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Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks

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ABSTRACT

Wireless sensor network (WSN) comprises a collection of sensor nodes employed to monitor and record the status of the physical environment and organize the gathered data at a central location. This paper presents a deep learning based distributed data mining (DDM) model to achieve energy efficiency and optimal load balancing at the fusion center of WSN. The presented DMM model includes a recurrent neural network (RNN) based long short-term memory (LSTM) called RNN-LSTM, which divides the network into various layers and place them into the sensor nodes. The proposed model reduces the overhead at the fusion center along with a reduction in the number of data transmission. The presented RNN-LSTM model is tested under a wide set of experimentation with varying number of hidden layer nodes and signaling intervals. At the same time, the amount of energy needed to transmit data by RNN-LSTM model is considerably lower than energy needed to transmit actual data. The simulation results indicated that the RNN-LSTM reduces the signaling overhead, average delay and maximizes the overall throughput compared to other methods. It is noted that under the signaling interval of 240 ms, it can be shown that the RNN-LSTM achieves a minimum average delay of 190 ms whereas the OSPF and DNN models shows average delay of 230 ms and 230 ms respectively.

1. Introduction

In general, Wireless Sensor Network (WSN) is a self-configured and infrastructure-less wireless networks that helps to observe the external and ecological status, like temperature, moisture, movements and pollutants to pass the information via network to sink from the data might be monitored as well as predicted. A sink or base station (BS) has been treated as interface among the network and user. By using such network, the user can able to derive essential data by inducing queries and collect the required details from BS. Generally, a WSN is composed of numerous sensor nodes. Here, sensors are capable of communicating with alternate nodes through the radio signals. It embeds processing units, storage, radio transceivers and power elements. A single node from WSN is composed of restricted computing speed, memory, communication bandwidth and so on. Once the sensor node has been injected, it is responsible to self-organize in a suitable network infrastructure along with multi-hop communication process within the system. Furthermore, wireless sensors acknowledge for queries provided from a "control site" in order to process only particular rules and sensing samples. Global Positioning System (GPS) as well as local positioning techniques could be applied to derive the position and related data. It is constrained with actuator which is considered as to be used only in specific situations. Sometimes, it is assumed to be Wireless Sensor and Actuator Networks.

WSN is capable to adopt novel techniques and acquires non-conventional method for a protocol development because of various conditions. Due to the need for minimum complexity and energy utilization for prolonged network lifespan, an appropriate balance among signal and data computing abilities should be identified. It leads to providing maximum energy in scientific events. Recently, various types of developments in WSN takes place in developing energy and computationally effective techniques, whereas the domain is limited to simple data-oriented and reporting fields. Moreover, a Cable Mode Transition (CMT)

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method that helps to compute the lower value of active sensor nodes to balance the K-coverage from terrain and K-connectivity of the system. In particular, it declares the time period of inactive cable sensors with no influence of coverage as well as connection requirements of network which is depend upon the local data.

Several energy efficient solutions for WSN operations based on optimization algorithms and deep learning (DL) models have been presented in the literature. In Cheng et al. [1], a delay-aware data collection network for WSN is deployed. It mainly aims in reducing the latency in data collecting process of WSN that tends to elaborate the network lifetime. In Rahman and Matin [2], it is assumed that more number of relay nodes has been adopted to decrease the network vulnerability as well as Particle Swarm Optimization (PSO) model is applied to place an optimized sink position in terms of relay nodes to resolve the lifespan issue.

The design of WSN includes several constraints. The most essential constraint is because of the fact that sensor nodes are placed in an adverse region and it should be often recharged with batteries. Hence, the sensor lifetime is dramatically reduced compared with quantity of power induced in battery and the way of conserving power. The management of power utilization of sensors has been developed as an active research area. The purpose of energy conservation is employed in data acquisition, computing, reduction, transmission, etc. [3–5]. The data transmission process is considered to be the initial step in saving energy. Therefore, such protocols could be treated as various layers in communication namely physical layer, MAC layer, routing layer as well as application layer. In case of MAC layer, maximum amount of power has been attenuated while retransmitting the data once the collision is completed, and control packet transmission in the absence of applicable data or determining packets to attain alternate sensor nodes. Only few protocols have been presented to be treated on energy consumption. The S-MAC protocol [6], applies time synchronization from sensors to isolate in a cycled manner.

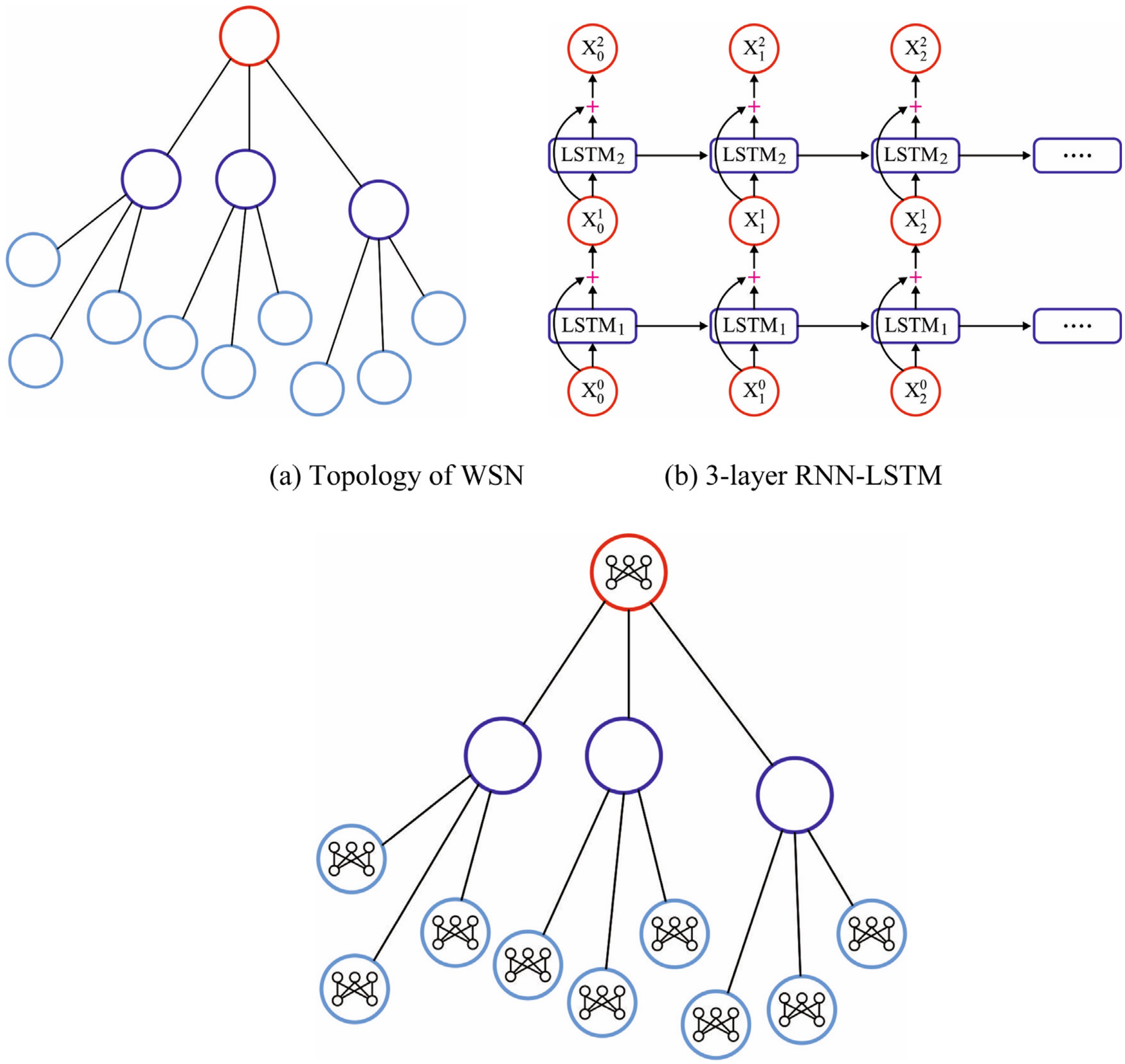
In order to save power and eliminate collision, PC-MAC protocol [7] has been deployed. In network layer, routing protocols helps to reduce the power application by the mechanism of packet delivery. Besides, it attempts to grab merits of higher density of WSN. By developing novel WSN routing protocols is a most promising issue. It is divided using the mechanism applied. Hence, routing protocols might be geocentric, data-centric, applies network topology as well as link states. In case of data-centric protocols, GKAR is assumed to be the instance of K-any cast protocol. EASPRP [8] seeks for shortest path including energy efficiency and EERT protocol [9] manages the Quality of Service (QoS). In real-time applications, REFER protocol [10] employs Kautz graphs. Only some of the routing protocols could be applied in a combined manner in order to encircle a particular region. Few routing protocols [11] apply the motion ability of mobile sensor nodes. The GAROUTE protocol [12] utilizes genetic algorithm (GA) to develop group of sensors to minimize communications. Here, cluster heads (CH) could be deployed to compute local information as well as to divide the respective data. LEACH protocol is an applied cluster to manage the network traffic. It has been altered [13] to enhance the delivery time and to reduce the interferences. EEDR protocol [14] mainly concentrates in transmitting packet to decrease the power application. Alternate models has been projected to minimize the power utilization and to improve the lifetime of WSB. Huang J.-W [15] followed sensor coverage is mainly applied for reducing the power application. The same operation has been repeated in [16] that applied an SCC (Sponsored Coverage Calculation) simulating model. Some other protocols alleviate data transmissions such as SEPSen protocol [17] that applies data processing throughout the system. The traffic as well as resource management is utilized in [18]. Major types of protocols apply wireless network simulators [19] respectively.

WSN has been employed in diverse applications namely land cover classification [20], SCR node forecasting in vehicular system, fault analysis, estimating the quality of groundwater [21]. Conventionally, such type of applications helps to determine the sample data from fusion center. In case, WSN is comprised of numerous sensor nodes, the function of computing sampling data has been restricted by using fusion center's hardware, which is assumed to be costlier and more complex in upgrading frequently. Therefore, data communication absorbs more amount of energy, specifically for wireless relaying nodes. Data mining (DM) methods are induced to obtain applicable data from numerous data in the last a decade, which is assumed to be more efficient tool applied in predicting larger data. For past decades, shallow DM techniques namely, Support Vector Machine (SVM), boosting, as well as Logistic Regression (LR) have been presented [22]. Also, by applying these shallow DM models, it tends to enhance the fusion center's function; however, the issue in energy consumption remained as unchanged. The solution to resolve these problems is by implementing the techniques in sensors to minimize data transmission, which is more tedious to be executed in WSN. In addition, Hinton and Salakhutdinov [23] developed a deep DM technique named called Deep Neural Network (DNN) that is used in extracting the inner representation as well as to alleviate data dimensionality. The DNN based DMM model has been presented in [24].

Though several models have been available in the literature, it is noted that there is still a need to enhance the fusion performance of the WSN. At the same time, there is a requirement to achieve minimum energy consumption, signaling overhead, average delay with maximum throughput. Sample data of WSN has grown in a rapid way owing to the existence of massive number of sensor nodes, a centralized data mining solution in a fusion center has come across the issue of minimizing the load of the fusion center as well as reducing the overall energy utilization. In this view, this paper presents a DL based distributed data mining (DDM) model with LSTM to achieve energy efficiency and optimal load balancing at the fusion center of WSN. The presented DMM includes a recurrent neural network with LSTM (RNN-LSTM) model which divides the network into various layers and place them into the sensor nodes. Using the RNN-LSTM model, the overhead of the fusion center in WSN is greatly reduced. At the same time, the amount of energy needed to transmit data by RNN-LSTM model is considerably lower than energy needed to transmit actual data. The presented RNN-LSTM model undergoes a wide set of experimentation under varying number of hidden layer nodes and signaling intervals. The experimental outcome stated that the RNN-LSTM reduces the energy consumption, signaling overhead, average delay and maximizes the overall throughput compared to other methods. The advantages of the paper contribution are listed here.

(a) No requirement of labeling quantity of training data in a manual process in case of various domains, where it is completely done automatically.
(b) Internal representations are integrated with alternate DM technique and enhanced the models to attain optimal results.
(c) The dimensionality of RNN-LSTM helps to minimize the data transmission by WSN as well as to conserve the energy of WSN.
(d) The distributed estimation decreases the overload in fusion center that leads to several benefits like less hardware requirement and delay.

The upcoming portions of the paper are organized as follows. Section 2 elaborates the RNN-LSTM model. Section 3 validates the experimental validation of the proposed model and Section 4 concludes the paper.



(a) Topology of WSN (b) 3-layer RNN-LSTM

(c) Topology of distributed data mining

Fig. 1. Principle of distributed DM.

2. Proposed method

The presented RNN-LSTM for DDM is intended to achieve energy efficiency and load balancing at the fusion center of the WSN. The presented DMM includes a recurrent neural network with LSTM (RNN-LSTM) model which divides the network into various layers and place them into the sensor nodes.

2.1. Basic principle

The basic principle involved in the RNN-LSTM model is given here. Assume a WSN existed with a fusion center which is divided into 3 stages (Fig. 1(a)) and three-layer RNN-LSTM (Fig. 1(b)). It is pointed that the topology of WSN as well as structure of RNN-LSTM is same in hierarchy. There is a possible solution which helps to divide the RNN-LSTM into layers and allocate various levels of WSN. Fig. 1(c) provides an instance of dividing RNN-LSTM into 2 portions as well as putting in fusion center. It is considered that a WSN has been segmented by m levels, and RNN-LSTM contains n layers. While dividing n layers to k parts ($k \leq m$, n), every portion is implemented by estimating the calculating units in related level of h_u in WSN, and RNN-LSTM could be demonstrated in the upcoming sections.

Step 1: Suppose $u = 1$. Sensors samples the actual data, where it is computed in calculating units from the level h_i using initial portion of RNN-LSTM and forwards the simulation outcome to calculating units in level $h_u + 1$, and $u = u + 1$.

Step 2: Estimate the input obtained from calculating units of previous level, if $u \geq k$, go to Step 4.

Step 3: When $h_u \geq m$, go to Step 5. Otherwise, go to Step 2 and transmit the result to calculating units of level $h_u + 1$, and $u = u + 1$.

Step 4: Forward the data to fusion center.

Step 5: DM process is completed.

2.2. RNN-LSTM

The LSTM method is applied to resolve the issue of diminishing gradients of RNN. It looks like a standard RNN along with hidden layer, where every normal node of hidden layer could be substituted using a memory cell as shown in Fig. 2. All memory cells are composed with a self-connected recurrent edge by assuring the gradient which is capable of passing over several times with no discharge. In order to determine some references of memory cell as well as not an ordinary node, subscript c has been applied.

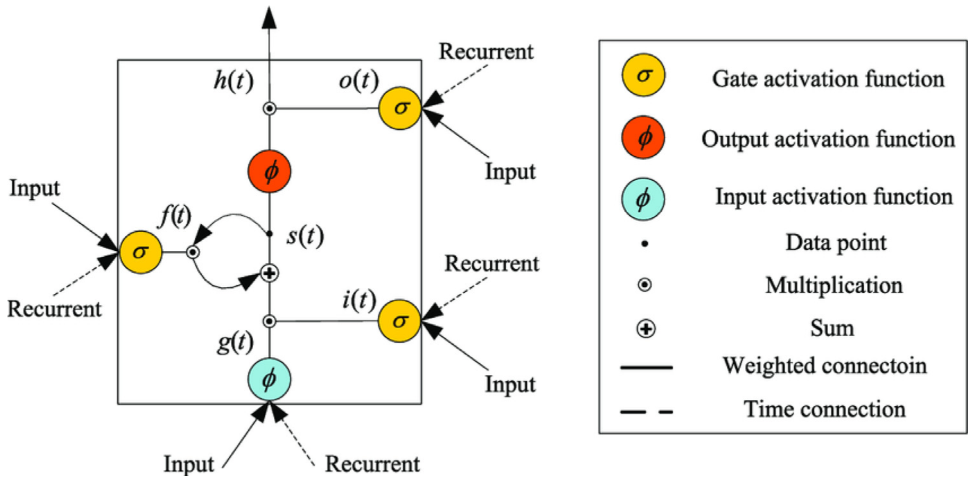


Fig. 2. Memory cell of LSTM.

The term "LSTM" emerges from upcoming instinct. A simple recurrent NN has long-term memory in terms of weights. It is altered gradually at the time of training, encoding general knowledge regarding a data. It is also composed with short-term memory with respect to develop an ephemeral functions, that passes from every single node to consecutive nodes. Here, LSTM technique denotes the middle type of memory cell. A memory cell is considered to be a composite element, developed from ordinary nodes in a particular connectivity procedure, by including the multiplicative nodes, which is denoted in images by letter Π. Every units of LSTM cell undergoes enumeration and defined as given below. For instance, s denotes a vector with value of s_c at every memory cell c from a layer. If subscript c is employed, then it helps to index a single memory cell.

- **Input node**: This unit, labeled g_c, is said to be anode which obtains the activation from a standard way of input layer $l^{(z)}$ in a present duration as well as from hidden layer at past time step $h^{(z-1)}$. Generally, the added weight input is an *tanh* activation function, though it is derived from LSTM paper, and activation function is denoted by a sigmoid.
- **Input gate**: The gates are assumed to be unique feature of LSTM model. A gate resembles a sigmoidal of input node, which grabs the activation from present data point $l^{(z)}$ and from hidden layer at past time step. It is termed as gate due to the multiplied value of alternate node. If the value is assigned to be zero, then it is named as a gate, where the flow of alternate node is cut off. When it is declared as one, every flow is passed. Additionally, value of input gate u_c increases the value of input node.
- **Internal state**: The kernel points of all memory cells are anode s_c including linear activation that is named from general paper as internal state of a cell. The interior state s_c is comprised with self-connected recurrent edge along with permanent unit weight. Due to the edge of adjacent time steps with similar weight, error flows over the time steps in absence of exploding. It is named as constant error carousel. For vector function, update for internal state is $s^{(z)} = g^{(z)} \odot u^{(z)} + s^{(z-1)}$ where $\odot$ indicates point-wise multiplication process.
- **Forget gate**: The gates f_c has been introduced. It offers a model to learn the context of the interior state. It is more applicable in frequently running networks. Using forget gates, the function to estimate the internal state in a forward pass is

$$s^{(z)} = g^{(z)} \odot u^{(z)} + f^{(z)} \odot s^{(z-1)} \quad (1)$$

- **Output gate**: Value v_c is generated by memory cell which is considered to be the measure of internal state s_c increased by value of resultant gate o_c. In addition, it is customary that internal state is implemented by *tanh* activation function, since it provides simulation outcome of every cell with similar dynamic range as gradual *tanh* hidden unit. But, in alternate NN research, resolved linear units are comprised with higher dynamic range which is simple to train. Hence, it is plausible for nonlinear function where the internal state may be removed.

Generally, the input node is labeled g. We remain to this convention however note that it can be confusing as g does not accept *gate*. In the original paper, the gates are known y_{in} and y_{out} but this is confusing as y usually withstand outcome in the ML literature. Seeking comprehensibility, we split through this convention and utilize u, f, and o to denote to input, forget and outcome gates correspondingly.

While the LSTM was initiated, many differences have been presented. Forget gates, explained exceeding, were presented in 2000 and were not part of the original LSTM proposed. But, they have confirmed as efficient and are standard in most present executions. The peephole relations that pass from the internal state straight to the input and outcome gates of that similar node lacking primary containing to be adapted with the outcome gate. They details that these connections enhance action on duration roles where the network should learn to measure precise intervals among measures. The intuition of the peephole connected is captured with subsequent instance. Assume a network that should learn to calculate objects and emit some needed outcome if n an object has been seen. The network may discover to allow various suitable total of activation into the internal state behind every object is seen. These activations are captured into internal state s_c with constant error carousel, and are increased iteratively every time other object is seen. If nth object is seen, the network requires identify to let out content from the internal state in order that it is involve the outcome. For achieve this, the outcome gates o_c have to know the satisfied of the internal state s_c. So s_c must be an input to o_c. The calculation in the LSTM form is based on memory cells and is set properly. The subsequent computations are executed at every time step. These equations provide the entire technique to recent LSTM with forget gates:

$$\begin{aligned} g^{(z)} &= \varphi(W^{gl}l^{(z)} + W^{gh}h^{(z-1)} + b_g) \\ u^{(z)} &= \sigma(W^{ul}l^{(t)} + W^{uh}h^{(z-1)} + b_u) \\ f^{(z)} &= \sigma\left(W^{fl}l^{(t)} + W^{fh}h^{(z-1)} + b_f\right) \\ o^{(z)} &= \sigma(W^{ol}l^{(t)} + W^{oh}h^{(z-1)} + b_o) \\ s^{(z)} &= g^{(z)} \odot u^{(u)} + s^{(z-1)} \odot f^{(t)} \\ h^{(z)} &= \phi\left(s^{(z)}\right) \odot o^{(t)}. \end{aligned} \tag{2}$$

The value of the hidden layer of the LSTM at time z is the vector $h^{(z)}$, as $h^{(z-1)}$ is the values outcome with every memory cell in the hidden layer at preceding time. Consider these equations contain the forget gate, although not peephole connections. The computations to easier LSTM without forget gates are achieved with setting $f^{(z)} = 1$ to every z. We utilize the *tanh* function φ to input node g subsequent the modern design. But, the LSTM paper, the activation function to g is the sigmoid σ.

Spontaneously, with respect to the forward pass, the LSTM is learned if let to activation into the internal state. Provided that input gate obtains value 0, no activation is included. Likewise, the outcome gate learns when to let the value out. If both gates are closed, the activation is captured in the memory cell, neither upward nor shrinking, nor disturbing the outcome at in-between time steps. With respect to the backwards pass, the constant error carousel allows the gradient to propagate back across several time steps, neither exploding norvanishing. In this sense, the gates are learning if let to fault in, and when to let it out. In practice, the LSTM has exposed a higher capability to learn long-range dependencies as related to easy RNNs. Thus, the popular of modern application papers enclosed in this review utilize the LSTM method.

One repeated point of confusion is the approach in that multiple memory cells are utilized together to contain the hidden layer of a working NN. The outcome from every memory cell flows in the following time step to the input node with every gates of all memory cells. It is ordinary to contain several layers of memory cells. Usually, in these designs of every layer gets input from the layer under at the similar time step and from the similar layer in the preceding time step.

2.3. Training

2.3.1. Training the distributed RNN-LSTM

By executing RNN-LSTM to DM, it is required to train the RNN-LSTM in the fusion center at primary stage. The training data are instance from every WSN sensors, and the trained RNN-LSTM parameters are sent to the RNN-LSTM layers allocated in various computing units. While a WSN is provided with a mass of trained data, this data also exhaust many network's power. In fact, a sensor's instances data do not alter in a short time. So, select one of them to train the RNN-LSTM. The issue is that we do not identify if data modify. An arbitrary data chosen technique have been verified helpful in solving this problem and a digital identification explore illustrated that a arbitrary chosen of 10% training is obtain better outcome, Thus, the arbitrary chosen technique is efficiently decrease set of redundant data to be broadcasted.

Afterwards, we provide the training process through the arbitrary chosen technique as pursues.

1. The fusion center arbitrarily creates a sensor's ID and transmits a request to the sensor.
2. The chosen senor obtains the request and transmits the instance data.
3. Fusion center gets the training data from the chosen senor and transmits the data to the GLT technique.
4. The GLT technique ensures if the training outcome obtains the stop state. When YES, go to step 5. Else, go to Step 1.
5. The fusion center transmits all part of the RNN-LSTM arrangement data to the equivalent computing unit.

The distribution hierarchy of RNN-LSTM is based on its function. But, some distribution hierarchy must be controlled with power utilization. The principle of planning the distribution hierarchy depends on the trade-off among computing and broadcasting power utilization. Suppose that there is a computing unit, and it performs c trainings to end DM role. All training utilizes E_{i} power. Also, the computing unit utilizes E_t power sending a bit to the destination node without some affect and decrease. With every affect disturbing and attenuation effects lead to further power utilization of E_o. Next, it is declared that a computing unit is allowed the RNN-LSTM part when the subsequent formula is fulfilled:

$$cE_{\mathrm{i}} \leq (b_{\mathrm{i}} - b_o)\,(E_t + E_o)\,, \tag{3}$$

where b_{i} is the size of computing unit's input in bit and b_o is the size of computing unit's outcome in bit, $b_{\mathrm{i}} \geq b$. If E_o is set to 0, next we contain

$$\frac{c}{b_{\mathrm{i}} - b_o} \leq \frac{E_t}{E_i}. \tag{4}$$

Noticeably, when Eq. (4) is fulfilled, Eq. (3) should be fulfilled too. In fact, Eq. (4) is a traditional constraint. It resolves the upper limit computing role that computing unit is obtain.

3. Experimental validation

For validating the results of the RNN-LSTM model for DDM in WSN, a set of experiments were carried out in MATLAB R2014a. Here, the results are validated under varying number of hidden layer nodes and signaling interval. The number of hidden layer nodes ranges from 5 to 40 and the signaling interval lies between 240–260. The set of measures used to analyze the performance are signaling overhead, average throughput and average delay. A comparative analysis is also made with OSPF and DNN models.

3.1. Results analysis under varying number of hidden layer nodes

In this section, the performance of the RNN-LSTM model has been validated under varying node count in hidden layers in terms of are signaling overhead, average throughput and average delay.

Fig. 3 investigates the results attained by the RNN-LSTM and other models in terms of signaling overhead. The figure portrayed that RNN-LSTM model shows effective outcome by achieving least signaling overhead. At the same time, the DNN model shows high signaling overhead compared to RNN-LSTM whereas the OSPF model exhibits least performance by offering maximum signaling overhead over the compared methods.

For instance, under the existence of 5 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 28 whereas the OSPF and DNN models shows maximum signaling overhead of 120 and 34 respectively. For instance, under the existence of 20 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 28 whereas the OSPF and DNN models shows maximum signaling overhead of 113 and 34 respectively. For instance, under the existence of 30 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 29 whereas the OSPF and DNN models shows maximum signaling overhead of 107 and 35 respectively. For instance, under the existence of 40 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 30 whereas the OSPF

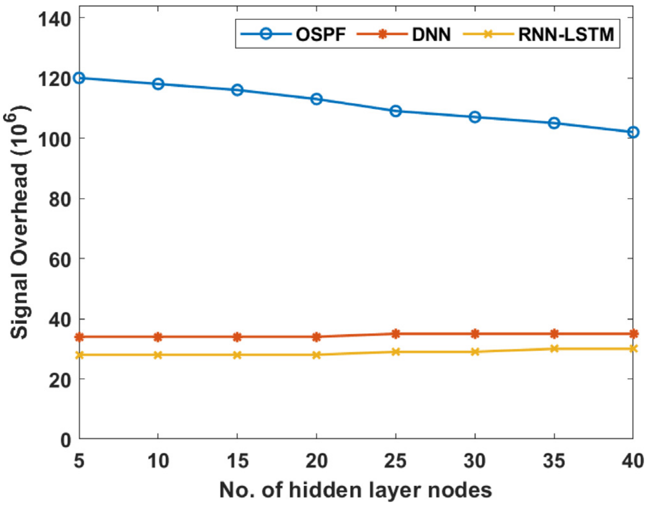


Fig. 3. Signaling overhead interms of hidden layer.

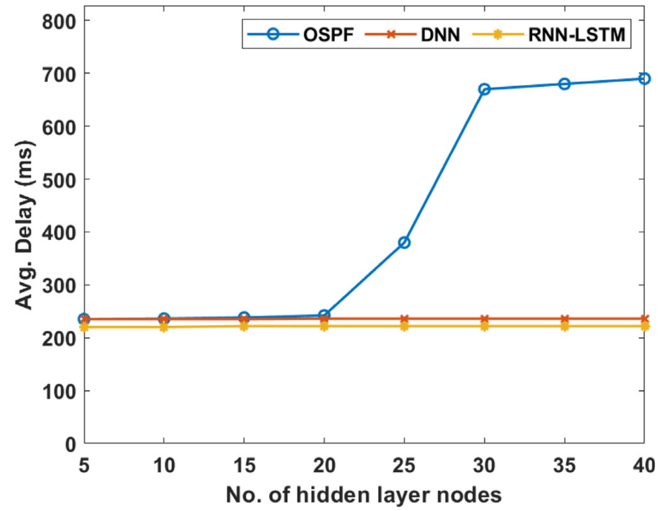


Fig. 5. Average delay interms of hidden layer.

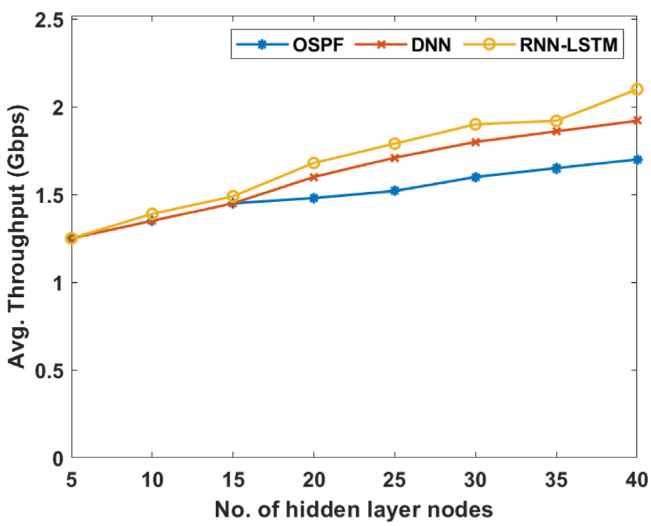


Fig. 4. Average throughput interms of hidden layer.

and DNN models shows maximum signaling overhead of 102 and 35 respectively.

Fig. 4 shows the outcome of the RNN-LSTM and other models interms of average throughput. The figure depicted that the RNN-LSTM model offers superior results by offering maximum throughput. At the same time, the DNN model shows moderate average throughput compared to RNN-LSTM whereas the OSPF model exhibits worse performance by offering least throughput over the compared methods.

For instance, under the existence of 10 hidden layer nodes, it can be shown that the RNN-LSTM achieves a maximum throughput of 1.39 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.35 Gbps respectively. For instance, under the existence of 20 hidden layer nodes, it can be shown that the RNN-LSTM achieves a maximum throughput of 1.68 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.52 Gbps and 1.6 Gbps respectively. For instance, under the existence of 30 hidden layer nodes, it can be shown that the RNN-LSTM achieves a maximum throughput of 1.9 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.6 Gbps and 1.8 Gbps respectively. For instance, under the existence of 40 hidden layer nodes, it can be shown that the RNN-LSTM achieves a maximum throughput of 2.1 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.7 Gbps and 1.92 Gbps respectively.

Fig. 5 exhibits the results attained by the RNN-LSTM and other models interms of average delay. The figure portrayed that RNN-LSTM model shows effective outcome by achieving least average delay. At the same time, the DNN model shows high average delay compared to RNN-LSTM whereas the OSPF model exhibits least performance by offering maximum average delay over the compared methods.

For instance, under the existence of 5 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum average delay of 220 ms whereas the OSPF and DNN models shows average delay of 235 ms respectively. For instance, under the existence of 20 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum average delay of 222 ms whereas the OSPF and DNN models shows average delay of 242 ms and 236 ms respectively. For instance, under the existence of 30 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum average delay of 222 ms whereas the OSPF and DNN models shows average delay of 570 ms and 236 ms respectively. For instance, under the existence of 40 hidden layer nodes, it can be shown that the RNN-LSTM achieves a minimum average delay of 222 ms whereas the OSPF and DNN models shows average delay of 690 ms and 236 ms respectively.

3.2. Results analysis under varying number of signaling interval

In this section, the outcome of the RNN-LSTM model has been validated under varying signaling interval interms of signaling overhead, average throughput and average delay.

Fig. 6 investigates the results attained by the RNN-LSTM and other models interms of signaling overhead with various signaling intervals. It is shown that the RNN-LSTM model shows extraordinary performance and offered a minimum signaling overhead under different signaling intervals over the compared methods.

For instance, under the signaling interval of 260 ms, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 17 whereas the OSPF and DNN models shows maximum signaling overhead of 120 and 20 respectively. For instance, under the signaling interval of 250 ms, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 18 whereas the OSPF and DNN models shows maximum signaling overhead of 125 and 30 respectively. For instance, under the

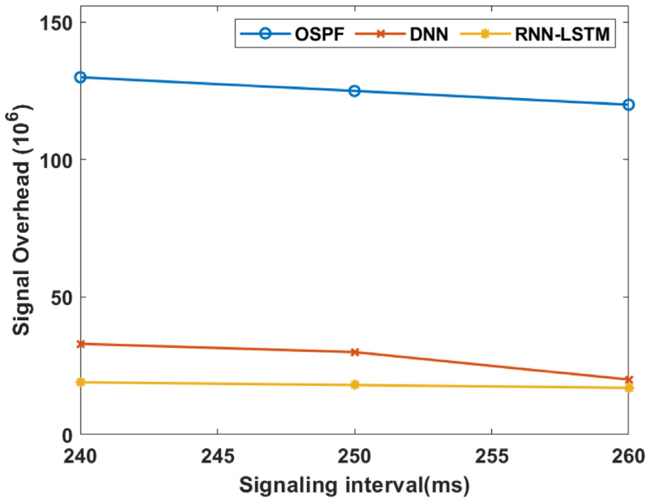


Fig. 6. Signaling overhead interms of signaling interval.

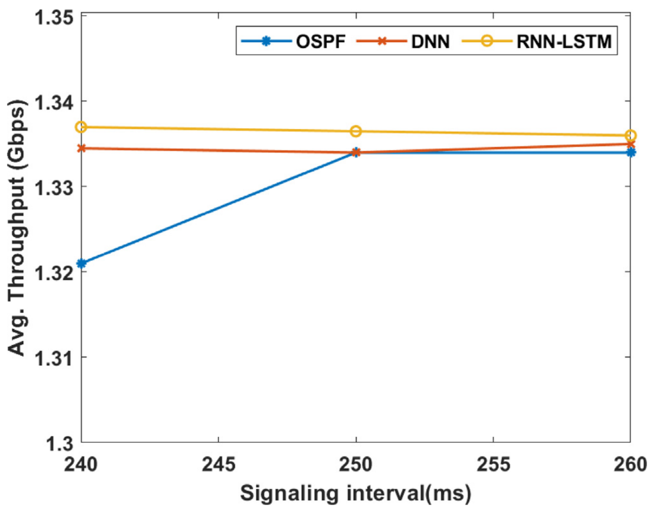


Fig. 7. Average throughput interms of signaling interval.

signaling interval of 240 ms, it can be shown that the RNN-LSTM achieves a minimum signaling overhead of 19 whereas the OSPF and DNN models shows maximum signaling overhead of 130 and 33 respectively.

Fig. 7 shows the outcome of the RNN-LSTM and other models interms of average throughput under different signaling intervals. The figure depicted that the RNN-LSTM model offers superior results by offering maximum throughput under all the signaling intervals applied.

For instance, under the signaling interval of 260 ms, it can be shown that the RNN-LSTM achieves a maximum throughput of 1.336 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.334 Gbps and 1.335 Gbps respectively. For instance, under the signaling interval of 250 ms, it can be shown that the RNN-LSTM achieves a maximum throughput of 1.3365 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.334 Gbps and 1.334 Gbps respectively. For instance, under the signaling interval of 240 ms, it can be shown that the RNN-LSTM achieves a maximum throughput of 1.337 Gbps whereas the OSPF and DNN models shows slightly lower throughput of 1.321 Gbps and 1.3345 Gbps respectively.

Fig. 8 exhibits the results attained by the RNN-LSTM and other models interms of average delay under different signaling intervals. The figure portrayed that RNN-LSTM model shows effective

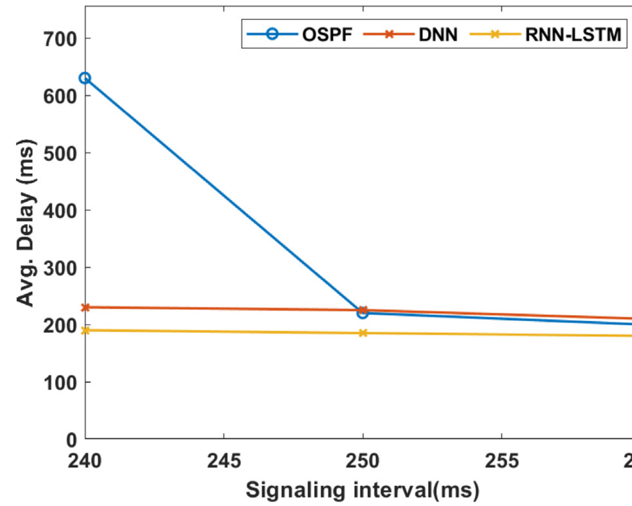


Fig. 8. Average delay interms of signaling intervals.

outcome by achieving least average delay under different signaling intervals. For instance, under the signaling interval of 260 ms, it can be shown that the RNN-LSTM achieves a minimum average delay of 180 ms whereas the OSPF and DNN models shows average delay of 200 ms and 210 ms respectively. For instance, under the signaling interval of 250 ms, it can be shown that the RNN-LSTM achieves a minimum average delay of 185 ms whereas the OSPF and DNN models shows average delay of 220 ms and 225 ms respectively. For instance, under the signaling interval of 240 ms, it can be shown that the RNN-LSTM achieves a minimum average delay of 190 ms whereas the OSPF and DNN models shows average delay of 230 ms and 230 ms respectively.

By looking into the above figures, it is evident that the DNN model shows high signaling overhead compared to RNN-LSTM whereas the OSPF model exhibits least performance by offering maximum signaling overhead over the compared methods. At the same time, the DNN model shows moderate average throughput compared to RNN-LSTM whereas the OSPF model exhibits worse performance by offering least throughput over the compared methods. Along with that, it is also observed that the amount of energy needed to transmit data by RNN-LSTM model is considerably lower than energy needed to transmit actual data. The simulation results indicated that the RNN-LSTM reduces the signaling overhead, average delay and maximizes the overall throughput compared to other methods.

4. Conclusion

This study has developed a new RNN-LSTM model for DDM in WSN to achieve energy efficiency and optimal load balancing at the fusion center of WSN. Using the RNN-LSTM model, the overhead of the fusion center in WSN is greatly reduced. At the same time, the energy consumption for processed data transmission by RNN-LSTM model is considerably lower than the transmission of actual data. Here, the results are validated under varying number of hidden layer nodes and signaling interval. The number of hidden layer nodes ranges from 5 to 40 and the signaling interval lies between 240–260. The set of measures used to analyze the performance are signaling overhead, average throughput and average delay. At the same time, the amount of energy needed to transmit data by RNN-LSTM model is considerably lower than energy needed to transmit actual data. The simulation results indicated that the RNN-LSTM reduces the signaling overhead, average delay and maximizes the overall throughput compared to other methods. It is noted that under the signaling interval of 240 ms, it can be shown that the RNN-LSTM achieves a minimum average delay of 190 ms whereas the OSPF and DNN models shows average delay of 230 ms and 230 ms respectively. In future, the performance of the proposed model can be further enhanced by the use of hyper parameter tuning techniques.

Declaration of competing interest

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

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