • Walsh transform with moving average filtering [10]
Soft computing	• Using neural networks in wireless sensor monitoring [11] • Seismic data compression using a neural network [12] • Biomedical data compression using a neural network [13]
Data reduction	• Based on a time correlation prediction model [14] • Combination of a time correlation prediction model and lossy compression [15] • Data reduction approach based on auto-regressive prediction and efficient compression [16]

II. RELATED WORKS

Various environmental EC algorithms can be used in combination with IoT devices. Based on the specific parameters of interest, the algorithms can be classified according to lossy (or lossless) compression or data volume reduction. Other parameters, such as computational complexity and communications interface type, are also important [2]. In principle, data compression methods can be applied to significantly reduce the energy requirements for data transmission [3]. Table I summarizes the state-of-the-art EC methods according to conventional mathematical approaches [4], soft-computing, and data reduction methods [5].

When data are compressed using the DWT, very efficient compression can be achieved if the wavelet type is appropriately selected [6], [7]. The shape of the mother wavelet should match the shape of the input signal as closely as possible. The algorithm's benefit is that training on historical data is not required. To achieve even more efficient compression, this method is often used in conjunction with other compression algorithms, such as Huffman coding or a discrete cosine transform [8]. This approach is not suitable, however, in deployments that use floating point variables, which complicate direct application to IoT sensor measurements. Another useful mathematically based compression method is the Walsh transform, which is very suitable for application to biosignals, but its applicability to smart cities or environmental data has not yet been demonstrated [10].

Many applications use soft-computing methods for data compression. Artificial neural networks are typical soft-computing compression methods, but their disadvantage is the need to use large volumes of specific historical data for training [11]. For example, a neural network trained on seismic data will unlikely function correctly with other types of variable, for example temperature data [12]. Another disadvantage is that the neural network always produces lossy compression [13] as a result of its characteristics.

Data volume reduction is a method for reducing the number of data records for transmission according to the importance of the information contained within that data. This type of approach generally is not considered a compression method. The algorithms for reducing data volume can be executed as time-correlated predictive models to estimate trends, and when these trends differ, the data are transmitted [14]. Data volume reduction based on a predictive model is often used in conjunction with compressed sensing [15]. A predictive model decides whether data are either sent or eliminated using a compression method based on adaptive piecewise constant approximation, symbolic aggregate approximation, or a fixed code dictionary using Huffman encoding [16].

III. Methods

This section describes the proposed EC method, which involves four parts: 1) the data decomposition and composition procedure; 2) the data priority engine; 3) the fuzzy logic controller; and 4) the transmission module.

A detailed scheme of the EC is illustrated in Fig. 2. The vertical dotted lines in the scheme separate the IoT device, whose components are depicted on the left, and the cloud, which is at the right. Measured data (32 samples) are decomposed by the DWT and stored in a memory table as A3, D3, D2, and D1 clusters. This procedure is detailed in Section III-A.

The principle behind the presented method is in driving data transmission according to the importance of the information contained within the data. To achieve this, the solution uses the data priority engine described in Section III-B. The engine applies various level data compositions to determine information loss according to GoF, and the GoF values are then stored in a GoF table which corresponds to the A3, D3, D2, and D1 clusters.

Since the design solution is applied to energy harvesting IoT sensors, data transmission must be controlled dynamically. The firmware of embedded devices is commonly implemented as

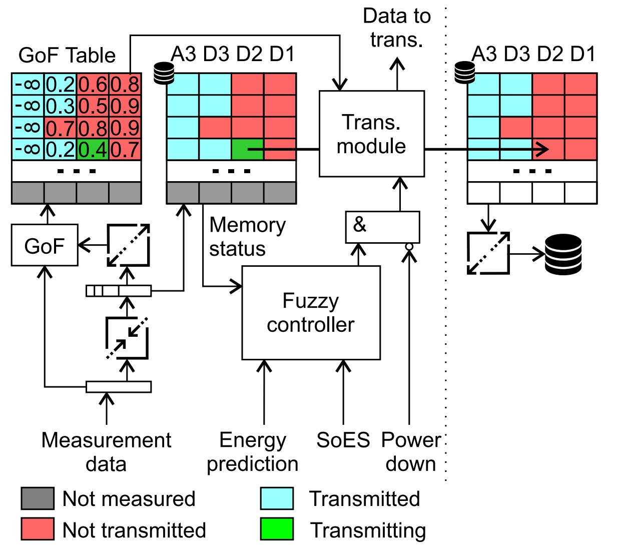

Fig. 2. Detailed block diagram of an EC method based on a discrete wavelet transformation driven by a fuzzy logic controller.

a finite state machine which applies a duty cycle scenario. A rule based controller is therefore a suitable option for the transition function. A fuzzy-based solution expands the options of the dynamic energy management strategy and permits future optimization of fuzzy set and rule settings. These are useful features which are exploited in the fuzzy-rule-based solution detailed in Section III-C to control the data transmission module described in Section III-D.

A. Data Decomposition

This section describes data decomposition method which applies a DWT for lossy compression. The DWT provides deterministic decomposition and composition at target level which is fully aligned with IoT transmission technology principles. The aim behind using this method is to transmit approximate data and minor details as soon possible according to the device's available energy.

The DWT decomposes according to the vector $\{a_m, d_m, d_{m-1}, \ldots, d_1\}$, forming a wavelet spectrum which describes the time-frequency localization of the input signal. The vector coefficients are obtained by applying a convolution of the input signal through a low-pass filter for approximate coefficients and a high-pass filter for detailed coefficients. The aforementioned decomposition can be reapplied to the approximation coefficients [17].

The decomposition scheme is shown in Fig. 3. For this particular EC method implementation, during data compression, the output vector is formed by approximate coefficients at the third decomposition level and detailed coefficients at the third, second, and first decomposition levels. Generally, depth of the decomposition level can be adjusted according to the targeted granularity of the measured data details and options available to the communications channel payload. In the presented solution, the decomposition level is selected as a tradeoff between the minimum transmission period (quantity of collected data to

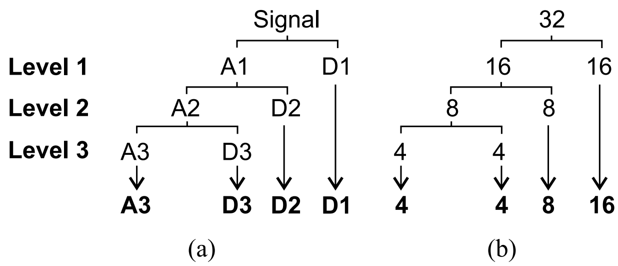

Fig. 3. Decomposition of the measured data by a DWT. (a) Decomposition. (b) Lengths.

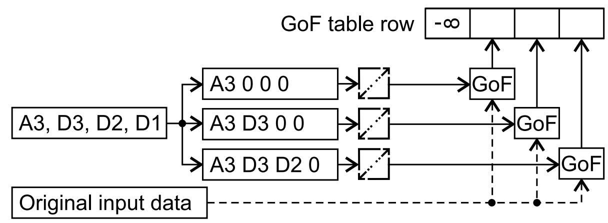

Fig. 4. Block diagram of GoF table calculations.

compress) and the compression granularity (available options to transmit data at various compression levels).

Decomposition is dependent on the type of mother wavelet used. Selecting a mother wavelet which matches the waveform of an input signal as closely as possible can increase the importance of the information in the approximate coefficients and decrease the importance in detailed coefficients. This results in a better approximation of the signal when detailed coefficients are not transmitted [18]. The Haar wavelet is used in the proposed solution since it represents a general data compression approach.

B. Data Priority Engine

The aim of the EC method is to gradually refine the measured data in the cloud. The approximation coefficients at the third decomposition level are transmitted with the highest priority, and the reconstructed data are then gradually refined by transmitting the detailed coefficients. This procedure results in approximated data being available in the cloud sooner than detailed data.

Generally, a full vector of decomposed coefficients contains the original information without any data loss. If any of the detailed coefficients are not transmitted, they are substituted with a zero during reconstruction, causing data loss at that particular level. The benefit of this approach is that detailed coefficients can to be added at any time to increase the data precision.

The proposed EC method clusters the measured data with the 32 samples decomposed by the DWT at the third level. The decomposed clusters form a memory buffer (Fig. 2), and a GoF table is created to determine which memory buffer cluster is important to transmit. A GoF value is defined by the following:

$$\mathrm{GoF} = 1 - \frac{\sqrt{\sum_{i=1}^{N} |x_i - \hat{x}_i|^2}}{\sqrt{\sum_{i=1}^{N} |x_i - \mathrm{mean}(x)|^2}} \tag{1}$$

where GoF is the goodness of fit (1 is a best fit), x is the original signal, and $\hat{x}$ is the decompressed signal.

The GoF table contains information about the transmission importance stored in the related memory buffer cluster. The calculation procedure for the GoF table is illustrated in Fig. 4. The first column in the GoF table always contains negative infinity, because if an approximate coefficient is not transmitted, the measured data cannot be reconstructed. The second column contains the GoF for the measured data reconstructed by DWT composition from the approximate coefficients A3 only. The third and fourth columns contains the GoF for reconstructed measured data from A3, D3 and A3, D3, D2, respectively. If all coefficients are transmitted (A3, D3, D2, and D1), the GoF is always 1.

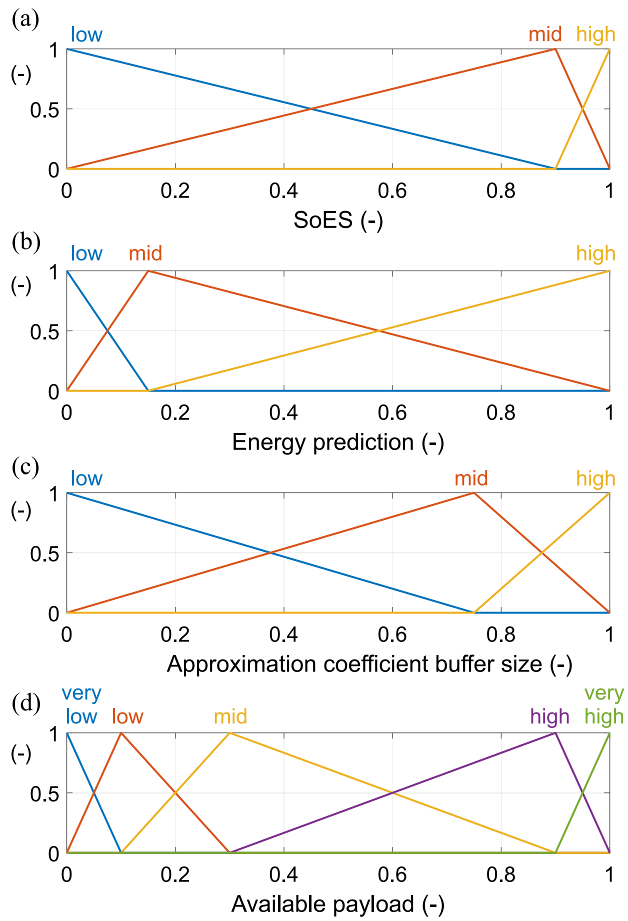

Fig. 5. Input and output fuzzy sets: (a) SoES fuzzy input, (b) EP fuzzy input, (c) approximation coefficient buffer size fuzzy input, and (d) AP fuzzy output.

C. Fuzzy Logic Controller

The fuzzy logic controller was designed to manage an adaptable transmission rate. The controller selects whether data transmission is required and how large the payload should be during a single transmission.

Fig. 5 describes three input sets and one fuzzy output set. All input fuzzy sets are represented by three functions (low,

```
 1. If SoES is low      and EP is not high and A3BS is not high then AP is very_low
 2. If SoES is low      and EP is not high and A3BS is high     then AP is low
 3. If SoES is not high and EP is high     and A3BS is low      then AP is low
 4. If SoES is not high and EP is high     and A3BS is mid      then AP is mid
 5. If SoES is not high and EP is high     and A3BS is mid      then AP is high
 6. If SoES is mid      and EP is low      and A3BS is not high then AP is very_high
 7. If SoES is mid      and EP is low      and A3BS is high     then AP is low
 8. If SoES is mid      and EP is mid      and A3BS is low      then AP is very_high
 9. If SoES is mid      and EP is mid      and A3BS is not low  then AP is low
10. If SoES is high                                             then AP is very_high
```

Fig. 6. Summary of fuzzy rules applied by the fuzzy logic controller.

mid, and high), with various shapes designed according to the settings created by an expert. The shape of the State-of-Energy-Storage (SoES) fuzzy sets represents the preference for higher SoES values. The middle fuzzy set corresponds to a 90% charge level, and the high and low-fuzzy sets are distributed across the rest of the interval. These settings prefer a conservative behavior as the IoT sensor accumulates energy. The energy prediction (EP) fuzzy sets use a paradigm similar to SoES fuzzy sets when a progressive strategy is applied. The middle fuzzy set corresponds to 15 % of the maximum predicted energy. The aim of the low-EP preference is to dynamically use energy when the EP input indicates incoming energy in the near future. The final input set represents the size of the buffer which contains untransmitted A3 coefficients and is calculated from memory status. This input is denoted A3BS and represents the A3 coefficient buffer size. The middle fuzzy set is set to 75 %, which results in the preference to use most of the available memory.

The fuzzy output available payload (AP) represents the maximum permitted payload in a single transmission. There are five fuzzy sets, representing very low, low, mid, high, and very high-transmission intensity. The low, middle, and high-fuzzy sets are extended by the minimum and maximum operational settings of the LoRaWAN communications interface with fuzzy functions (very low and very high). The positions of the output fuzzy sets are developed asymmetrically when the low and mid fuzzy functions are set in a low interval for the AP, resulting in the preference for early transmission.

Fig. 6 depicts the expert-defined fuzzy logic rules. Several principles are applied to designing rules. The first principle establishes the preference for the SoES. The AP is set to maximum when the SoES fuzzy set is high. The second principle is determined by EP, where higher energy states generally lead to a higher AP. The final principle sets the untransmitted approximate coefficients represented by A3BS. When A3BS reaches higher values, information latency carries a significant weight, and therefore the AP is set to higher values.

D. Data Transmission Module

The transmission module decides which data are transmitted. The transmission module's input is the maximum AP permitted for the current period. The AP is obtained from the fuzzy controller and may be blocked by a power down flag which signals no available energy.

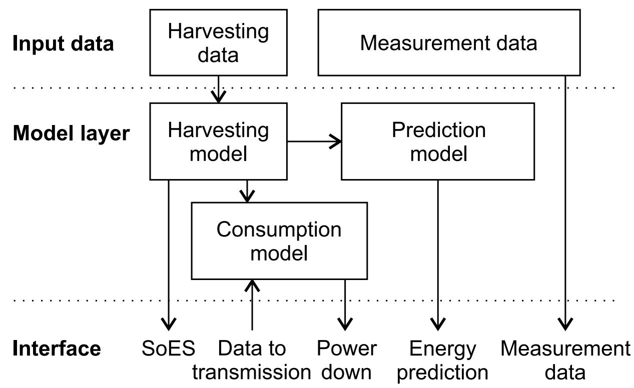

Fig. 7. Structure of the input data and hardware model with data, model, and interface layers.

The transmission module selects data clusters of a total size less than or equal to the AP with the highest importance (i.e., data clusters with the least GoF are selected). The data length in the cluster is defined by wavelet decomposition. Metadata should also be transmitted with each cluster. The required payload for cluster transmission is calculated from

$$\text{Payload} = 5 + 4 \cdot \text{Cluster size}. \tag{2}$$

The payload required for a specific cluster is calculated as the sum of the metadata length (5 bytes) and the cluster size multiplied by the size of the floating point datatype (4 bytes). The transmission module than calculates the payload.

The clusters contain a timestamp value and a column identity. The cloud gradually reconstructs the measured data, applying refinements each time new data are received from the IoT sensor.

IV. Experiment

The experimental setup uses a hardware model to simulate an IoT device and EP model. The models presented in this section were used as plug-in modules for a simulation designed to evaluate wavelet-based EC driven by a fuzzy logic controller.

The structure of the hardware model and input data (Fig. 7) contains three layers. The first layer provides the input data for calculating the quantities of harvested energy and predicted harvested energy. The input data layer also provides measurement data for the sensors on the IoT device. The model layer contains three blocks, representing a harvesting model, an EP model, and a consumption model. The harvesting model calculates the harvested energy according to the input conditions and outputs a quantity in joules. The EP model processes and prepares the harvested energy data for use in predicting future harvested energy, and the consumption model simulates the behavior of the IoT device and total power consumption of its components, which includes a microcontroller, sensors, and a transmission module. Finally, the third layer provides an interface to the behavior simulated by the EC method.

The interface layer contains components that link the hardware and EP model to the rest of simulation. The SoES describes the remaining energy as a percentage of the maximum energy stored, indicated as a value in the range 0–1. Energy consumption is calculated by the consumption model according to the data designated for transmission. The value is normalized to the 0–1 range and corresponds to 0–240 bytes. A power down flag signals transmission failure due to a lack of energy. The predicted energy value is normalized to the 0–1 range and indicates the estimated available energy for the next seven days. In this simulation, 10-min historical air temperature measurement data provided the input for a sensor's operation.

A. Hardware Model

As mentioned above, the hardware model contains a harvesting model and consumption model. The harvesting model incorporates a TEG and a DC/DC converter, and its input is the difference in temperature between each side of the TEG. Another integral part of the harvesting model is a supercapacitor with a capacity of 22 J to store energy for the IoT device. The consumption model calculates the IoT device's power consumption. All the hardware model's parameters are measured experimentally on the assembled hardware setup. Power consumption is measured in the following components.

1) Microcontroller during sleep and run modes.
2) Device sensor.
3) Wireless transmission module.

The microcontroller's standby power consumption is 3.63 μW, which fully complies with modern low-power microcontrollers in sleep or stop mode. The required energy for measurement and the microcontroller in run mode is 9.5 mJ. The power consumption of the transmission module varies according to the size of the transmitted payload. The parameters of a SemTECH LoRaWAN module were measured for this purpose and used to establish a linear approximation for transmission, defined by

$$E_{\mathrm{T}} = k \cdot \text{Payload} + q \tag{3}$$

where E_{T} is the required energy in joules for a payload of 21–240 bytes, $k = 2.4 \cdot 10^{-3}$ mJ/B is required energy for transmitting one byte via LoRaWAN, and $q = 168 \cdot 10^{-3}$ mJ is the static power consumption involving overheads, such as establishing a connection and acknowledging receipt.

Final consumption is consistent with the static consumption of establishing a connection. The remaining dynamic consumption is dependent on the volume of data transmitted during the transmission window. For parameter estimation, the LoRaWAN module was set to a data rate of 0 and TX-power 0.

B. Input Data and Estimated Energy Data

The input data were originally collected at the Churanov Station, part of the Czech Hydro-Meteorological Institute's extensive network of meteorological stations. Churanov Station is located at coordinates 49.0683° latitude, 13.615° longitude and 1117.8-m elevation.

10-min air temperature data from 2016–2019 were used as measurement data for the IoT sensor. For energy harvesting purposes, the simulated TEG used a soil temperature profile with 10-min intervals. A detailed description of temperature difference estimation on the TEG and the total energy obtained is given in this article [19].

The transmission management controller used weekly EPs to estimate the amount of available energy in the near future. The estimated energy value was normalized to the interval 0–1 and derived from harvested energy calculated by the harvesting model. These data simulated real EPs provided by local sensors or from the cloud.

C. Evaluation Criteria

Several assessment criteria were defined for evaluation purposes: maximum outage between two transmissions, percentage of transmitted data, penalty, percentage time with no energy, and data availability parameters.

The maximum outage between two transmissions relates to the data availability requirement. Because the data transmission module's power consumption is relatively high, data transmission can be delayed and transmitted when sufficient energy is available. However, this outage should be brief since the cloud stores no online data; the first aim therefore is to maintain as brief as possible outages.

The second aim is to transmit the most detailed data as possible. Using the advantages of wavelet-based compression, it is possible to first transmit approximate coefficients while delaying or not transmitting detailed coefficients, but the eventual target is to transmit all data as best as possible. The third aim is to minimize the number of power downs or failures due to lack of energy.

To assess data availability, a penalty is defined. The penalty is the sum of each untransmitted block (approximate coefficients and details), weighted according to a coefficient and accumulated in each simulation step. The weight coefficients are 1, 2, 4, and 16; 1 for D3 details (minor details) and 16 for approximation parameters.

V. RESULTS

This section presents the results of the experiment and simulated fuzzy-controlled wavelet-based EC method, from two perspectives. First, the method is evaluated according to a time domain analysis of the reliability and amount of transmitted data and the maximum transmission delay. A data availability analysis is then discussed in terms of the delay parameters of the approximate and detailed coefficients.

For evaluation purposes, two different reference control algorithms were implemented and compared to the proposed fuzzy logic controller which managed the EC policy.

TABLE II
OVERALL COMPARISON OF RESULTS ACHIEVED BY THE REFERENCE ALGORITHMS AND FUZZY CONTROL ALGORITHM

Case	Max. outage (days)	Transmitted (%)	Penalty (mil.)	No en. (%)
240	15.49	100.00	22.92	7.80
360	15.99	99.88	32.49	7.59
480	15.33	92.29	251.31	5.80
600	14.99	83.10	586.15	4.62
720	14.49	75.79	899.49	3.92
1,080	13.49	59.19	1897.80	2.40
1,440	9.99	48.40	2732.30	1.53
MS	26.04	100.00	62.12	0.00
FC	13.34	100.00	33.47	3.83

MS – Maximum SoES strategy, FC – Fuzzy controller

1) The first reference algorithm applied a fixed transmission period with a maximum transmission payload. This solution was tested with seven different fixed-period controllers.
2) The second reference was based on the maximum SoES strategy, where the controller transmitted data only when the SoES indicated a full charge.

A. Time Domain Analysis

This section presents a time domain analysis which compares the dynamic behaviors of the fuzzy controlled EC method to the reference solutions.

Table II compares the results for the reference control algorithms and the fuzzy controller used with the EC method.

Regarding the total transmitted data, only fixed periods of 240 and 360 min were applied the detailed coefficient. The reference controllers with fixed periods greater than 360 min were unable to transmit all the data because of the payload limitation. The fixed algorithm with a period of 1440 min had the shortest maximum outage (approximately 10 days).

The maximum SoES strategy controller was able to transmit all the data. This algorithm also achieved the best results in the percentage of total uptime and the time with an empty SoES without failure. Its maximum outage, however, was the longest of all the controllers (approximately 26 days).

The fuzzy-controlled EC method provides the best trade-off between the presented evaluation criteria. The controller was able to transmit all data, with a maximum outage of 13.49 days; this result is one of the best, and even the best among the controllers able to transmit complete data without compression loss. The uptime ratio ranked fourth best, which is also acceptable.

Fig. 8 displays the behavior of the fuzzy-controlled EC method over a 60-day interval. AP indicates the fuzzy controller's output, *transmitted* refers to the volume of transmitted bytes, *SoES* represents the amount of available energy, *A3BS* is the buffer size storage of approximate coefficients, EP contains normalized data on predicted incoming energy, and *details buffer size* represents the detailed coefficients storage. It is interesting that when the SoES level fell, the fuzzy controller applied a conservative strategy and reduced transmission to prevent device failure. However, as a result, details buffer storage increased. When the SoES level increased again, the fuzzy controller first transmitted mainly approximate coefficients, followed by details.

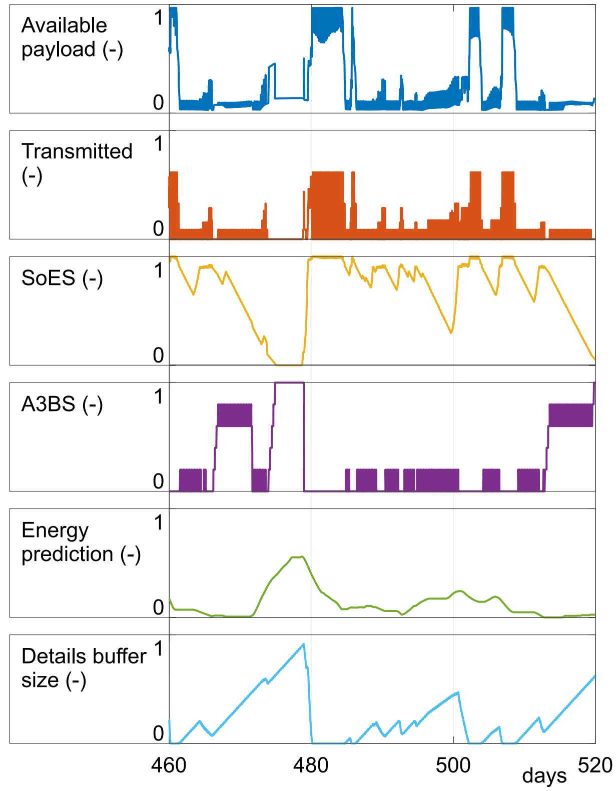

Fig. 8. Fuzzy controlled EC method, where AP indicates the fuzzy controller's output, *transmitted* refers to the volume of transmitted bytes, *SoES* represents the amount of available energy, *A3BS* is the buffer size storage of approximate coefficients, EP refers to the predicted energy for seven days, and *details buffer size* represents the detailed coefficients storage.

B. Data Availability Analysis

This section presents an analysis of the data availability in the IoT device at particular times. The data availability analysis evaluated only the three the best performing algorithms (i.e., 360 min, maximum SoES strategy, and the fuzzy controller). The aim of this analysis was to determine the accuracy of the total information value of the transmitted data at a certain time in the cloud.

Table III summarizes the average transmission delays for the DWT coefficients of decomposed measured data. Using the fuzzy controller, the A3 approximate coefficient produced the shortest delay, with an average of 0.51 days and median of 0.01 days. This is a very interesting result, because the approximate values are available in the cloud very quickly as a result of using the DWT compression method. We can also observe that the most significant detailed coefficients were transmitted with a maximum delay of three days. In the case of the D3 coefficients, the average upload time was approximately one week. Fig. 9 indicates the average transmission delay for the DWT-based compression coefficients. The maximum SoES strategy transmitted only when the SoES indicated a full

TABLE III
AVERAGE TRANSMISSION DELAY FOR SPECIFIC COEFFICIENTS OF DECOMPOSED MEASURED DATA

	A3	D3	D2	D1
Average delay (days)				
360 min. fixed	0.91	1.51	2.62	8.42
Max. SoES strategy	2.75	2.94	3.21	3.55
Fuzzy controller	0.51	2.79	4.37	7.35
Median delay (days)				
360 min. fixed	0.14	0.14	0.17	0.22
Max. SoES strategy	0.73	0.86	1.06	1.31
Fuzzy controller	0.01	0.30	1.73	3.68

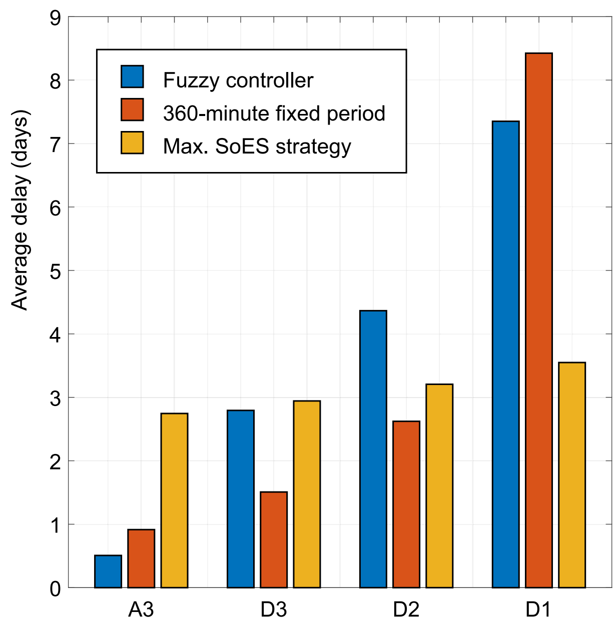

Fig. 9. Average transmission delay for wavelet-based compression coefficients.

charge, and at this moment, all the DWT coefficients were uploaded simultaneously. This behavior did not achieve the objective of to DWT compression, which includes consecutive transmission of approximated and detailed coefficients.

As described in Section III, the controller examines the data set and transmits mainly the data with the highest priority. Approximate coefficients are prioritized, and detailed coefficients are weighted according to GoF without any evaluation of their depth. The average GoF value for the approximate coefficients was 0.52; for D3 it was 0.68; and for D2 it was 0.80.

Table IV and Fig. 10 indicate the delay in data availability in the cloud for various GoF values in the best performing controllers. Data availability with the maximum SoES strategy controller was not dependent on a GoF value, corresponding to the results presented in the previous section. The controller with a 360-min fixed period produced the shortest delay with a GoF of 0.1, but the delay increased with higher GoF values. The fuzzy controller produced the shortest delay of 0.55–1.42 days with a GoF in the interval 0.1–0.5. More precise data became available in the cloud after a delay of 2.1–7.35 days.

TABLE IV
AVERAGE DELAY OF TRANSMITTED COMPRESSED DATA ACCORDING TO GOF

GoF	FC	FP 360 min.	MS
0.1	0.55	0.92	2.75
0.2	0.63	0.92	2.75
0.3	0.76	0.93	2.75
0.4	1.02	0.96	2.76
0.5	1.42	1.00	2.79
0.6	2.10	1.13	2.84
0.7	3.17	1.50	2.96
0.8	4.54	2.21	3.16
0.9	6.64	4.80	3.47
1.0	7.35	8.42	3.55

FC – Fuzzy controller,
FP – Fixed period,
MS – Maximum SoES strategy

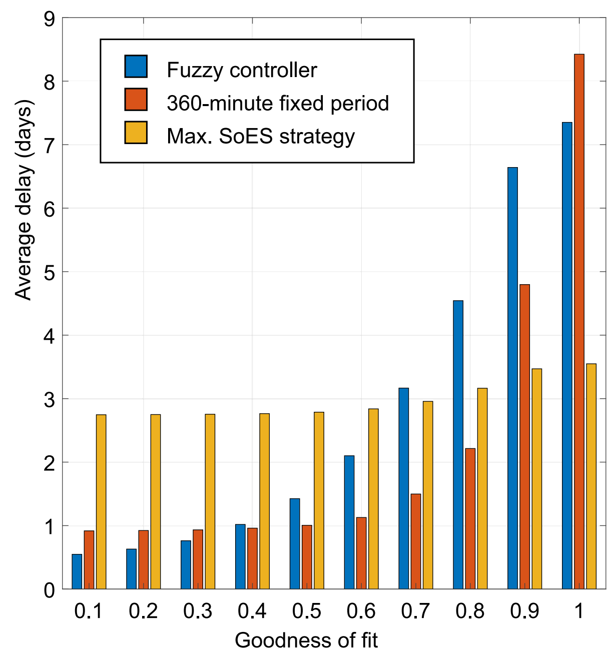

Fig. 10. Average delay for transmitted compressed data according to GoF.

VI. DISCUSSION

This section discusses SoA-related studies and compares their methods with the proposed EC method. The limitations and implications of the proposed solution are also reviewed.

A. Comparison With SoA Approaches

Table V summarizes the key parameters of the related studies listed in Section II and compares the mathematical, neural network, data reduction, and wavelet-based EC methods. The EC methods are compared according to their capabilities for lossless transmission, lightweight implementation, compression level variability, gradual data refinement, and suitability for IoT sensors. None of the presented EC methods are capable of transmitting approximate data and subsequently refining the data after details are transmitted. The methods based on neural networks exhibit high-computational complexity and

TABLE V
COMPARISON OF THE FEATURES IN STATE-OF-THE-ART METHODS WITH THE PROPOSED EC METHOD

EC method	**Lossless compression**	**Lightweight implementation**	**Variable compression level**	**Gradual refinement of data**	**IoT suitable**
Mathematical transforms [6]–[10]	✓	✓	✓	×	✓
Neural networks [11]–[13]	×	×	×	×	✓
Data reduction [14]–[16]	✓	✓	✓	×	✓
Proposed EC method	✓	✓	✓	✓	✓

are therefore unsuitable for lightweight implementation in low-power IoT devices. The data reduction techniques offer lossless compression with variable compression levels and lightweight implementation, but they do not support gradual data refinement.

The current study identified the functional parameters for energy consumption and the transmission parameters for an IoT sensor powered by a TEG. The proposed approach addresses challenges, such as limited bandwidth and limited computational resources, linked to data transmission in IoT systems. A suitable compression method capable of varying the compression level and a fuzzy-based control algorithm enabling early transmission of approximated data and subsequent enhancement with detailed data were also presented. The proposed solution ensures efficient data transmission while observing the limited resources and energy constraints of the sensors. By using a variable compression level and a fuzzy control algorithm, the solution optimizes data transmission while maintaining an acceptable level of detail.

The fuzzy controller is well-suited to the specific requirements of energy harvesting IoT sensors and the need for dynamic control of transmission. Firmware implementations in embedded devices commonly follow a finite state machine approach and employ duty cycle scenarios. In such cases, a rule-based controller is a suitable solution, acting as a transition function in the implemented finite state machine. However, by incorporating a fuzzy-based solution, the options for dynamic energy management strategies are expanded and allow future optimization of fuzzy set and rule settings. The fuzzy controller provides a flexible and adaptable approach for controlling the data transmission modules of energy harvesting IoT sensors and enables efficient use of available energy resources, thereby enhancing overall system performance.

B. Implications and Limitations

The data compression process is limited by its requirement for a sufficiently long data input data vector to achieve worthwhile compression. Consequently, this leads to a delay in data transmission since the measurement of a data vector of the same length is necessary. Longer data vectors, however, enable deeper decomposition and a more extensive compression process.

Another limitation arises from the impact of the compression level on computational complexity. As the compression level increases, the method becomes more computationally demanding. This should be factored in when implementing compression techniques, especially in lightweight low-power IoT devices.

The length of the input data vector and the selected compression level represent a compromise between computational complexity, the delay caused by measuring the complete input data vector, and the compression variability. Balancing these factors is crucial to achieving an optimal tradeoff between efficiency and effectiveness of the compression process.

The proposed solution applied compression to reduce the volume of transmitted data. Compression was lossy to improve data availability and decrease information latency. The results of the experiment demonstrate that the proposed EC method and fuzzy controller prioritized the A3 coefficients, which represent data with high-information density.

A significant contribution from this study is a method for sequentially refining data and reducing data volume during transmission when an IoT device lacks sufficient energy. In optimal cases, this approach leads to a minimum loss of information with all detailed coefficients being transmitted. The results indicate that the proposed EC method was able to transmit a complete input data set.

The fuzzy logic controller inputs were normalized to a range of values, which means that the fuzzy set configuration and fuzzy rules can be applied to other application areas with different energy inputs or harvesting sources and exhibit similar behavior. The DWT compression method is also completely independent of domain. Although different measured parameters can produce variability in the GoF values, this behavior does not affect transmission priority.

The DWT compression method is suitable for execution in microcontrollers, especially digital signal processors which implement MAC (multiply–accumulate operation) instructions. DWTs can also be deployed as multiplication arrays. To decompose 32 samples into the third level, 1344 MAC instructions are required, but this number can be reduced by using a compressed sparse matrix technique. This feature allows the application of EC methods in low-power IoT devices characterized by limited computational power.

VII. Conclusion

The study presented a wavelet-based fuzzy logic EC method applied in an IoT hardware model consisting of modules for energy harvesting, energy consumption, and EP. The study also presented an experiment to simulate the behavior of the EC method and to test the IoT hardware model.

The results of the experiment demonstrated that the proposed EC solution significantly improved the information latency in the cloud produced by an energy harvesting IoT device. With the proposed fuzzy controller EC method, the average delay in uploading approximated data was 0.51 days; the reference methods had an average delay of at least 0.91 days. The novelty of the proposed EC solution was discussed in relation to the state-of-the-art methods applied in the proposed solution.

Future work will test the hypothesis that the EC method works independently in a range of scenarios by evaluating the its transfer principle and comparing it to other measured parameters and hardware models that function with different harvesting sources.

References

[1] M. Borova, P. Svobodova, M. Prauzek, and J. Konecny, "Comparison of edge computing methods for environmental monitoring IoT sensors using neural networks and wavelet transform," in *Proc. IEEE Symp. Comput. Intell.*, 2022, pp. 217–222.

[2] V. K. Singh, V. K. Singh, and M. Kumar, "In-network data processing based on compressed sensing in WSN: A survey," *Wireless Pers. Commun.*, vol. 96, no. 2, pp. 2087–2124, 2017.

[3] Q. Han, L. Liu, Y. Zhao, and Y. Zhao, "Ecological big data adaptive compression method combining 1D convolutional neural network and switching idea," *IEEE Access*, vol. 8, pp. 20270–20278, 2020.

[4] A. M. Shaheen, T. R. Sheltami, T. M. Al-Kharoubi, and E. Shakshuki, "Digital image encryption techniques for wireless sensor networks using image transformation methods: DCT and DWT," *J. Ambient Intell. Humanized Comput.*, vol. 10, no. 12, pp. 4733–4750, 2019.

[5] A. J. Ahmed, M. M. Hamdi, A. S. Mustafa, and S. A. Rashid, "WSN application based on image compression using AHAAR wavelet transform," in *Proc. Int. Congr. Human-Comput. Interact., Optim. Robot. Appl. (HORA)*, 2022, pp. 1–4.

[6] A. Genta and D. Lobiyal, "Performance evaluation of wavelet based image compression for wireless multimedia sensor network," in *Proc. Int. Conf. Adv. Comput. Data Sci.*, 2018, pp. 402–412.

[7] P. Kumsawat, N. Pimpru, K. Attakitmongcol, and A. Srikaew, "Wavelet-based data compression technique for wireless sensor networks," in *Proc. World Acad. Sci., Eng. Technol.*, 2013, p. 125.

[8] M. A. Hussin, F. A. Poad, and A. Joret, "A comparative study on improvement of image compression method using hybrid DCT-DWT techniques with Huffman encoding for wireless sensor network application," *Int. J. Integr. Eng.*, vol. 11, no. 3, pp. 149–158, 2019.

[9] L. Kou, C. Liu, G.-W. Cai, and Z. Zhang, "Fault diagnosis for power electronics converters based on deep feedforward network and wavelet compression," *Electr. Power Syst. Res.*, vol. 185, Aug. 2020, Art. no. 106370.

[10] M. Elsayed, M. Mahmuddin, A. Badawy, T. Elfouly, A. Mohamed, and K. Abualsaud, "Walsh transform with moving average filtering for data compression in wireless sensor networks," in *Proc. IEEE 13th Int. Colloq. Signal Process. Appl. (CSPA)*, 2017, pp. 270–274.

[11] M. A. Alsheikh, S. Lin, D. Niyato, and H.-P. Tan, "Rate-distortion balanced data compression for wireless sensor networks," *IEEE Sensors J.*, vol. 16, no. 12, pp. 5072–5083, Jun. 2016.

[12] H. H. Nuha, A. Balghonaim, B. Liu, M. Mohandes, M. Deriche, and F. Fekri, "Deep neural networks with extreme learning machine for seismic data compression," *Arabian J. Sci. Eng.*, vol. 45, no. 3, pp. 1367–1377, 2020.

[13] B. Zhang, J. Zhao, X. Chen, and J. Wu, "ECG data compression using a neural network model based on multi-objective optimization," *PloS One*, vol. 12, no. 10, 2017, Art. no. e0182500.

[14] H. Deng, Z. Guo, R. Lin, and H. Zou, "Fog computing architecture-based data reduction scheme for WSN," in *Proc. 1st Int. Conf. Ind. Artif. Intell. (IAI)*, 2019, pp. 1–6.

[15] P. H. Li and H. Y. Youn, "Gradient-based adaptive modeling for IoT data transmission reduction," *Wireless Netw.*, vol. 26, no. 8, pp. 6175–6188, 2020.

[16] A. M. Hussein, A. K. Idrees, and R. Couturier, "Distributed energy-efficient data reduction approach based on prediction and compression to reduce data transmission in IoT networks," *Int. J. Commun. Syst.*, vol. 35, no. 15, 2022, Art. no. e5282.

[17] S. El-Sharo, A. Al-Ghraibah, J. Al-Nabulsi, and M. M. Matalgah, "Evaluation of the carotid artery using wavelet-based analysis of the pulse wave signal," *Int. J. Electr. Comput. Eng.*, vol. 12, no. 2, pp. 1456–1467, 2022.

[18] A. Achmamad and A. Jbari, "A comparative study of wavelet families for electromyography signal classification based on discrete wavelet transform," *Bull. Electr. Eng. Inform.*, vol. 9, no. 4, pp. 1420–1429, 2020.

[19] T. Paterova et al., "Environment-monitoring IoT devices powered by a TEG which converts thermal flux between air and near-surface soil into electrical energy," *Sensors*, vol. 21, no. 23, p. 8098, 2021.

Jaromir Konecny (Member, IEEE) was born in Frydek-Mistek, Czech Republic, in 1986. He received the bachelor's degree in control and information systems, the master's degree in measurement and control engineering, and the Ph.D. degree in technical cybernetics from VSB—Technical University of Ostrava, Ostrava, Czech Republic, in 2008, 2010, and 2014, respectively.

He has worked with the Department of Cybernetics and Biomedical Engineering, VSB–Technical University of Ostrava, Ostrava, Czechia, since 2012 and is currently an Associate Professor. He has authored more than 50 articles and conference papers and has four registered inventions. His research areas include embedded systems, electronics, environmental monitoring systems, and localization systems in robotics.

Dr. Konecny is an IEEE member active in the Systems, Man and Cybernetics Society, the Computational Intelligence Society, and Internet of Things Community.

Michal Prauzek (Senior Member, IEEE) was born in Ostrava, Czech Republic, in 1983. He received the bachelor's degree in control and information systems, the master's degree in measurement and control systems, and the Ph.D. degree in technical cybernetics from VSB–Technical University of Ostrava (TUO), Ostrava, Czech Republic, in 2006, 2008, and 2011, respectively.

He has worked with the Department of Cybernetics and Biomedical Engineering, VSB–TUO since 2010, and is currently an Associate Professor. He also worked as a Research Postdoctoral Fellow with the University of Alberta, Edmonton, AB, Canada, from 2013 to 2014. He has authored over 100 articles and conference papers and has eight registered inventions. His research topics include embedded systems, data and signal analysis, control design, and machine learning.

Dr. Prauzek is an IEEE Senior Member active in the Systems, Man and Cybernetics Society, the Engineering in Medicine and Biology Society, and the Internet of Things Community.

Monika Borova was born in Ostrava, Czech Republic, in 1993. She received the bachelor's degree in biomedical technology, the master's degree in biomedical engineering, and the Ph.D. degree in technical cybernetics from VSB–Technical University of Ostrava, Ostrava, Czech Republic, in 2015, 2017, and 2023, respectively.

She is also active in projects in the Czech Republic and internationally. She has coauthored conference papers and articles published in journals mainly in the field of embedded systems, the IoT, and environmental monitoring systems.