Environmental Impact Assessment Review 86 (2021) 106499

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

journal homepage: www.elsevier.com/locate/eiar

Research on deep integration of application of artificial intelligence in environmental monitoring system and real economy

Xiaheng Zhang [a,e], Kunliang Shu [b,*], S. Rajkumar [c], V. Sivakumar [d]

[a] Business School, Northwest University of Political Science and Law, Xi'an 710122, Shaanxi, China
[b] Institute of Agricultural Economy and Information, Jilin Academy of Agricultural Sciences, Changchun 130033, Jilin, China
[c] School of Computer Science and Engineering, Vellore Institute of Technology, India
[d] School of Computing, Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, India
[e] School of Economics and Management, Qinghai Nationalities University, Xining 810007, Qinghai, China

ARTICLE INFO

Keywords:
AI
Environmental monitoring system
Wireless sensor network
Internet of things

ABSTRACT

Environmental monitoring, modeling, and managing allow a better understanding of major processing and techniques for managing environmental changes. The pollution level has risen over time due to many factors such as a rise in population and the use of the vehicle, industrialization, and urbanization that have a direct impact on people 's health. Hence, in this paper, Artificial intelligence assisted Semantic Internet of Things (AI-SIoT) has been proposed using a wireless sensor network (WSN) for the environmental monitoring system and the real economy. The Artificial Intelligence technique can very effectively analyze data and make precise decisions on the provision of services in different types. This study provides a mathematical framework for the analysis of interdependent aspects of the WSN protocol for communication and design of signal processing. The Internet of Things (IoT) based framework comprises the complete information system from the sensor level to data management about the environment. The experimental results show that the proposed method provides an effective way to analyze the long-term monitoring of environmental data. The proposed AI-SIoT method using the WSN method enhances accuracy(95.6%), performance(98.7%) increase efficiency (93.7%) with reliability (97.4%) when compared to other existing methods.

1. Background study

Climatic change and environmental monitoring and management have received much attention nowadays (Nabavi-Pelesaraei et al., 2018). The continuous improvement of the quality of life is directly associated, among other factors, with the quality of the environment (Ghoreishi and Happonen, 2020). This can be achieved by utilizing advanced equipment and technology-based intelligent monitoring, analysis, decision-making, and control systems (Ezhilmaran and Adhiyaman, 2017). Environmental monitoring defines the required procedures and practices to recognize and monitor environmental quality (Sun et al., 2019). Environmental monitoring is used to prepare environmental impact analyses, as well as other circumstances under which human activities pose the risk of harmful environmental impacts, and it needs the use of sensors concerning cost, performance, and opportunity constraints (Ngan et al., 2020). Environmental monitoring plays an important role in assessing health and safety problems for public or environmental health purposes. Monitoring helps us to keep their wellbeing updated and informs of potential future issues. Ecosystem surveillance is close to human health surveillance. Ecosystems tracking can provide information on the improvement of the ecosystems by calculating physical, chemical or biological component over time.Monitoring may generally be characterized as repeated measurements for a series of variables at one or more places under prearranged schedules in space and time over a longer period (Ramadoss et al., 2018). To become successful, however, a monitoring system, which includes all the other activities required for the findings to be interpreted in the appropriate format, has to be more than the collection of data, like data analysis and interpretation (Manogaran et al., 2009; Sun and Medaglia, 2019; Strigaro et al., 2019; Jegadeesan et al., 2019; Zhang et al., 2018a; Dhar and Lee, 2018). Fig. 1 shows the environmental monitoring system and its impacts.

AI technology has enormous potential and will expand environmental inspection's reach and effectiveness and substantially enhance

* Corresponding author.
E-mail addresses: kunliangshu@protonmail.com (K. Shu), drsivakumarv@veltech.edu.in (V. Sivakumar).

https://doi.org/10.1016/j.eiar.2020.106499
Received 11 August 2020; Received in revised form 30 September 2020; Accepted 13 October 2020
Available online 23 October 2020
0195-9255/

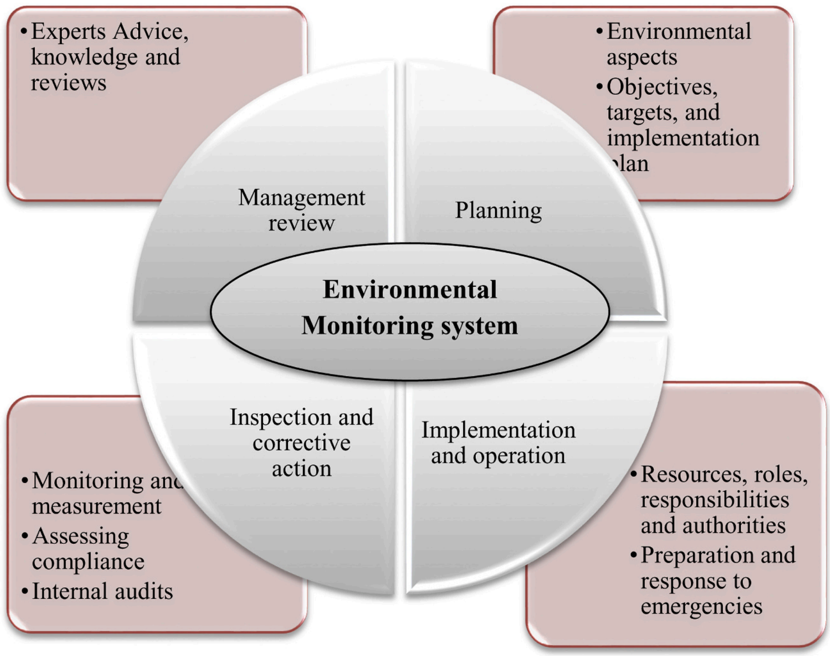


Fig. 1. Environmental monitoring system.

regulatory efficiency (Dincer et al., 2019; Chen, 2019). Machine learning models may boost resource utilization by predicting where manual inspection services on the ground will be most useful (Kumar et al., 2019). Companies are subject to increased monitoring and regulatory supervision, as authorities can share a resource-effectively track or predict possible violations (Kumar et al., 2017; Lv et al., 2019; Yang and Deng, 2019; Haque et al., 2020). The probability of potential violations and respective measures is high. As a result, the risk is reduced (Martinico-Perez et al., 2018; Kamelia et al., 2018). The wireless sensor network is a low-cost, low-power wireless network consisting of thousands of intelligent sensor nodes that track conditions of physical or environmental performance, such as pressure, temperature, humidity, in various regions or locations (Zhang et al., 2018b). The Internet of Things is developing technology for future environmental monitoring. The Internet of Things (IoT) is interpretable as connecting everyday items, such as laptops, internet TVs, sensors, and actuators, to the internet where the machines are intelligent in connecting devices and people and things (Cifelli et al., 2018; Sanchez-Iborra et al., 2019; Fan et al., 2019).

In this paper, Artificial intelligence assisted Semantic Internet of Things (AI-SIoT) has been proposed using a WSN for the environmental monitoring system and the real economy. This study describes environmental monitoring and quality analysis systems based on a combination of artificial intelligence methods and IoT with WSN models. The smart environmental monitoring system monitors and regulates the impacts induced by environmental changes in animals, plants, and humans. Initially, sensor systems are used for parameter identification (for example, noise, CO levels, etc.) while acquiring data, calculating, and controlling actions (for example, for the specified costs, noise variations, and CO level). The sensor devices are positioned at various positions to prevent the behavior of a specific area and to capture the information. The approach offers intelligent consideration for a particular field of interest.

The major involvement of the study is,

- To propose Artificial Intelligence assisted Semantic Internet of Things (AI-SIoT) using a WSN for the environmental monitoring system and the real economy.
- Designing the mathematical framework based on WSN protocol and signal processing for environmental monitoring.
- The numerical results have been performed, and the proposed method enhances the accuracy((95.6%) and performance ratio (98.7%) when compared to other existing approaches.

The remainder of the paper discussed as follows: Sections 1 and 2 discussed the background and existing methods on the environmental monitoring system and the real economy. In Section 3, Artificial Intelligence assisted Semantic Internet of Things (AI-SIoT) has been proposed using a WSN for the environmental monitoring system and the real economy. In Section 4, numerical results have been performed. Finally, Section 5 concludes the research article.

2. Literature survey

Kadir et al. (2018) proposed the Long Range Wide Area Network and Internet of Things (LoRa- WAN-IoT) for environmental monitoring. The goal of this article is to develop a system of sensors that can detect land and forest fires. The sensors are positioned in many areas that have previously been significantly affected. To have a platform to link the sensor, the LoRaIoT technology will be implemented. An early sign that forest or land fires can become uncontrollable and overwhelming is crucial for quick prevention. The strategy and development of LoRa sensors allow users to solve current problems caused by land and forest fire in the province of Riau. The proposed system allows the sending of environmental data to the application server for a real-time monitoring system, in a minimum of time.

Wu and Ning (2018) suggested the System Dynamic Model and Geographic information system (SD-GIS) to assess the urban economy-environment-energy system. First, they simulate the adjustments of the SD model and then spatially evaluate the simulated effects through GIS. In particular, they adapt the SD model parameter to compare simulated outcomes for shifting priorities in line with four sustainable economic development policy approaches protection of the environment, progress in technology, conservation of energy, and the status quo. The results in the SD model show that none of these policies support sustainable development priorities. High-tech investment is good for the economy and is not eco-sustainable and environmental investments would hamper economic development in return.

Ullo and Sinha (2020) introduced the Internet of Things and Wireless

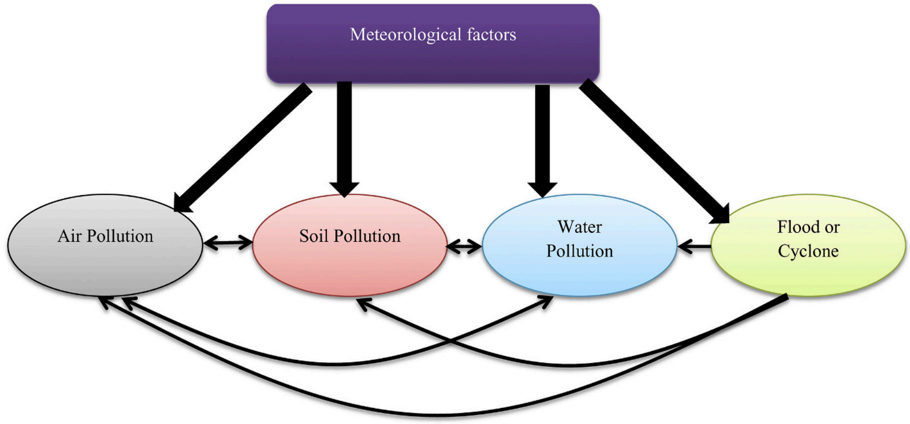


Fig. 2. Interconnections between various critical environmental situations.

Sensor Networks (IoT-WSN) for Smart Environment Monitoring systems (SEM). The study is divided according to the purposes in which SEM methods are applied, and each object is analyzed more closely in terms of the sensors used, machine learning techniques, and methods for classification. The detailed analysis is followed by an extensive examination that has provided the basis for analyzing discussion outcomes and research trends for important recommendations and the impacts of SEM research. The authors have studied critically how advances in sensor technology, IoT, and machine learning make the environment a particularly interactive monitoring system. Finally, the framework of robust machine learning methods was proposed, methods of denoising were developed, and appropriate Wireless Sensor Network standards (WSNs) developed.

Fijani et al. (2019) suggested the Complete Ensemble Empirical Mode Decomposition Algorithm with Adaptive Noise and Variational Mode Decomposition (CEEMDAN-VMD) for environmental monitoring of water quality parameter. The parameter was then divided into validation, training, and test subsets, where the superiority of the ELM over the LSSVM algorithm is reported during the first step of model testing. The second step of decomposition with the variable incoming oscillations, reflecting the intrinsic mode function (IMF) using the CEEMDAN Algorithm, was used to improve such standalone predictive models. The disintegration of the Chl-a and time-series utilizing the CEEMDAN method were employed with a view to improved models' efficiency, which resulted in an enhanced output of the standalone method.

To overcome these issues, in this paper, Artificial intelligence assisted Semantic Internet of Things (AI-SIoT) has been proposed using a WSN for the environmental monitoring system and the real economy. Environmental monitoring is becoming more concerned for IoT devices, as environmental technology develops a major field for sustainable growth in the world. Different environment monitoring is particularly challenging, for example, because of the usual tough working circumstances and complexity and expense of physical access for positioning and preservation on the environment. Wireless Sensor Network (WSN) consists of thousands of smart sensor nodes, which track physical and environmental settings like temperature, noise, humidity, light, moisture, and pollution at various locations or areas. In a wide range of IoT environmental monitoring systems, the prescriptive WSN systems are used with good results. For a coherent model, the major necessities for low-cost, fast-delivery of several sensors, and long service and reliable at all design levels are considered. A variety of trade-offs are defined, evaluated, and utilized to guidelines for design decisions between platform features and requirements. The proposed architecture approach can be used in certain application areas for the platform design or the development of an environmental monitoring system. The flexibility and reusability need a platform for a wide range of related uses that have been measured from the start. The application was chosen and used as a guide and during the design process as a real-time application illustrative in this industrial field. Eventually, the experimental findings show that the strategy of the platform satisfies the specifications in environmental monitoring.

3. Artificial Intelligence assisted Semantic Internet of Things (AI-SIoT)

In this paper, Artificial Intelligence assisted Semantic Internet of Things (AI-SIoT) has been proposed using a WSN for the environmental monitoring system and the real economy. In the context of sustainable development and increasing human environmental pressures, the monitoring of ecosystems' health status is of primary importance. The basis of environmental monitoring is the processing of data that helps people to understand the natural environment by monitoring better.

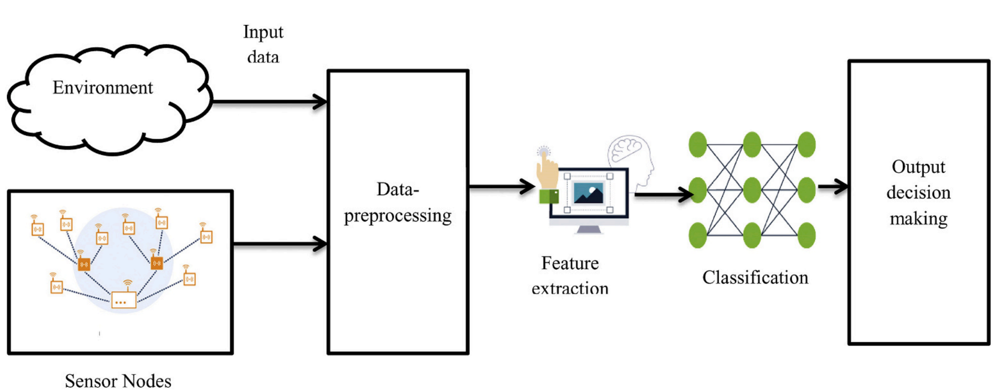


Fig. 3. The architecture of the proposed AI-SIoT method.

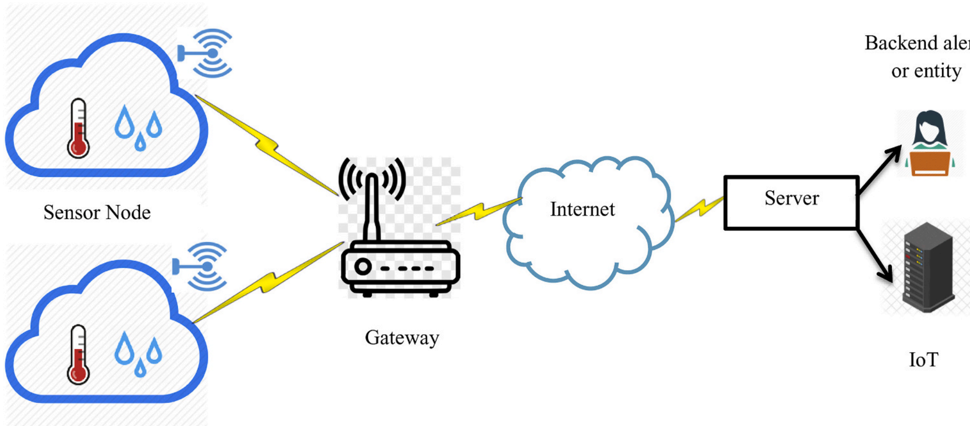


Fig. 4. Internet of Things based Wireless Sensor Network for environmental monitoring system.

Environmental monitoring scientifically includes physics, chemistry, and biology. Various factors and difficult environmental situations are impacting the quality of life. It is important to provide smart devices in place to warn the population, such that the effects of extreme environmental incidents on prevention or reduction. Fig. 2 shows the meteorological factors interconnections.

Many environmental problems can be resolved with efficiency through artificial intelligence techniques (monitoring, analysis, diagnosis, forecasting, control, strategic planning). The data acquisition system in use must allow a representative sampling to be collected, addressing problems such as measurement intrusion, quality of sampling, or the storage of samples. The impact of such concerns relies on the application on the one side (e.g., the sensitivity of the physical value observed, which may be externally impacted) and the method of data acquisition system employed on the other. Fig. 3 shows the architecture of the proposed AI-SIoT method.

While several sensors connect directly (for instance, via local area networks) to the controllers and processing stations, there are more and more sensors relay the captured data to the centralized processing station wirelessly. It is a significant network implementation, which needs hundreds or thousands of sensor nodes that many become inaccessible in remote areas. A wireless sensor, therefore, does not only have a sensing part, and can be processed, the communication and stored in the system on-board. For these enhancements, the data processing, the network analysis, correlations, integration of its sensor data, and data from other sensor nodes are responsible for a sensor node. When several sensors monitor broad physical environments in collaboration, they build a WSN. In addition, the sensor nodes interact with every Base Station (BS) that can distribute their sensor data to the remote process, simulate, evaluate, and store structures through its wireless frequencies. Fig. 4 shows the wireless sensor network architecture for an environmental monitoring system.

Fig. 4 shows the Internet of Things based Wireless Sensor Network for the environmental monitoring system. Reduce energy usage and increase network life has been the key design targets for wireless next-generation networks mainly through wireless devices that have limited power resources. Because the Wireless Sensor Networks consist of small energy-hungry sensor nodes, maintaining the energy level of these nodes for a long time is a difficult process. Wireless sensor networks consist of small sensors used for data tracking or sensing. Due to its limited capacity, a limited battery is powered by power supplies that can not be replaced or regularly recharged while deployed at a position not easily reachable. Energy efficiency is one of the major constraints on the network of wireless sensors.

The sensor nodes operate with very small energy supplies to be cost-effective. Premature power loss can seriously restrict network operation, which is important to resolve the cost, deployment, maintenance, which service availability IoT device requirements. If reusable hardware and software systems, like flexible Internet-enabled servers, capture and process field data on IoT applications, it satisfies the internet of things applications' low-cost, long-term, and reliable service requirements. This paper contributions of interest in the AI-SIoT with wireless sensor network field can be precised as (i) specific requirements for the WSN long term environmental monitoring application which can be utilized to assess the best usage of existing wireless sensor network technologies based on artificial intelligence assisted internet of things (ii) platform component parameters, architecture criteria and testing findings that satisfy the standard low cost, high optimistic and long cycle requirements for IoT applications. (iii) platform re-usability requirements and architecture criteria for a wide variety of dispersed event-based environmental observing, (iv) fast field implementation, configuration-free, ideal for broad-scale IoT applications.

It can be considered that the situation where nodes are uniformly and randomly located with spatial density σ and with a subset of nodes, with density σ_0 contribute to the sampling process with known positions. Nodes are typically placed in sleep mode and receiving mode regularly to save energy. By sending the packet sequence sufficient to cover the activity duration of every node, the supervisor wakes up a certain number of nodes. For the successive phases of communication, only woken nodes take part. In the supervisor, which has more compound capabilities in the signal cycle and transmission energy concerning the nodes, it supposes energy consumption.

The study mentions that a whole series of operations begins with the triggering event generated by the supervisor and lead to the estimate of the supervisor. In comparison with the delivery time of a packet by WSNs, the typical environment occurrences (e.g., pressure or temperature levels) differ slowly. A quasi-static situation has been found in this article, which implies the cycle time is measured much less than the changing rate of the field perceived. No specific time synchronization constraints are present between nodes in this scenario. The signal to be sampled is labeled via k-dimensional spatial random process $Z(w)$ with realizations $z(w)$. Let's deliberate the sample space as finite zone B, where the process is perceived, centered in the supervisor. B circular zone has been considered with radius T, and without loss of generality. Therefore, the real signal of interest is $y(w) = z(w) \cdot t_B(w)$,

$$t_B(w) = \begin{cases} 1 \; w \in B \\ 0 \; otherwise \end{cases} \tag{1}$$

As shown in Eq. (1) where the signal $y(w)$ has finite energy D_0 and relating to the random process $Y(w)$. The objective is to make an evaluation of $y(w)$, which indicated by $\widehat{Y}(w)$.

The Fourier transform has been defined $W_Y(u)$ for showing data latency, the number of sensor node communication, and energy consumption. The autocorrelation function, $T_Y(\tau)$ and energy spectral density, $D_Y(u)$ as expressed by,

$$W_Y(u) = \mathscr{L}^{(k)}[y(w)] \quad (2)$$

$$T_Y(\tau) = \int y(w)y(w-\tau)dw \quad (3)$$

$$D_Y(u) = \mathscr{L}^{(k)}[T_Y(\tau)] \quad (4)$$

As inferred from the Eqs. (2), (3), and (4) where $\tau = (\tau_1, \tau_2, \dots \tau_k)$ and $u = (u_1, u_2, \dots u_k)$ are the spatial frequency. The operator $\mathscr{L}^{(k)}[]$ Denotes the $k-$dimensional Fourier transform. The statistical expectation $\mathbb{N}[.]$ can be represented in the following equations.

It is to be assumed that $z(w)$ is bandlimited, $W_Z(u) = \mathscr{L}^{(k)}[z(w)]$ is not consist of important spectral elements outside W_0, where $W_0 = \{u$ *subject to* $(-A_0 < u_1 < A_0, -A_0 < u_2 < A_0, \dots -A_0 < u_k < A_0)\}$ and A_0 denotes the bandwidth per dimensions of $z(w)$. The Fourier transform of $y(w)$ as follows,

$$W_Y(u) = W_Z(u) \otimes T_B(u) \quad (5)$$

As discussed in Eq. (5) where $T_B(u) = \mathscr{L}^{(k)}[t_B(w)]$ and $\otimes$ is the convolution operator. In applied bidimensional case, it is $k = 2$ then

$$T_Y(u) = \frac{T}{\|u\|} I_1(2\pi T\|u\|) \quad (6)$$

As derived in Eq. (6) where $I_1(\cdot)$ is the first-order derivative function and $\|.\|$ is the norm operator. The $m-th$ node is placed in the spatial point w_m and receipts the sample $y(w_m)^2$. Because of the sensors arbitrarily located with spatial density σ_0 in the monitored environment, the sequence $\{w_m\}$ statistically described the spatial samples. The respective counting procedure derivative is the stationary random process $G(w) = \sum_m \beta(w - w_m)$, that have mean $\mu_G = \mathbb{N}\{G(w)\} = \sigma_0$, and computational power spectral density and autocorrelation function are provided as,

$$T_G(\tau) = \sigma_0 \cdot \beta(\tau) + \sigma_0^2 \quad (7)$$

$$W_G(u) = \sigma_0 + \sigma_0^2 \cdot \beta(u) \quad (8)$$

As shown in Eqs. (7) and (8) where $G(w)$ denotes the sampling process, $\beta(\cdot)$ is the Dirac pseudo function.

Because of communication failure, there occurs a likelihood q that a node is incapable of sending its data to the entity performing signal processing. In this scenario, the respective sample does not subsidize the signal evaluation. It is to denote $p = 1 - q$ the likelihood of correct sample reception.

The sample-set received by the entity performing signal processing forms a fresh stationary sampling process, $Q(w)$. Utilizing the outcome derived with $Q_1(w) = G(w)$ and Eqs. (7) and (8), the computational autocorrelation function and mean of $Q(w)$ are $T_Q(\tau) = \delta(\tau)\sigma_0 p + p^2\sigma_0^2$ and $\mu_Q = \mathbb{N}\{Q(w)\} = p \cdot \sigma_0$, correspondingly. The new process has been expected similar features as the actual one with density $p \cdot \sigma_0$ and power spectral density

$$W_Q(u) = p\sigma_0 + p^2\sigma_0^2 \cdot \beta(u) \quad (9)$$

The sampled version, $X(w)$ of the objective signal conditioned to the comprehension$y(w)$, can be calculated as $X(w) = y(w) \cdot Q(w)$, demonstrating finite energy non-stationary random process. The generic process realization autocorrelation function $x(w)$ is expressed by,

$$T_x(\tau) = \int y(w)y(w-\tau)q(w)q(w-\tau)dw \quad (10)$$

As inferred from the Eq. (10), where signal $q(w)$ is the random process realization $Q(w)$.

The study defines the mean computational autocorrelation function of $X(w)$ as,

Table 1
Environment description.

Variable	Value
Number of source node	30
Number of sensor node	300
Channel type	Wireless channel
Simulation area	100 × 100m
Receiving energy	50nJ/bit
Energy model	Battery
Data compression rate	0.45
Transmission energy	50nJ/bit
Data processing energy	5nJ/bit

$$\overline{T_X}(\tau) = \mathbb{N}\left\{\int y(w)y(w-\tau)Q(w)Q(w-\tau)dw\right\} \quad (11)$$

$$= \int y(w)y(w-\tau)T_Q(\tau)dw = T_Q(\tau) \cdot T_Y(\tau),$$

The mean energy spectral density is expressed by,

$$\overline{D}_X(u) = \mathscr{L}^{(k)}\left[\overline{T}_Y(\tau)\right] = D_Y(u) \otimes W_Q(u) \quad (12)$$

$$\overline{D}_X(u) = p^2\sigma_0^2 D_Y(u) + D_0 \cdot \sigma_0 \cdot p \quad (13)$$

In this study, the evaluated signal is determined via linear interpolation of the received sample-set $X(w)$. The evaluated $\widehat{Y}(w)$ can be calculated as

$$\widehat{Y}(w) = \varphi(w) \otimes X(w) \quad (14)$$

As discussed in Eq. (14) where $\varphi(w)$ is the linear interpolator impulse response, whose transfer function is $\varphi(u) = \mathscr{L}^{(k)}[\varphi(w)]$.

An ideal low-pass interpolator with transfer function can be considered in this case,

$$\varphi(w) = \begin{cases} \frac{1}{\mu_\varphi} \; u \in W^* \\ 0 \; otherwise \end{cases} \quad (15)$$

With μ_φ and $W \subseteq W^*$ is the reconstruction bandwidth.

This study provides a statistical structure that illustrates the inter-reliant characteristics of the wireless sensor network signal processing and communication protocol architecture when a two-dimensional random process is estimated for effective environmental monitoring.

4. Numerical results

To assess the performance of the suggested AI-SIoT model, the simulation experiments have been done in the wireless sensor network. The following assumption has been made as follows, Every node 's initial energy is the same; in the simulation phase, the source nodes stay unchanged; the data size transmitted by the node is constant, and the energy of the sink node and the mobile agent is limitless. The sensor nodes are assigned uniformly in a square region in all the simulation cases. The proposed Artificial Intelligence assisted Semantic Internet of Things (AI-SIoT) using a WSN for the environmental monitoring system output is superior to other subclasses, which indicates that data from neighboring areas can be used to assess environmental quality analyzes. Including additional details will further improve the quality of the measurement substantially. Table 1 shows the environment description utilized in WSN simulation.

The proposed module aims to link the local sensor network to the outside world. Wifi, long-range radio communication, and GSM / GPRS are the common implementations of this regional communication platform. The proprietary radio transceiver, which mostly functions in the 900 MHz range, was used when wireless sensor networks were initially

Table 2
Reliability of communication.

Available datasets	LoRa-WAN-IoT	SD-GIS	IoT-WSN	CEEMDAN-VMD	AI-SIoT
5	23.4	24.5	25.6	26.8	28.1
10	35.4	39.5	33.3	38.7	37.6
15	41.2	40.9	43.2	47.2	49.2
20	65.7	54.1	58.9	65.1	66.9
25	76.1	43.2	47.5	54.2	57.2
30	81.1	42.9	53.2	55.2	65.2
35	77.8	83.2	88.2	78.3	89.3
40	72.3	89.1	75.3	77.2	90.9
45	65.4	78.1	70.9	84.2	94.3
50	66.6	88.8	80.7	76.7	97.4

developed. For resource-constrained devices such as sensor nodes, communication through RF is costly. In even idle mode and listening only to surrounding noise, the contact module's energy usage is tremendous and can be achieved at speeds close to those involved in data transmission. The sensor nodes will then disable their Communication modules wherever possible to reduce energy usage by many magnitude orders. However, the main issue may be to wake up to collect a packet for this node. The proposed AI-SIoT method enhances the reliability in data transmission when compared to other existing methods. Table 2 shows the reliability of communication.

For controlling and assessing conditions, and efficient environmental monitoring device is required if the defined parameter amount is exceeded. Where objects such as systems with sensory sensors, segments, and sub-controllers and different device software are a self-protection and self-monitoring system, it is often referred to as a smart environment. In such a scenario, when an event happens, the alarm or LED alerts occur automatically. An intelligent environmental monitoring program can monitor and control the effect of environmental changes on animals, plants, and humans. The system developed illustrates atmospheric carbon dioxide sensing performance simulation and ambient noise emission. The sensor data is transmitted to the cloud and accessible online. The proposed AI-SIoT method improves overall performance when compared to other existing methods. Fig. 5 (a) shows the overall performance ratio using the proposed AI-SIoT method.

Fig. 5(b) shows the environmental pollutions. Pollution is widely regarded as the incorporation of dangerous waste, certain kinds of pollution which are a danger to the life-sustaining environment of the planet earth. Pollution impacts the planet's ecosystem, causing discomfort for almost any single creature in the world. The ozone layer over the planet that defends ourselves from the damaging ultraviolet rays of the environment is being destroyed as a result of the pollution in the environment. Perhaps the product of the latest increase in temperature in many countries across the world. Typically there is the main type of pollution, which are, air, water, soil, light, noise, radiation pollution. Table 3 shows the overall performance ratio analysis using the proposed AI-SIoT method.

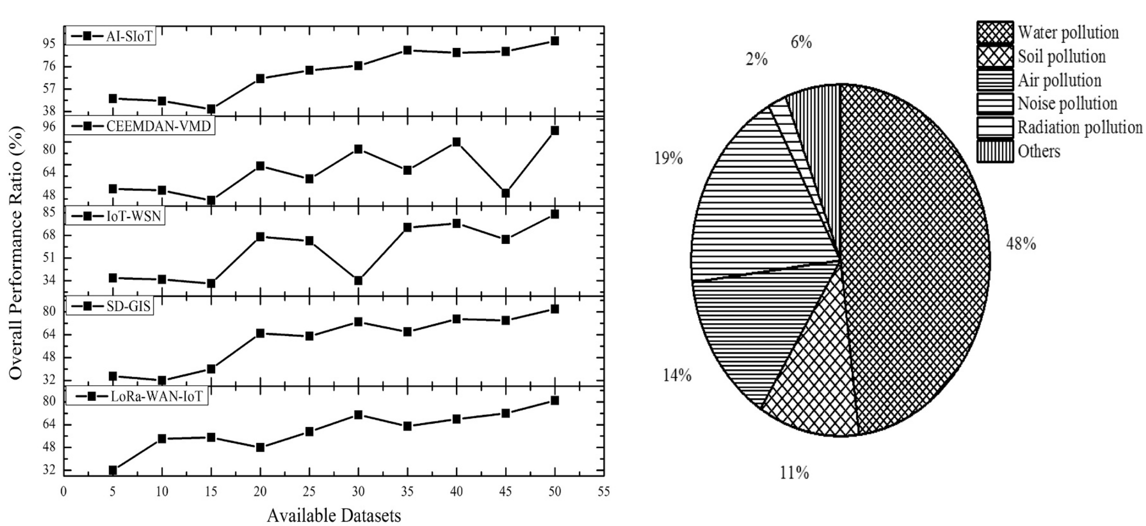
Wireless Sensor Networks (WSN) deal in emergency prevention by assessing how many disasters occurred at a particular location to reduce environmental damage and major losses related to climate change. Appropriate remedial steps may be made using Wireless Sensors (WS) calculated depending on the physical parameters of different forms of

Table 3
Overall performance ratio analysis.

Available datasets	LoRa-WAN-IoT	SD-GIS	IoT-WSN	CEEMDAN-VMD	AI-SIoT
5	32.1	35.6	36.7	47.7	49.9
10	54.5	32.7	35.5	46.6	47.8
15	55.3	40.5	32.4	39.5	40.3
20	48.2	65.1	67.6	63.4	66.1
25	59.7	63.2	64.5	54.2	73.2
30	71.3	73.3	34.1	75.4	77.3
35	63.5	66.6	74.2	60.6	90.5
40	68.7	75.8	77.2	80.8	88.6
45	72.2	74.4	65.3	44.8	89.6
50	81.1	82.2	84.5	88.9	98.7

Table 4
Sensor group and sensor type.

Sensor group	Sensor type
Climate	Air Pressure, Air Temperature, Wind Speed, Humidity, Rainfall, and Wind Direction
Plant	Leaf Wetness and Sap Rise
Soil	Soil Temperature and Soil Moisture
Radiation	UV Radiation and Solar Radiation
Gases	Carbon Dioxide (CO2), Carbon Monoxide (CO), Ozone (O3) and Methane (CH4)



5(a) 5(b)

Fig. 5. (a) Overall performance ratio (b) environmental pollutions.

Table 5
Accuracy ratio evaluation.

Available datasets	LoRa-WAN-IoT	SD-GIS	IoT-WSN	CEEMDAN-VMD	AI-SIoT
5	45.1	56.6	59.8	65.9	78.1
10	46.2	34.9	56.1	60.9	70.2
15	83.2	84.8	80.9	81.2	75.6
20	79.8	66.2	82.3	56.4	80.1
25	59.1	69.8	67.6	47.5	85.7
30	72.3	74.3	68.7	49.7	90.1
35	78.4	76.2	73.4	40.9	92.3
40	48.7	44.1	75.6	34.6	94.3
45	57.1	66.7	74.3	33.1	94.9
50	69.2	71.4	64.1	31.2	95.6

Table 6
Efficiency ratio analysis.

Available datasets	LoRa-WAN-IoT	SD-GIS	IoT-WSN	CEEMDAN-VMD	AI-SIoT
5	60.2	70.8	80.2	90.3	91.1
10	77.3	78.2	89.3	83.2	90.2
15	62.4	73.1	83.4	88.9	92.1
20	66.3	77.9	89.8	83.2	82.9
25	63.4	71.7	81.7	89.1	88.2
30	79.4	80.3	89	83	90.4
35	65.2	75	85	79	89.5
40	77.8	78	89	83	91.6
45	67.9	77	87	90	92.7
50	68.7	78	88	91	93.7

disasters. Communications systems and transportation infrastructure are very useful in critical emergencies to save thousands of people's lives. Table 4 shows the different sensor groups and sensor types utilized in this study.

IoT sensors can give accurate real-time data on environmental monitoring. Environmental indicators operate by identifying tiny changes in current induced by reaction with different molecules. The more reliable the circuitry to recognize these changes, the more accurate the performance, and the lower the overall detection limit would be. Better quality increases cost. Therefore, cities need to determine whether to best balance the accuracy of environmental monitoring by knowing what the data would be used for, against the cost. The proposed AI-SIoT method increases the accuracy rate in the detection of abnormal behavior in the environment when compared to other existing methods. Table 5 shows the accuracy ratio evaluation using the proposed AI-SIoT method.

Statistical uncertainty may boost environmental monitoring efficiency, enabling sampling designs to optimize the information obtained from the resources needed to capture and interpret data. WSN comprises of low-cost sensor nodes with minimal capacity. The main challenge is energy consumption, as such sensors are used to track the large-scale environment because a battery operates the sensors. The energy performance of the control device will be increased. The goal of this paper is to highlight strategies for evaluating environmental monitoring schemes' effectiveness and efficiency. Table 6 shows the efficiency ratio analysis using the proposed AI-SIoT method. Smart cities will be built through the usage of the WSN tool to monitor environmental quality more effectively and reliably. The WSN elements include sensors, microcontrollers, portable modules and tools to incorporate an energy-efficient network for the monitoring of the environment.

The proposed Artificial Intelligence assisted Semantic Internet of Things (AI-SIoT) using a WSN for the environmental monitoring system, and the real economy achieves high accuracy and performance, low energy consumption and latency when compared to other existing Long Range Wide Area Network and Internet of Things (LoRa- WAN-IoT), System Dynamic Model and Geographic information system (SD-GIS), Internet of Things and wireless sensor networks (IoT-WSN), Complete Ensemble Empirical Mode Decomposition Algorithm with Adaptive Noise and Variational Mode Decomposition (CEEMDAN-VMD) methods.

5. Conclusion

This paper presents the Artificial intelligence assisted Semantic Internet of Things (AI-SIoT) using a WSN for the environmental monitoring system and the real economy. The proposed architecture can be used to measure weather parameters such as sunlight, rainfall, fire, and gas leakage remotely. The data can be stored on-line to forecast and subsequently evaluate climate patterns and other meteorological activities. The WSN system examines and describes all key elements. WSN technology that transforms the study's measurement, knowledge, and sustainability of the environment monitoring. The experimental findings demonstrate that the system can accurately collect data from a set time interval and can accurately calculate the location of the acquisition phase. The results show that the variability of the calculated parameters may not need to be distributed more frequently via several network nodes than was proposed in the experiment presented. The level of transmission obtained under such conditions is therefore very high and is sufficient for this task. The proposed AI-SIoT method using the WSN method enhances accuracy(95.6%), performance(98.7%) increase efficiency (93.7%) with reliability (97.4%) when compared to other existing methods.

Declaration of Competing Interest

None.

Acknowledgements

This work was supported by Social Science Foundation of Shaanxi Province "Sustainable trade promotion of cross border e-commerce in China's Silk Road Economic Belt" (2019S037) and the Young Academic Innovation Team of Northwest University of Political Science and Law.

This work was supported by Key R & D projects of science and Technology Department of Jilin Province, Project number:20200402003NC; National Key Research and Development Project, Project number: 2018YFD0300204;Agricultural Science and Technology Innovation Project for Distinguished Young Scholars in Jilin Province, Project number:CXGC2017JQ011.

References

Chen, P., 2019. Visualization of real-time monitoring data graphic of urban environmental quality. Eurasip J. Image Video Process. 2019 (1), 42.
Cifelli, R., Chandrasekar, V., Chen, H., Johnson, L.E., 2018. High-resolution radar quantitative precipitation estimation in the San Francisco Bay Area: rainfall monitoring for the urban environment. J. Meteorol. Soc. Japan. Ser. II 96, 141–155.
Dhar, B.C., Lee, N.Y., 2018. Lab-on-a-Chip technology for environmental monitoring of microorganisms. BioChip J. 12 (3), 173–183.
Dincer, C., Bruch, R., Costa-Rama, E., Fernández Abedul, M.T., Merkoçi, A., Manz, A., Güder, F., 2019. Disposable sensors in diagnostics, food, and environmental monitoring. Advanced Materials 31 (30), 1806739.
Ezhilmaran, D., Adhiyaman, M., 2017. Fuzzy approaches and analysis in image processing. In: Advanced Image Processing Techniques and Applications. IGI Global, pp. 1–31.
Fan, Y., Fang, C., Zhang, Q., 2019. Coupling coordinated development between social economy and ecological environment in Chinese provincial capital cities-assessment and policy implications. J. Clean. Prod. 229, 289–298.
Fijani, E., Barzegar, R., Deo, R., Tziritis, E., Skordas, K., 2019. Design and implementation of a hybrid model based on a two-layer decomposition method coupled with extreme learning machines to support real-time environmental monitoring of water quality parameters. Sci. Total Environ. 648, 839–853.
Ghoreishi, M., Happonen, A., 2020, May. Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: three case studies. In: AIP Conference Proceedings, 2233(1). AIP Publishing LLC, p. 050008.
Haque, Tipu Sultan, Chakraborty, Avishek, Mondal, Sankar Prasad, Alam, Shariful, 2020. Approach to solve multi-criteria group decision-making problems by exponential operational law in generalised spherical fuzzy environment. CAAI Trans. Intell. Technol. 9.

Jegadeesan, Subramani, Azees, Maria, Kumar, Priyan Malarvizhi, Manogaran, Gunasekaran, Chilamkurti, Naveen, Varatharajan, R., Hsu, Ching-Hsien, 2019. An Efficient Anonymous Mutual Authentication Technique for Providing Secure Communication in Mobile Cloud Computing for Smart City Applications, 49. Sustainable Cities and Society, p. 101522.

Kadir, E.A., Efendi, A., Rosa, S.L., 2018. Application of LoRa WAN sensor and IoT for environmental monitoring in Riau province Indonesia. Proceed. Electr. Eng. Comput. Sci. Inform. 5 (1), 281–285.

Kamelia, L., Ramdhani, M.A., Faroqi, A., Rifadiapriyana, V., 2018, January. Implementation of automation system for humidity monitoring and irrigation system. In: IOP Conference Series: Materials Science and Engineering, 288 (1), p. 012092.

Kumar, N., Vasilakos, A.V., Rodrigues, J.J.P.C., 2017. A multi-tenant cloud-based DC nano grid for self-sustained smart buildings in smart cities. IEEE Commun. Magaz. 55 (3), 14–21.

Kumar, S.S., Kumar, V., Kumar, R., Malyan, S.K., Pugazhendhi, A., 2019. Microbial fuel cells as a sustainable platform technology for bioenergy, biosensing, environmental monitoring, and other low power device applications. Fuel 255, 115682.

Lv, Z., Hu, B., Lv, H., 2019. Infrastructure monitoring and operation for smart cities based on the IoT system. IEEE Trans. Ind. Inform. 16 (3), 1957–1962.

Manogaran, Gunasekaran, Shakeel, P. Mohamed, Priyan R, Vishnu, Chilamkurti, Naveen, Srivastava, Abhishekh, 2009. Ant colony optimization-induced route optimization for enhancing driving range of electric vehicles. Int. J. Commun. Syst. (3964), 1–16.

Martinico-Perez, M.F.G., Schandl, H., Fishman, T., Tanikawa, H., 2018. The socio-economic metabolism of an emerging economy: monitoring the progress of decoupling of economic growth and environmental pressures in the Philippines. Ecol. Econ. 147, 155–166.

Nabavi-Pelesaraei, A., Rafiee, S., Mohtasebi, S.S., Hosseinzadeh-Bandbafha, H., Chau, K. W., 2018. Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Sci. Total Environ. 631, 1279–1294.

Ngan, Roan Thi, Ali, Mumtaz, Fujita, Hamido, Giang, Nguyen Long, Manogaran, Gunasekaran, Priyan, M.K., 2020. A New Representation of Intuitionistic Fuzzy Systems and Their Applications in Critical Decision Making. IEEE Intelligent Systems.

Ramadoss, T.S., Alam, H., Seeram, P.R., 2018. Artificial intelligence and the internet of things-enabled circular economy. Int. J. Eng. Sci. 7 (9), 55–63.

Sanchez-Iborra, R., Liaño, I., Simoes, C., Couñago, E., Skarmeta, A.F., 2019. Tracking and monitoring system based on LoRa technology for lightweight boats. Electronics 8 (1), 15.

Strigaro, D., Cannata, M., Antonovic, M., 2019. Boosting a weather monitoring system in low-income economies using open and non-conventional systems: data quality analysis. Sensors 19 (5), 1185.

Sun, T.Q., Medaglia, R., 2019. Mapping the challenges of artificial intelligence in the public sector: evidence from public healthcare. Gov. Inf. Q. 36 (2), 368–383.

Sun, A.Y., Zhong, Z., Jeong, H., Yang, Q., 2019. Building complex event processing capability for intelligent environmental monitoring. Environ. Model. Softw. 116, 1–6.

Ullo, S.L., Sinha, G.R., 2020. Advances in smart environment monitoring systems using IoT and sensors. Sensors 20 (11), 3113.

Wu, D., Ning, S., 2018. Dynamic assessment of urban economy-environment-energy system using system dynamics model: a case study in Beijing. Environ. Res. 164, 70–84.

Yang, Y., Deng, Z.D., 2019. Stretchable sensors for environmental monitoring. Appl. Phys. Rev. 6 (1), 011309.

Zhang, H., Zhu, Z., Fan, Y., 2018a. The impact of environmental regulation on the coordinated development of the environment and economy in China. Nat. Hazards 91 (2), 473–489.

Zhang, Y., Chen, D., Wang, S., Tian, L., 2018b. A promising trend for field information collection: an air-ground multi-sensor monitoring system. Inform. Process. Agric. 5 (2), 224–233.