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A Deep Learning Framework for Industrial Wireless Networks

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Abstract

In this report, we introduce a framework to analyze, monitor, and identify the state of industrial wireless networks and their impact on industrial use cases. This framework is based on a deep learning approach for modeling the interactions between the wireless network and industrial use cases. The framework uses the information from different system layers including the spectrum measurements, physical layer metrics, network layer packets, and application layer production-related metrics in order to study the industrial wireless network behavior. The output of the framework can be generally used to improve system management and optimization functions.

Keywords

cyber-physical system modeling; deep learning; industrial wireless; system identification.

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1. Introduction

Industrial wireless communications networks are envisioned to play a crucial role in enabling the next generation of industrial evolution which is anticipated to be based on three main elements; resilience, sustainability, and human-centric industries [1]. These core elements are added to the current focus of the smart manufacturing and industry 4.0 visions of enhancing digitization in smart production and the increased intelligence in industrial automation. The enablers of the current and future industrial revolutions include industrial wireless, artificial intelligence, data infrastructure and analytics, industrial process digitization, and human-machine interaction improvement technologies [2].

The integration of artificial intelligence (AI) capabilities within industrial wireless networks is being considered to achieve various goals including providing hybrid and configurable wireless services to the industrial use cases, providing performance analysis and monitoring tools, and supporting better knowledge and understanding for various interactions within the industrial wireless networking layers. Precisely, AI can be viewed as a tool to achieve industrial wireless networks goals of being responsive to the operational demands, customizable following the application process requirements, and efficient from various resource perspectives [3].

For an industrial wireless network to be analyzed, managed, and optimized, certain information needs to be gathered including network configuration parameters, key performance indicators (KPIs), traffic data, and the industrial operational metrics. However, the interaction and integration of these heterogeneous types of data are complex and its associated complexity increases proportional to the size of the available data. As a result, AI can play a crucial role in achieving two main goals. First, AI can be used in extracting useful information from large set of available data. Second, deep learning can be employed to model the complex interactions between different layers of the industrial cyber-physical system (CPS) [4].

In this report, we introduce a framework that can be used to analyze, monitor, identify the state of industrial wireless networks, and evaluate their impacts on industrial use cases. In this framework, a deep learning approach is proposed to monitor the behavior patterns of the collected data streams to be able to detect and identify the deviation of these patterns from the normal behavior of an industrial process. The normal behavior of the industrial process is used to train a generative adversarial network (GAN) such that the discriminator part of the network can be later used to detect the behavior variations and identify the system operation mode. GANs can be used to detect the deviation in behavior through training a generative and a discriminative neural networks such that the generative network captures the data distribution without labels and the discriminative network estimates the probability that a sample does not follow the distribution of the generative network [5]. The GANs have been proven to be successful for unsupervised problems with implicit probability distribution to model the system interactions [6].

2. Related Work

The use of AI for wireless network analysis and management was presented in multiple works. In [7], the authors used machine learning for automating management tasks such as anomaly detection and fault management. In [8], a resource allocation optimization technique was proposed using machine learning techniques. In [9], a semi-supervised approach was proposed to detect cell outages in a mobile network using handover statistics. In [10], a framework for wireless network diagnosis deployed unsupervised machine learning techniques.

The use of AI to predict specific events in wireless networks was also proposed in [11] where machine learning is used to anticipate possible failures in a network. The use of K-means clustering in pattern identification in mobile network behavior was described in [12]. In [13], a similar goal of behavior pattern identification of a radio-access network was achieved for a self-organizing network. In [14], a Naive Bayes technique was used for cell classification based on their network traffic patterns. Also, a random forest-based approach was used for traffic pattern detection in the application layer [15]. Finally, in [4], the authors proposed an approach that combined unsupervised and supervised techniques for the analysis of the performance of a mobile network by monitoring the real-time traffic to detect possible changes.

In this report, we propose a framework that can be used for the analysis of industrial wireless networks and their impact on the operational industrial process. The proposed framework trains a deep neural network with the normal behavior of a CPS on various system layers. The trained network can be used to identify the system mode of operation, the real-time behavior changes, and operational system anomaly prediction. The output of the proposed framework can be integrated into various resource management and network optimization blocks of the CPS.

3. Framework Description

In this section, we describe the proposed framework's various components, the data flow through its various blocks, and the underlying neural network processing. We further explain various types of data that can be used throughout the framework, and describe the use of the framework in various applications related to monitoring, analysis, and prediction for various industrial wireless use cases.

3.1. Overview

In modern CPSs, a large volume of heterogeneous data is generated and transferred within a variety of equipment, sensors, controllers, and computing platforms. Data analytics for CPSs play a critical role in improving factory operation and product quality, reducing machine downtime, and enhancing manufacturing efficiency. Modeling industrial wireless and its impact on CPSs includes identifying the normal behavior of various system components such as the wireless network and the physical operational equipment. This modeling process is highly complex because of the heterogeneity of the data and the dependency between various data flows and correlations in their temporal behaviors. The use of unsupervised learning for such tasks allows the detection of any deviation in the performance from the normal behavior without being trained using labeled data. As a result, the use of unsupervised deep learning-based techniques for modeling CPS performance abnormalities can be applied to achieve the required CPS identification and analysis.

3.2. Framework Data Processing

The framework data flow starts with the data collection to go through various data processing stages to evaluate the required system metrics. A block diagram of the framework data processing at various stages is shown in Fig. 1. The upper part of the block diagram presents the GAN training process while the lower part describes the deployment of the trained network for CPS testing and assessment. In the following, we describe the function of each block and the data processing through various stages of the proposed approach.

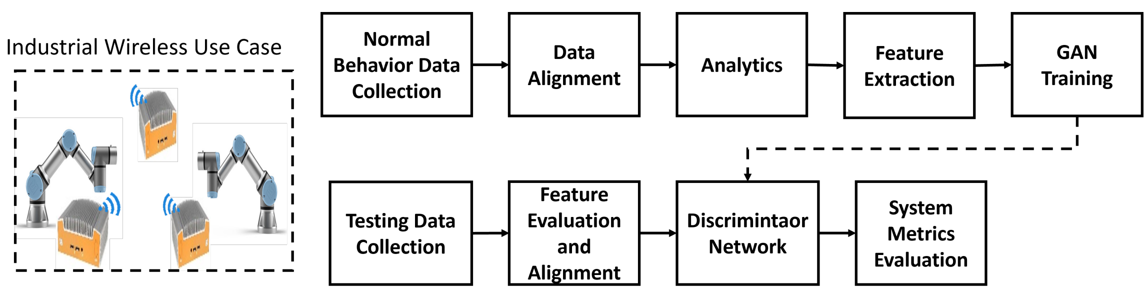

Fig. 1. A block diagram of the framework data processing at various stages.

3.2.1. Data Collection

The data used by the framework is collected in two different phases, namely, the normal behavior data collection and the testing data collection. In both phases, the same streams of data are collected. The collected data may include all variables that can be impacted by the industrial wireless network used. All data streams are formed as multi-dimensional time series. This framework can be applied to the data collected at different system levels including the network and operational measured data streams. However, the framework can also be used for the simpler cases of data collected from a single layer of the system under test. Initially, the framework will include the spectrum data, wireless channel physical and medium access layers data, network layer data, and application-based operational layer data.

3.2.1.1. Normal Behavior Data Collection

The normal behavior is defined to be the behavior of the CPS when it is not affected by wireless network impairments. It can be measured and used for training the deep-learning model. The first option is to collect normal behavior data by deploying the wired CPS behavior, if possible. If the CPS's industrial wireless network can be replaced by wired connections, then this option is applicable. Thus the framework can be used to measure the performance of wireless network due to its various impairments. The second option, which is more widely applicable, is to measure the normal behavior over the wireless network without the impact of the impairments included on the testing stage. This can be done either through operating the CPS in a controlled wireless environment or through post-processing of the data where the deep-learning model is trained only using data without the impairments. This can be achieved by setting thresholds on the physical metrics of the use case.

3.2.1.2. Testing Data Collection

The testing data streams are the same data streams of the normal behavior data but it is collected from the deployed industrial wireless network under test. It will be collected when the network is deployed under normal working conditions and hence impacted by various impairments that could exist and affect its performance.

3.2.2. Data Alignment

Data alignment is the next processing stage after data collection. In this stage, the heterogeneous data streams collected from the multiple sources are aligned and resampled such that the measuring instants of all streams are identical or time synchronized. Hence, these streams can be combined for further processing. This process is required to overcome the issues of having different update rates, different series lengths, and asynchronous data collection devices. This process will depend mainly on applying interpolation techniques while taking into consideration the various constraints with respect to the data streams.

3.2.3. Analytics and Feature Extraction

Then, the data is analyzed and the features to be used for training and industrial wireless testing are selected. The main goal of this block is identifying the statically relevant features with respect to the testing goals and understating the correlation between different factors. As a result, the statistical behavior of each measured data stream is assessed and the correlation to other streams is evaluated. The result of this block includes a selected set of features that are impacted by the wireless network impairments and does not include a large set of dependent features. Principal component analysis can be deployed for this task to project the selected set of features onto an independent set of principal components.

3.2.4. GAN Training and Deployment

GANs are powerful modeling frameworks for high-dimensional data that build on two competing networks, namely, a generator G and a discriminator D. The generator network is trained to produce synthetic data examples that are similar to real data patterns by taking a random vector z, drawn from an input distribution $P_z(z)$ in a latent Z-Space. If trained only with normal data patterns, the generator captures the hidden multivariate distribution of the training sequences and can be seen as an implicit model of the system at a normal state. On the other hand, the discriminator network is trained to distinguish between the generated synthetic examples and real data patterns, and then classify data patterns into one of these two classes.

The continuous measurements of various system metrics produce multivariate time-series data streams, which are used to monitor the system's working conditions. In order to deal with these intrinsically multivariate time-series data, the discriminator and the generator are constructed as Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) networks. Such networks assume that data samples are not independent of each other and that there is a temporal dependency among them. Thus, instead of dealing with isolated data samples, sequences of data are considered and stored in memory units. In this context, computations are performed for every element of a sequence such that the computation outputs for one element of the sequence serve as input for the computation of the following element in that sequence.

3.2.5. System Metrics Evaluation

The final processing stage is the system performance metrics and the evaluation process from the discriminator neural network score (S_{D}). The discriminator score represents a probabilistic indicator of the deviation of a measured feature vector from the normal behavior of the CPS. Two main approaches for network metric evaluation can be achieved. First, evaluating average performance metrics which include averaging the discriminator score over time to evaluate the deviation of the tested network from the normal behavior on average. This approach can be used to identify the mode of the industrial wireless network or more generally, the average impact of a specific set of parameters on the network performance. The second approach is using the real-time value of the discriminator score to either detect the anomalies in the CPS performance and how a specific event in the industrial wireless network can impact the CPS performance in different layers. It can also be used for predicting failures in the wireless network in order to take actions for better resiliency.

4. Conclusions and Future Directions

This work presents an initial prototype describing the use of deep learning to study the system performance of an industrial wireless system. We propose a framework that uses a

GAN to model the behavior of the industrial wireless system in order to use the discriminator loss for identifying the deviation of the performance from the normal behavior of the system. The discriminator loss of a trained GAN can provide insights into the wireless communications state within an industrial use case. More specifically, the temporal tracking of the discriminator loss identifies the instants at which the industrial wireless system performance deviates from the normal behavior so more analysis can be performed at these instances for identifying the cause of the problem. On the other hand, the various statistical metrics of the discriminator loss can be used as a comparison tool for various deployment scenarios and parameter settings.

In future, we plan to extend this work to identify and characterize industrial wireless systems by including various operational, network, and spectrum features. Moreover, post-processing metrics that use the discriminator loss are to be defined for identifying the operating modes of the system. We plan to identify the specific statistical metrics and their use in specific scenarios such as studying the impacts of various interference types on the network and hence the suitability of wireless technologies for deployment. Another important directions is the use of the proposed tool as an integrated part in the feedback control of the CPS and the industrial wireless network which used the real-time version of this approach to make decision on optimizing the wireless network and the control decisions. This specific direction requires more work towards obtaining the real time version of the proposed prototype and more collaboration with wireless network and CPS control system designers in order to achieve this envisioned integration.

Disclaimer

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