Optimizing Radiation Patterns in Wireless Networks Using LSTM Neural Networks

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***Abstract*— In this paper, we present a model to optimize wireless network radiation patterns using a Long Short-Term Memory (LSTM) neural network. The objective is to increase the signal-to-noise ratio (SNR) and received power for users. We improve the selection between omnidirectional and directional radiation patterns of access points. In the simulation, we set the environment with user distributions and obstacles. The LSTM model achieved a training RMSE of 8.62 dB and a test RMSE of 25.82 dB for the omnidirectional radiation pattern, and a training RMSE of 7.3 dB and a test RMSE of 28.37 dB for the directional radiation pattern. We integrated LSTM predictions into a proposed decision-making method. We discovered that the omnidirectional radiation pattern is often appropriate in environments with uniformly distributed users, while the directional radiation pattern is suitable for environments with a small number of users. This study demonstrates the potential of machine learning for optimizing radiation patterns to improve wireless networks.**

***Keywords*— Wireless network, LSTM neural networks, Radiation pattern selection**

I. Introduction

In recent years, wireless network users have increased rapidly. Therefore, present technology must improve to maximize benefits. Additionally, since OpenAI became available for public use, machine learning has been extensively used to develop wireless networks. From a survey of research on wireless networks, we find that in reference [1], the Random Forest algorithm selects access points (AP), thus improving channel quality and throughput. In reference [2], ML predicts handover from AP 1 to AP 2 in Cognitive Wi-Fi Networks, reducing the burden of handover by 60%. In reference [3], the development of WIFI 7 focuses on increasing data transmission rates. This support for multiple users using ML improves WLANs. In reference [4] ML is used to increase network capacity, Quality of Service (QoS), and security. In reference [5], guidelines for architectural requirements for ML are applied to WLANs. From a survey of past research, it can be seen that ML has the potential to help develop wireless networks in many areas.

One of the challenges of ML is its application in radiation pattern modeling. Therefore, reference [6] uses ML in antenna array design to increase the efficiency of the radiation pattern. However, using radiation patterns has limitations depending on their characteristics. Omni-directional radiating patterns are often used for APs in densely populated areas because they cover all users within the range of the radiation pattern. However, the main disadvantage of this type of radiation pattern is that transmission efficiency is relatively low and does not perform well in delivering power specifically to priority groups of users. On the other hand, using a directional radiation pattern has the benefit of being focused on a specific user. Reference [7] uses directional antennas such as microstrips are effective for wireless networks in urban environments. Normally, urban environments use an omnidirectional radiation pattern. However, in specific cases, users may use directional radiation patterns, but the coverage area is limited. This makes it impossible to support all users around the AP. Therefore, research that utilizes the potential of these two types of radiation patterns is beneficial. Reference [8] presents an antenna that can adjust the type of radiation pattern. This allows devices that use this type of antenna to adjust their power distribution patterns to suit the network situation. Moreover, references [9], [10], and [11] improve antennas for radiation pattern advantages. From the above research survey, it can be concluded that there is still a lack of guidelines for developing wireless networks in terms of radiation pattern patterns. Therefore, developing new techniques to solve these challenges is still necessary.

Machine Learning (ML) encompasses a wide range of techniques, including Reinforcement Learning (RL), which can learn and adapt to dynamic environments in wireless networks; Unsupervised Learning (UL), which does not require labeled data; Semi-Supervised Learning (SSL), which uses less labeled data; and Self-Supervised Learning (SSL), which can use unlabeled data. Nonetheless, there are many benefits to employing Supervised Learning for precise wireless network research. A relevant development role for Supervised Learning, particularly Long Short Term Memory (LSTM), is seen in constantly deployed wireless networks. In reference [12], a channel prediction method using Long Short Term Memory-Projected Layer (LSTM-PL) is proposed by detecting OFDM signals in wireless network systems. In reference [13], LSTM replaces Back Propagation (BP) and Maximum Likelihood Sequence Estimation (MLSF) in terms of bit error rate in signal detection. In reference [14], LSTM increases the efficiency of SNR estimation. Reference [15] proposed LSTM to improve accuracy in wireless networks. In reference [16] a new novel model of LSTM is proposed to improve energy efficiency. From the above research, it can be seen that using LSTM in wireless networks allows the network to increase its performance potential.

Although there is research on network optimization every year, challenges related to radiation patterns and signal quality remain, and gaps exist in the application of LSTM to wireless

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networks. In addition, AP settings can now be configured directly through the cloud, providing resilience in configuration. Therefore, this research focuses on applications to upgrade wireless networks using LSTM, working with a proposed algorithm decision-making tool for APs through the cloud. This proposal breaks the limits of conventional applications in radiation patterns.

The objectives of this research are:

- To aid in deciding on adjusting the AP radiation pattern to suit the situation.
- To increase the efficiency of the signal in the wireless network.
- To apply LSTM with radiation pattern simulation techniques.

This article is structured as follows: The network environment is described in Section II. The research hypothesis, LSTM model, and selection algorithm are presented in Section III. The results and discussion are shown in Section IV. The conclusions are provided in Section V.

II. CHANNEL MODEL

In wireless communications, the electromagnetic transmission from the AP to the user is an important factor affecting the simulation. We take each factor into consideration as follows:

$$P_{r,\text{total}} = P_t - \text{FSPL} + X_\sigma + \text{Multipath} \qquad (1)$$

Where P_t is the transmitted power, FSPL is the free-space path loss, X_σ represents shadowing, and Multipath accounts for the multipath fading. The power available to the user depends on the AP's transmit power, attenuation due to FSPL, attenuation caused by line-of-sight (LOA) obstructions, LOA related to shadowing, and multi-path transmission effects, including diffraction and scattering.

A. Free-Space Path Loss

FSPL is a loss that depends on the distance between the user and the AP. This depends mainly on the operating frequency, as shown in the following equation:

$$\text{FSPL} = \left(\frac{4\pi df}{c}\right)^2 \qquad (2)$$

Where d is the distance between the transmitter and receiver, f is the frequency of the transmitted signal, and c is the speed of light in a vacuum.

B. Shadowing

Shadowing or fading is the reduction of signal attenuation due to obstructions. This significantly affects the signal strength, as described by the following equation:

$$P_{r,\text{shadow}} = P_r + X_\sigma \qquad (3)$$

Where P_r is the received power without shadowing, and X_σ is a zero-mean Gaussian random variable with standard deviation σ

C. Multipath Effects

Multipath effects occur when signals are sent via multiple paths. Some routes are fast, while others are slow, causing signal attenuation when the signal reaches the user. We simulate the gain that occurs in each path as shown in the following equation:

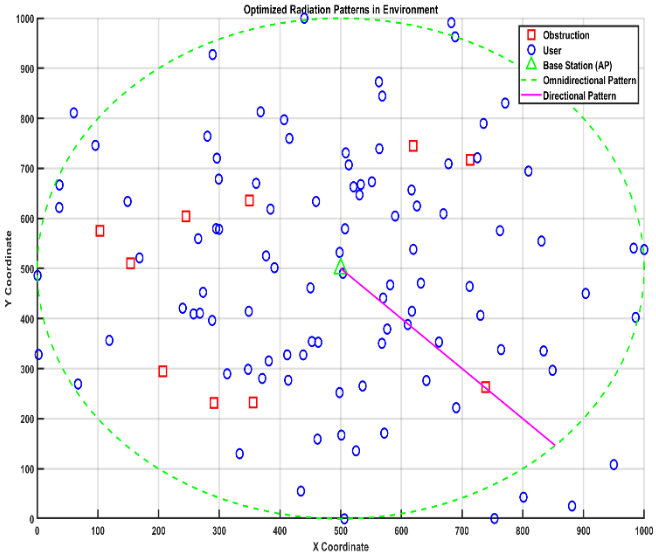

Figure 1 Network scenario configurable from the cloud

$$\text{Multipath Effect} = 10\log_{10}\left(\sum_{i=1}^{N} 10^{\frac{g_i}{10}}\right) \qquad (4)$$

Where g_i is the gain of the i-th multipath component in dB, N and is the number of multipath components.

III. HYPOTHESIS MODELLING

The wireless network model consists of random users and obstacles, with the AP located in the middle of the network as shown in Figure 1. Moreover, the AP can use both types of radiation pattern models, where the AP estimates the number of users in the network. Then, the AP sends data to the cloud for processing. In the cloud, an algorithm and LSTM are installed. The AP data includes the user's location, received power, and Signal-to-Noise Ratio (SNR) of each user. After receiving the data, we use the LSTM model to predict the received power for both omnidirectional and directional radiating patterns. Moreover, factors include user location and work power of each user. This data is used to estimate in the algorithm for deciding the type of radiation pattern, as referenced in [8], that can switch radiation patterns

In this research, we create a model using simulation data from the channel model section. We simulate the received power, Signal-to-Noise Ratio (SNR) values, and user positions for both radiation patterns. The simulated data incorporates various signal attenuation factors such as free-space path loss, shadowing, and multipath effects. The next step is data preprocessing. We assign non-readable values, such as infinite values, to ensure accurate predictions. The data is also normalized to keep the levels between 0 and 1.

A. LSTM architecture

The LSTM architecture is designed to have multiple layers. This research consists of an Input Layer, which uses data from the wireless network simulation, including received power, Signal-to-Noise Ratio (SNR) values, and user location from both types of radiation patterns. LSTM Layers capture long-term dependencies in the data. Dropout Layers are used to prevent overfitting Dense Layers are used to map features to data predictions. Key aspects of the LSTM model are as follows:

- Data Preprocessing: After receiving input, the model preprocesses the data to focus on received power.
- Splitting Data: In this model, the data is split into training and testing sets with a ratio of 70% to 30%, respectively.
- Network Model: This model uses the LSTM network from the TensorFlow Keras Sequential API for simulation.
- Training: The model is trained for 1000 epochs with a batch size of 30, using 20% of the training data for validation.

B. *Radiation pattern selection algorithm*

After using the LSTM model, we employ an algorithm to select the appropriate radiation pattern for the current network. We define two possible types of radiation patterns: omnidirectional and directional. The beamwidth of the specified directional radiation pattern is 60 degrees. Then, we clean the data by dealing with infinite values and values that cannot be read. For the directional radiation power model, we calculate the received power and the average SNR of users in the AP's coverage area in 15-degree increments. For the omnidirectional model, it is calculated for users in all directions. After the calculations are completed, this research compares the received power and SNR of each radiation pattern and all directions to select the most suitable one for the network. Then, the proposed algorithm works as follows:

Algorithm : Radiation Pattern Selection Algorithm

Cloud use data after LSTM prediction before send data to change radiation at AP

Begin

1. Initialization: Define pattern with Omnidirectional and directional radiation pattern. Set angle in range 0 to 360 degree. AP position at center. Directional radiation pattern beamwidth 60 degree
2. Data Collection: Collect prediction receive power, SNR, and location of each users from LSTM model. Then, normalize and clean data.
3. Evaluation of omnidirectional pattern: Calculate the total received power and average SNR. Moreover, Store total received power (P_{omni}) and average SNR ($\mathrm{SNR}_{\mathrm{omni}}$)
4. Evaluation of directional pattern:

   For each angle $\theta \in$ angles:

   a. Calculate received power ($P_{\mathrm{dir}}(\theta)$) and SNR ($\mathrm{SNR}_{\mathrm{dir}}(\theta)$) within the beamwidth.

   b. Sum $P_{\mathrm{dir}}(\theta)$ and $\mathrm{SNR}_{\mathrm{dir}}(\theta)$ for users within the coverage area.

   c. Store total $P_{\mathrm{dir}}(\theta)$ and $\mathrm{SNR}_{\mathrm{dir}}(\theta)$
5. Comparison and Selection: compare received power and SNR of directional and omnidirectional pattern. Then, Select the pattern and angle that have total received power maximize and best average SNR
6. Pattern Switching Decision:

   If the selected radiation pattern differ from the current pattern in use:

   a. Switch the AP to the new radiation pattern

   If the selected radiation pattern is the same as the current pattern in use:

   b. Do not send configuration data to the AP.

End

TABLE I. WIRELESS NETWORK PARAMETERS

Parameter	Value
Number of Users of Omnidirectional/Directional Radiation Pattern	100 and 20
Simulation Area	1000 x 1000 m
Base Station Position (AP)	[500, 500]
Frequency	2.4 GHz
Bandwidth	20 MHz
Transmission Power	20 dBm
Path Loss Model	Free-space
Shadowing Standard Deviation (σ)	4 dB
Beamwidth of Directional Pattern	60 degrees
Directional Pattern Angles	0 to 360 degrees in 15-degree increments

TABLE II. LSTM MODEL PARAMETERS

Parameter	Value
LSTM Training Epochs	1000
LSTM Batch Size	30
Learning Rate	0.001
Dropout Rate	0.2
Number of LSTM Layers	2

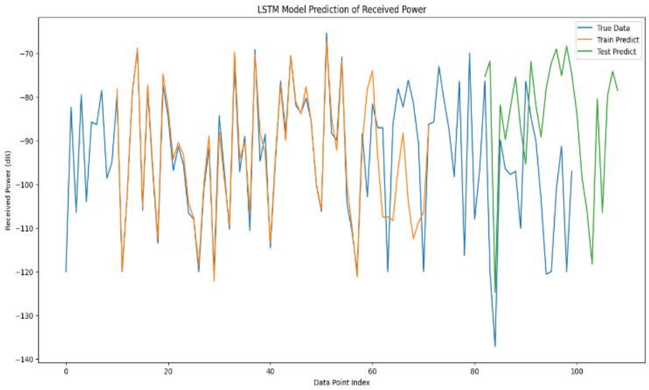

Figure 2. LSTM model prediction of received power of omnidirectional radiation pattern

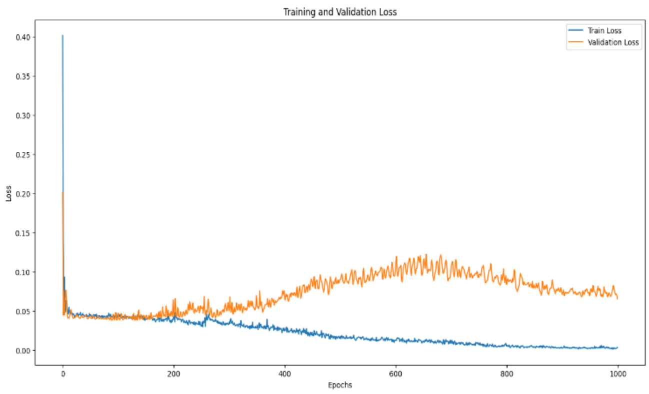

Figure 3. Training and validation loss omnidirectional radiation pattern

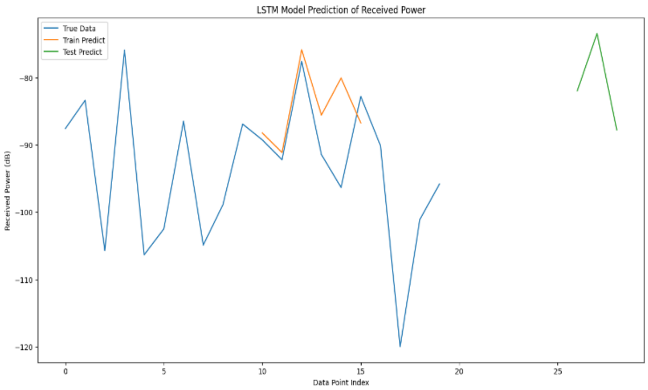

Figure 4. LSTM model prediction of received power of directional radiation pattern

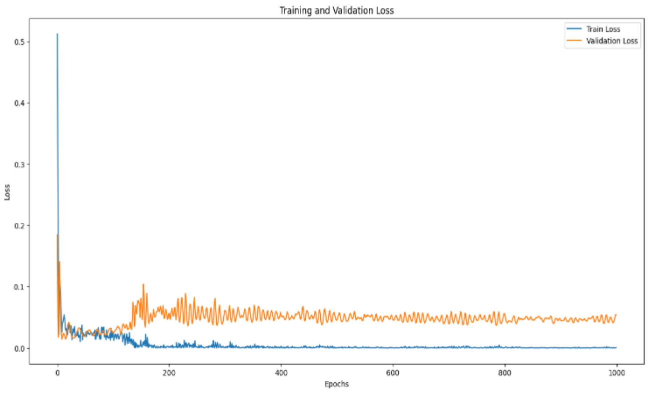

Figure 5. Training and validation loss directional radiation pattern

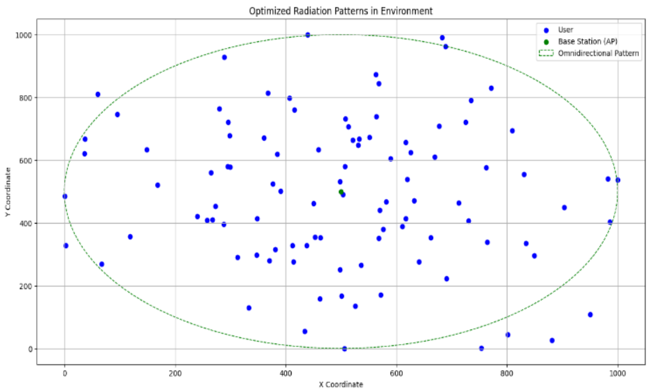

Figure 6. Optimized radiation patterns in environment with omnidirectional radiation pattern

IV. RESULT AND DISCUSSION

In this experiment, the wireless parameters are set as shown in Table 1 and the LSTM parameters are shown in Table 2. This approach uses LSTM to train the data and predict the received power. Moreover, this evaluates the model's performance with Root Mean Squared Error (RMSE) of omnidirectional radiation pattern and directional radiation pattern, achieving a training RMSE of 8.62 dB and 7.3 dB and a test RMSE of 25.82 dB and 28.37 dB, respectively. Moreover, as shown in Figures 2 and 4, the test and train data received power stay within the scope of true data. This shows that the model predicts correctly. In Figures 3 and 5, the low validation loss is shown, indicating that this model performs

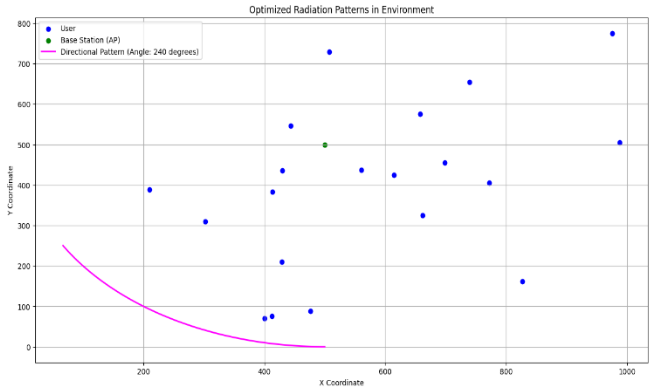

Figure 7. Optimized radiation patterns in environment with directional radiation pattern

well for prediction. However, it still exhibits some overfitting when the number of epochs increases.

For deciding on the radiation pattern, there are two types of radiation patterns: directional and omnidirectional. The most appropriate radiation pattern for the user in the model is the omnidirectional pattern. This research considers the total power received. Additionally, the algorithm collects data from users from 0 to 360 degrees, providing more coverage to accommodate users.

LSTM model analysis shows that the model has accurate prediction performance based on the relatively low RMSE indicator value. The model can determine the relationship between user location, signal propagation effects, and received power. Moreover, after using LSTM model with an algorithm to select the radiation pattern, it is found that the algorithm chooses to use an omnidirectional radiation pattern as shown as in Figure 6. This conflicts with the antenna gain because it is used in an environment where wireless users are relatively evenly distributed within the AP's coverage. However, when the number of users in the wireless network decreases, the directional radiation pattern is better than the omnidirectional radiation pattern, as shown in Figure 7 with an angle of 240 degrees.

From the results of the experiment, it is also found that choosing the type of radiation pattern must take into account the distribution of users to suit the network environment. In addition, the omnidirectional radiation pattern scheme is less complex than directional schemes. However, using an omnidirectional radiation pattern still has a higher chance of receiving interference than a directional radiation pattern. This requires using other techniques to help reduce signal interference, such as noise reduction techniques.

V. CONCLUSION

The study object is creating a selection radiation pattern algorithm for AP. Moreover, it is suitable in the present situation. This paper proposes using the LSTM model to predict the received power and the SNR value. The study found that LSTM can detect the relationship between various factors in the wireless network. The proposed algorithm can evaluate both radiation patterns and improve their application. This makes AP installation planning easier. Research has shown the effectiveness of using LSTM in predicting and optimizing wireless network performance.

VI. REFERENCE

[1] Militani, D., Vieira, S., Valadão, E., Neles, K., Rosa, R., & Rodríguez, D. Z. (2019, September). A machine learning model to resource allocation service for access point on wireless network. In 2019 international conference on software, telecommunications and computer networks (SoftCOM) (pp. 1-6). IEEE.

[2] Khan, M. A., Hamila, R., Gastli, A., Kiranyaz, S., & Al-Emadi, N. A. (2022). ML-Based Handover Prediction and AP Selection in Cognitive Wi-Fi Networks. Journal of Network and Systems Management, 30(4), 72.

[3] Szott, S., Kosek-Szott, K., Gawłowicz, P., Gómez, J. T., Bellalta, B., Zubow, A., & Dressler, F. (2022). Wi-Fi meets ML: A survey on improving IEEE 802.11 performance with machine learning. IEEE Communications Surveys & Tutorials, 24(3), 1843-1893.

[4] Abuzainab, N., Erpek, T., Davaslioglu, K., Sagduyu, Y. E., Shi, Y., Mackey, S. J., ... & Yener, A. (2019, November). QoS and jamming-aware wireless networking using deep reinforcement learning. In MILCOM 2019-2019 IEEE Military Communications Conference (MILCOM) (pp. 610-615). IEEE.

[5] Wilhelmi, F., Barrachina-Muñoz, S., Bellalta, B., Cano, C., Jonsson, A., & Ram, V. (2020). A flexible machine-learning-aware architecture for future WLANs. IEEE Communications Magazine, 58(3), 25-31.

[6] Rani, M. L. P., Satyanarayana, M., & Rao, N. S. (2022). Radiation Patterns from Thinned and Unthinned Linear Arrays with Different Spacings Using ML Algorithms. In Antenna Arrays-Applications to Modern Wireless and Space-Born Systems. IntechOpen.

[7] Wang, Y., & Zeng, X. (2023). Impact of antenna design, electromagnetic propagation, and RF frequency on the performance of wireless communication systems in urban environments. Journal of Computing and Natural Science, 3(2), 103-112.

[8] Jose, M. C., Sankararajan, R., Sreeja, B. S., Alsath, M. G. N., & Kumar, P. (2022). A compact omnidirectional to directional frequency reconfigurable antenna for wireless sensor network applications. International Journal of Microwave and Wireless Technologies, 14(7), 859-870.

[9] Quddious, A., Abbasi, M. A. B., Antoniades, M. A., Vryonides, P., Fusco, V., & Nikolaou, S. (2020). Dynamically reconfigurable UWB antenna using an FET switch powered by wireless RF harvested energy. IEEE Transactions on Antennas and Propagation, 68(8), 5872-5881.

[10] Lee, S., Lee, Y., & Shin, H. (2021). A 28-GHz switched-beam antenna with integrated Butler matrix and switch for 5G applications. Sensors, 21(15), 5128.

[11] Trzebiatowski, K., Rzymowski, M., Kulas, L., & Nyka, K. (2020). Simple 60 GHz switched beam antenna for 5G millimeter-wave applications. IEEE Antennas and Wireless Propagation Letters, 20(1), 38-42.

[12] Olickal, S. J., & Jose, R. (2023). LSTM projected layer neural network-based signal estimation and channel state estimator for OFDM wireless communication systems. AIMS Electronics & Electrical Engineering, 7(2).

[13] Cao, M., Yao, R., Xia, J., Jia, K., & Wang, H. (2022). LSTM attention neural-network-based signal detection for hybrid modulated Faster-Than-Nyquist optical wireless communications. Sensors, 22(22), 8992.

[14] Liu, Q., Yin, Z., Wu, M., Wu, Z., & Xu, Z. (2022, August). LSTM Network-based SNR Estimator for DS-UWB Wireless Sensor Network. In 2022 9th International Conference on Dependable Systems and Their Applications (DSA) (pp. 965-973). IEEE.

[15] Dalgkitsis, A., Louta, M., & Karetsos, G. T. (2018, November). Traffic forecasting in cellular networks using the LSTM RNN. In Proceedings of the 22nd Pan-Hellenic Conference on Informatics (pp. 28-33).

[16] Mohanty, S. N., Lydia, E. L., Elhoseny, M., Al Otaibi, M. M. G., & Shankar, K. (2020). Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks. Physical Communication, 40, 101097.