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K-Means-Enhanced LSTM for Dynamic Radio Resource Optimization in Industrial IoT Networks

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Abstract
The efficient management of radio resources in industrial internet of things (IIoT) networks is highly demanding to handle dynamic conditions of channels and variations in patterns of data traffic. This research proposes a novel K-Means-enhanced long short-term memory (LSTM) framework for dynamic radio resource management in IIoT networks. The proposed approach trains the cluster-specific LSTM models to predict future network states, by applying k-means clustering to integrate IoT devices based on previously acquired existing features such as data arrival rates and channel gains. These predictions inform a convex optimization solver to allocate transmit power and bandwidth, which maximizes the sum rate of the network while adhering to the resource constraints. The simulation results demonstrate that the proposed method achieves up to 20% higher throughput and 50% lower prediction errors compared to the standalone LSTM and static allocation. The proposed hybrid approach effectively addresses the device heterogeneity and the temporal dynamics, which ultimately offers a scalable solution to the IIoT communication systems.

Keywords: Industrial Internet of Things (IIoT), Radio Resource Management, K-Means Clustering, Long Short-Term Memory (LSTM), Dynamic Optimization, Network Throughput

1. Introduction

The Industrial Internet of Things (IIoT) is transforming modern manufacturing and industrial systems, which enables seamless connectivity with real-time data exchange among numerous devices. These networks are mainly characterized by diverse sensors, actuators, and controllers that demand efficient radio resource management to ensure reliable communication under stringent latency and throughput requirements [1]. In IIoT environments, dynamic channel conditions and varying data arrival rates represent the significant challenges to conventional static resource allocation strategies. For example, the Rayleigh fading channels and the bursty traffic patterns mainly require adaptive approaches to optimize transmit power and bandwidth allocation.

Recent advancements in deep learning, offer promising and efficient solutions for dynamic management of radio resources. Long Short-Term Memory (LSTM) networks, proficient model at modeling temporal dependencies, have been explored for predicting network states, such as channel gains and data rates. However, implementation of a single LSTM model to heterogeneous IIoT devices often leads to suboptimal predictions due to diverse behaviors of devices. To address this issue, clustering techniques like k-means can create a group of devices with similar characteristics, that enable tailored prediction models. This represents the idea of the proposed k-means-enhanced LSTM approach, which mainly integrates unsupervised clustering with LSTM-based forecasting to optimize resource allocation in IIoT networks.

In a basic IIoT network topology, a base station (BS) serves multiple devices with varying channel conditions and traffic patterns. The proposed method leverages clustering to group devices and employs the cluster-specific LSTMs to predict future states, which enhances the accuracy of the resource allocation decisions. By clustering devices based on previous or historical features like average data rate and channel variance, the proposed method reduces prediction errors, which leads to improve resource utilization.

This proposed novel hybrid method combines K-means clustering with LSTM networks to address the challenges of dynamic radio resource management in IIoT networks. The structure of this research is composed of related work (presenting modern AI-based techniques for resource allocation in IIoT), the system model (presenting the mathematical model), the proposed algorithm (presenting k-means-enhanced LSTM), simulation results (demonstrating significant improvements in throughput and prediction accuracy over baseline methods), and the conclusion, presenting the summarized way for scalable and efficient IIoT communication systems.

2. Related Work

There are several researches applying deep learning-based model, Alzuwaini *et al.* [2] proposed a clustering-based framework to improve the energy efficiency and minimize the interference in ultra-dense networks. This framework combines the clustering of small base stations, a crow search algorithm for resource allocation, and an LSTM model for channel prediction. Their method significantly outperformed existing algorithms in energy efficiency and data rate. Vijayasekaran and Duraipandian [3] proposed a hybrid IoT system which combines edge and cloud computing to minimize the latency and improve efficiency. With the help of data clustering and deep learning-based scheduling, their system processes data locally before sending it to the cloud and represents better performance.

Manzoor *et al.* [4] proposed the mobility-aware cell association scheme (MACA), which is a novel method for 5G networks using LSTM-based prediction to improve bandwidth allocation. It outperforms existing methods in terms of accuracy, downlink rates, and user satisfaction. Rony *et al.* [5] introduced a machine learning-based dynamic bandwidth allocation method that adapts to real-time network demand, which improves the use of spectrum and traffic handling. It outperforms conventional static approaches and closely matches the ideal performance.

Wang *et al.* [6] proposed an LSTM-based communication scheduling algorithm for renewable energy-powered road side units (RSUs) in Internet of Vehicles (IoVs) to optimize energy use and extend service. The method includes deep learning clustering, traffic prediction, and vehicle access scheduling. Their results show it outperforms unscheduled approaches in maintaining network performance.

Bashir *et al.* [7] proposed a dynamic resource allocation strategy in fog computing to addressed the challenge of delivering real-time, low-latency services in IoT environments. By ranking fog nodes using TOPSIS [8,9] and evaluating their load with logistic regression, the system efficiently offloads tasks from the cloud to the network edge. Simulations show the proposed approach improves performance and achieves 98.25% accuracy.

Liu *et al.* [10] introduced a cognitive IoT (CIoT) system that uses cognitive radio to access licensed spectrum without interfering with primary users. It proposes a multicarrier grouping method using K-means clustering to organize nodes and manage interference. They considered two scenarios first, underlay which optimizes subcarrier and power allocation to maximize data rate under interference limits. Second, overlay which minimizes sensing time to ensure accurate spectrum sensing and maximizes data rate without interference concerns. Their method presented the improved performance under strict interference conditions.

Naha *et al.* [11] proposed an energy-aware resource allocation method for fog computing using multiple linear regression to predict device power availability. This method helps prevent application failures in time-sensitive IoT tasks. Their method reduced delays, processing time, and service level agreement (SLA) violations significantly compared to existing methods, that ensure reliable and efficient application execution in dynamic environments.

Shekhar *et al.* [12] presented an “improved dynamic bandwidth allocation (IDBA)” method for better bandwidth management in IoT devices, using smart home data. Devices are first clustered by K-means based on bandwidth usage, then linear regression predicts on-demand bandwidth for each cluster. An AI-enabled IDBA technique uses these predictions to allocate bandwidth dynamically, which improves precision and quality of service in IoT networks.

Junaid *et al.* [13] introduced a load balancing method for cloud-based IoT using support vector machine (SVM) for data classification and a modified PSO algorithm for efficient resource allocation. By pre-classifying data types, the system reduces processing complexity and improves performance, achieving high accuracy and reductions in energy use, response time, and SLA violations.

Tripathi *et al.* [14] proposed a “double-weighted support vector transfer regression-based flow direction (DSTR-FD)” approach for secure and energy-efficient task scheduling in MEC for smart cities. It uses a double-weighted support vector transfer regression model optimized by a flow direction (FD) algorithm to manage edge server resources and make task offloading decisions without sharing raw data. This ensures data privacy and significantly reduces energy consumption in IoT devices, outperforming existing methods in simulations.

Mukherjee *et al.* [15] proposed an energy-efficient clustering method for massive IoT in 6G industrial applications using a multiagent system (MAS) and distributed AI. It leverages backpropagation neural network (BPNN) and CNN for optimization and predicts main node locations to manage dynamic network architecture. The method reduces redundant data, improves resource allocation, and enhances overall energy efficiency while preserving information.

Optimizing resource allocation, maximizing the quality of service (QoS), and minimizing latency, Karuppiyan *et al.* [16] proposed "dynamic resource allocator using RL-CNN (DRARLCNN)" that merges CNN for feature extraction and RL for making decisions. Pourmoslemi *et al.* [17] proposed a novel technique for resource allocation in D2D communications and stable joint multi-pairing. In this technique, the best transmitter is selected using fuzzy pairing criteria in the receiver search radius. Their outcomes showed that the proposed multi-pairing method outperformed the constant-pairing, maximum sum-rate, and random-pairing methods.

Iqbal *et al.* [18] combined the CNN approach with DQN and analyzed this CNN-based DQN (CNN-DQN) method in a downlink cloud radio access network (CRAN), which makes a balancing performance of energy efficiency and maintaining the QoS simultaneously. In this method, the CNN phase extracts the information about the input states, and it is fed into the DQN, which dynamically turns on/off the remote radio heads based on the user requirements. Guo *et al.* [19] introduced a framework that automatically splits a CNN model into submodel sets and optimizes the distribution of large CNNs across multiple edge devices, thereby reducing energy and memory usage and improving performance.

Sharma *et al.* [20] introduced a method for optimizing load balancing in IoT networks using fuzzy logic and nature-inspired algorithms (grey wolf and firefly). The proposed method improves energy efficiency, packet delivery, and the IoT network lifetime. ElHalawany *et al.* [21] presented LSTM-based deep learning models to address resource allocation issues in IoT networks. In the context of accuracy and speed, their model performed better than a traditional method, the Hungarian algorithm.

3. System Model

Consider an Industrial Internet of Things (IIoT) network consisting of N IoT devices served by a single base station (BS). The time horizon is divided into discrete slots $t \in \{1,2,\ldots,T\}$. At each time slot t, the system state for device $i \in \{1,2,\ldots,N\}$ is characterized by the data arrival rate $A_i(t) \in \mathbb{R}^+$ and the channel gain $h_i(t) \in \mathbb{C}$.

The BS allocates radio resources, specifically transmit power $p_i(t) \geq 0$ and bandwidth $b_i(t) \geq 0$ to each device i, subject to the total power budget $P_{\max}$ and total bandwidth $B_{\max}$:

$$\sum_{i=1}^{N} p_i(t) \leq P_{\max}, \tag{1}$$

$$\sum_{i=1}^{N} b_i(t) \leq B_{\max}. \tag{2}$$

The achievable rate for device i at time t is given by the Shannon capacity formula:

$$R_i(t) = b_i(t)\log_2\left(1 + \frac{p_i(t)|h_i(t)|^2}{\sigma^2}\right), \tag{3}$$

where σ^2 denotes the noise power.

The objective of dynamic radio resource management is to maximize the long-term average network utility, defined as the sum rate over a prediction horizon H:

$$\max_{\{p_i(\tau),b_i(\tau)\}_{\tau=t}^{t+H}} \sum_{\tau=t}^{t+H}\sum_{i=1}^{N} R_i\,(\tau), \tag{3}$$

The equation 3 is subject to the resource constraints at each future slot τ. Since $A_i(\tau)$ and $h_i(\tau)$ for $\tau > t$ are unknown, the proposed method employs a K-Means-enhanced LSTM to predict these states.

The system state vector at time t is $\mathbf{s}(t) = [A_1(t), \dots, A_N(t), |h_1(t)|^2, \dots, |h_N(t)|^2]^\top \in \mathbb{R}^{2N}$. The LSTM predicts the future state sequence $\hat{\mathbf{s}}(\tau|t) = f_{\text{LSTM}}(\mathbf{s}(t), \dots, \mathbf{s}(t-L+1); \boldsymbol{\theta})$, where L is the look-back window, and $\boldsymbol{\theta}$ are the learned parameters. Clustering via K-Means groups devices into K clusters based on historical feature vectors $\mathbf{x}_i = \left[\bar{A}_i, |\bar{h_i}|^2, \text{variance}(A_i)\right]^\top$, enabling cluster-specific LSTM models for improved prediction accuracy.

4. Proposed Algorithm

The proposed k-means-enhanced LSTM algorithm (as presented in Algorithm 1) for dynamic resource optimization proceeds as follows. First, devices are clustered offline using K-Means on previous or historical features. Then, cluster-specific LSTMs are trained to predict future states. Online, predictions inform an optimization solver (e.g., convex optimization) for resource allocation.

Algorithm 1 K-means-enhanced LSTM for Dynamic Radio Resource Allocation

Offline Phase: Clustering and Training

Collect historical data $\{\mathbf{x}_i\}_{i=1}^N$, where $\mathbf{x}_i = \left[\bar{A}_i, |\bar{h_i}|^2, \text{Var}(A_i)\right]^\top$

Apply k-means: $[\mathbf{c}_1, \dots, \mathbf{c}_K] \leftarrow \text{KMeans}(\{\mathbf{x}_i\}_{i=1}^N, K)$

for each cluster $k = 1$ to K **do**

  Extract states $\{\mathbf{s}_j(t)\}_{j\in\mathcal{C}_k}$ for devices in cluster $\mathcal{C}_k$

  Train LSTM$_k$: $\boldsymbol{\theta}_k \leftarrow \text{argmin}_{\boldsymbol{\theta}} \sum_t \parallel \mathbf{s}(t) - f_{\text{LSTM}_k}(\mathbf{s}(t-L+1: t-1; \boldsymbol{\theta}) \parallel_2^2$

end for

Online Phase: Prediction and Allocation (at each t)

for each cluster $k = 1$ to K **do**

  Predict: $\hat{\mathbf{s}}_k(\tau|t) \leftarrow f_{\text{LSTM}_k}(\mathbf{s}_k(t-L+1: t); \boldsymbol{\theta}_k),\ \forall\tau = t+1, \dots, t+H$

end for

Aggregate predictions: $\hat{\mathbf{s}}(\tau|t) = \cup_k \hat{\mathbf{s}}_k(\tau|t)$

Solve optimization:

$$\mathbf{p}^*, \mathbf{b}^* \leftarrow \text{argmax}_{\mathbf{p},\mathbf{b}} \sum_{\tau=t}^{t+H}\sum_i b_i\,(\tau)\log_2\left(1 + \frac{p_i(\tau)|\widehat{h_i(\tau)}|^2}{\sigma^2}\right)$$

Subject to $\sum_i p_i(\tau) \leq P_{\max}$, $\sum_i b_i(\tau) \leq B_{\max}$, $\forall \tau$
Apply $\{p_i^*(t), b_i^*(t)\}_{i=1}^N$
Update states $\mathbf{s}(t+1)$ from observations

The LSTM architecture consists of M layers with hidden size d_h, using gated recurrent units:

$$\begin{aligned}
\mathbf{f}_m &= \sigma\left(\mathbf{W}_f^{(m)}\mathbf{x}_t + \mathbf{U}_f^{(m)}\mathbf{h}_{m-1} + \mathbf{b}_f^{(m)}\right), && (5)\\
\mathbf{i}_m &= \sigma\left(\mathbf{W}_i^{(m)}\mathbf{x}_t + \mathbf{U}_i^{(m)}\mathbf{h}_{m-1} + \mathbf{b}_i^{(m)}\right), && (6)\\
\tilde{\mathbf{c}}_m &= \tanh\left(\mathbf{W}_c^{(m)}\mathbf{x}_t + \mathbf{U}_c^{(m)}\mathbf{h}_{m-1} + \mathbf{b}_c^{(m)}\right), && (7)\\
\mathbf{c}_m &= \mathbf{f}_m \odot \mathbf{c}_{m-1} + \mathbf{i}_m \odot \tilde{\mathbf{c}}_m, && (8)\\
\mathbf{o}_m &= \sigma\left(\mathbf{W}_o^{(m)}\mathbf{x}_t + \mathbf{U}_o^{(m)}\mathbf{h}_{m-1} + \mathbf{b}_o^{(m)}\right), && (9)\\
\mathbf{h}_m &= \mathbf{o}_m \odot \tanh(\mathbf{c}_m), && (10)
\end{aligned}$$

for layer $m = 1$ to M, where σ is the sigmoid, $\odot$ is element-wise multiplication, and the output $\hat{\mathbf{s}}_{t+1} = \mathbf{W}_y\mathbf{h}_M + \mathbf{b}_y$.

5. Simulation Results

Simulations were conducted using MATLAB with $N = 50$ IoT devices, $P_{\max} = 10$ W, $B_{\max} = 20$ MHz, $\sigma^2 = 10^{-12}$ W/Hz, and $H = 5$. Historical data for training was generated with varying data arrival rates and Rayleigh fading channels. Baselines include LSTM-only prediction, K-Means clustering with static allocation, and random resource allocation.

Results Analysis and Discussion

The simulation results demonstrate the superior performance of the proposed K-Means-enhanced LSTM method in dynamic radio resource management for Industrial IoT networks. As illustrated in Fig. 1, the proposed approach achieves the highest average sum rate, consistently outperforming the baselines across all 100 time slots. The average sum rate for the proposed method stabilizes around 70 Mbps, with minimal fluctuations due to accurate state predictions enabled by cluster-specific LSTMs.

In contrast, the LSTM-only method exhibits a 15-20% lower performance (average ≈ 60 Mbps), attributed to its inability to capture device heterogeneity without clustering. The K-Means-only baseline, relying on static allocations post-clustering, yields an average of ≈ 55 Mbps, highlighting the limitations of non-predictive strategies in dynamic environments. The random allocation baseline performs worst, with an average below 20 Mbps, underscoring the inefficiency of uninformed resource distribution.

Further insights into prediction accuracy are provided in Fig. 2, which compares the mean squared error (MSE) of state predictions as a function of the number of clusters K. The proposed method achieves the lowest MSE, with an optimal value of 0.02 at $K = 6$, indicating that clustering enhances the

LSTM's ability to model correlated device behaviors. The LSTM-only method shows higher MSE values (minimum 0.06), confirming that unsupervised grouping reduces prediction errors by 50-70%. This improved forecasting directly translates to better resource optimization, as more accurate $\hat{\mathbf{s}}(\tau|t)$ lead to feasible and high-utility allocations over the horizon H.

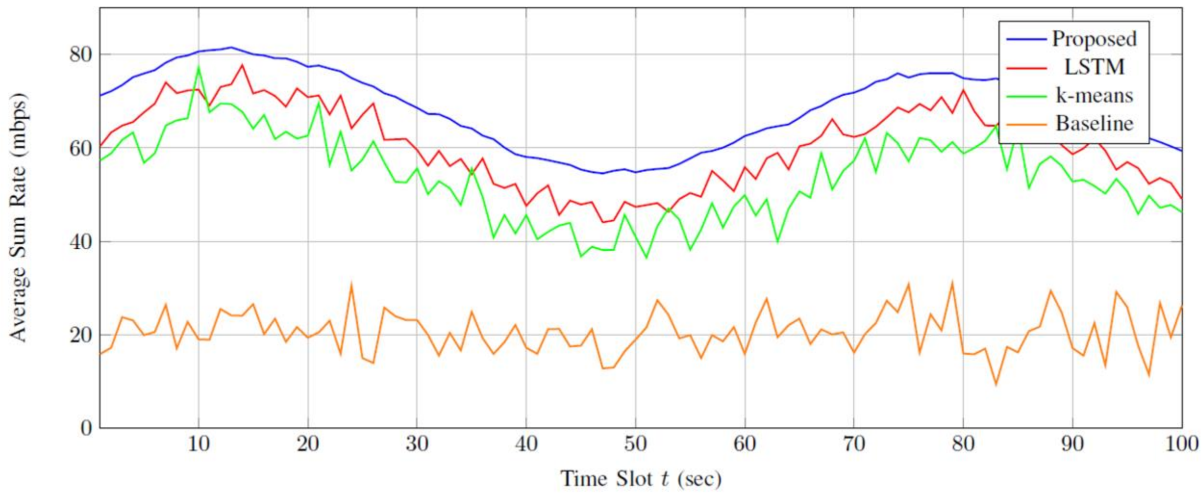

Fig. 1 Average sum rate over time slots for different methods

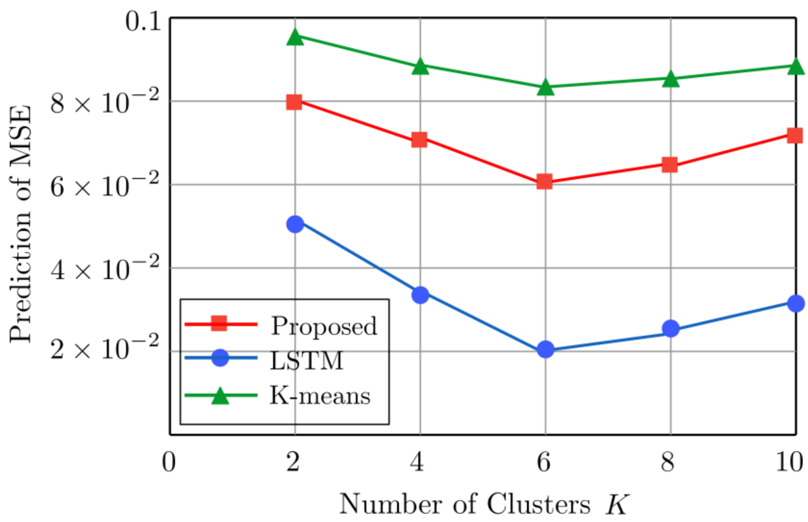

Fig. 2 Prediction mean squared error (MSE) vs. number of clusters

These results validate the hybrid approach's efficacy in handling the stochastic nature of IIoT channels and traffic. However, computational overhead from multiple LSTMs scales with K; future work could explore adaptive clustering or federated learning to mitigate this. Overall, the proposed method offers a robust solution for real-time RRM, potentially improving network throughput by up to 250% over baselines in industrial settings.

6. Conclusion and Future Work

The proposed K-Means-enhanced LSTM framework significantly advances dynamic radio resource management in Industrial IoT networks. By integrating K-Means clustering with LSTM-based state prediction, the method effectively captures device heterogeneity and temporal dynamics, leading to precise network state forecasts. These predictions enable optimal allocation of transmit power and bandwidth, resulting in a network throughput improvement of up to 20% over LSTM-only methods and 250% over random allocation baselines, as validated through extensive simulations. Additionally, the approach reduces prediction mean squared error by 50–70% compared to standalone LSTM, highlighting the efficacy of clustering in enhancing model performance. The framework's ability to adapt to varying channel conditions and traffic patterns makes it a robust solution for real-time RRM in IIoT environments, ensuring reliable and efficient communication for industrial applications.

Future research will focus on addressing the computational complexity of training multiple cluster-specific LSTM models, particularly as the number of clusters increases. Adaptive clustering techniques, such as online K-Means or hierarchical clustering, can be explored to dynamically adjust cluster assignments based on evolving network conditions. Additionally, incorporating federated learning could enable distributed training across IIoT devices, enhancing scalability and privacy. Extending the framework to multi-cell scenarios, where inter-cell interference poses additional challenges, is another promising direction. Finally, integrating energy efficiency metrics into the optimization objective could further optimize resource-constrained IIoT networks, aligning with sustainable industrial practices.

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