Deep Learning-Based Optimization of Adaptive Data Rate Mechanism for Intelligent Radio and Channel Resource Allocation in LoRa-based AIoT Systems

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Abstract

The internet of things, artificial intelligence, and high-performance computing can revolutionize agriculture by offering efficient and cost-effective solutions. Implementing IoT technology in agriculture provides low-cost and simple communication between different smart devices. My research focuses on developing DL models for AIoT-based intelligent agriculture monitoring and recommendation systems. This research focuses on the development of a DL-based adaptive data rate algorithm tailored specifically for LoRa and LoRaWAN networks within the vast IoT domain. The objective is to facilitate intelligent resource allocation in these networks to meet diverse communication requirements. Additionally, this research aims to overcome scalability challenges while investigating the influence of various factors on link quality, network performance, and link-level performance. Advanced AI and DL techniques are employed to enhance the efficiency and effectiveness of agriculture monitoring systems. These techniques enable the extraction of valuable insights from collected data, contributing to higher yields while minimizing environmental impact.

Research Focus

Methodology

A. Problem Statement

- Consider $m_t \in Q^L$ signify the multivariate variable value of L dimension at time step t, and $m_t[j] \in Q$ symbolize the j^{th} variable value.
- Provided a series of historic K time steps of multivariate variable measurements, $M=\{m_{(t_1)}, m_{(t_2)}, \dots, m_{(t_K)}\}$, we aim to estimate the P-step in the future value of $N=m_{(t_{(K+1)})}, m_{(t_{(K+2)})}, \dots, m_{(t_{(K+P)})}$.
- In general, the input variables can be combined with auxiliary characteristics like the time of the day, the date of the month, and the year.
- In the concatenation of input variables with the supporting characteristics, we consider the inputs to become $\mathcal{M}=\{S_{(t_1)}, S_{(t_2)}, \dots, S_{(t_K)}\}$ where $S_{(t_i)} \in Q^{(L \times D)}$ and D represents a dimension of features.
- The objective is to developed a Bayesian Surrogate Gaussian Process model (DL-based Adaptive Data Rate Algorithm) by minimizing the mean square error with hyper-parameter optimization for multivariate multi-step time series forecasting.

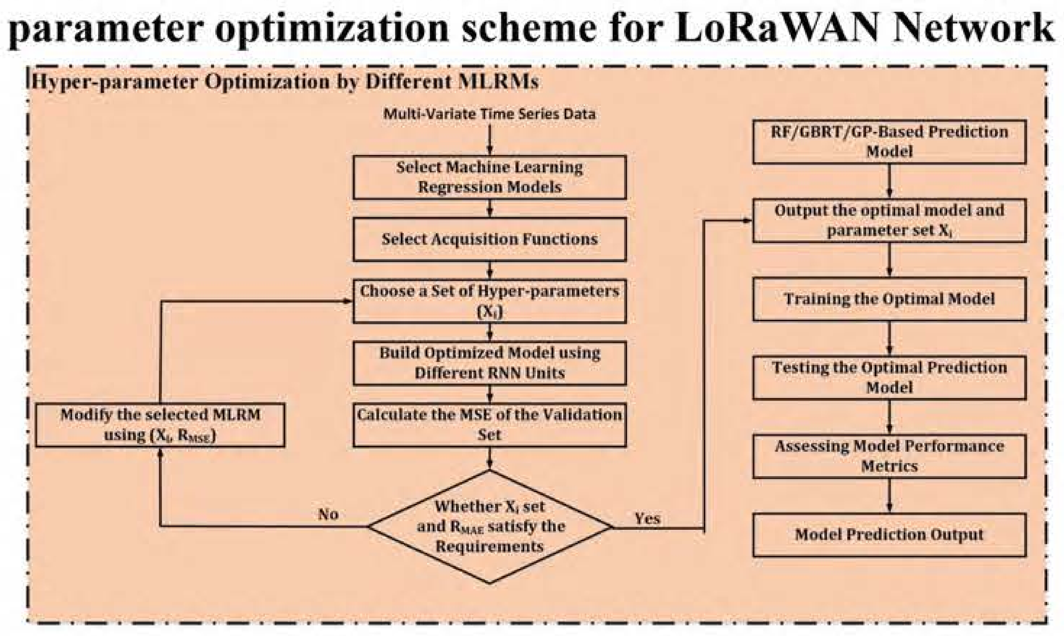
B. Experiment Design

Experimental System Parameters

Parameters	Values	Parameter	Values
Transmission	Uplink and Downlink	Activation Methods	OTAA or ABP
Acknowledgment	Yes	Carrier Frequency	868MHz
CR	4/5	Deployment Area	400 m x 30 m
SF	7	Tinovi PM-IO-5-SM (LoRaWAN Nodes)	8
BW	125 kHz	MikroTik wAP LR8 (Gateway)	1
Packet Size	26-byte UL and 5 bytes DL	Davis Vantage Pro2 weather station	1

The Bayesian Optimization scheme was introduced for the developed model to optimize the hyper-parameters automatically. To obtain the optimum hyperparameter combinations, three machine learning regression algorithms (such as GP, GBRT, and RF) with different acquisition functions (like EI and PI) are employed.

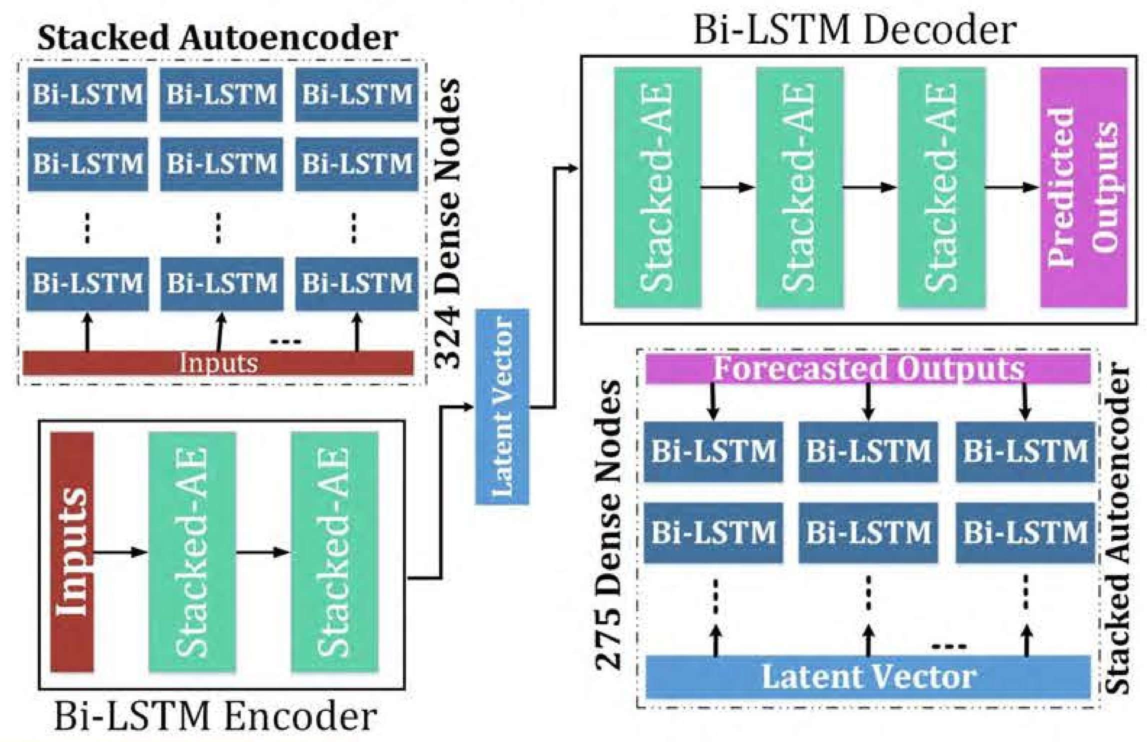
Machine learning regression model (MLRM) hyper-parameter optimization scheme for LoRaWAN Network



Selected Range of Hyperparameters for DNN Optimization

Hyperparameters	Range	Hyperparameters	Range
Learning Rate	0.0001 to 0.1	Initial-Bias	uniform, lecun_uniform, normal, zero,glorot_normal, glorot_uniform, he_normal, he_uniform
Dense Layers	1 to 10	Optimizer	SGD, RMSprop, Adagrad, Adadelta, Adam,Adamax, Nadam
Dense Nodes	1 to 500	Batch Size	1 to 975
Activation Functions	softmax, softplus, softsign, relu, tanh, sigmoid, hard_sigmoid, linear	Epochs	1 to 150
Initialization Mode	uniform,lecun_uniform, normal, zero, glorot_normal, glorot_uniform, he_normal, he_uniform	Dropout	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
Decay		0.000006 to 0.01	

Structure of the optimized BSGP-BLSTM-SAE model for LoRaWAN channel performance estimation



C. Model Complexity

The autoencoder used in the development of the proposed model has 7 LSTM layers including 3 layers of each encoding and decoding side. Therefore, if L represents the number of LSTM layers in a single AE, then AE has the time complexity of $O(L(4Hd))$. Consequently, the overall time complexity of the proposed model can be calculated by multiplying the $O(L(4Hd))$ by the number of AE's (N_{AE}) in the stacked AE Model. Thus, the overall time complexity of the BSGP-BLSTM-SAE model is $O(N_{AE}L(4Hd))$.

Results

Correlation Results

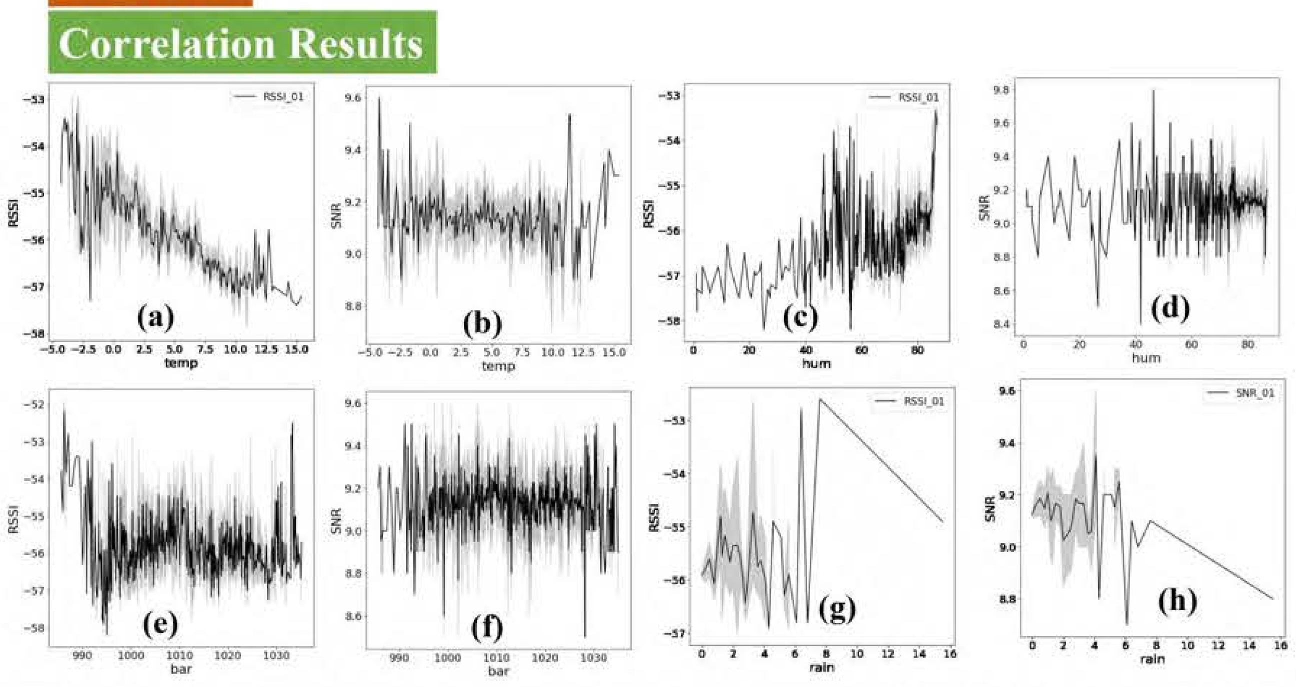


Figure 1 represents the impact of different ambient conditions on the channel performance indicators of the LoRaWAN Network. Pearson correlation coefficient (*r*) has been used to calculate the correlation between the channel performance metrics and weather conditions.

Prediction Results

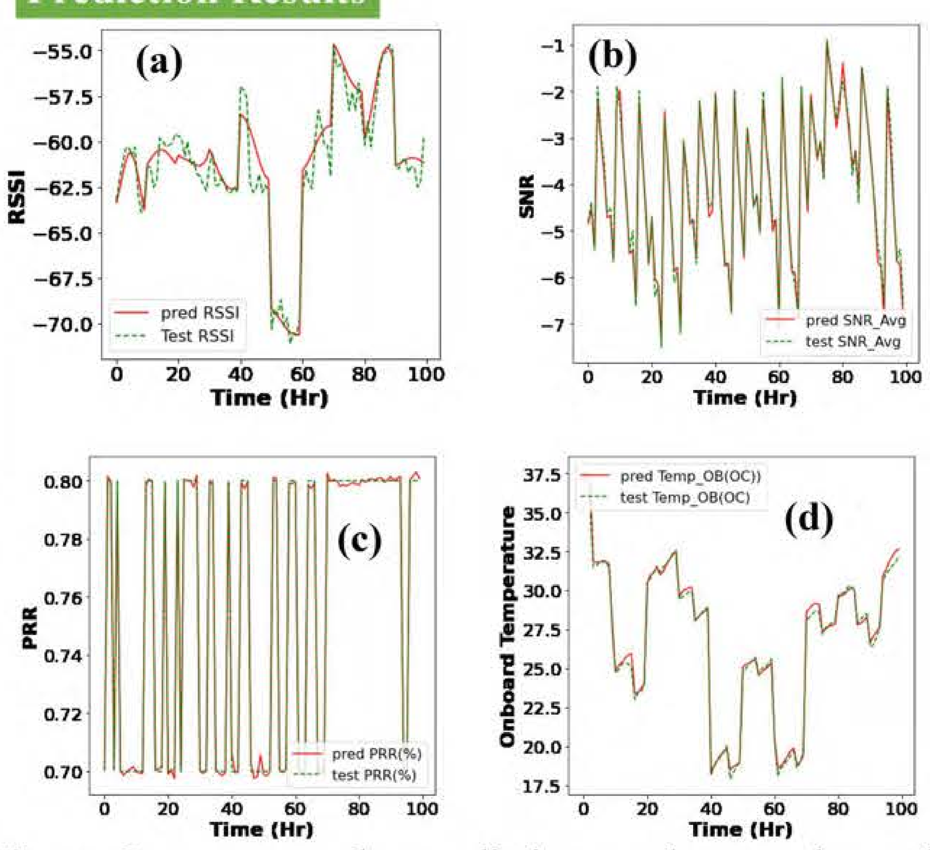


Figure 2 represents the predictions and test values of the channel performance indicators along with the onboard temparture of LoRaWAN gateway for first 100 hours. Plotting the experimental and estimated RSSI and SNR with time (hours) enabled the evaluation of the predictive model's performance.

Thus, this work explores the impact of LoRaWAN transmission parameters, ambient conditions, node deployment density, and onboard temperature on the network and link-level performance of both LoRaWAN networks. The proposed approach incorporates predictive modeling and state representation techniques to accurately predict key data communication network parameters for both LoRaWAN channel, as well as ambient conditions. Experimental evaluations on real-world datasets demonstrate the effectiveness and feasibility of the approach, achieving high levels of accuracy and performance.

Conclusion

By integrating the developed models with Adaptive Data Rate (ADR) operations, channel performance indicators can be predicted based on current ambient conditions. This optimization capability allows for real-time configuration of LoRa transmission parameters, resulting in reduced message ToA, improved SNR and RSSI values, and decreased energy consumption across various operational conditions. The introduction of computational intelligence in LoRa networks facilitates parameter composition optimization, parameter optimization, reliable communication in diverse conditions, and throughput optimization through self-regulation. Each device in the network regulates energy consumption and adjusts transmission parameters based on changing ambient conditions. This process utilizes AI-controlled channel performance metrics to predict future link quality trends, enabling efficient resource allocation and improved network performance.

Acknowledgement

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