LSTM-Based Energy-Efficient Wireless Communication With Reconfigurable Intelligent Surfaces

Koyel Datta Gupta, *Member, IEEE*, Ritu Nigam, Deepak Kumar Sharma, and Sanjay K. Dhurandher, *Senior Member, IEEE*

***Abstract*—A Reconfigurable Intelligent Surface is an eminent approach for improving the net data rate and maximizing the energy efficacy of wireless Base Stations (BS). Due to the vast number of surface elements, the task of optimizing the BS's transmission and Reconfigurable Intelligent Surface (RIS) element's configuration is incredibly challenging. In principle, to enhance energy conservation and diminish the BS power consumption, it is essential to optimize the transmission power of the BS and phase configuration of the RIS. This paper proposes a Long Short-Term Memory (LSTM) based scheme which performs decision-making using dynamic information of the wireless networks following channel intricacy and RIS's energy harvesting while increasing the energy efficacy. Once trained in a real-time environment, the proposed LSTM model foretells optimal RIS configuration for each transmission. The transmissions considered are designated for users located in various regions in the corresponding wireless network. The LSTM model and Adam optimizer are used to build the RIS-aided downlink system model and explore its energy efficiency and robustness. The results achieved after performing various simulations determine that the LSTM framework raises energy efficacy to 35.42% while increasing the RIS elements from 9 to 25. In addition, the model can achieve more than 100 bps/Hz net data rate.**

***Index Terms*—Adam optimizer, energy efficiency, long short-term memory, phase configuration, reconfigurable intelligent surfaces.**

I. Introduction

THE RAPID demand of data rate requirements of high-level multimedia applications and future wireless networks have raised severe attention towards their consumed energy [1], [2]. These networks are expected to deploy impenetrable multi-antenna Base Stations and access points [3], [4] to link massive numbers of devices [5]. As an outcome, spectral efficiency over power consumption has appeared as an indicator of primary performance to assure sustainable and green wireless networks [6], [7]. Recently, Buzzi *et al.* [8] have performed a study on the diverse strategies for implementing energy-efficient next-generation wireless networks. In this work, multiple approaches have been studied such as energy-efficient hardware components, renewable energy sources, and green resource allocation algorithms that need to be used to overcome the energy issue. Zappone and Jorswieck [9] discussed the problem of allocating radio resources for maximizing energy efficiency in wireless networks in detail. Increasing the vast number of antennas can cause significant energy-efficient gains, examined in [10], [11]. Modern research in cellular networks also addresses energy issues [12], [13] by considering machine learning, nature-inspired algorithms [14], [15], and game theory techniques [16]. A recent emerging hardware technology, RIS [17], [18] for green communication has been envisaged as a superior technique to diminish energy consumption and enhance the transmission by reconfiguring the electromagnetic waves' propagation environment artificially. Fundamentally, RIS has the immense potential to revolutionize wireless networks' design to accomplish intelligent radio environments [19], specifically when integrated with artificial intelligence-enabled wireless networks and terahertz communications. Few key aspects that make RIS distinct from currently available technologies, as shown in [20], incorporate the novel design restrictions contained with the approximately passive character of RIS elements that are not able to determine channel assessment directly. Also, RIS's possibilities for re-evaluating the conventional approach of communication without providing distinct electromagnetic signals instead of reusing present radio waves and utilizing cost-efficient substances to accomplish RIS to serve sustained wireless design. This article considers RIS configuration optimization's challenge, primarily originating from enhancing network performance by optimizing the vast number of contextual information-based parameters. The proposed research work contributes an LSTM based novel transmission framework for RIS-enabled downlink wireless communications employing an energy accumulation mechanism at the RIS. In the LSTM framework, a BS dynamically acclimates to the wireless systems and operates against the uncertain channel gain and future energy conservation of the RIS scheme. This

Manuscript received April 30, 2021; revised August 25, 2021 and November 13, 2021; accepted December 6, 2021. Date of publication December 14, 2021; date of current version May 20, 2022. *(Corresponding author: Deepak Kumar Sharma.)*

Koyel Datta Gupta is with the Department of Computer Science and Engineering, Maharaja Surajmal Institute of Technology, New Delhi 110058, India (e-mail: koyel.dg@msit.in).

Ritu Nigam is with the Division of Computer Engineering, University of Delhi, Netaji Subhas Institute of Technology, New Delhi 110078, India (e-mail: ritu.nigam2106@gmail.com).

Deepak Kumar Sharma and Sanjay K. Dhurandher are with the Department of Information Technology, Netaji Subhas University of Technology, New Delhi 110078, India (e-mail: dk.sharma1982@yahoo.com; dhurandher@gmail.com).

Digital Object Identifier 10.1109/TGCN.2021.3135437

paper reveals an optimization problem to intensify the system's energy efficiency by adequately distributing the downlink transmit power while accurately configuring the RIS elements' phase shift. The major contributions comprise.

i. A solution to this optimization problem is provided by proposing a new LSTM-based energy-efficient model that intends to learn the traits such as users' approximate location, the RIS elements' current configuration, and communication devices' BS transmission power in the propagation environment.

ii. After learning, the proposed model can be used to optimize the BS transmission power, RIS configuration and energy harvesting, raising the average energy efficacy of the system.

iii. The proposed model is assessed on ray-tracing scenarios, which is a real-life network. The proposed LSTM based RIS model is compared against the basic deep neural net and the Bayesian network. The results display better prediction accuracy, energy efficiency, and net data rate over the basic deep neural net and Bayesian network.

The ordering of the remaining paper is as follows. Section II addresses the related work, Section III demonstrates the proposed scheme, which includes the motivation, system model, energy consumption model, proposed framework, and the algorithms. Section IV displays the simulation results. Section V lastly concludes the proposed framework and suggests the future direction.

II. Related Work

Classical or analytics-based solutions are developed based on mathematical models, communication methods, and optimization algorithms. The challenges faced by traditional Mulitple-Input Multiple-Output(MIMO) arrays to support RIS-assisted systems are highlighted in [21]. Initially, most of the recent analytics-based work optimized the RIS parameters by assuming that there is the availability of the appropriate channels and designed algorithms for configuring the RIS phase shift based on given channel knowledge [17], [22]. As per [21], the RIS elements should not be deployed with signal processing techniques or onboard sensing capability. These strategies would confront more difficulties to evaluate multiple parameters in RIS-empowered wireless systems. Likewise, an RIS-empowered MIMO system's channel model still has not been explored. Acquiring information about channel state is generally "after-fact," and the model can particularly respond to what previously occurred, which makes it very difficult to resist an adverse or unexpected change of transmission conditions, particularly for high-frequency signals. Finally, from the viewpoint of deployment, such strategies would require the tools and communication devices to uphold the communication network's essential signal processing methods and protocols. The before-mentioned prerequisites impose limitations on the RIS systems' candidate application scenarios. Furthermore, the most significant trait of RIS technology is the low energy consumption aspect which shows the probability of amplifying and transmitting the arriving signal without applying any booster. Instead, each reflecting element appropriately designs the phase shifts to combine each reflected signal constructively. As compared to a conventional "Amplify and Forward" relay transceiver, an RIS consumes very little energy since no amplifier is used.

A principal solicitude is to optimize the network's performance by allocating radio resources in RIS-assisted wireless transmissions. The work in [23] is focused on reducing the BS's transmit power by advancing the RIS model's discrete phase shifter and the BS's constant transmit beamforming in an RIS-aided downlink system configuration. Furthermore, in [24], a collaborative beamforming has been designed to maximize the RIS receivers' obtained signal power. Additionally, in [18], the issue of developing the RIS phase shift to maximize the downlink capacity by employing analytical channel state information has been examined. Also, in [25], maximization issue of energy efficacy in an RIS environment has been studied when each associated channel is well identified at BS to apply zero-forcing communication.

As explained in [26], the current advancements in Machine Learning (ML) techniques, particularly in Deep Learning (DL), various applications of wireless communication which are utilizing machine learning ML-based schemes are exhibiting promising outcomes. The domain of RIS-assisted wireless communication included the ML-based strategy, which provides strength and potential to handle non-convex and high-dimensional optimization problems [27], [28]. In [29], a supervised-learning-based Deep Neural Network (DNN) model is presented, which trains the DNN model offline by applying examined channel information as input from some active elements of RIS to anticipate the optimal matrix of RIS reflection beamforming. Further, in [30], and [31], authors introduced the method to train the suggested DNNs by utilizing received pilots as input to anticipate the optimal RIS phase shifts, including the BS's beamforming vector while circumventing the channel assessment, which is an intermediate step. Also, in [32] the author proposed a DNN model which absorbs the inherent relationship within the estimated receiver positions and the RIS configuration by offline training. The supervised learning framework's overhead is to accumulate the labeled data for decision making, which is circumvented in [33].The authors designed an RIS beamforming neural network architecture by employing an unsupervised learning technique. This work predicted the phase-shift configuration by inputting the BS's expected channels and neutralizing the transmission rate. Deep Reinforcement Learning (DRL) is one more feasible learning technique, which trained the model by applying online accumulated data, particularly in numerous optimization problems of wireless network scenarios. Moreover, the work in [34] introduced an actor-critic DRL strategy for RIS-enabled wireless communication, which studies the collaborative method of the RIS phase-shift configuration and transmits beamforming matrix at the BS for multiuser Multiple-Input Single-Output(MISO) systems. Further, in [35], a DRL-based inherent RIS solution has been presented to resolve the RIS beamforming vector optimally. One more DRL-based scheme has been proposed in [36] which allows the BS to find out the usual transmit power and most reliable RIS configuration to increase the energy efficiency.

It is observed that these ML-based approaches [26]–[36] generally considered parameters such as predicted channel knowledge or identified pilots at BS. These parameters are then used to determine the RIS configuration by employing only users' positions without examining the propagation environment between the transmitter and receiver or to foretell the optimal RIS beamforming matrix. Also, the work presented in [18], [22]–[25] assumed that environment information such as power consumption and wireless channels is wholly known. Certainly, performing precoding with deficient channel knowledge is strenuous for a cellular BS. Hence, no prior knowledge of RIS configuration and dynamic Spatio-temporal channel allocation creates an inherent vagueness stemming. Besides the above issue, most of the current works also [18], [22]–[25], commonly assumed that an RIS scheme is functioned by applying a power grid. But, practically, RIS can employ energy accumulation methods to overcome the dependence on the regular power grid and empower the idea of green networks. As amplifier is not used in RIS, its energy consumption is very low. Hence, an RIS system should embrace energy accumulation mechanisms. Framework for channel estimation and intelligent techniques for spectrum learning are a few recent works which are discussed in [37], [38].

III. Proposed Work

A. Motivation

The primary obstacles to restrain the widespread implementation of wireless systems among devices are the massive cost of hardware and vast energy consumption. Various energy-efficient procedures are presented in the past and considered effective solutions to surmount these obstacles and obtain green communication. RIS can efficiently reflect incident signals that inspire RIS to support transmission among BS and receivers compared to earlier solutions.

Previously, RIS-enabled smart radios can cope with adverse propagation circumstances by handling the radio propagation environment. Various empowering technologies for future wireless communications have been envisioned, such as Terahertz and Millimeter-wave communications. As the radio frequency increases, the installation of a huge number of antenna elements will be required on BS and mobile devices. To provide exceptional channel gains to match the high rise in the demand for wireless services, large MIMO with an array of antenna deployed at Base Stations and device ends. However, the diffraction and scattering impact diminishes while incrementing the radio frequency, also rendering electromagnetic waves inclined to blockage by obstructions. Therefore, it isn't easy to guarantee universal coverage of wireless assistance in future wireless communications using standard cellular routines. The current improvement of the RIS system offers an unprecedented unique solution to undertake the issue by artificially restraining electromagnetic waves' propagation environment. By intelligent deployment and passive/reflect beamforming, an RIS can render a unique, high-quality channel link to defeat the hostile propagation circumstances of wireless communication systems.In this paper, an LSTM [39] based framework is proposed to optimize the energy conservation of a RIS-enabled wireless communication system for downlink data transmission by determining the appropriate RIS configuration. The use of optimizers has been proven to significantly improve the accuracy of any deep learning model. Adam Optimizer [40] is simple and is capable of optimizing the weights effectively for LSTM models.

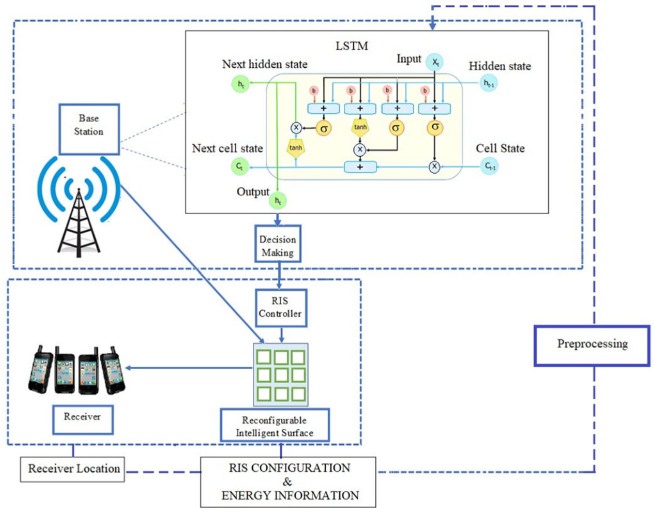

Fig. 1. System Model.

B. Assumptions

Before probing into the proposed work for designing energy efficient wireless communication network, the following assumptions are made about the network environment.

i. The channels in the network are mutually orthogonal, and there is no external interference.
ii. All the nodes are mutually cooperative and are proficient in retrieving the desired energy information from the received signal.
iii. All end-to-end transmissions are secured. Though the assumptions made here are to simplify the network environment and to focus on the problem at hand; the model is flexible enough to incorporate channel allocation and network security solutions.

C. System Model

This work presents an RIS-aided MIMO-based system model in Fig. 1. This model is considered where an RIS is deployed, comprising of N elements that support the downlink communication system. Each Base Station has M number of antennas assisting k number of receivers; each enabled with a single antenna. BS and receivers are outfitted with omnidirectional antennas and have no direct link. The transmission process between the BS and receivers is assisted by RIS, which is generally placed on the adjacent encircling walls. The information exchange between the BS and receivers is performed by intelligent surface elements which are dynamically reconfigurable, and a controller is connected to the RIS to configure it. It is also considered that there is no straight link between BS and users for transmission. All transmissions are established through the RIS elements, which provide seamless energy-efficient connectivity. The transmission signal at the BS is represented as:

$$x = W * s \tag{1}$$

where $W = [w_1,\ w_2, \ldots,\ w_M]^T \in Z^{M\times K}$ is the beamforming vector represented by a linear precoding matrix at the BS; $s = [s_1,\ s_2, \ldots,\ s_K]^T$ comprises the unit-power transmitted data symbols which are mutually not dependent and distributed symmetrically to receivers each having zero mean and unit variance. The transmission power constraint is given by $t_r\{W^H * W\} \leq T_{max}$. The $t_r\{\}$ determines the trace of a matrix and W^T and W^H denotes transpose and conjugate transpose respectively. T_{max} is the maximum transmission power. Later, the signal incident at the RIS is presented as

$$y = A * x \tag{2}$$

where $A \in Z^{N\times M}$ denotes the information about the channel state from the BS to the intelligent surface. The RIS is a reflection device and it effectively applies a phase shift to each component of the received information *y* and then forwards it to the users. The signal received at the user end (calculated using equation (1)-(2)) is then expressed by

$$r = [r_1, r_2, \ldots, r_K]^T = F * \Omega * A * W * s + u \tag{3}$$

where $F = [f_1,\ f_2, \ldots,\ f_K]^T \in Z^{K\times N}$ denotes the information about the state of the channel between the intelligent surface elements and the users; $\Omega = diag\{\omega\}$ with $\omega = [\omega_1,\ \omega_2, \ldots,\ \omega_N]^T$ and $\omega_n = e^{j\theta n}$ is the phase shift at the n^{th} RIS antenna element, $n = 1, 2, \ldots, N$. The diag() represents the diagonal matrix.The phase shift Ω consists of N real variables $\theta = [\theta_1, \theta_2, \ldots, \theta_N]^T \in [0, 2\pi]^N$. $u = [u_1, u_2, \ldots, u_K]^T$ contains complex Gaussian noise, which are symmetrically and independently distributed with mean zero and variance γ^2, at the user, that is, $u_k \sim CN(0, \gamma^2)$. Finally, each user *k* scales its received signal r_k (calculated using equation (3)) by $c_k \in C$, which is represented by

$$s_c = C * r = C * F * \Omega * A * W * s + C * u \tag{4}$$

where $C = diag\{c_1, c_2, \ldots, c_K\}$.

Spectral efficiency or achievable rate in a wireless communication system depends on the signal-to-interference noise ratio (SINR). The increase in the SINR ratio improves spectral efficiency.Suppose, the SINR of the k^{th} user(calculated using equation (4)) is expressed by Γ_k, then the possible sum rate or overall system achievable rate R, that can be achieved by a RIS-enabled MIMO system is given by

$$R = \sum_{k=1}^{K} \log_2(1 + \Gamma_k). \tag{5}$$

Energy Consumption Model: The considered system in this work uses the self-powered RIS reflectors and depends entirely on energy harvesting sources. The solar panel-assisted RIS reflectors can be used to obtain energy for the process of signal propagation. Since the energy harvesting process can be very dynamic, this work does not consider any particular assumptions on the energy harvesting method. Therefore, the proposed model can contain any kind of energy conservation method. To improve the complete energy efficacy of the assumed model, the intelligent surface reflecting elements can be turned ON or OFF to regulate the phase shift on the impinging signal, based on the performance of the network and conserved energy state. Accordingly, the RIS system is implemented with an Energy Storage Model (ESM) to maintain the irregular and unpredictable energy harvesting method. Additionally, the RIS model can conserve energy irrespective of its RIS elements' ON/OFF state. Furthermore, the RIS model can still save the abundance of harvested energy when the intelligent surface elements are turned ON, if the instant conserved energy is sufficient for the functioning of the RIS elements.

Suppose, for the transmission at time *t*, the ON/OFF states of the intelligent surface elements be expressed as ρ_t, then the RIS model's power consumption is computed as $P\_RIS_t = \sum_{n=1}^{N} \rho_t * P_b$ where P_b denotes a b-bit resolution phase shifter's power consumption. A transmission based system is assumed with a time spell duration Δ for each transmission. The RIS model's energy consumption during the transmission at time *t* is $SU_t = P\_RIS_t * \Delta$.If the RIS components utilise the conserved energy,then the proportion of energy saved in the ESM is presented by

$$SE_t = \min(SE_{t-1} - SU_{t-1} + \beta_{t-1}, E_{max}) \tag{6}$$

where $SE_{t-1} \geq 0$ indicates the RIS model's stored energy at transmission at time $t - 1$, SU_{t-1} denotes the energy utilized by the intelligent surface elements, β_t expresses the conserved energy's amount at the intelligent surface system, and E_{max} shows the energy storage system's maximum energy saving limit. β_t is arbitrarily produced since the RIS system is incapable of knowing the amount of impending conserved energy, and, consequently, arbitrariness takes the unprecedented ambiguity of the energy conservation process. Suppose for transmission at time *t*, the RIS model does not have sufficient energy to make the state of every RIS element ON, that is, $SU_t > SE_t$, then certain elements on the intelligent surface should be turned OFF. However, the data rate of users can be affected over the ON/OFF state of every element on the RIS, that is, ρ_t.

D. Problem Formulation

The objective of this work is to frame a potential solution to optimize the energy conservation of an RIS enabled wireless communication system for downlink power transmission.

$$\max_{T_p, \Omega, \rho} \min_t FO_t\big(T_p,\ \Omega,\ \rho\big) \tag{7}$$

such that

$$\sum_t T_p < T_{max} \tag{8}$$

$$SU_t \leq SE_t\ \forall\ transmission\ at\ time\ t \tag{9}$$

where, $FO_t = t_r\{F * \Omega * A * W * W^H * A^H * \Omega^H * F^H\} + \gamma^2 * K$, estimates the energy conservation during a transmission measured as the energy of the received signal. In addition, ρ is used for assessing achievable data rate.

T_p denotes the transmission power.

Equation (7) represents the total harvested energy which is utilized by the BS for decision making to achieve energy efficacy, obtained by maximizing the minimum of the conserved power in each transmission. Equation (8) represents the constraints that the sum of the transmission power should be less than the maximum existing transmission power. Equation (9) represents the consumption of energy by the RIS element at each transmission should be less than the total conserved energy (calculated using equation (6)). Since the channel state information is not known to the Base Station, the direct computation of the optimization function is impossible. In reality, the users have to transmit feedback about the received data rate, and the Base Station is aware of its transmit power. In addition, the phase shift and ON/OFF state of the RIS elements are assessed to understand the effect of individual value on the overall communication and energy efficacy of the system. The objective function is treated as a black box function with input variables Ω (the phase shift at the RIS element), ρ (the on-off state of the RIS elements), and T_p (the transmission power). Since the problem space is discrete and non-smooth, it makes the optimization through analytical computation impossible. So, this can be presented as a problem of sequential data prediction. DL-based methods like LSTM can identify intricate relations between input-output where input includes the distance between the RIS and the user device, configurations of the RIS elements, transmission power, and output is the corresponding RIS configuration to maximize energy conservation. Unlike other deep learning-based algorithms, LSTM has the ability to store information over a period of time and "forget" information that does not contribute to the outcome. This characteristic is extremely useful to deal with Sequential data. In the training phase, the BS, with the aid of RIS, transmits data to the users, following which the user computes the objective value and sends feedback to the BS. Then the BS computes the Mean Squared Error (MSE) of the actual outcome and the expected outcome and updates the RIS controller about the new configuration. Finally, by using the training samples, the sum of MSE is minimized.

E. Proposed Framework

The proposed framework (Fig. 2) involves three phases, the first one is the data preprocessing phase, followed by the training of the LSTM module [39] optimized by Adam [40], and the decision process constitutes the last phase.

1) Data Preprocessing Module: The original feedback data of downlink transmission have randomness, making data processing an impending step for cleaning and standardization of numeric data. If these data are input into the LSTM model directly, the prediction accuracy will degrade. There are three steps in the preprocessing segment.

i. All data is subjected to cleaning segment for removing structural anomalies and treating missing information.
ii. Each numeric data is fed into the standardization segment.

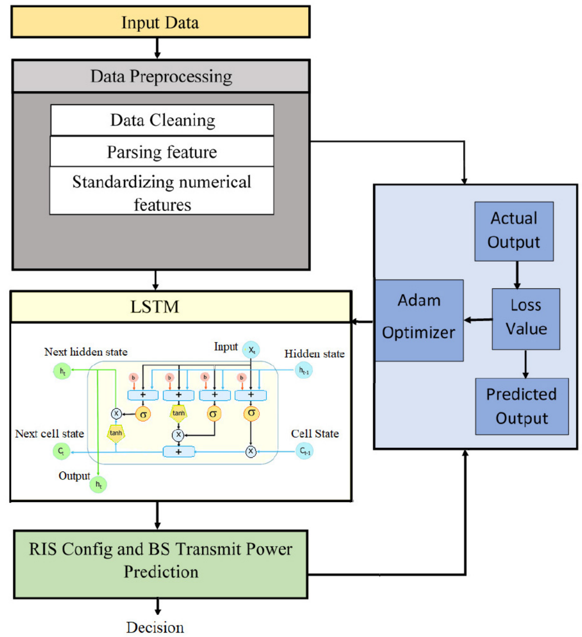

Fig. 2. Proposed framework for optimizing energy efficiency of RIS enabled wireless communication system.

iii. Calculate derived information like distance vector of user and RIS elements.

2) Optimization and Training Module: Adam optimization is based on an adaptive objective function that computes the learning rates of different parameters. This evaluation is based on the values of the average of the first and second moment of the gradient and has the ability to improve the model convergence speed and can even provide better prediction accuracy. The Adam optimizer with the loss function [41] estimates the learning rate as well as the number of hidden layers of the LSTM module to reduce the loss function. In this study, MSE is considered as the loss function and calculated as,

$$loss = \frac{1}{L}\sum_{l=1}^{L}\left(y_{actual} - y_{predicted}\right)^2 \tag{10}$$

where, L is the number of training samples.

y_{actual} is the actual output of a specific observation.

$y_{predicted}$ is the predicted output of the aforementioned observation and is calculated as follows:

$$y_{predicted} = \sigma\left(W_o * \left[h_{prev}, x\right] + b_o\right) \tag{11}$$

σ is the sigmoidal activation function [39].

x is the input vector to the LSTM model.

h_{prev} is the hidden state vector also referred as output vector of the model, in previous step.

W_o is the weight vector of output gate of the model.

b_o is the output gate bias vector of the model.

The complete flow of computing predicted output is given in Algorithm 2.

The MSE based loss function is calculated across all training samples using equation (10)-(11). The proposed model then minimizes the loss function through the use of the Adam

Algorithm 1 Optimizing Energy Efficiency Using LSTM

Input: User/Receiver location R_l**, RIS Current_Configuration** R_Config**, BS Transmission Power** T_p **, Maximum Transmission Power** T_{max}
Output: New RIS Configuration R_Config_new **to maximise Energy conservation and optimal BS Transmission Power** T_{opt}
Begin
Load input data R_l, R_Config, T_p, T_{max}.
Pass the input through pre-processing pipeline to generate desired input features format.
Split the input data into training and testing set as 3:1.
for a : 1 to *epoch* **do**
    Pass the processed data to build the LSTM model using Call Proc-LSTM();
    Calculate the loss using equation (10);
    Call Proc-Adam-Optimizer() to update the learning rate α and weights;
end for
After the completion of the training phase, testing data is loaded and the corresponding output is analysed.
The final model uses test dataset for prediction of the RIS Configuration suitable for energy conservation and optimal transmission power of BS.
The input vector is cleaned and passed to the LSTM module.
The value of ρ are predicted.
The updated value of T_p, ω, are computed using equation (7)-(9) and accordingly the values of *R_Config_new* and T_{opt} are assessed.
End

Algorithm 2 Proc-LSTM()

Begin
The LSTM identifies the irrelevant data from the input vector and discard the information using the forget gate [39].
    $f_{it} = \sigma(W_f * [h_{it-1}, x_{it}] + b_f)$
The LSTM module estimates the values to be updated via the input gate [39].
    $i_{it} = \sigma(W_i * [h_{it-1}, x_{it}] + b_i)$
The cell state information is updated as per the current input. State and hidden state vectors, using input activation vector and cell state vector [39].
    $\check{c}_{it} = \sigma(W_c * [h_{it-1}, x_{it}] + b_i)$
    $c_{it} = f_{it} * c_{it-1} + i_{it} * \check{c}_{it}$
Finally, the output state vector and the hidden state vector are calculated [39].
    $o_{it} = \sigma(W_o * [h_{it-1}, x_{it}] + b_o)$
    $h_{it} = o_{it}*\tanh(c_{it})$
End

optimizer. The optimizer expedites the rate of convergence and improves prediction stability.

3) Forecast Module: After the LSTM is trained using the available transmission data like the approximate location of the users, the current configuration of the RIS elements, and BS transmission power, the model predicts the optimal BS transmission power and RIS configuration for improving the average energy efficacy of the system.

F. Algorithm

This section presents the LSTM based prediction model for configuring the RIS elements and controlling the transmission power to ensure optimal conservation energy (Algorithm 1).

TABLE I
NOTATIONS USED FOR THE ESSENTIAL PARAMETERS

Symbol	Details
x_{it}	Input vector to the LSTM at iteration it
h_{it-1}	Hidden state vector at iteration $it-1$
f_{it}	Activation vector of Forget Gate at iteration it
W_f	Weight vector of Forget Gate
b_f	Forget gate Bias Vector
σ	Sigmoidal activation function
i_{it}	Activation vector of Input gate at iteration it
W_i	Weight vector of Input Gate
b_i	Input gate Bias Vector
$\check{c}_{it}$	Input activation vector of Cell state at iteration it
c_{it}	Cell state vector at iteration it
W_c	Weight vector of Cell state
b_c	Cell state Bias Vector
o_{it}	Activation vector of the Output gate at iteration it
h_{it}	Hidden state vector at iteration it
W_o	Weight vector of Output gate
b_o	Output gate Bias Vector
tanh	Hyperbolic tangent function

Algorithm 3 Proc-Adam-Optimizer()

Begin
Initialize the moment vectors (first and second) and time stamp δ to 0.
while parameters converge **do**
    $\delta = \delta + 1$
    Compute gradients according to stochastic objective function at δ.
    The biased first moment and second moment vectors are estimated.
    The bias-corrected first and second moment vectors are computed.
    Update parameters using learning rate, first and second moment vectors.
    Return updated parameters.
end while
End

The algorithm accepts the current configuration of the intelligent surface elements, the BS's transmission power, and the receiver's location. Following this, the distance vector between the elements of RIS and users is calculated. The data set generated is cleaned and standardized to prepare it for the training procedure. In the training phase, the information is used as input to the LSTM model. After completion of the training phase, the model is subsequently tested with test data. The new configuration of the RIS is used to determine the optimal transmission power. This information is computed to ensure that the energy efficiency of the overall system is improved.

The notation used for the Algorithm 2 is defined in Table I:

The LSTM model (Algorithm 2) comprises a "cell", an "input gate", an "output gate" and a "forget gate". The gates regulate the decision to "forget" or "remember" values over a random period of time, and accordingly, the values are regulated. The Adam optimization method (Algorithm 3) estimates the learning rate on the basis of the mean (first moment) and the uncentered variance (second moment) and updates the hyperparameters accordingly.

G. Computational and Space Complexity Analysis

1) Computational Complexity: The computational complexity of the LSTM model with W_f parameters (excluding

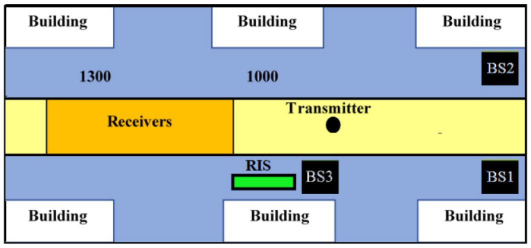

Fig. 3. The DeepMIMO 'O1' scenario with a fixed Transmitter based on the dataset [42].

biases) is given as

$$O(W_f) = n_i * n_h * 4 + n_h * n_h * 4 + n_h * n_o + n_h * 3 \tag{12}$$

where n_h is the number of memory cells, n_i is the number of input cells, and n_o is the number of output cells. The computational complexity of learning LSTM models per weight and time step with the Adam optimizer has low time complexity since it is a first-order method. Therefore, the learning computational complexity per time step is simply $O(W_f)$.

Computational complexity of k iterations: $O(k)$

Computational complexity of L training samples: $O(L)$

Now the overall complexity CC is given as

$$CC = O(k * L * n_i * n_h * 4 + n_h * n_h * 4 + n_h * n_o + n_h * 3) \tag{13}$$

The complexity of the model during the training phase is given by equation (13) since it is being trained over k iterations and L observations. Since during the testing phase, input is applied once, and the output is obtained, the complexity is represented as equation (12).

2) Space Complexity: The proposed LSTM model uses its memory vector c_{it} as a register of counters, and the corresponding space complexity is given in equation (14)-(15):

$$Space\ Complexity = O(\log n) \tag{14}$$

for each iteration with n units. With k number of iterations, the space complexity is

$$Space\ Complexity = O(k * \log n). \tag{15}$$

IV. Simulation Results

With the system model presented in Section III, the optimization problem formulated for the proposed work can only be evaluated with real-life network conditions generated by ray-tracing scenarios. For achieving this, the ray-tracing scenario 'O1' of the DeepMIMO dataset in [42] is used with some modifications to generate the outdoor network conditions. The DeepMIMO 'O1' scenario with a fixed Transmitter connected to the nearest Base Station BS3, is shown in Fig. 3. The parameters are presented in Table II.

In Fig. 4, the size of the testing data set is varied from 100 to 500, and the performance of the proposed model in terms of prediction accuracy is compared with a baseline DNN [43] and Bayesian network [44]. The baseline DNN consists of an input layer followed by a 128 fully connected neuron layer with Rectified Linear Unit (RELU) activation, successively followed by a dense layer of 64 neurons with RELU activation, with a last dense layer of 2 neurons and a softmax activation function. The LSTM network consists of an input layer, then a dense layer with 128 neurons is applied on top of the hidden layer and another dense layer (output layer) with softmax activations is used to get the output. The accuracy increases with the increase in the number of RIS elements.

TABLE II
DeepMIMO Parameter Configuration

Parameter	Value
Number of BSs	3
Rx (Receiver) Location	Row 1,000 to Row 1,300
(Transmitter)	Column 90 of Row 950
Count of BS Antennas	1; 16; 8
Spacing between Antenna	0.5
Bandwidth of the system model	10 MHz
OFDM subcarriers count	512
Sampling factor(OFDM)	1
OFDM limit	16
Number of paths	5
Maximum Transmit Power	43dBm

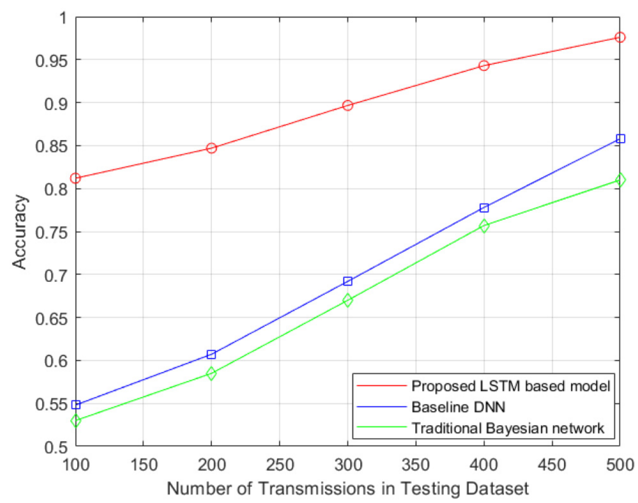

Fig. 4. Prediction accuracy of the proposed model.

Fig. 5 shows the comparison of energy efficiency achieved by the proposed model and the baseline DNN. The energy efficiency improves with the increase in the number of RIS elements. The energy efficiency is measured in terms of bits/Joules [45] which is basically the maximum number of bits that can be transmitted by the network per unit (in Joules) of energy consumed. From these results, it is visible that the rise in the number of deployed RIS components can enhance the rate of data transmission and energy efficacy of RIS-enabled wireless communication. In this experimental setup, the count of RIS elements are altered from 4 and to 25. The improvement in the energy efficiency is by 35.42% when count of RIS element is increased from 9 to 25. The comparison reveals that for 25 RIS elements, the LSTM gives 20.11% better performance than the Bayesian network.

The achievable rate or sum rate using the proposed model (equation(5)) is presented in Fig. 6 and is compared to the baseline DNN model and Bayesian network. It is observed that the increase in RIS elements, increases the net data rate. The

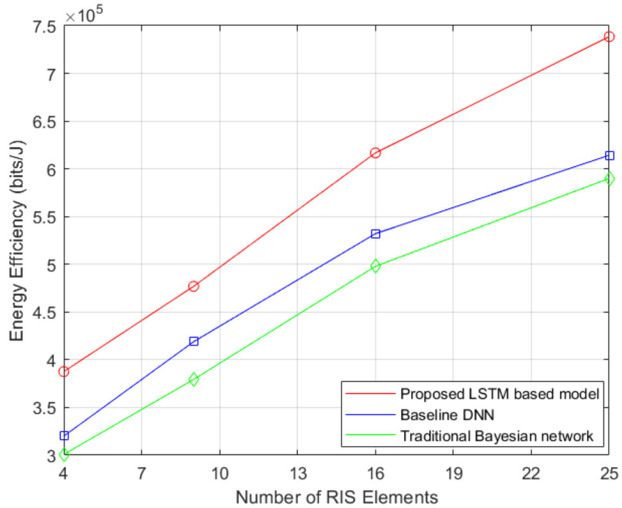

Fig. 5. Energy efficiency of the proposed model.

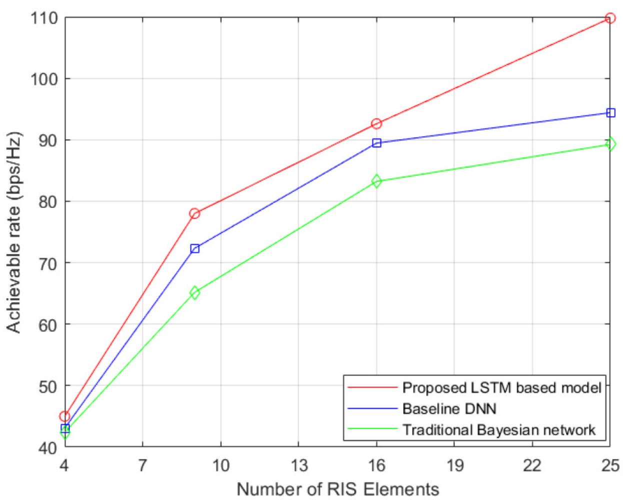

Fig. 6. The achievable rate of the proposed model.

achievable rate depicts the maximum number of data bits that can be transmitted per second while maintaining the quality of service. The proposed model achieves a net data rate of nearly 110 bps/Hz with 25 RIS elements and is 18.71% better than the Bayesian network.

Fig. 7 shows the cumulative energy efficiency achieved by the proposed LSTM based model by varying the number of transmissions from 100 to 500 while fixing the number of RIS elements at 25. The value of cumulative energy efficiency is achieved to be 22.3×10^5 bits/Joules after 500 transmissions.

V. Conclusion and Future Work

In this work, the downlink transmission of an RIS-enabled wireless communication network is explored and an Adam optimized LSTM model is proposed to optimize the energy efficiency of the network. The proposed deep learning-based model predicts the optimal RIS configuration suitable to achieve maximum energy conservation in a realistic environment without having information about the state of the channel. Various diverse machine learning approaches have been deployed in past to control the RIS-enabled communication environment; however, the proposed model shows significant improvement over the basic deep neural net and Bayesian network. Although the use of RIS in wireless communication is at the initial stage, its potential is evident. The proposed scheme can improve the network performance and contribute towards seamless energy efficient communication. It achieves 20.11% more energy efficiency and 18.71% higher net data rate than the Bayesian network when the number of RIS elements is fixed at 25.

The work can further be extended for multiple moving transmitters. In addition, machine learning-based hybrid models can be deployed in the future. These models can learn from reasonably smaller datasets when much information about the environment and network is not available.

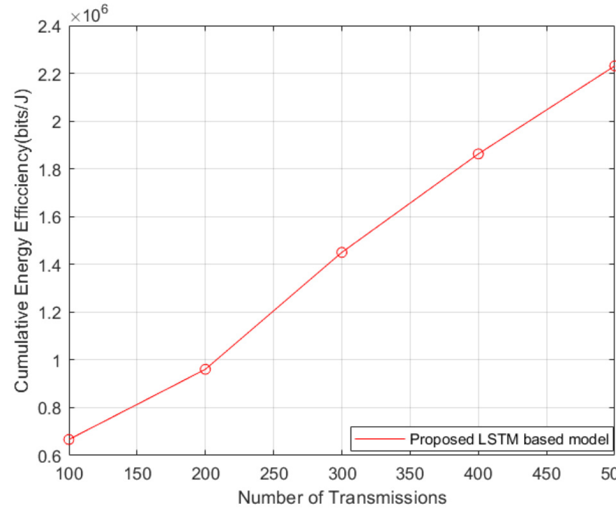

Fig. 7. Cumulative Energy Efficiency with 25 RIS elements.

References

[1] Q. Wu, G. Y. Li, W. Chen, D. W. K. Ng, and R. Schober, "An overview of sustainable green 5G networks," *IEEE Wireless Commun.*, vol. 24, no. 4, pp. 72–80, Aug. 2017.

[2] S. Misra and D. Mohanta, "Adaptive listen for energy-efficient medium access control in wireless sensor networks," *Multimedia Tools Appl.*, vol. 47, no. 1, pp. 121–145, 2010.

[3] G. C. Alexandropoulos, P. Ferrand, J.-M. Gorce, and C. B. Papadias, "Advanced coordinated beamforming for the downlink of future LTE cellular networks," *IEEE Commun. Mag.*, vol. 54, no. 7, pp. 54–60, Jul. 2016.

[4] J. Zuo, J. Zhang, C. Yuen, W. Jiang, and W. Luo, "Energy-efficient downlink transmission for multicell massive DAS with pilot contamination," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1209–1221, Feb. 2017.

[5] L. Ericsson, "More than 50 billion connected devices," Stockholm, Sweden, Ericsson, White Paper, 2011, p. 124.

[6] R. Mahapatra, Y. Nijsure, G. Kaddoum, N. U. Hassan, and C. Yuen, "Energy efficiency tradeoff mechanism towards wireless green communication: A survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 686–705, 1st Quart., 2016.

[7] S. Misra and P. D. Thomasinous, "A simple, least-time, and energy-efficient routing protocol with one-level data aggregation for wireless sensor networks," *J. Syst. Softw.*, vol. 83, no. 5, pp. 852–860, 2010.

[8] S. Buzzi, I. Chih-Lin, T. E. Klein, H. V. Poor, C. Yang, and A. Zappone, "A survey of energy-efficient techniques for 5G networks and challenges ahead," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 697–709, Apr. 2016.

[9] A. Zappone and E. Jorswieck, "Energy efficiency in wireless networks via fractional programming theory," *Found. Trends Commun. Inf. Theory*, vol. 11, nos. 3–4, pp. 185–396, 2015.

[10] S. Hu, F. Rusek, and O. Edfors, "Beyond massive MIMO: The potential of data transmission with large intelligent surfaces," *IEEE Trans. Signal Process.*, vol. 66, no. 10, pp. 2746–2758, May 2018.

[11] F. Rusek *et al.*, "Scaling up MIMO: Opportunities and challenges with very large arrays," *IEEE Signal Process. Mag.*, vol. 30, no. 1, pp. 40–60, Jan. 2013.
[12] A. Samanta and S. Misra, "Energy-efficient and distributed network management cost minimization in opportunistic wireless body area networks," *IEEE Trans. Mobile Comput.*, vol. 17, no. 2, pp. 376–389, Feb. 2018.
[13] F. Zabin, S. Misra, I. Woungang, H. F. Rashvand, N.-W. Ma, and M. A. Ali, "REEP: Data-centric, energy-efficient and reliable routing protocol for wireless sensor networks," *IET Commun.*, vol. 2, no. 8, pp. 995–1008, 2008.
[14] S. K. Dhurandher, D. K. Sharma, I. Woungang, R. Gupta, and S. Garg, "GAER: Genetic algorithm-based energy-efficient routing protocol for infrastructure-less opportunistic networks," *J. Supercomput.*, vol. 69, no. 3, pp. 1183–1214, 2014.
[15] S. K. Dhurandher, D. K. Sharma, I. Woungang, and A. Saini, "An energy-efficient history-based routing scheme for opportunistic networks," *Int. J. Commun. Syst.*, vol. 30, no. 7, p. e2989, 2017.
[16] A. Chhabra, V. Vashishth, and D. K. Sharma, "SEIR: A Stackelberg game based approach for energy-aware and incentivized routing in selfish opportunistic networks," in *Proc. 51st Annu. Conf. Inf. Sci. Syst. (CISS)*, Baltimore, MD, USA, 2017, pp. 1–6.
[17] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5394–5409, Nov. 2019.
[18] Y. Han, W. Tang, S. Jin, C.-K. Wen, and X. Ma, "Large intelligent surface-assisted wireless communication exploiting statistical CSI," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 8238–8242, Aug. 2019.
[19] M. Di Renzo *et al.*, "Smart radio environments empowered by reconfigurable AI meta-surfaces: An idea whose time has come," *EURASIP J. Wireless Commun. Netw.*, vol. 129, no. 1, pp. 1–20, 2019.
[20] M. Di Renzo *et al.*, "Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 11, pp. 2450–2525, Nov. 2020.
[21] M. A. ElMossallamy, H. Zhang, L. Song, K. G. Seddik, Z. Han, and G. Y. Li, "Reconfigurable intelligent surfaces for wireless communications: Principles, challenges, and opportunities," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 3, pp. 990–1002, Sep. 2020.
[22] Q. Wu and R. Zhang, "Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1838–1851, Mar. 2020.
[23] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE Access*, vol. 7, pp. 116753–116773, 2019.
[24] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Abu Dhabi, UAE, 2018, pp. 1–6.
[25] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, "Reconfigurable intelligent surfaces for energy efficiency in wireless communication," *IEEE Trans. Wireless Commun.*, vol. 18, no. 8, pp. 4157–4170, Aug. 2019.
[26] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?" *IEEE Trans. Commun.*, vol. 67, no. 10, pp. 7331–7376, Oct. 2019.
[27] T. Lin and Y. Zhu, "Beamforming design for large-scale antenna arrays using deep learning," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 103–107, Jan. 2020.
[28] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for wireless resource management," in *Proc. IEEE 18th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Sapporo, Japan, 2017, pp. 1–6.
[29] A. Taha, M. Alrabeiah, and A. Alkhateeb, "Deep learning for large intelligent surfaces in millimeter wave and massive MIMO systems," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Waikoloa, HI, USA, 2019, pp. 1–6.
[30] Ö. Özdogan and E. Björnson, "Deep learning-based phase reconfiguration for intelligent reflecting surfaces," 2020, *arXiv:2009.13988*.
[31] T. Jiang, H. V. Cheng, and W. Yu, "Learning to reflect and to beamform for intelligent reflecting surface with implicit channel estimation," 2020, *arXiv:2009.14404*.
[32] C. Huang, G. C. Alexandropoulos, C. Yuen, and M. Debbah, "Indoor signal focusing with deep learning designed reconfigurable intelligent surfaces," in *Proc. IEEE 20th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Cannes, France, 2019, pp. 1–5.
[33] J. Gao, C. Zhong, X. Chen, H. Lin, and Z. Zhang, "Unsupervised learning for passive beamforming," *IEEE Commun. Lett.*, vol. 24, no. 5, pp. 1052–1056, May 2020.
[34] C. Huang, R. Mo, and C. Yuen, "Reconfigurable intelligent surface assisted multiuser MISO systems exploiting deep reinforcement learning," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 8, pp. 1839–1850, Aug. 2020.
[35] A. Taha, Y. Zhang, F. B. Mismar, and A. Alkhateeb, "Deep reinforcement learning for intelligent reflecting surfaces: Towards standalone operation," in *Proc. IEEE 21st Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Atlanta, GA, USA, 2020, pp. 1–5.
[36] G. Lee, M. Jung, A. T. Z. Kasgari, W. Saad, and M. Bennis, "Deep reinforcement learning for energy-efficient networking with reconfigurable intelligent surfaces," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Dublin, Ireland, 2020, pp. 1–6.
[37] B. Yang, X. Cao, C. Huang, C. Yuen, L. Qian, and M. Di Renzo, "Intelligent spectrum learning for wireless networks with reconfigurable intelligent surfaces," *IEEE Trans. Veh. Technol.*, vol. 70, no. 4, pp. 3920–3925, Apr. 2021.
[38] L. Wei, C. Huang, G. C. Alexandropoulos, C. Yuen, Z. Zhang, and M. Debbah, "Channel estimation for RIS-empowered multi-user MISO wireless communications," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 4144–4157, Jun. 2021.
[39] J. Q. Wang, Y. Du, and J. Wang, "LSTM based long-term energy consumption prediction with periodicity," *Energy*, vol. 197, Apr. 2020, Art. no. 117197.
[40] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. 3rd Int. Conf. Learn. Represent. (ICLR)*, San Diego, CA, USA, May 2015, pp. 1–14, [Online]. Available: http://arxiv.org/abs/1412.6980
[41] E. L. Lehmann and G. Casella, *Theory of Point Estimation*, 2nd ed. New York, NY, USA: Springer, 1998.
[42] A. Alkhateeb, "DeepMIMO: A generic deep learning dataset for millimeter wave and massive MIMO applications," 2019, *arXiv:1902.06435*.
[43] L. Dai, R. Jiao, F. Adachi, H. V. Poor, and L. Hanzo, "Deep learning for wireless communications: An emerging interdisciplinary paradigm," *IEEE Wireless Communications*, vol. 27, no. 4, pp. 133–139, Aug. 2020.
[44] N. Friedman, D. Geiger, and M. Goldszmidt, "Bayesian network classifiers," *Mach. Learn.*, vol. 29, nos. 2–3, pp. 131–163, Nov. 1997. [Online]. Available: https://doi.org/10.1023/A:1007465528199
[45] H. Kwon and T. Birdsall, "Channel capacity in bits per joule," *IEEE J. Ocean. Eng.*, vol. 11, no. 1, pp. 97–99, Jan. 1986.

Koyel Datta Gupta (Member, IEEE) received the M.Tech. degree from Jadavpur University, India, in 2007, and the Ph.D. degree from Jamia Millia Islamia, India, in 2015. She is currently working as an Associate Professor with the Department of Computer Science and Engineering, Maharaja Surajmal Institute of Technology, New Delhi. Her area of research includes deep learning, IoT, and wireless networks.

Ritu Nigam is currently working as a Research Scholar with the University of Delhi (Netaji Subhas Institute of Technology), New Delhi, India. Her area of research includes opportunistic networks, IoT, social networks, machine learning, and wireless networks.

Deepak Kumar Sharma received the M.E. and Ph.D. degrees from the University of Delhi, New Delhi, India. He is working as an Assistant Professor with the Department of Information Technology, Netaji Subhas University of Technology, New Delhi. His current research interests include opportunistic networks, wireless ad hoc networks and sensor networks, and IoT.

Sanjay K. Dhurandher (Senior Member, IEEE) received the M.Tech. and Ph.D. degrees in computer science from the Jawaharlal Nehru University, New Delhi, India. He is currently working as a Professor with the Department of Information Technology, Netaji Subhas University of Technology (Formelry, NSIT), New Delhi. His current research interests include wireless ad hoc networks, sensor networks, computer networks, opportunistic networks, network security, and underwater sensor networks.