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Optimizing the LoRa network performance for industrial scenario using a machine learning approach

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ABSTRACT

In this article, the performance of the LoRa network for an industrial scenario has been optimized using a machine learning approach. The network performance is analyzed in terms of received power, outage probability, spectral efficiency and bit error rate (BER). A link-level performance of the LoRa network for an indoor industrial area considering both the non-obstructive and obstructive scenarios has been experimentally evaluated in terms of received signal strength indicator (RSSI) and signal-to-noise ratio (SNR). Using the measured values of RSSI and SNR at the LoRa gateway, the received power is mathematically modelled which is further considered as an optimization problem. First, an artificial neural network (ANN) model was built and trained to predict the received power. Particle swarm optimization (PSO) algorithm was further used to find the optimal values of LoRa parameters corresponding to maximum received power. Simulation results reveal that the proposed optimization approach significantly improves the outage probability, spectral efficiency and BER of the LoRa network.

1. Introduction

Internet of things (IoT) endeavours to connect billions of low-end devices to a common interface communicating with one another without any human intervention. The advancement in internet technology is driving automation in factory manufacturing processes. Through condition monitoring systems and predictive monitoring, these smart industries can timely detect the deformities at various production stages and instantly respond to the unwanted events to prevent huge financial losses [1]. In the past few decades, the fourth industrial revolution or industry 4.0 has emerged emphasizing the adoption of digital technology with the help of interconnection through IoT to access real-time data and control the industrial processes. Industry 4.0 strongly relates to the industrial internet of things (IIoT) paradigm that defines intelligent, interconnected industrial equipment communicating and optimizing the whole manufacturing process [2]. The industrial scenario differs from other IoT application scenarios in certain aspects that include quality of service (QoS) requirements, industrial wireless channel, and traffic patterns. In contrast to a typical smart city setup, the industrial setup has stronger signal attenuation and higher interference. Also, the packets transmitted are more recurrent and need to be delivered with high reliability and low latency.

The focus of the current work is the high-level network performance for industrial IoT applications. To facilitate the connectivity of a broad range of factory equipment to the internet, IIoT presents a set of prevalent wireless standards such as low-cost wireless access, high power wireless access, and low power wide area network (LPWAN). LPWAN has been adopted as the key enabler of the industry

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4.0 paradigm due to its competency to meet energy-efficient, long coverage, and massive scalability requirements of the IIoT deployment [3]. The main players capturing the LPWAN market are Narrow Band IoT (NB-IoT), Long Term Evolution (LTE-M), Sigfox, Weightless, and long-range (LoRa). Among these LoRa developed by the LoRa alliance is considered to be the most suitable for various IIoT use cases due to its low power consumption, extensive geographical coverage, enormous scalability, and low network deployment cost [4]. As compared to other LPWAN technologies, LoRa provides full control of the network configuration making it possible to optimize the network performance [5]. LoRa network can be customized by independently adjusting the transmission configuration of its integral device. Each LoRa device is provided with its transmission configuration such that it could reduce packet collisions. However, a particular radio propagation environment and the existence of an interfering wireless device operating at the same frequency as the LoRa device provide the ideal network configuration that sturdily depends upon the specific deployment location [6]. Thus, it is essential to characterize the type of radio propagation environment and the type of wireless link. The link quality defines the quality of the signal received at the gateway. The link quality of the LoRa network can be analyzed in terms of SNR, RSSI, received power, outrage probability, BER, spectral efficiency, etc.

This work aims to maximize the link performance of the LoRa network in an industrial scenario by optimizing the received power. An indoor industrial scenario considering both non-obstructive and obstructive environments is studied and the link-level performance of the LoRa network is experimentally analyzed in terms of SNR and RSSI at various SFs. Further, the system model for both the environments is numerically formulated using the measured values of SNR and RSSI and the network performance is evaluated in terms of received power. Evaluation reveals the dependency of the received power on various constrained as well as non-constrained LoRa parameters. A data set is generated for each SF to be utilized in building an ANN model to predict the LoRa network performance and optimal LoRa parameters. PSO technique is further utilized to optimize the non-constrained LoRa parameters on which received power depends thereby improving the SNR, outage probability, spectral efficiency, and BER of the LoRa network.

The rest of the article is structured as follows: Section 2 introduces the literature review and the comparison of various optimization techniques adopted. Section 3 presents the LoRa technology. Section 4 highlights the measurement setup used to estimate the performance of the LoRa network. In Section 5 the system model using measured values of SNR and RSSI has been formulated and its performance analysis has been described. The optimization of received power using ANN-PSO for efficient link performance of the network is presented in Section 6. Simulation work and results are presented in Section 7 followed by the conclusion of the work in Section 8.

2. Related work

The performance of the LoRa network has been investigated both analytically as well through experimental measurements considering different scenarios in literature. A considerable amount of contribution has been made to improve the performance of the LoRa network. In Sandoval et al. [5], the average per-node throughput of the LoRa network is mathematically modelled as the maximization problem to optimize the network performance using the evolution strategy algorithm. The authors of Sandoval et al. [6] derived an optimal network-level transmission configuration to optimize the network performance. To enable the derivation of the

Table 1
Summary of the related work.

Reference	Approach Employed	Optimization technique	Performance Metrics Evaluated	Outcomes
[5]	Network-level configuration mathematically modelled and posed as optimization problem	Reinforcement Learning	Throughput	147% increase in Throughput
[6]	Mathematically model the propagation environment to derive the optimal network-level configuration	Bounding technique	Throughput, power consumption, packet reception rate	15% increase in Throughput and packet reception rate,73% less energy consumption
[7]	The multi-objective problem formulated to find the appropriate resource reservation and best transmission configuration	Maximum likelihood estimation combined with the slice-based optimization method	Throughput, delay, reliability and energy consumption	A significant improvement in throughput, delay, reliability and energy consumption has been observed
[8]	Mixed Integer Linear Programming model to fine-tune the radio parameters	Mathematical Optimization	Data Extraction Rate, packet collision rate, energy consumption	5% increase in DER, 13.3 times less packet collision rate, 3.9 times less energy consumption
[9]	Modelled the inner state of LoRa nodes using the Markov mathematical framework	Genetic algorithm and simulated annealing	Throughput	238.8% increase in Throughput
[10]	Formulated constrained optimization problem	Distributed Genetic Algorithm	Throughput, packet reception ratio	A significant improvement in throughput, packet reception ratio has been observed
[11]	Integer linear programming model to assign SFs and TPs	Mathematical Optimization	Packet delivery ratio, energy consumption	8% higher packet delivery ratio with minimal energy consumption
Current work	Formulated a constrained optimization problem	ANN-PSO	Received power, outage probability, BER, spectral efficiency	19% and 584% increase in received power and spectral efficiency, respectively; 22% and 100% decrease in outage probability and BER, respectively

network level configuration a bounding technique is proposed reducing the time and energy to attain the radio propagation performance of each node. To flexibly manage heterogeneous IoT applications, a method of network slicing is adopted by the authors in Dawaliby et al. [7] using maximum likelihood estimation. In Sallum et al. [8] the performance of the LoRa network is optimized by finding the optimal setting of the spreading factor and code rate transmission parameters through a mixed integer linear programming optimization approach. Considering the duty cycle implications a mathematical model is formulated by Sandoval et al. [9] to improve the LoRa node transmission and power efficiency. The maximum achievable performance of the nodes is calculated and optimized in terms of throughput concerning optimal transmission policy. The authors of Narieda et al. [10] presented a spreading factor allocation technique under the energy consumption constraint to optimize the performance of the LoRa network. The optimization problem defined is solved using distributed genetic algorithm to maximize the packet perception ratio of the end device. In Premsankar et al. [11], authors formulated a linear integer programming approach to configure the LoRa nodes with optimal transmission parameters which are evaluated in different radio propagation environments.

Table 1 summarizes the related work. Metaheuristic optimization techniques are widely used in literature to compute the maximum achievable performance of the LoRa nodes. The above studies provide an insightful idea and motivation for incorporating the optimization techniques to enhance the LoRa network performance. The novelty of this work is the employment of an intelligent ANN-PSO incorporated technique for optimizing the performance of the LoRa nodes in an industrial scenario.

The key contributions of this work are outlined as.

1. Performance of the LoRa network in an industrial indoor area considering non-obstructive and obstructive environmental scenarios is experimentally investigated in terms of SNR and RSSI.
2. The system model is formulated relating the measured values of RSSI and SNR in terms of received power for both the considered scenarios.
3. The data set is created at various SFs for both scenarios and is utilized to build an ANN model to predict the performance of the LoRa network and optimal LoRa parameters.
4. Using the PSO algorithm, the LoRa network parameters are optimized on which received power depends to improve the network performance analyzed in terms of outage probability, BER, and spectral efficiency.
5. A critical comparative analysis of the results obtained using the optimized and non-optimized received power values have been made for both the environmental scenarios.

In the next section, an overview of LoRa technology has been described.

3. LoRa technology overview

LoRa is widely employed to provide energy-efficient, inexpensive, and easily configurable wireless networks covering a wide geographical area. It is a physical layer protocol that operates in unlicensed ISM bands at 433, 868, and 915 MHz depending upon the geographical region of the deployment [11]. The LoRa end device can be configured to be deployed in any scenario by adjusting its inherent parameters such as spreading factor (SF), coding rate (CR), bandwidth (BW), and transmission power to maximize the overall network performance. LoRa utilizes the chirp spread spectrum (CSS) modulation technique which makes it immune to fading, noise, and interference. The data to be transmitted modulates the chirp signal and the number of data bits modulated depends on the spreading factor whose value ranges from 7 to 12 [12]. Higher the spreading factor more is the communication range and less is the data rate. It integrates forward error-correcting code (FEC) defined in terms of Coding rate $\left(CR = \frac{4}{4+m}\right)$, where m indicates the code rate whose value ranges from 0 to 4 with $m = 0$ points to no FEC is used. Three scalable bandwidths of 125, 250, and 500 kHz are used by the LoRa device. The transmission power of the LoRa device is limited to the range of 2–20 dBm where maximum power is limited to 17 dBm due to hardware operation restrictions. LoRa devices can be deployed in different environments by appropriately configuring these transmission parameters.

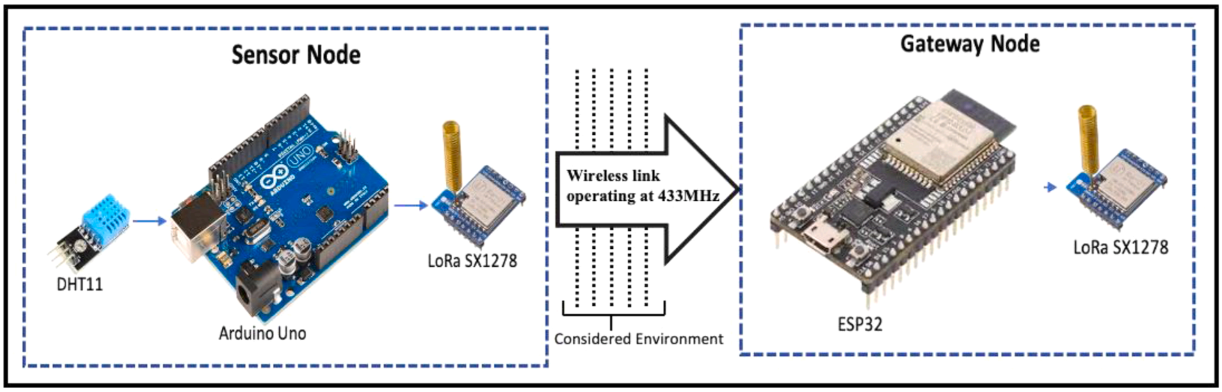

Fig. 1. Block diagram of the experimental set-up used.

In the next section, the experimental setup used to evaluate the link performance of the LoRa network in an indoor area considering both non-obstructive and obstructive environmental scenarios has been described.

4. Measurement setup

In this section, a LoRa network deployment in an indoor industrial scenario is considered where the gateway is connected to the end device deployed at a distance of 70 m. This deployment differs from a typical smart city use case where the gateway node is connected to the LoRa devices covering an area of several kilometers. The end device is assumed to be a wireless sensor node used for monitoring purposes collecting the measurement of temperature and humidity. The block diagram of the measurement setup employed to measure the link quality of the LoRa network is shown in Fig.1. The transmitter side consists of a DHT11 sensor measuring temperature and humidity data supported by an Arduino Uno microcontroller and a LoRa module. In this, Semtech's SX1278 LoRa module which operates in the 433 MHz ISM band has been used. The receiver end also consists of a LoRa SX1278 module along with an ESP32 microcontroller with a built-in Wi-Fi module to communicate the measured data to the database.

The work defines two propagation scenarios: non-obstructive or line of sight having a direct path between the LoRa end device and the gateway, and the obstructive scenario affected by the obstructions from 2 floors and 3 concrete walls. To achieve the non-obstructive scenario, both the transmitter and gateway are placed in a room covering the line-of-sight area. For both scenarios, measurement is done at a fixed communication range of 70 m between the LoRa end device and the gateway.

The link performance of the network in each scenario is sequentially studied by configuring both the LoRa device and the gateway with identical transmission parameters. During the experiment, the LoRa device is configured to transmit 100 packets each of payload size 25 bytes using the constant transmission power P_t=13 dBm, BW = 250 kHz, and CR = 4/5 cycling through various SF values ranging from 7 to 12. The performance metrics considered for the experimental study is SNR and RSSI. The LoRa gateway tuned to the same set of LoRa transmission parameters receives the packets and measures the SNR and RSSI in both scenarios. Through the experiment, the impact of various SFs in both scenarios on the link-level performance of the LoRa network in the indoor area has been studied. The logged values of SNR and RSSI at the gateway are further utilized to formulate the system model as discussed in a subsequent section.

5. System model

In this work, the uplink LoRa network to be configured in an indoor area consists of a single gateway and a single LoRa device. The gateway is deployed at a fixed location and the LoRa device is uniformly placed at two random locations to cover both the considered environmental scenarios. For both the environmental scenarios, the distance, d between the LoRa device and the gateway is fixed. The end device transmits with the transmission power, P_t in an uplink channel using various SFs with the transmission occurring over a constant BW. Further, it is also assumed that the LoRa device is a class A device and transmits the packets of fixed payload size to the gateway. The sensitivity of the LoRa gateway is described by the minimum received power required to detect the signal. This is attained for minimum SNR equal to $\frac{E_b}{N_o}$ as described in Nguyen et al. [13] and expressed as.

$$\frac{E_b}{N_o} = SNR \times \frac{2^{SF}}{BW} \tag{1}$$

Where, E_b is the energy per bit received at the gateway and N_O is noise power spectral density whose value is equal to $N_O = NF \times k \times T \times BW$ where NF is the receiver noise figure, k is the Boltzmann constant and T is the temperature.

The received power of each transmitted packet from the LoRa device at the gateway is the ratio of energy per bit to each bit duration T_bi.e. $P_r = \frac{E_b}{T_b}$ where, $T_b$is equal to $2^{SF}/BW$ [14]. Using Eq. (1), the received power of each transmitted packet at the LoRa gateway can be calculated as

$$P_r = \frac{SNR \times NF \times k \times T \times (BW)^2}{SF} \tag{2}$$

RSSI is the crucial parameter to calculate the strength of the signal received at the gateway deployed at a distance d from the LoRa device. It indicates the amount of signal attenuation during the transmission process and as given in Savazzi et al. [15] and using Eq. (2), RSSI can be denoted as

$$RSSI = \frac{SNR \times NF \times k \times T \times (BW)^2}{SF \times d^{\eta}} \tag{3}$$

where, d is the between the LoRa device and the gateway and η is the path loss exponent

From (3), the estimated communication range between the LoRa device and the gateway can be represented by.

$$d = \left(\frac{SNR \times NF \times k \times T \times (BW)^2}{SF \times RSSI}\right)^{\frac{1}{\eta}} \tag{4}$$

The strength of the signal degrades as it propagates through a medium due to certain effects such as refraction, reflection, diffraction, and scattering of the signal from the obstacles in the path. The reduction in the strength of the received signal at the gateway is predicted by the path loss models. Assuming the worst case scenario with no antenna gains, the expected received signal power, P_r at the gateway node from the LoRa device as stated in Narieda et al. [10] is expressed as.

$$P_r = \frac{P_t}{PL(d)} \tag{5}$$

where, $PL(d)$ is the path loss suffered by the transmitted signal with power P_t to reach the gateway placed at distance d from the LoRa device.

The performance of the LoRa system in the AWGN channel can be estimated by considering the channel propagation model for a particular environment. The free space path loss model is considered to measure the PL when there is no obstruction between the transmitter and the receiver and they are deployed in a line-of-sight area in free space. Although free-space propagation is not used in an indoor propagation environment, it can be used to calculate the path loss at a reference distance.

$$PL = \left(\frac{4\pi f}{c}\right)^2 \times d^\eta \tag{6}$$

where, f is the carrier frequency, c is the speed of light and η is the path loss exponent that indicates the rate at which the strength of the received signal declines with an increase in distance and its value depends upon the type of propagation environment.

To evaluate the link-level performance of the LoRa network in an industrial indoor area, the received power is estimated at the gateway with increasing SF by defining a path loss model usable for both the considered scenario. Further, the link-level performance of the LoRa network is analyzed in terms of outage probability, BER, and spectral efficiency.

5.1. Scenario-I: non-obstructive environment

In an indoor area, the signal attenuation due to shade and absorbance by the obstructions needs to be considered. The general path loss model that has been used in an enormous number of indoor areas is the long-distance path loss model which assumes that path loss varies exponentially with distance. For a non-obstructive scenario when the LoRa end device and the gateway are placed in an empty room in the line of sight area, the path loss as stated in Kulkarni et al. [16] is represented as.

$$PL(d) = PL(d_o) \times \left(\frac{d}{d_o}\right)^\eta \tag{7}$$

Where, η is the path loss exponent of an indoor environment whose value is considered to be 2.25 for non-obstructive scenarios and 2.16 for an obstructive scenario [17]. Using Eqs. (4), (5) and (7), the estimated received power in an indoor area for a non-obstructive environment can be calculated as.

$$P^{rx}_{non\_obs} = \frac{P_t \times SF \times RSSI}{PL(d_o) \times SNR \times NF \times k \times T \times (BW)^2} \tag{8}$$

Here reference distance d_o is taken to be 1 meter, SNR and RSSI represent the respective measured values at the gateway. Path loss at the reference distance is calculated using the free space path loss Eq. (6).

To have an insight into the attenuation level and the link level performance of the proposed network, SNR can be calculated. The higher the SNR of the received packet, the better the performance of the LoRa network. The instantaneous SNR at the gateway node in an indoor area for a non-obstructive environment was obtained using Eq. (2) and can be expressed as.

$$SNR_{non\_obs} = \frac{P^{rx}_{non\_obs} \times SF}{NF \times k \times T \times (BW)^2} \tag{9}$$

The LoRa device is assumed to be not linked to the gateway if the SNR of the received signal at the gateway is below a certain threshold level (SNR_{TH}) and the communication channel is said to be in the outage. The condition of the outage as given in Georgiou et al. [18] is expressed as.

$$P_{out} = \mathbb{P}[SNR \le SNR_{TH}] \tag{10}$$

Thus, the outage probability in an indoor area for a non-obstructive environment can be evaluated using Eq. (11)

$$P^{out}_{non\_obs} = 1 - exp\left(-\frac{SNR_{non\_obs}}{SNR_{TH}}\right) \tag{11}$$

Another vital parameter to compute the capacity of the communication channel of the proposed LoRa system is spectral efficiency. Using the Shannon theorem, the spectral efficiency of a non-obstructive environment in an indoor area can be evaluated using Eq. (13).

$$\eta^s_{non\_obs} = (1 + SNR_{non\_obs}) \tag{12}$$

LoRa features the CSS modulation technique and to confirm the efficiency of the proposed LoRa system, it is necessary to site the performance of the CSS modulation in the LoRa network in terms of BER. SNR has a direct impact on BER. The higher the SNR more robust the transmissions. For an indoor area considering a non-obstructive scenario the BER in terms of SNR and SF as given in [19] can be calculated using Eq. (12).

$$BER_{non\_obs} = Q\left(\frac{log_{12}(SF) \times 2^{SF} \times SNR_{non\_obs}}{\sqrt{2} \times SF}\right) \tag{13}$$

5.2. Scenario-II: obstructive environment

To characterize the path loss due to obstructions within the building, the attenuation losses due to walls and floors are taken into consideration. Thus the path loss of an obstructive indoor environment as stated in El Chall et al. [20] can be modeled as.

$$PL(d) = PL(d_o) \times \left(\frac{d}{d_o}\right)^{\eta} \times waf \times faf \tag{14}$$

Using Eqs. (4), (5), and (9), the estimated received power at the gateway node in an indoor area for an obstructive environment can be calculated as

$$P^{rx}_{obs} = \frac{P_t \times SF \times RSSI}{PL(d_o) \times SNR \times NF \times k \times T \times (BW)^2 \times waf \times faf} \tag{15}$$

Here, the wall attenuation factor (*waf*) is proportional to the number of walls (n_w) the signal transverse through with $waf = n_w \times L_w$ where L_w is the penetration loss of the wall. *faf* is the floor attenuation factor which is expressed as $faf = n_f \times L_f$ where n_f is the number of floors and L_f is the penetration loss of the floor.

The instantaneous SNR at the gateway node due to obstructions in the path of the signal obtained using Eq. (2) and can be expressed as.

$$SNR_{obs} = \frac{P^{rx}_{obs} \times SF}{NF \times k \times T \times (BW)^2} \tag{16}$$

The outage probability, spectral efficiency, and BER for the obstructive environment can be estimated using Eqs. (17), (18) , and (19), respectively.

$$P^{out}_{obs} = 1 - exp\left(-\frac{SNR_{obs}}{SNR_{TH}}\right) \tag{17}$$

$$\eta^{s}_{obs} = (1 + SNR_{obs}) \tag{18}$$

$$BER_{obs} = Q\left(\frac{log_{12}(SF) \times 2^{SF} \times SNR_{obs}}{\sqrt{2} \times SF}\right) \tag{19}$$

where, SNR_{obs} is the instantaneous SNR of the received signal at the gateway node for obstructive environment computed using Eq. (16).

It is evident from the above equations that outage probability, spectral efficiency, and BER in both scenarios depend upon the SNR of the signal received at the gateway. Further, from Eqs. (9) and (16) it is clear that SNR in non-obstructive, as well as obstructive scenarios, respectively depends upon received power, NF (receiver noise figure), k (Boltzmann constant), T (temperature), BW (bandwidth and spreading factor (SF). Out of these parameters NF (receiver noise figure), k (Boltzmann constant), and T (temperature) are the constrained parameters, and received power, BW (bandwidth), and spreading factor (SF) is the free parameters. Free parameters can be optimized to attain the efficient performance of the LoRa network. As the impact of various spreading factors on the performance of the network is analyzed at a constant BW therefore in the current work received power is optimized to elevate the link performance of the LoRa network. The optimized values of received power in non-obstructive, as well as obstructive environments, are further utilized to improve the network performance in terms of SNR, outage probability, spectral efficiency, and BER

6. Optimization

6.1. Problem formulation

The optimization in the current work aims to find the optimal values of LoRa network parameters maximizing the received power at the gateway resulting in improved LoRa network performance. In this work, the main objective function is the received power at the gateway node expressed by Eqs. (8) and (15) for both the scenarios which are intended to be maximum. The measured values of RSSI and SNR obtained from the experimental setup are used to compute the value of received power. From the equations it is observed that the received power depends upon Pt (transmitted power), NF (receiver noise figure), k (Boltzmann constant), T (temperature), BW (bandwidth), $PL(do)$ (path loss at reference distance do) and the measured values of RSSI and SNR at various values of SFs for both the considered scenarios. In addition to the above parameters, the received power also depends upon waf (wall attenuation factor) and faf (floor attenuation factor) for the obstructive scenario. Among these P_t and BW are free parameters and the remaining are the constrained parameters. The BW is set constant at 250 kHz. An increase in transmission power increases RSSI and SNR but it also increases the power consumption of the LoRa device. To determine the optimal LoRa performance, the LoRa network system must satisfy certain constraints concerning the power consumption of the LoRa device. Thus, Pt is considered a constraint in the optimization problem. Optimizing the transmission power maximizes the performance of the LoRa network. Therefore, the threshold value of Pt is taken to be less than 13dBm.

To find the optimal values of SNR and RSSI an ANN model has been implemented. The minimum value of MSE obtained is utilized to determine the finest value of SNR and RSSI for each SF. Further, the ANN model is integrated with the PSO algorithm to optimize the performance of the LoRa network for both environmental scenarios.

6.2. ANN model

An artificial neural network (ANN) based on the working of the human nervous system has been developed and researched as an intelligent tool to process information [21]. The simple feed-forward ANN framework is the multilayer perception (MLP) network which constitutes the input layer, hidden layer, and output layer. In this study, the neural network toolbox available in MATLAB 2019 is used for implementing ANN. Fig. 2 provides the schematic representation of the proposed network. RSSI, SNR, and Pt are considered as the model inputs, and received power is taken as neural network model output.

To accomplish the network's best performance, the network's training is done through a backpropagation algorithm by which weights and biases are updated such that minimum error between the actual output and the predicted output is achieved. Levenberg-Marquardt (L-M) is the most efficient method to train the neural network, hence in this work it has been used. The choice of several hidden layer neurons plays a crucial role in avoiding underfitting and overfitting problems. Here, the number of hidden layer neurons selected for the network is 10. Data set of 100 samples are created at various SFs to formulate the ANN model. The collected database is utilized to train and test the ANN model to estimate the efficient performance of the network. 70% of the data has been devoted to the training phase, 15% for validation, and the rest 15% of the data set is assigned to the testing phase. The performance of the network is accounted for in terms of the mean square error (MSE) function and the correlation coefficient (R) function which is computed as.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_a - y_p\right)^2 \tag{20}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(y_a - y_p\right)^2}{\sum_{i=1}^{n}\left(y_a - y_{avg}\right)^2}} \tag{21}$$

where n is the number of data points, $y_a$is the actual output, y_p is the predicted output and y_{avg} is the mean of the actual values.

MSE and R are employed as the ANN model's performance indices, which are utilized to handle the constraints in the optimization function. When MSE is at minimum value and R is high, the model is judged to provide good predictive capabilities. The minimum value of MSE is further utilized to discover the best values of SNR and RSSI at each SF.

6.3. Hybridized ANN-PSO optimization

In recent years, several metaheuristic optimization strategies have been adopted to address various single objective and multi-

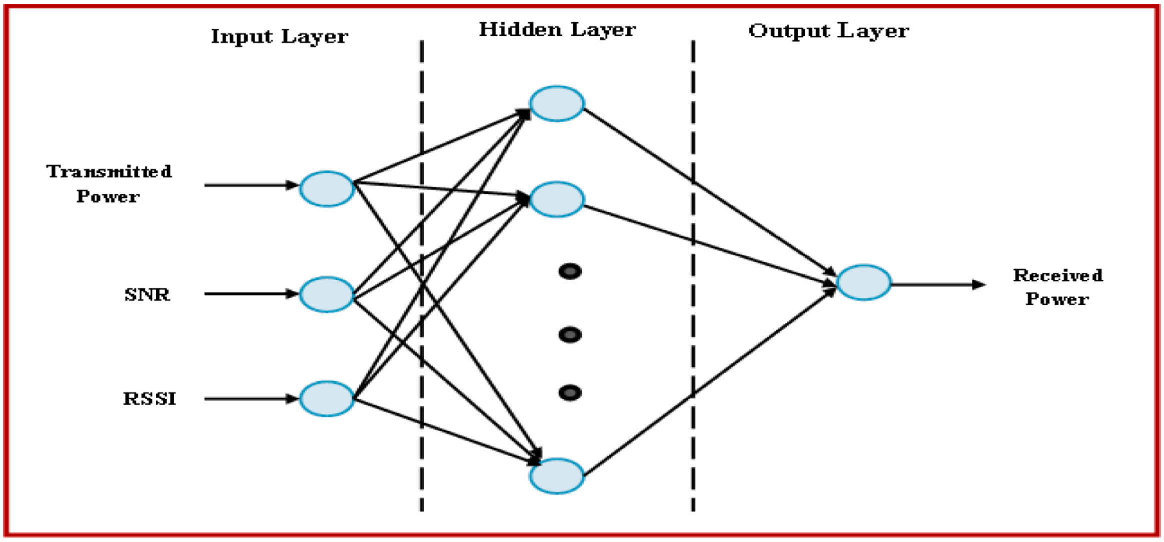

Fig. 2. Developed ANN model.

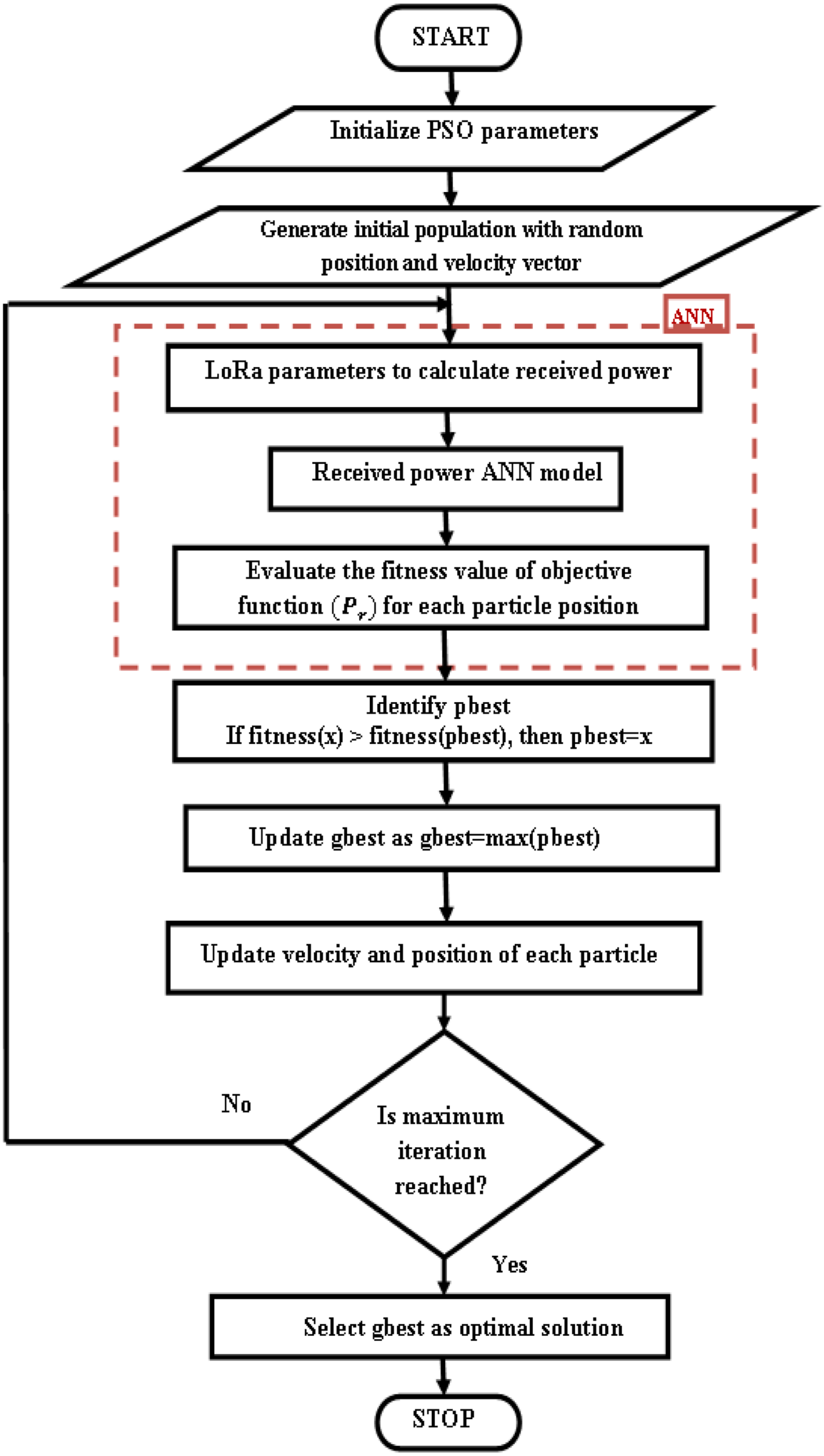

Fig. 3. Flowchart of the hybrid ANN-PSO algorithm.

objective optimization problems [22]. The particle swarm optimization (PSO) algorithm is a simple metaheuristic optimization technique that focuses on single-objective optimization problems. It is a swarm intelligence algorithm inspired by the behavior of social animals such as birds or fishes. The PSO algorithm works accordingly to find out the best solution to the problem based on the experience of the overall population in the data space thus optimizing the continuous function. Although it is an efficient optimization technique that can solve diverse optimization problems but it has got some limitations of convergence speed and premature convergence. To address these concerns various researchers have proposed several hybridized PSO algorithms [23]. In the current work, optimization is done using the hybrid ANN-PSO algorithm. ANN has got a slow rate of learning that can be improved by hybridizing with optimization techniques like PSO. Thus, the hybrid ANN-PSO optimization approach results in a fast convergence rate with the efficient computational complexity of ($it_{max} \times N \times d_{min}$) where, it_{max} is the maximum iterations, N is the size of the swarm population and d_{min} is the dimension of the optimization problem.

Fig. 3 illustrates the working flowchart of the hybrid ANN-PSO algorithm. Initially the PSO parameters i.e., number of the particles, swarm size, acceleration constants, and maximum number of iterations are defined and smarm particles are initialized with random position and velocity. Using the implemented ANN model with output as an objective function and input as LoRa parameters, the fitness of each particle is evaluated. The particle with a maximum objective function value is considered better than others as the defined optimization problem is the maximization problem. For each iteration, the personal best (pbest) and global best (gbest) values are recorded by assessing the fitness value of the objective function and are then updated by comparing it with previously calculated values. Each particle then travels towards its pbest and gbest position by revising its velocity and position. The optimization process is repeated until maximum iterations are reached. Thus, input LoRa parameters are optimized within the maximum number of iterations and the final recorded gbest value over all iterations is reflected as the optimal solution to the optimization problem. Table 2 shows the parameters adopted for optimization using PSO.

7. Results

7.1. Measurement results

The link measurement is carried out by configuring the LoRa modules used at the transmitter and the gateway with the same transmission parameters cycling through various SF values ranging from 7 to 12 maintaining a constant value of CR = 4/5 and 250 kHz of BW. The carrier frequency considered is 433 MHz since the LoRa module used is SX1278 operating at 433 MHz bands. The LoRa end device periodically transmits 100 packets with the transmission power of 13 dBm to the LoRa gateway for each SF.

The performance metrics considered in the experimental study are RSSI and SNR reported at the LoRa gateway corresponding to varying values of SF and their average measured values are presented in Table 2. From the table, it can be observed that RSSI and SNR value increases with an increase in SF and records maximum in the non-obstructive environment (non-obs).

7.2. Assessment of ANN model

Using the measured values of SNR and RSSI at various SFs, received power at LoRa gateway is calculated for both the scenarios as expressed by Eqs. (8) and (15) above and a data set has been created. The created data set of 100 samples each for various SFs have been utilized to formulate the ANN model. 70% of the data has been devoted to the training phase, 15% for validation and the rest 15% of the data set is assigned to the testing phase. The performance of the ANN model for predicting the received power of the LoRa network in a non-obstructive indoor environment at SF = 7 is shown in Fig. 4. It illustrates the neural network regression plots of the target received power vs. ANN model predicted received power for training samples, validation samples, test samples and the total data set with the Levenberg-Marquardt algorithm.

The correlation coefficient (R) value for the testing is 0.93, validation is 0.94, testing is 0.93 and the overall R-value is 0.93. High *R*-values (more than 0.92) indicate a good correlation between actual and the predicted values which implies good accuracy of the developed ANN model. The MSE and R values determined for the ANN model formulated for each SF for both the considered scenarios are presented in Table 3.

7.3. LoRa network optimization

In this work, the ANN model is integrated with the PSO algorithm to optimize the performance of the LoRa network for both

Table 2
Link quality performance of the LoRa network.

SF	RSSI (dBm)		SNR (dB)	
	non-obs	obs	non-obs	obs
7	-77.54	-113.10	8.01	2.45
8	-73.74	-111.14	8.42	2.58
9	-71.36	-109.35	8.96	3.01
10	-69	-106.95	9.72	3.42
11	-68	-105.15	10.29	4.08
12	-67.39	-104.32	10.88	5.03

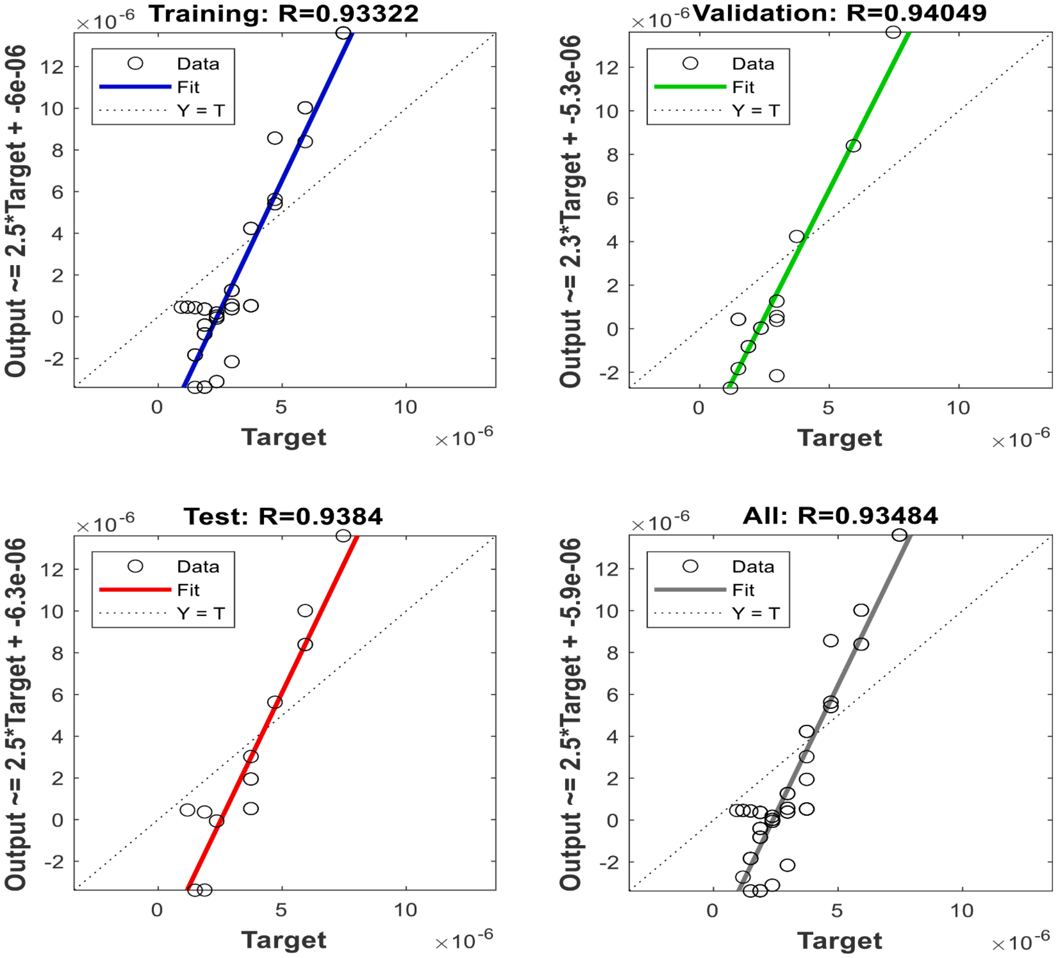

Fig. 4. Regression plot of the developed ANN model for SF = 7 for non-obstructive scenario.

Table 3
ANN model performance at various SFs.

SF	non-obs R	non-obs MSE	obs R	obs MSE
7	0.9348	$1.50*10^{-08}$	0.9463	3.49*10-14
8	0.9567	$1.11*10^{-07}$	0.9534	$2.97*10^{-13}$
9	0.9533	$2.41*10^{-06}$	0.9312	$1.46*10^{-13}$
10	0.9445	$4.45*10^{-08}$	0.9523	$4.39*10^{-13}$
11	0.9323	$1.59*10^{-06}$	0.9646	$2.12*10^{-13}$
12	0.9632	$1.73*10^{-08}$	0.9676	$1.40*10^{-13}$

environmental scenarios. The optimization of the LoRa network performance is aimed at maximizing the received power subjected to a set of constraints i.e., the limit of Pt. Pt and RSSI are optimized using the PSO algorithm which in turn will optimize the received power at the LoRa gateway. Table 4 presents the PSO Parameters adopted for optimization of the received power. The threshold value of P_t is

Table 4
PSO parameters adopted for optimization of the received power [24].

Parameter	Value
Population size	500
Final weight (w_{min})	0.4
Initial weight (w_{max})	0.9
No. of iterations (it_{max})	100
Acceleration constant (c_1, c_2)	1.4455, 1.4455

taken to be < 13 dBm. Further, the minimum value of MSE is utilized to discover the optimal value of SNR and RSSI for each SF.

Fig. 5 demonstrates the comparative analysis of optimized and non-optimized received power vs. SF. For non-optimized values, the average value of SNR and RSSI measured at the LoRa gateway for various SFs and $P_t = 13$ dBm is taken. For optimized one, optimal values of SNR and RSSI obtained using minimum MSE of ANN model and P_t obtained for each SF with the help of PSO are taken into consideration. The investigation is done for both the environmental scenarios i.e., non-obstructive (non-obs) and obstructive (obs). It is clearly shown that the received power for the optimized values is higher than that obtained with non-optimized values. The optimized value of received power has been attained by placing the optimal value of $P_t = 12.88$ dBm at SF = 7 for the non-obstructive environment and $P_t = 12.72$ dBm at SF = 7 for the non-obstructive environment. These optimized values have been attained using PSO.

Using the non-optimized and optimized values of received power at various SFs, the SNR value is estimated for both the environmental scenarios, and its comparative analysis is illustrated in Fig. 6. It illustrates the higher SNR obtained using the optimized value of received power as compared to SNR obtained using the non-optimized value of received power. These optimized and non-optimized values of estimated SNR for both the environmental scenarios are further considered to calculate the outage probability, spectral efficiency, and BER thereby optimizing the LoRa network performance.

Using Eq. (11) and substituting the optimized and non-optimized values of SNR at various SFs outage probability has been evaluated for non-obstructive scenarios. Fig. 7 shows the comparative analysis of outage probability vs. SF. It shows that the outage probability for the optimized values of SNR is higher than the outage probability achieved with non-optimized values of SNR. Similarly, using Eq. (17) the outage probability at various SFs has been evaluated for obstructive scenarios and illustrated in Fig. 8. It noticeably shows that outage probability for the optimized values of SNR is higher than the outage probability attained with non-optimized values of SNR.

To evaluate the capacity of the LoRa communication link for both the environmental scenarios, spectral efficiency has been computed using Eqs. (12) and (18). Fig. 9 explains the comparative analysis of spectral efficiency obtained from the optimized and non-optimized values of SNR for non-obstructive environmental scenarios. It is clearly shown that spectral efficiency increases using optimized values of SNR in comparison to the spectral efficiency obtained using non-optimized values of SNR.

Similarly, Fig. 10 shows the comparative analysis of spectral efficiency obtained using the optimized and non-optimized values of SNR for obstructive environmental scenarios. It is clearly shown that spectral efficiency computed using optimized SNR values is higher than the spectral efficiency obtained using non-optimized values of SNR.

The optimized and non-optimized values of SNR are utilized to compute the BER for both the scenarios using Eqs. (13) and (19). The BER is approximately zero for non-obstructive scenarios. Fig. 11 shows the BER performance for different SFs for obstructive scenarios. It illustrates the comparative analysis of BER obtained using the optimized and non-optimized values of SNR. It is clearly shown that BER reduces using the optimized value of SNR resulting in BER = $9.15*10^{-184}$ at SF = 12 as compared to its value obtained using non-optimized SNR with BER = $7.59*10^{-84}$ at SF = 12.

To further assess the performance of the LoRa achieved by implementing the ANN-PSO approach, a comparison is made in Table 5 and Table 6 for both non-obstructive and obstructive scenarios, respectively. This comparison brings a clear understanding of the improvement in the link level performance of the LoRa network.

The results indicate that by employing the ANN-PSO approach the received power of the signal at the gateway node is optimized. Using the optimized and non-optimized values of the received power an improvement in the SNR, outage probability (P-out), spectral

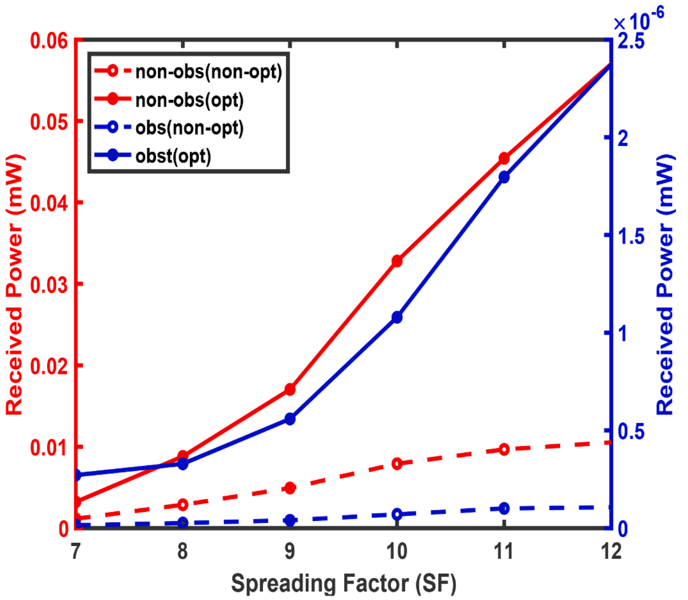

Fig. 5. Comparative analysis of optimized and non-optimized received power.

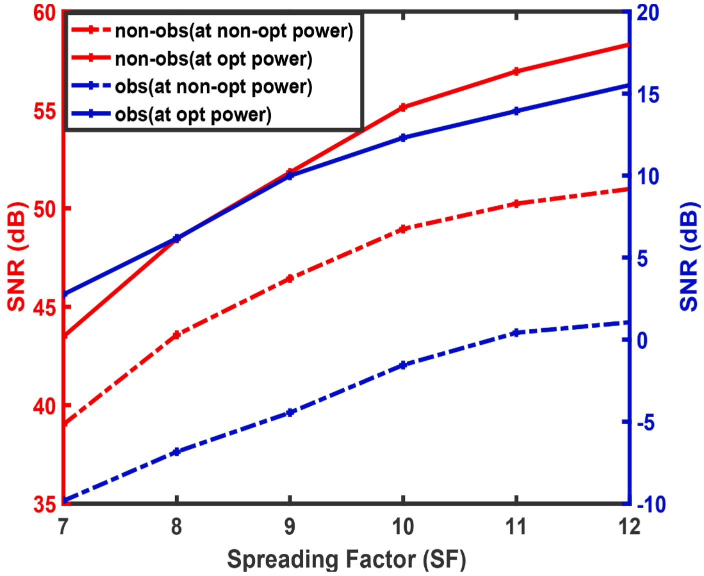

Fig. 6. Comparative analysis of SNR obtained using optimized and non-optimized values of received power.

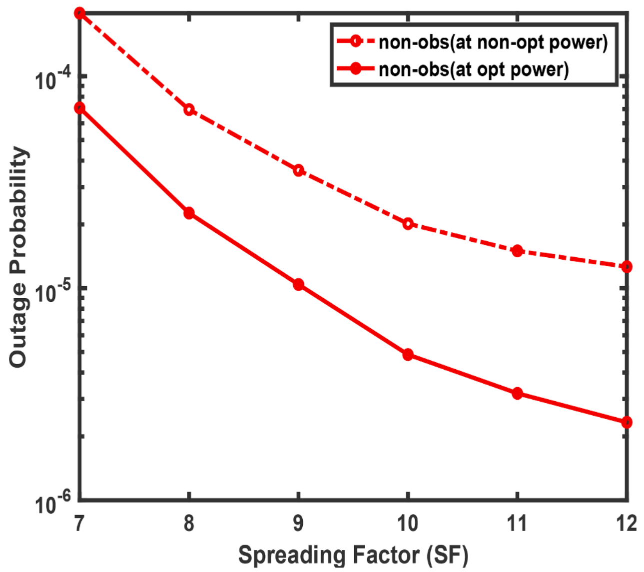

Fig. 7. Outage probability obtained using optimized and non-optimized received power values for the non-obstructive environment.

efficiency (η), and BER of the LoRa network can be observed. Further, analysis in terms of percentage change is made in Fig. 12 for both the considered scenarios. It illustrates that the received power is optimized by 26% in the non-obstructive scenario and by 19% in an obstructive scenario using the ANN-PSO approach. Utilizing the optimized and non-optimized values of received power, the performance of the LoRa network is further analyzed. It can be observed that SNR improves by 12% and 256%, outage probability reduces by 72% and 22%, spectral efficiency improves by 12% and 584%, and BER reduces by 33% and 100% in non-obstructive and obstructive scenarios, respectively.

8. Conclusion

In this work, an approach to optimize the received power at the gateway node of the LoRa network and thereby maximize the link-level performance of the network for an industrial scenario is presented. To compute the power of the received signal at the gateway, an uplink LoRa network is configured in an indoor area aiming to consider two different environmental conditions including non-obstructive and obstructive scenarios. The link-level performance of the LoRa setup is investigated in terms of RSSI and SNR. Using

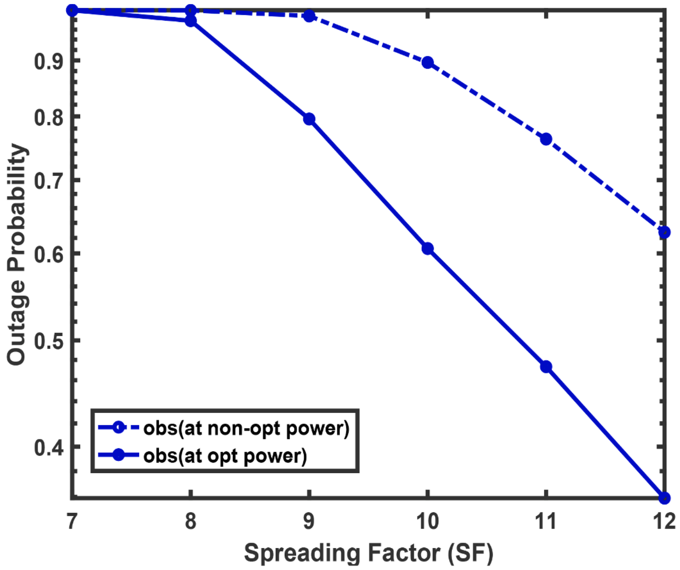

Fig. 8. Outage probability obtained using optimized and non-optimized received power values for the obstructive environment.

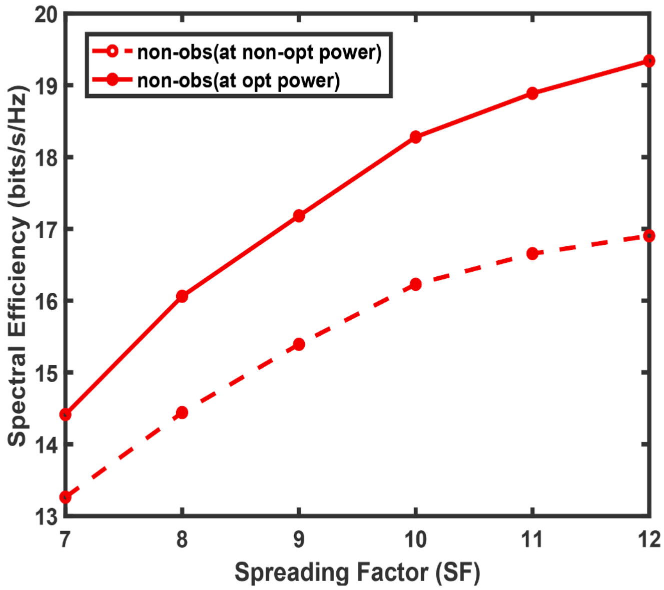

Fig. 9. Spectral efficiency obtained using optimized and non-optimized received power values for the non-obstructive environment.

the measured values of RSSI and SNR, the received power at the LoRa gateway is mathematically modelled which is further considered an optimization problem.

It has been observed that received power is a function of RSSI, SNR, and transmitted power which can be critically chosen to maximize the received power. The optimization technique based on the integrated ANN-PSO approach has been presented. First, an ANN model has been implemented to obtain the minimum MSE which is used to get the optimal values of RSSI and SNR. Further, using the optimal values of RSSI and SNR achieved from the ANN model, the PSO algorithm is implemented to optimize the transmitted power on which the received power depends. Using the non-optimized and optimized values of received power, the SNR value is estimated for both the environmental scenarios which are further utilized to analyze the performance of the LoRa network in terms of outage probability, spectral efficiency, and BER. A critical comparative analysis has been made and it has been shown that the link performance of the LoRa network is maximized with improvement in SNR by 12% and 256% and spectral efficiency by 12% and 584%, and reduction in outage probability by 72% and 22% and BER by 33% and 100% in non-obstructive and obstructive scenarios, respectively.

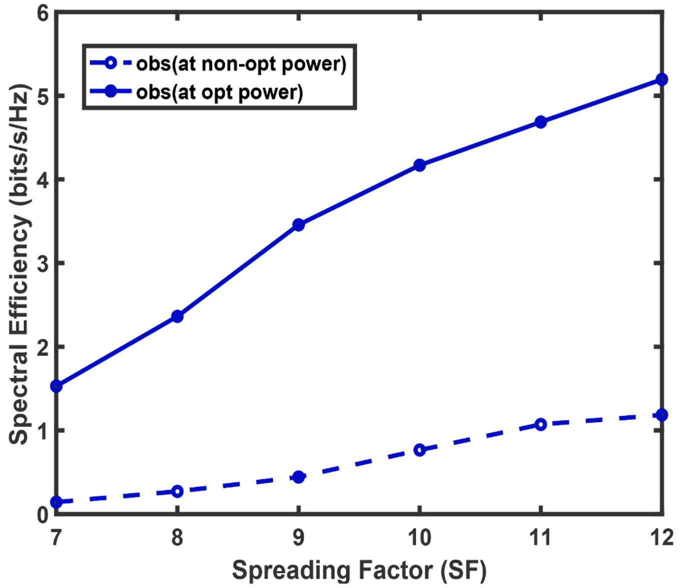

Fig. 10. Spectral efficiency obtained using optimized and non-optimized received power values for the obstructive environment.

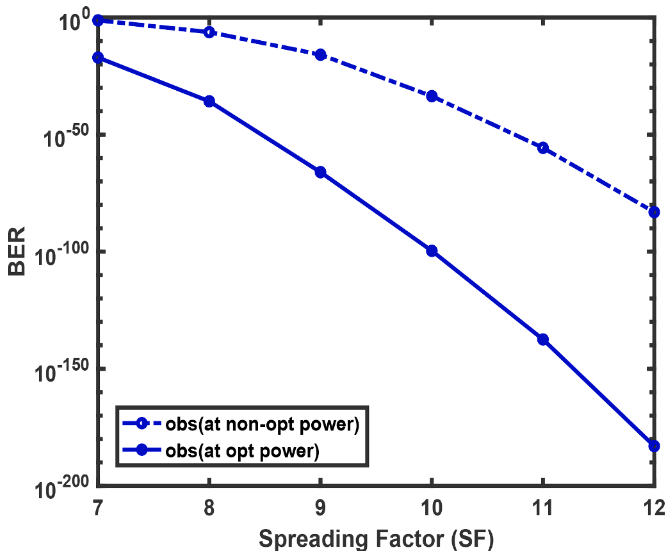

Fig. 11. BER obtained using optimized and non-optimized received power for obstructive environment.

Table 5
LoRa network performance at various SFs by employing ANN-PSO approach for non-obstructive environment.

SF	P_r (dBm) non-opt	opt	SNR (dB) non-opt	opt	P_{out} non-opt	opt	η non-opt	opt	BER non-opt	opt
7	-29.39	-24.93	39.02	43.49	$0.19*10^{-3}$	$0.70*10^{-4}$	12.96	14.44	$3.54*10^{-180}$	$2.80*10^{-212}$
8	-25.42	-20.55	43.57	48.45	$0.06*10^{-3}$	$0.22*10^{-4}$	14.47	16.09	$5.38*10^{-264}$	$2.45*10^{-309}$
9	-23.07	-17.68	46.43	51.82	$0.03*10^{-3}$	$0.10*10^{-4}$	15.42	17.21	0	0
10	-21.02	-14.84	48.95	55.13	$0.02*10^{-3}$	$0.04*10^{-4}$	16.26	18.31	0	0
11	-20.14	-13.42	50.24	56.96	$0.015*10^{-3}$	$0.03*10^{-4}$	16.68	18.92	0	0
12	-19.77	-12.43	50.98	58.32	$0.012*10^{-3}$	$0.02*10^{-4}$	16.93	19.37	0	0

Table 6
LoRa network performance at various SFs by employing ANN-PSO approach for obstructive environment.

SF	P_r (dBm)		SNR (dB)		P_{out}		η		BER	
	non-opt	opt	non-opt	opt	non-opt	opt	non-opt	opt	non-opt	opt
7	-78.25	-65.66	-9.82	2.75	0.9999	0.9997	0.14	1.52	0.06	$8.32*10^{-18}$
8	-75.84	-62.82	-6.83	6.17	0.9995	0.9781	0.27	2.36	$5.84*10^{-07}$	$1.72*10^{-36}$
9	-73.97	-59.52	-4.45	9.98	0.9879	0.7958	0.44	3.45	$1.32*10^{-16}$	$9.56*10^{-67}$
10	-71.52	-57.66	-1.54	12.30	0.8960	0.6063	0.76	4.16	$2.62*10^{-34}$	$2.30*10^{-100}$
11	-69.96	-56.45	0.41	13.93	0.7628	0.4731	1.07	4.68	$2.32*10^{-56}$	$3.41*10^{-138}$
12	-69.71	-55.24	1.05	15.51	0.6274	0.3590	1.38	5.19	$7.59*10^{-84}$	$9.15*10^{-184}$

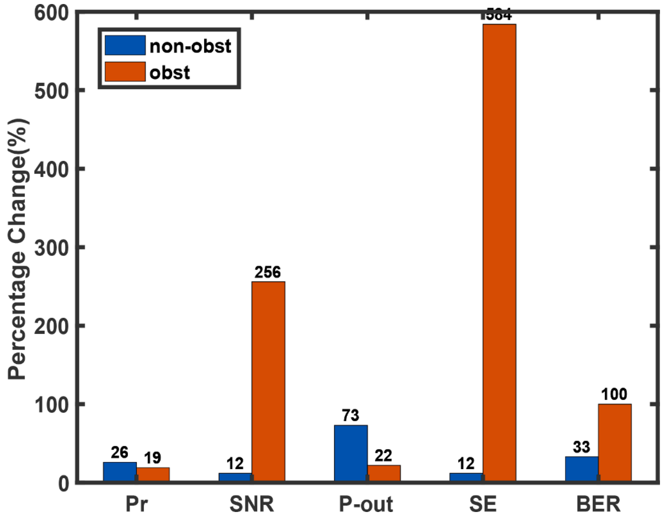

Fig. 12. Performance analysis of the LoRa network by employing ANN-PSO approach expressed in percentage change.

9. Future work

In the current work, the link performance of the LoRa network is analyzed in an indoor industrial scenario that is limited to a single end device connected to a gateway deployed at a distance of 70 m. In the future, the link performance of the LoRa network for an industrial scenario will be analyzed using more than one LoRa device that will be deployed at a distance of more than 100 m from the gateway. Also, the effect of interference and collision due to multiple LoRa devices involved will be considered in analyses of the LoRa network performance. In addition to that, to address the long battery lifetime challenges for industry 4.0, the energy consumption model of the LoRa monitoring devices will also be investigated in an industrial environment [25].

Declaration of Competing Interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version; This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue; The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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