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Low-power Mesh Network Based on Message Queue Telemetry Transport Broker for Industrial IoT with Long Short-term Memory Forecasting

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The Industrial Internet of Things (IIoT) connects devices with the ability to monitor sensor data and exchange it through the internet. The necessities of reliability and high-quality data mean that data monitoring must be able to meet the requirements of the IIoT industrial standards as soon as possible. Recently, researchers have created more capable communication protocols for IIoT devices, each with their own advantages. These protocols include Extensible Messaging and Presence Protocol (XMPP), Message Queue Telemetry Transport (MQTT), and Advanced Message Queuing Protocol (AMQP), of which the MQTT protocol is the most widely used. We propose the use of an MQTT broker as a communication protocol; MQTT has shown its abilities in data communication protocols for IIoT. We used temperature and humidity sensors, vibration sensors, and current and voltage sensors because the digital and analog parameters often serve as parameters of IIoT conditions. We also used wireless mesh networks (WMNs) to deliver data from the source to the destination efficiently. A long short-term memory (LSTM) framework was applied for the energy consumed by communication in mesh networks to forecast time series and save energy. Experimental results show that power consumption is reduced by 16.66 to 50% at different nodes. LSTM forecasting results show that the mean squared error (MSE) is less than 0.07%, ensuring the quality and reliability of the transmission of data using MQTT protocol and power saving in mesh networks.

1. Introduction

With the rapid growth of technology, machines and appliances have become increasingly irreplaceable and a fundamental aid in most human work and life. This is one reason for the industrial revolutions that have created additional opportunities as well as problems for global companies. With advances in hardware and software, and the vast number of smart devices, the Industrial Internet of Things (IIoT) has exploded in recent years, with the number of electronic devices in smart cities, home security, and traffic management rising. It is important for data

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generated by sensors to be handled in a diversified system architecture that can further process the sensor data and store all such data in databases or display them in an application interface.

Researchers are familiar with the advantages and popularity of HTTP.[1] This protocol exchanges data and can particularly be used for hardware data processing. However, HTTP is less suitable and adaptable for IIoT applications. Communication protocols for IIoT applications require less bandwidth, real-time responses, and minimal energy consumption, because these applications are commonly used for low-power devices. The problem for developers is to choose the optimal solution for their specific IIoT requirements, with specialized handling and sharing of data. For example, data transmission between different devices is extremely important because an IIoT system has to deliver an instruction or direction to a further appliance in order to handle a system. Message Queue Telemetry Transport (MQTT) protocol, Extensible Messaging and Presence Protocol (XMPP), and Constrained Application Protocol (CoAP) are data transfer protocols used for exchanging messages on middleware platforms and can work with wireless mesh networks (WMNs).[2,3] It is necessary to connect IIoT devices to an internet network to allow them to communicate with other devices and maintain a robust connection. TCP/IP is the internet's primary network protocol, and MQTT, which is built on top of TCP/IP, has become the industry standard for IIoT communications. MQTT may also run on SSL/TLS, a TCP/IP-based stabilized protocol that ensures that all data transferred between network devices are encrypted and safe. Moreover, MQTT provides advantages for many IIoT purposes and supplies low-power machines as a lightweight protocol.

WMNs are widely used in the communication technology sector. Because of the lack of resources in wireless networks, optimization in communication performance is critical.[4] It is possible to avoid wasting energy in communication by dividing resource provision and employing resources wisely. However, across all wireless industries, the energy consumption of wireless communication networks is a major problem. WMNs have grown in popularity as a result of their ease of configuration and adaptability to cellular system architectures. As a result, WMNs are the most often utilized network, providing connection stabilization and many services. Despite these benefits, they have significant infrastructural issues, such as large data size and node coordination failure,[5] as well as high energy consumption because of their transmission of large amounts of data. In this paper, we present an energy-saving method for WMNs based on the long short-term memory (LSTM) model, which forecasts data transmission and activates a sleep mode through each WMN node.

In this paper, a low-power mesh network based on an MQTT broker for IIoT with LSTM forecasting is proposed, which can reduce power consumption by 16.66 to 50% at different nodes. LSTM forecasting results show that the mean squared error (MSE) is less than 0.07%, indicating very high accuracy. The advantages of the proposed method are (1) the proposed WMN based on an MQTT broker framework is especially suitable for different applications, such as IIoT and smart sensors; (2) the proposed low-power methodology can help increase the power lifetime of a sensor without extra overhead; (3) the mesh network is suitable for larger-scale data measurement for multiple nodes.

This paper is organized as follows. In Sect. 2, WMNs are briefly introduced. In Sect. 3, the MQTT broker based on WMNs is discussed. The proposed low-power mesh network based on an MQTT broker for IIoT with LSTM forecasting is presented in Sect. 4. Experimental results are given in Sects. 5 and 6, while Sect. 7 concludes this paper.

2. Low-power Methodology in WMNs

2.1 Low power in network layers

The two main duties of a network layer are network self-configuration and data routing. Network layers define the network topology by selecting an appropriate mode for each node and finding the most relevant nodes with which to associate and establish communication links. Although routing protocols appear to function satisfactorily, there are still difficulties with energy efficiency. In this section, we review different power-saving strategies for ad hoc multi-hop wireless networks, aiming to reduce energy consumption while maintaining data transmission and network stability. Because WMNs and ad hoc networks have many similarities, energy-saving strategies established for ad hoc networks can usually also be applied to WMNs.

A connected dominating set (CDS) is used to verify all nodes that use information from nearby nodes or the topology, resulting in a reliable network connection.(6) Every node in the network is either a CDS member or an immediate neighbor of at least one CDS member. To ensure global connection, nodes in the CDS are essentially designated as routing nodes and stay active at all times.

Each node in the network utilizing the Span protocol can make periodic, local judgments on whether it is preferable to sleep or stay awake as a coordinator and participate in the transmission backbone topology in Span.(7) Each node chooses whether to be a coordinator. Probabilities are used to make the transition between the two states. A node having stronger signals will be defined as a coordinator, thus guaranteeing fairness. The value that a node contributes to a total network connection is another factor considered in selecting coordinators. A node that links many other nodes has a higher probability of being chosen as the coordinator. To prevent several coordinators from functioning at the same time, the network uses the notion of randomization. Span adaptively selects coordinators from all nodes in the network. Span coordinators are always awake and conduct multi-hop packet routing into the ad hoc network, while the remaining nodes are in power-saving mode (PSM) and only check whether they should wake up and become a coordinator. The primary advantage of this protocol is that it is inherently energy-efficient because of its emphasis on node density.

Geographic adaptive fidelity (GAF) is another method that selects coordinators based on information about the geographic locations of nodes.(8) These locations partition the whole topology into fixed-size regions. Areas are designed such that any two nodes in two neighboring zones can interact with each other. The radio range of the nodes, which is intended to be fixed, therefore determines the size of the zone. Each zone must have only one node that is awake, which may be the coordinator. As a result, GAF streamlines the selection process significantly by utilizing information about geographical locations. The protocol's main flaw is that it requires all nodes in the network to know their geographical locations.

The EMM-DSR protocol is a novel technique for balancing energy efficiency while using the most convenient path for data packet transmission.(9) This protocol can reduce energy usage while maintaining good end-to-end latency and throughput performance.

Minimal energy routing (MER) maintains power automatically by minimizing overall power consumption as a result of choosing routes across an ad hoc multi-hop network.(10) By spreading power consumption evenly, this method attempts to optimize the total lifetimes of nodes in the network. As a result, nodes alter their transmission power levels and administrative routes to achieve optimal performance.

The pulse protocol is concerned with the creation of a flood event, which is defined as a pulse that is transmitted at a predetermined interval on a regular basis.(11) This avalanche of pulses begins in the infrastructure of access nodes and spreads across the whole network component.

2.2 Low power in data link layers

In this section, we discuss various difficulties with the energy conservation provided in medium access control (MAC) layers. These layers play a key role in the energy efficiency of nodes. The PSM aims to convert wireless interface nodes into active modes for the period during which it transmits packets and then into sleep mode once the nodes become inactive.(12) A node in PSM is mostly in a low-power state, preparing to transition to a fully powered state. The active state uses at least an order of magnitude more power than the low-power mode.

A sleep-optimal fair-attention (SOFA) scheduler determines a downlink traffic scheduler on the AP of a WLAN,(13) which enhances the PSM to save power by giving it more time in saving mode, boosting battery life. SOFA attempts to reduce the loss of energy and enhance the total sleep time of all nodes. SOFA helps nodes requiring less attention to sleep more deeply by letting them expend less energy to obtain one unit of attention.

The low-energy adaptive clustering hierarchy (LEACH) was the first and is the most widely used clustering method for energy-efficient wireless sensor networks.(14) Clustering techniques divide the network into a number of clusters, each of which authorizes itself to become a member node, sending data to the cluster leaders on a local basis. When the cluster head has received and analyzed the data packet, the findings are transmitted to the base station.

Periodic listening and sleeping, collision and overhearing, and message transmission are all strategies that Sensor-MAC (S-MAC) protocol uses to solve the problems of energy loss and self-configuration ability.(15) A node turns off its radio and stops listening to the channel when sleeping. S-MAC protocol reduces the listening time by putting the node into sleep mode on a regular basis and setting a timer to wake it up later. The goal of S-MAC protocol is to avoid collisions and overhearing. After hearing a request to send (RTS) or clear to send (CTS) a packet, interfering nodes go to sleep, and the duration field in each sent packet specifies how long the remaining transmission will be, as well as the communication between the sender and receiver.

According to many metrics, MER and PSM in WMNs seem to respectively be optimal and suboptimal solutions to balance the energy consumption among nodes. Furthermore, we can use these approaches in an LSTM model to optimize time series for network and datalink layers and evaluate their effectiveness for lowering error rates. To achieve the goal of saving energy, MER is selected due to its ad hoc multi-hop network. Analogously, and as a traditional form of power saving, PSM is used to indicate the period of time for which a node has been chosen to sleep. The results for PSM and MER in Sect. 6 determine which is optimal for saving energy in WMNs.

3. MQTT Broker Based on Mesh Networks

IIoT is a network of sensors and other devices that communicate with each other in industrial and manufacturing systems to improve applications and implementation. Machine-to-machine communication (M2M), which is defined in this paper as communication between numerous sensor devices and a single data collection device, is a requirement of IIoT devices. These sensor devices typically operate in remote locations with limited access to the Internet. Manufacturing, power consumption, energy, oil and gas, and other industries use a large number of sensors. Most factories, for example, are constructed in isolated environments with Internet access via a low-speed digital subscriber line or cellular network. Unreliability of connection is unavoidable in such a setting, and a large transmission loss rate is one of the most serious issues. However, various protocols have been developed for M2M/IIoT communication in restricted settings, with MQTT being the most widely utilized. MQTT can send data via low-bandwidth or dependable communication networks while using very little electricity.

As shown in Fig. 1, MQTT is a low-power protocol designed to link devices on low-bandwidth networks. Although it has been around for more than a decade, it was only recently popularized by M2M and IIoT. MQTT is one of the most widely utilized protocols in the IIoT field. It allows IIoT devices with limited resources to communicate with or publish data on a specific subject to a server that acts as an MQTT message broker. The broker then sends the information to subscribers. IIoT, in particular, requires the capacity to operate with low-power

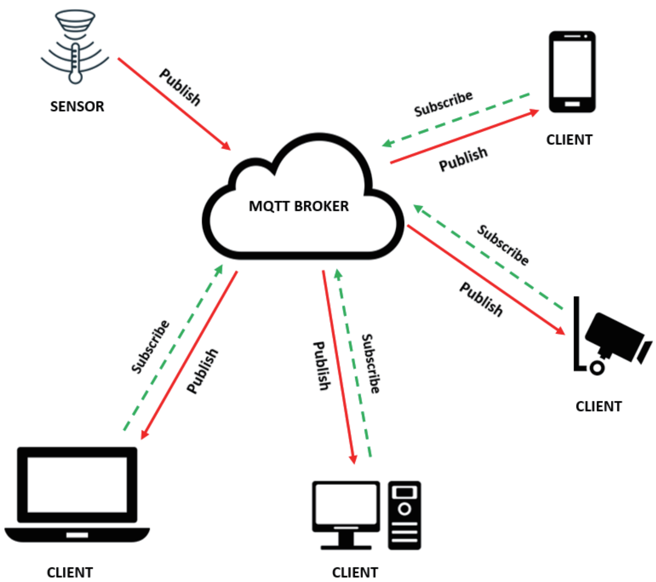


Fig. 1. (Color online) Data transmission in MQTT broker.

devices to function, and MQTT fulfills all the requirements of IIoT. MQTT is adaptable to the level of performance and message transmission, which is crucial because many IIoT devices have low performance, making it a reasonable option for low-power wireless devices with unstable connections.

IIoT is a future Industry 4.0 scenario in which everything and every person is connected to a single network without the need for direct human-to-human or human-to-computer contact. Wireless technology, micromechanical technology, and the Internet have all come together to form IIoT. Simply defined, IIoT is a collection of gadgets that can communicate with one another, the internet, and the outside world to complete a task. To provide complete compatibility for actual physical devices in IIoT, a new connection protocol is required. MQTT is increasingly gaining favor as a solution to this problem.

Smartphones, self-driving vehicles, smart homes, AI, and even smart cities are all examples of IIoT's increasing use and growth. To make our lives easier, safer, and more comfortable, millions of sensors generate, process, and communicate vast volumes of data. This has resulted in multiple issues that need to be addressed, ranging from the high cost of hardware and technology to the low rate of data transport. WMNs are the best way to organize IIoT platforms for device-to-device communication as shown in Fig. 2.

While WMN technologies have been around for a while, their power and availability from chip and silicon suppliers have only recently reached a point of maturity. WMNs have become useful for IIoT applications due to their low cost. Meshes are now widely accessible and have a sufficiently low cost to scale for production owing to the increase in the number of connected homes and industries.

WMNs are a good technique for efficiently managing data transmission among IIoT devices. Furthermore, they are more effective than current networks such as ad hoc or sensor networks. They are ideal for sending small data packets and allow users to connect more nodes while maintaining a good network speed. Furthermore, WMNs can expand the communication range, making them ideal for confined spaces, nooks, and crannies. They may be used in a variety of IIoT applications to create and maintain network connectivity, configure flexibility, and satisfy the needs of all devices.

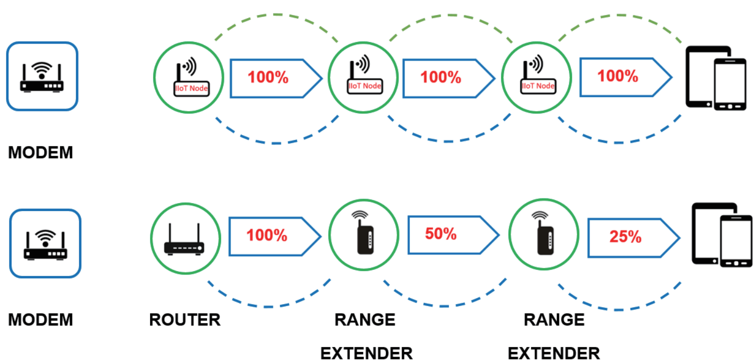


Fig. 2. (Color online) WMN.

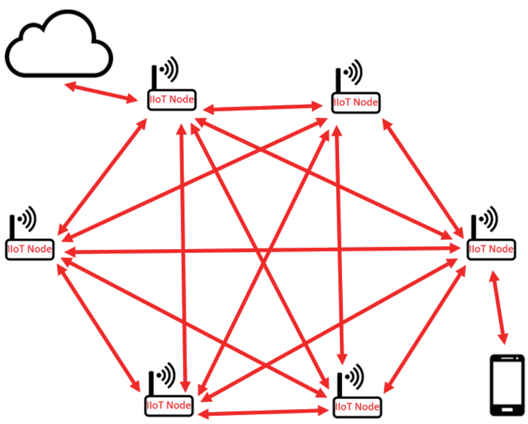
4. System Architecture

4.1 Topologies of WMNs

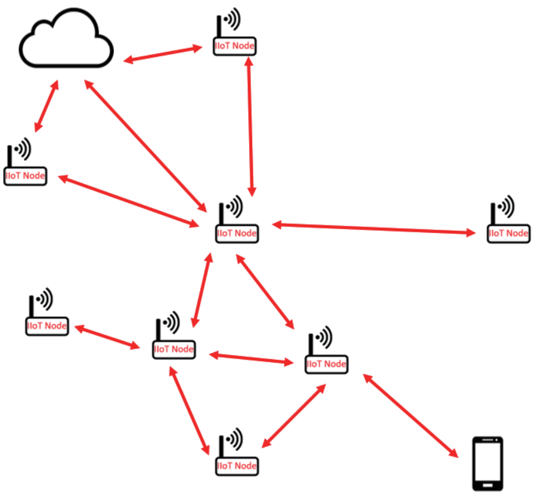
The two most common topologies for connecting WMNs are fully connected and partially connected mesh topologies.(16) In a fully connected topology, all nodes in the network are connected to one another as shown in Fig. 3(a). During error conditions, such as the failure of one node in the network, alternative nodes with a path to the destination are instantly selected to continue the transmission process. This can improve the robustness of the network. In a partially connected mesh topology, only partial nodes are connected to nodes as shown in Fig. 3(b). Usually, partially connected networks are used in small-scale connections. By using multi-hop routing capability schemes, the coverage area of a WMN can be extended.

4.2 Data monitoring of WMNs

IIoT nodes are placed around a factory. These nodes connect to multiple other nodes and communicate with each other to transfer data across a large area. Every machine or device that can send and receive information can access the mesh network. All the sensors, i.e., temperature, humidity, vibration, voltage, and current sensors, automatically collect data from machine tools, computer numerical control (CNC) machines, electrical cabinets, transfer machines, and grinders. IIoT nodes upload data to the broker after gathering data from machines, and they are responsible for receiving all data measurements, filtering, deciding which users are subscribed to which data measurements, and transmitting them to the subscribers. Users can monitor the trend or inconsistency of result readings by subscribing to information about the subject on IIoT nodes. When a connection is created, the broker maintains it until it is broken or the client sends a disconnect order.



(a)



(b)

Fig. 3. (Color online) (a) Fully connected mesh topology and (b) partially connected mesh topology.

Figure 4 shows an online platform allowing users to monitor data. All these data are accompanied by a function that allows users to store information in a MySQL database.(17) Users connect with the MQTT broker through WebSocket, allowing full-duplex and real-time data transactions. The data of each sensor node are presented on a web page created to allow users to select which nodes should be displayed based on the device ID.

In this platform, four parameters are measured in the WMNs: temperature, humidity, current, and voltage. The MQTT broker used a script to post sensor data to a previously named topic that includes sensor data and device IDs. Data from each sensor were presented on the web page and database after logging into the MQTT server. Clients were given access to a web page that allowed them to choose which data sensors would be shown on the screen and were provided with information about them.

4.3 System diagram of sensor node

In this paper, a sensor node with a low-power communication protocol based on WMN technology is proposed. In addition to wireless network transmission, it also has the important function of transferring data to a monitor. For signal extraction and wireless network transmission, a 32-bit microcontroller unit (MCU) and a 12-bit, 18-channel sampling successive approximation register (SAR) analog-to-digital converter (ADC) are employed, which can transfer huge amounts of data via a WMN, increasing the system's versatility. Figure 5 shows a block diagram of the sensor node system architecture.

System control, signal acquisition, power management, and communication transmission are the four primary components of the system. The control signal extraction unit synchronizes the WMN sensors. The system control unit is connected to the control communication transmission unit, which then connects to the server through TCP/IP. The data from the sensors are received by the communication transmission unit, which then sends it to the protocol system via the control unit.

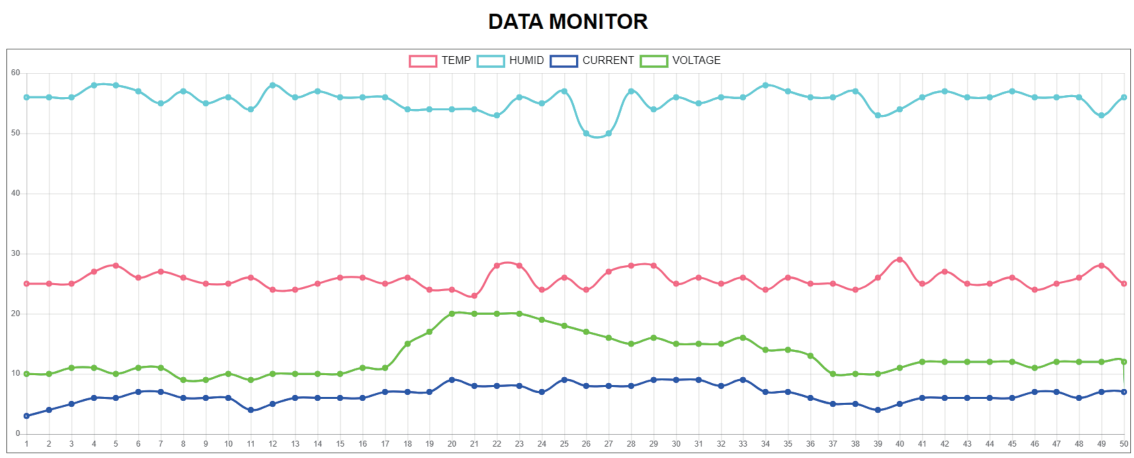


Fig. 4. (Color online) Measured data in MQTT Broker through WebSocket.

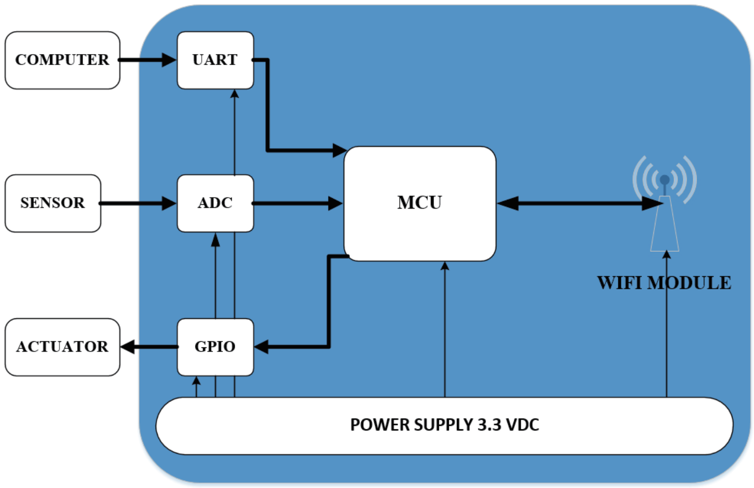


Fig. 5. (Color online) Block diagram of sensor node system architecture.

5. Forecasting Time Series in LSTM

One of the most important applications of machine learning in general, and artificial neural networks in particular, is forecasting time series. In time series forecasting networks, LSTM networks have been shown to be very effective.(18) The goal of this research was to create and assess forecasting results using predictive models based on an LSTM network.

5.1 Data collection process

The data transmitted across each node in the mesh network provided the dataset for the proposed technique. As an example of the transfer of time series data for four nodes, node 1 transferred temperature data, node 2 transferred vibration data, node 3 transferred current data, and node 4 transferred voltage data. Data collection from the four nodes occurred from 2021-06-12 0:00:00 AM to 2021-06-22 00:00:00 AM. Figures 6 and 7 respectively show the average data transfer of nodes 1 and 4.

5.2 LSTM network

LSTM is an expanded version of the recurrent neural network (RNN) used to reveal long-term dependences. The RNN is a looped neural network that can store data that have been passed from one layer to the next. At all times, the output of the hidden layer is dependent on the information in the layers. RNNs have been widely used in natural language processing or problems with sequential data. However, because the architecture of an RNN is quite simple, its ability to link layers over long distances is weak. An RNN is essentially incapable of remembering information from long-distance data, and thus the first elements in an input sequence usually have little effect on the result of element prediction for the output sequence.

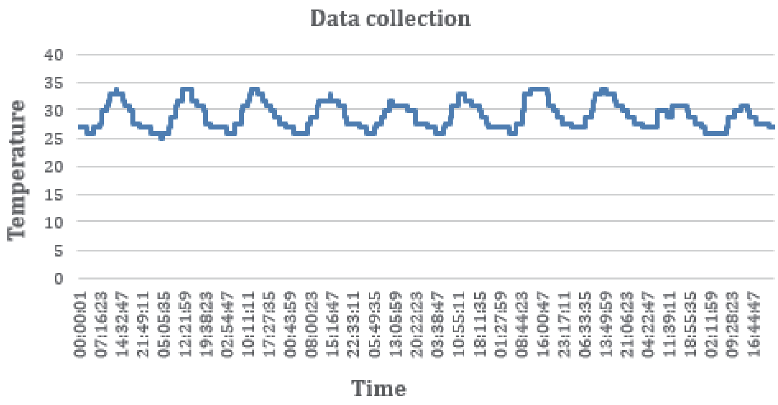


Fig. 6. (Color online) Temperature data transfer in node 1.

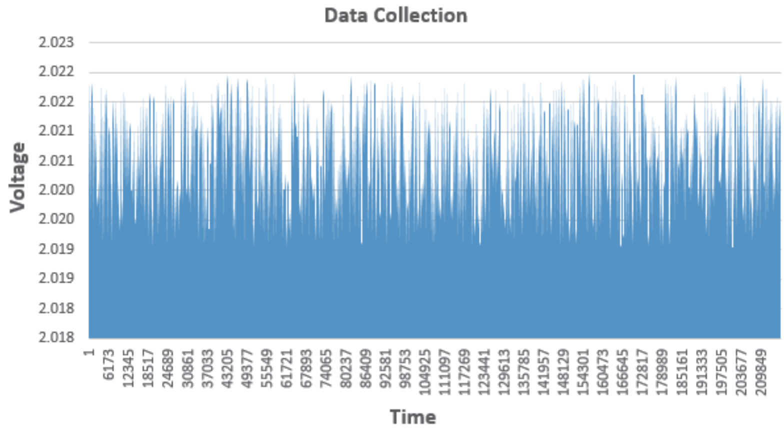


Fig. 7. (Color online) Voltage data transfer in node 4.

This is because the RNN is affected by the lower derivatives in the learning process, i.e., vanishing gradients. An LSTM network is designed to overcome this problem. The mechanism of action of LSTM is to remember only relevant information, or that important for prediction, and ignore other information. The structure of an LSTM network is shown in Fig. 8.

6. Experimental Results

6.1 Performance evaluation

The LSTM forecasting results were evaluated in terms of three error measurements: MSE, mean absolute error (MAE), and coefficient of determination (R^2).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - t_i}{y_i}\right| \tag{1}$$

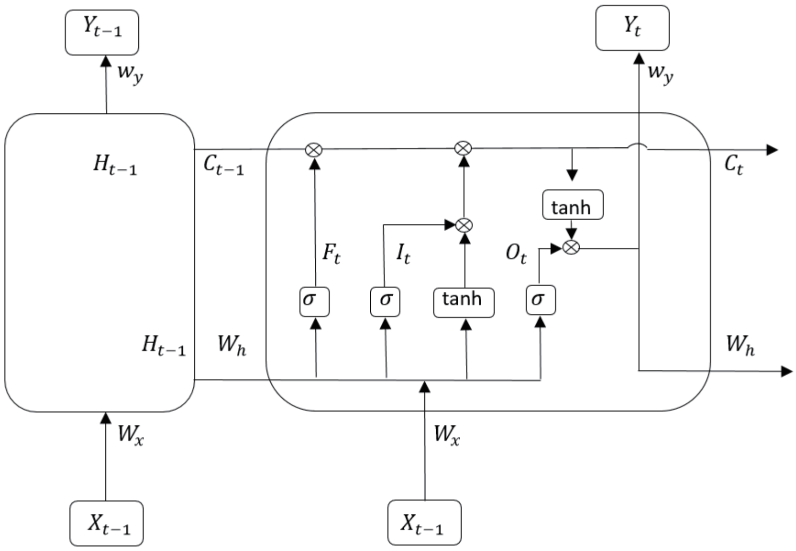


Fig. 8. Schematic representation of LSTM network.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - t_i\right)^2 \tag{2}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)\left(t_i - \overline{t_i}\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2\left(t_i - \overline{t_i}\right)^2}}\right)^2 \tag{3}$$

Here, y_i and t_i are the true value and predicted value, respectively, and n is the number of samples in the test set.

6.2 LSTM forecasting results

The network structure has a significant effect on the computational complexity of the model and the accuracy of the predictions. Also, the performance prediction of the LSTM forecasting model is strongly related to the number of hidden neurons. While an insufficient number of neurons can cause common problems such as incompatibility, an excessive number of neurons can cause overfitting. Our experimental setup comprised a visible input layer with 200 units in the LSTM network. Moreover, it analyzed a model function with 50 to 250 epochs of batch size 1 to 500. Eventually, all neurons were connected: 100 epochs with a batch size of 50 turned out to have the lowest MSE.(19) Parameter optimization determined that the best learning rate was 0.01 for the LSTM structure.

The datasets used in this paper were collected from node 1, which covered the temperature data. Furthermore, as LSTM is sensitive to the scale of the input datasets, the time series dataset used for experimental work was preprocessed before being used to train and test the proposed model. The dataset was normalized to the range of 0 to 1. In the experiments, the dataset was split into two subsets: a training dataset and test dataset. The training dataset (approximately 90% of the original dataset) was used exclusively for training and model development, and the test dataset (the remaining 10% of the dataset) was used for testing the accuracy of prediction. Table 1 and Fig. 9 show the datasets for forecasting and testing.

These measurements were evaluated for forecasting accuracy of the LSTM. These performance measurements can be applied in PSM, which has low power in data link layers.

6.3 Power consumption in PSM and MER

After configuring the nodes in the WMNs, the energy model can be summarized through the performance of the nodes, which is expressed using two different methods: PSM and MER. Table 2 shows the experimental results of power consumption in PSM, the power in each node being based on the amount of data transferred in every message.

Table 1
Results of LSTM forecasting.

	MSE	*MAE*	R^2
Training set	0.00307	4.064	1
Test set	0.0007	2.375	0.99

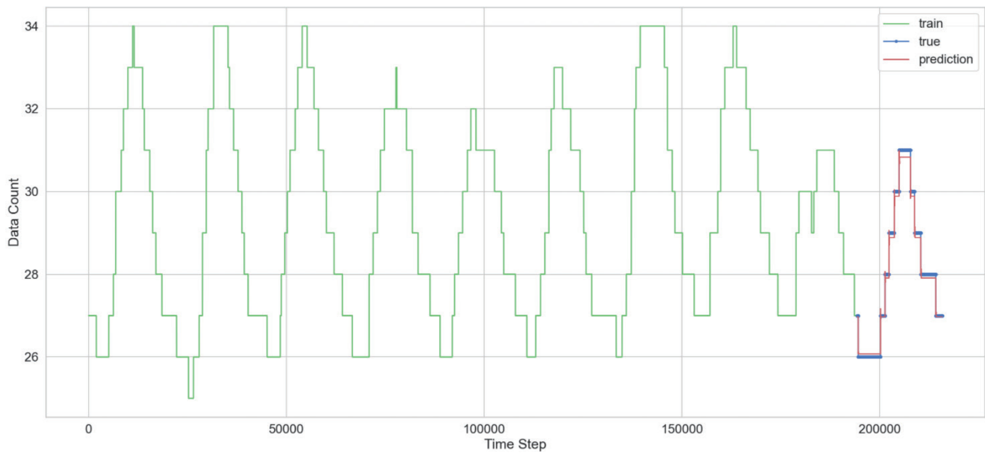


Fig. 9. (Color online) LSTM forecasting temperature in node 1.

Table 2
Power consumption of node 1.

	Power without PSM (mW)	Power with PSM (mW)	Percentage saving (%)
Send one message	0.05022	0.033	65.71
Node 1	1084.80222	741.77982	68.38

For the proposed model, data transmission was performed on the basis of the transaction time and the length of the data transfer in node 1, which used power of 0.05022 mW to remain in active mode. After node 1 applied PSM to power off most of the RAM and all the digital peripherals, PSM reduced the power consumption at node 1 by 65.71% from that without PSM.

The MER method calculates the connection cost to the transmission power and searches for the lowest energy path using a shortest path algorithm. To decrease the transmission power, one or more intermediary nodes chooses to forward packets on behalf of source-destination pairs in this system. This acquires the energy consumed for transferring data packets from the source (node 1) to the destination (node 2) in this series of simulations (node 2, 3, 4, 5, or 6).

Furthermore, the nodes have no sleep mode; thus, even if a receiving node does not receive a packet, it will spend the same amount of energy monitoring the channel. As a result, in simulations, this solution must focus solely on transmission power and be compared with the transmission power predicted by other models.

In Fig. 10, nodes are randomly displaced in a stationary network of size 80 cm×100 cm, and data are transferred from node 1 (10,10) to node 2 (60,70). Data can be transferred along different paths, such as node 1-4-3-2, node 1-4-2, node 1-4-6-2, node 1-4-6-5-2, node 1-6-2, node 1-6-5-2, and node 1-6-4-2. Data are transmitted from node 1 to node 2 through node 4, which is the shortest path. Unlike PSM, MER does not use all the nodes. It only uses three, four, or five nodes, with up to three nodes powered off to save power. Table 3 shows the power consumption for different paths in the mesh network.

In comparison with PSM, MER uses more energy because it consumes power when both transferring data and not transferring data. Some typical nodes work all the time if they belong to the shortest path, which could degrade them because of the unequal division of work. If data are sent frequently, PSM will switch a node to sleep mode to save power. Experimental results show that PSM has better load balancing and reduces the amount of energy consumed per node during a relatively long period between transmissions, after which it maximizes the network lifetime. On the other hand, in artificial neural networks, which are suited to and beneficial for

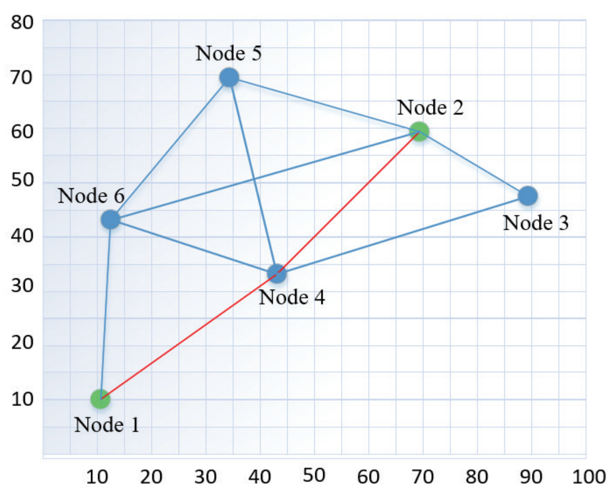


Fig. 10. (Color online) Distribution of six nodes.

Table 3
Power consumption results.

	Power without MER (mW)	Power saved with MER (mW)	Percentage saving (%)
Node 1-4-3-2	4339.2088	2169.6044	33.33
Node 1-4-2	3254.4066	3254.4066	50
Node 1-4-6-2	4339.2088	2169.6044	33.33
Node 1-4-5-2	4339.2088	2169.6044	33.33
Node 1-4-6-5-2	5424.0111	1084.8022	16.66
Node 1-6-2	3254.4066	3254.4066	50
Node 1-6-5-2	4339.2088	2169.6044	33.33
Node 1-6-4-2	4339.2088	2169.6044	33.33
Node 1-6-4-3-2	5424.0111	1084.8022	16.66

long-term trends, the LSTM model is used to forecast time series in WMNs and observe long-term price trends.

7. Conclusions

In this paper, we present a low-power mesh network based on an MQTT broker for IIoT with LSTM forecasting in WMNs, which can reduce power consumption by 16.66 to 50% at different nodes. The benefits of the MQTT protocol are mostly utilized in IIoT applications that collect data such as temperature, humidity, vibration, current, and voltage sensors. The quality and reliability of the transmission of data using MQTT protocol and efficient power saving in mesh networks are demonstrated. LSTM forecasting results show that the MSE is less than 0.07%, indicating very high accuracy. Meanwhile the proposed low-power methodology can help increase the power lifetime of a sensor without extra overhead.

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