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INDUSTRIAL WIRELESS CYBER-PHYSICAL SYSTEMS PERFORMANCE USING DEEP LEARNING

Mohamed Kashef (Hany)*, Richard Candell, Karl Montgomery,

Smart Connected Systems Division
Communications Technology Laboratory
National Institute of Standards and Technology *(NIST)*, Gaithersburg, MD

ABSTRACT

Industrial wireless communications networks have a major role in the future industrial cyber-physical systems (CPSs) by allowing higher flexibility and massive machine connectivity. However, the reliability and latency of industrial wireless networks need to be evaluated accurately to ensure satisfying the industrial CPS requirements and analyze degradation factors. In order to measure the impact of deploying industrial wireless on cyber-physical system performance, a deep learning framework based on the generative adversarial network (GAN) is introduced. The GAN is used to model the performance of the system and identify the impact of various wireless impairments on the system performance. The GAN model can deploy features from both the wireless network and operational performance spaces. The loss function of the discriminator part of the GAN is deployed as a performance metric that can be used to model the average performance of a specific wireless scenario and compare to the normal behavior of the industrial wireless system. The proposed GAN-based methodology is validated using a dual-robot collaborative lift use case in which IEEE 802.11ac is employed.

Keywords: industrial wireless, deep learning, generative adversarial networks, performance evaluation

1. INTRODUCTION

Wireless communications is crucial to the future vision on industrial control systems but it is still facing challenges in achieving the required reliability and latency of such systems [1–4]. One main cause of deployment challenges of industrial wireless systems (IWSs) is the random nature of wireless channels that requires a special attention to the wireless network design to deal with this special nature of the industrial wireless environment [5, 6]. Currently, the application space of industrial wireless in cyber-physical systems (CPSs) is getting larger by supporting flexible manufacturing and safety application with more strict communications requirements. More specifically, the adoption of wireless in CPSs requires innovative methods and approaches to quantify the impact of wireless technologies in terms of industrial application production efficiency and measure the cost of wireless link failures on performance [7]. In order to improve the deployment of industrial wireless in CPSs, effective and easy-to-use strategies have to be offered for the test and evaluation of such systems in a way that correlates network performance with operational performance. The needed data for this purpose is collected from various CPS activities and networks, and is generally found to be in large amounts, heterogeneous, and correlated.

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 in industrial applications is critical for improving factory operation and product quality, reducing machine downtime, and enhancing manufacturing efficiency [8, 9]. Generally, data analytics performs the tasks of extracting information, analyzing performance, and predicting production forecast. In [8], the life cycle of data analytics in CPSs includes data acquisition, preparation, storage, and analysis. Data acquisition includes adding various points of data collection and data transfer to the storage and processing units. Afterwards, typical preprocessing techniques for cleaning, integration, and compression are deployed because of the large volume, redundancy, and heterogeneity of the raw data. Finally, data analysis is performed for data modelling and visualization.

Modeling industrial wireless and its impact on CPSs includes identifying the normal behavior profile of various system components such as the wireless network and the physical operational equipment. This process includes dealing with the correlations of various multivariate time series representing the variations in various data flows [10]. 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 has been proposed and deployed, such as in [11, 12], and the

*Corresponding author: mohamed.kashef@nist.gov

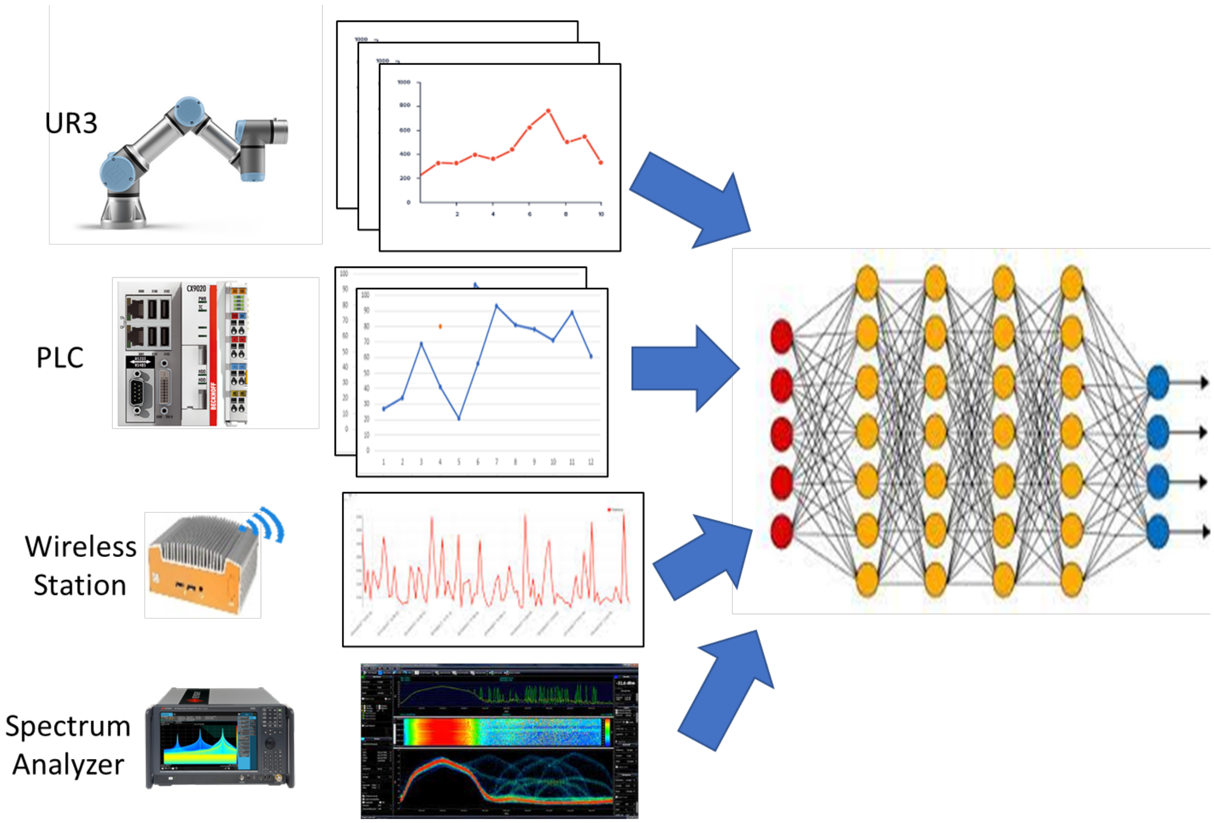

FIGURE 1: THE USE OF DEEP LEARNING FOR PERFORMANCE EVALUATION OF CYBER-PHYSICAL INDUSTRIAL WIRELESS SYSTEMS

references therein. The concept of using deep learning for performance evaluation of cyber-physical industrial wireless systems is shown in Fig. 1.

In this work, we deploy a generative adversarial network (GAN)-based approach to evaluate the impact of using industrial wireless in a leader-follower robotics testbed where the follower robot receives the leader positions wirelessly. The approach depends on training the GAN two neural networks in order to optimize the ability of the generator network to produce samples that have similar distribution to the original data and the discriminator network ability to distinguish fake samples from the original samples [13]. While doing so, the GAN networks are implicitly trained to the model of the original data. As a result, we use the GAN to model the normal behavior of the testbed with no interference impairing the connection between the leader and the follower robots. The discriminator network of the trained GAN then can be used to distinguish the impact of any impairments on the wireless network that deviates the behavior from the normal behavior.

More specifically, once the GAN is trained with the normal behavior of the CPS, only the discriminator network of the GAN is used to measure the impacts of wireless impairments on the overall deviation of the performance from the normal behavior. This innovative approach only deploys the discriminator loss function of the trained GAN to study the performance of a wireless network under various scenarios that may impact the operational performance. Note that the normal behavior includes both the performance of the wireless network and the physical equipment, which are represented by a number of correlated time series.

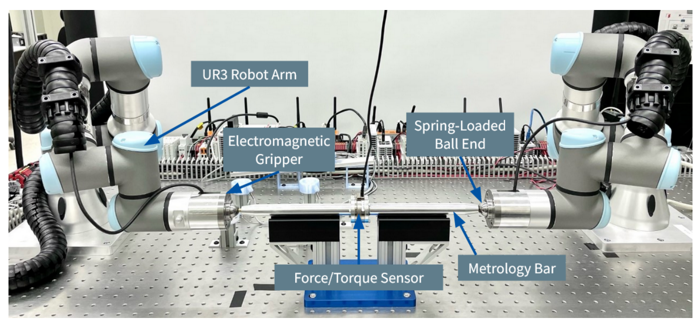

FIGURE 2: DUAL ROBOTIC USE CASE PERFORMING A CIRCLE PATTERN

2. DUAL-LIFT ROBOTIC USE CASE

In this section, we describe the use case, its data flows, and the various features that represent its performance. Later, we describe the use of these features to train the GAN when the use case is not impacted by interfering traffic. Additionally, test data is also collected for validating the proposed approach.

The dual-lift robotic use case performs coordinated movements with a leader and follower robot to jointly lift and move an object as shown in Fig. 2. The object lifted is a custom metrology bar with an integrated force-torque sensor (ATI mini45). The robots are two Universal Robots (URs), UR3s, and are directly controlled by Robot Operating System (ROS) nodes. ROS is a communication middleware that was used to control and coordinate the motion of the robots. The ROS nodes are implemented on SuperLogics microbox-PCs, running Ubuntu 18.04 and ROS Melodic and can communicate over a network through topics, services, and actions.

Additionally, there are a number of Next Unit of Computing (NUC) machines used as Ethernet-wireless bridges and serve as the wireless stations (STAs), and one NUC is configured as the wireless access point (AP). They have 2x2 MIMO wireless capability with IEEE 802.11ac Wi-Fi cards. The AP was configured to use a 20 MHz channel. Also, all of the NUCs for the wireless bridges and wireless AP are synchronized over Ethernet using the IEEE 1588 Precision Time Protocol (PTP) [14].

The data streams, which are collected using Ethernet tap devices called SharkTaps, are routed to the collection machine to capture the network packets. This allows us to capture the times on a collection machine that is globally synchronized to the grand leader (GL) clock. Also, a traffic source and a wireless traffic sink are used to create a wireless traffic stream using iPerf [15] from the AP to the sink STA.

The follower's control algorithm utilizes a velocity-based controller with input from the leader, using the desired topic data streamed at 125 Hz. This topic contains the position and orientation information of where the follower should move to next. This data stream directly impacts the follower movement, as any significant latency disturbances or loss in this stream will cause the follower to jerk or even stop briefly. Since this stream is a ROS topic, the protocol used is Transmission Control Protocol (TCP). This application is latency sensitive by design, as we are able to see and measure small latency disturbances in real time with the leader-follower error.

3. THE GAN ARCHITECTURE AND EXPERIMENTAL METHODOLOGY

3.1 Brief Description of the GAN Architecture

A GAN is composed of two neural networks, namely, the generator (G) and the discriminator (D). While training, real measured data samples are introduced to the GAN. The generator has an input Gaussian random variable and produces samples that are trained to have similar statistical distribution to the real measured data. On the other hand, the discriminator receives the generated samples and the real data to perform classification on them in order to distinguish them from each other.

Each of the two neural networks is optimized to achieve its goal while the discriminator feeds back its classification result to the generator. At equilibrium and after both networks are trained using the normal behavior data, the trained generator is able to generate samples has similar statistical features to the real samples while the trained discriminator is able to classify its received samples to either follow the normal behavior or not. The discriminator employs its loss function to perform this classification task. In our work, we will use the value of the discriminator loss function to identify deviation from the normal behavior. Additionally, we will only train the GAN by the normal behavior data and will not use the CPS data that is impacted by any wireless impairments for any further training. More details about the mathematical definitions and expression can be found in [12].

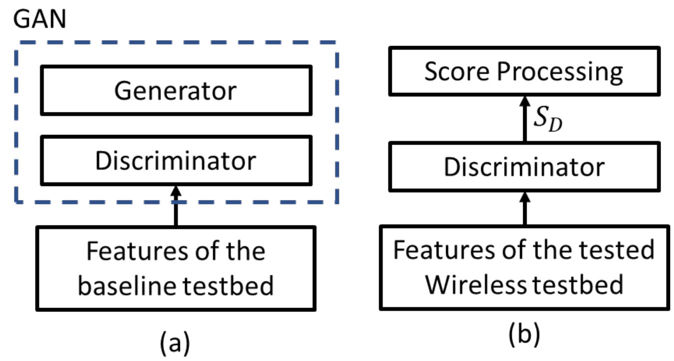

FIGURE 3: THE GAN TRAINING AND EVALUATION BLOCK DIAGRAM

3.2 Approach Justification

The goal of this work is developing an approach which is capable of measuring the deviation of an industrial wireless system performance from its normal behavior due to the existence of wireless impairments. The approach should benefit from measurable system features at the wireless network level and the operational use case level. In order for this approach to work, the normal behavior of the CPS system has to be modeled. The CPSs are usually nonlinear and complex, and hence, deep learning is a suitable way for achieving this purpose. Moreover, the unsupervised estimation of the deviation from the normal behavior is required because, in many cases, few outlier events due to wireless impairments are only captured and no availability of the data under all the expected impairments that allows for a supervised learning approach.

As a result, GANs can be used to model nonlinear systems where a GAN model consists of two networks where the discriminator, once trained, can be used separately to identify samples that are not following the statistical behavior of the normal operation of the CPS under test. The discriminator loss can be used to distinguish any deviation from the neural network model which is trained only on the normal behavior so no need for supervised learning in this case. Moreover, GANs do not depend on prior knowledge of the system model but rather model the real data from its samples and varying features.

3.3 Measurement Methodology

The results presented in the paper consist of physical performance data collected by sensors on the leader and follower robots and the metrology bar that is handled by the two robots. The measurement machine, to which the SharkTaps are routed, collects the network packets along with Real-Time Data Exchange (RTDE), [16], data at 125 Hz from the robots, to calculate the error between the leader and follower. For the measurement machine, the clocks on multiple 4-port gigabit Ethernet PCI cards, based on Intel i210, are time synchronized to the GL clock using PTP time synchronization for <1 us error with 99% confidence. The ground truth error is also accurate in time synchronization, as the same collection machine is used for both the RTDE data streams from the leader and follower robot controllers.

In the use case, the leader and follower carried the metrology bar together to follow a specific path. In this work, each collected measurement was taken for the duration of 40 revolutions of a circle, taking approximately two and a half minutes to finish. A circle is chosen as the error between the leader and follower under perfect conditions should be a constant value due to the constant radial acceleration.

3.4 Data Processing

Through these measurements, a specific set of data streams are collected to represent the behavior of the use case. These data streams are typically heterogeneous such that they present various physical quantities with different units and different ranges. Moreover, not all collected data streams are affected by the various wireless events in the use case. As a result, a preprocessing phase is needed to make sure that the training and evaluation of the GAN model is able to identify the deviation in the performance due to the deployed industrial wireless network.

The collected features at the normal conditions case and the case of coexisting traffic are statistically compared using box plots and the corresponding statistical measures such as the mean, the standard deviation, and the various population percentile measures. The features, which have their statistical behavior not changed due to the coexisting traffic, are removed from the set of features to train the GAN model. This step is followed by a normalization to the range between 0 and 1, such that the remaining features have equal impact during the training and evaluation phases. Note that a weighting scheme can be used to differentiate the features importance in a controllable fashion.

The basic block diagram of the training and evaluation of the proposed GAN-based approach is shown in Fig. 3. In this work, we start with a number of measured features through the operation of the use case. We collect baseline measurements in the case where the leader and the follower communicate through a wireless channel that is not affected by other interfering traffic in the network. In the evaluation phase, other traffic streams are allowed to share the same WiFi network with the leader-follower use case. As a result, the proposed approach is used to assess the impact of coexisting WiFi traffic on the operational performance of the use case. A detailed block diagram for the evaluation is presented in Fig. 4.

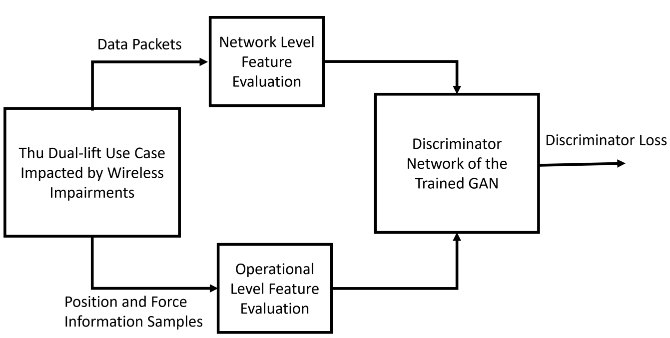

FIGURE 4: THE GAN DETAILED EVALUATION BLOCK DIAGRAM

4. RESULTS

In the results section, we consider the case of using the thirteen features from the operational metrics of the testbed. Specifically, we include the linear and angular position errors in all the xyz directions, the magnitude error, and the force and torque values of the metrology bar in the xyz directions as well. We collected, in this work, two data sets, namely, the normal behavior data where the testbed traffic is being transferred over the wireless network, and the case of having an interfering traffic stream of 48Mbps that shares the same WiFi network with the dual-lift use case.

4.1 GAN Parameters Setup

We built the generator and discriminator networks using long short-term memory (LSTM) networks with depth 3 and 100 hidden layers. For the training and testing of the GAN, we set the sequence length to 30, the number of epochs to 20, the batch size to 100, and the latent dimension to 25. The data set used include the normal behavior data of the 13 features that contains 15000 samples while the data for the case that is impacted by an interfering traffic has 13000 data sample of the same 13 features.

4.2 GAN Training Results

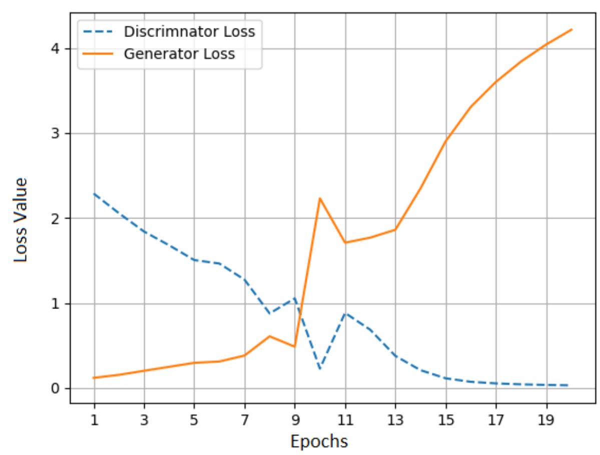

FIGURE 5: THE GENERATOR AND DISCRIMINATOR LOSSES EVOLUTION DURING TRAINING

In Fig. 5, the evolution of the discriminator and generator losses during the GAN training is presented against the epochs. This figure shows the convergence of the trained GAN and provides the discriminator loss and generator loss values for the normal behavior of the use case performance. The discriminator loss is defined as the mean negative cross-entropy between its predictions and sequence label, and hence, it is a decreasing function while training. On the other hand, the generator loss function is the independent cross entropy for the training data that increases by faking the discriminator and make it not able to distinguish real data. Hence, it is an increasing function while the generator is being trained. The equations for the loss functions, as defined in this work, can be found in [12].

4.3 Using Discriminator Loss in the Proposed Approach

The second set of the results provides a comparison between the discriminator losses when a wireless connection is deployed between the leader and follower when no other competing traffic is introduced and when interfering traffic over the same network is introduced. The interfering traffic has a data rate of 48 Mbps. In the following set of results, we use the trained discriminator to evaluate the performance of the network under two different interference levels. In the no interference case, we use a different test set than the one used in the training phase. In these experiments, we let the level of interference fixed during the whole time of the experiment and we compare the average performance of the two cases.

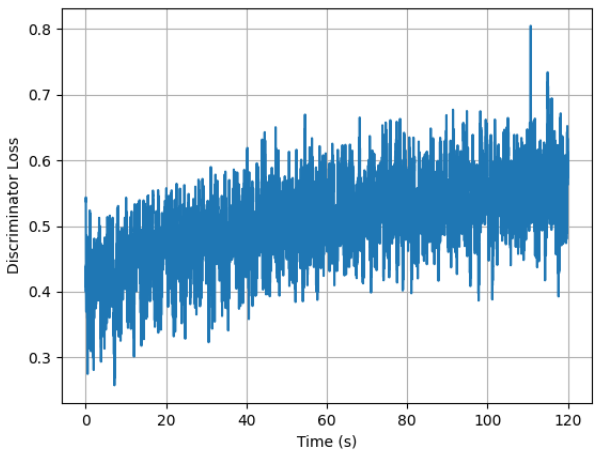

FIGURE 6: THE DISCRIMINATOR LOSS AGAINST TIME FOR WIRELESS TRANSMISSIONS WITH NO INTERFERENCE

In Fig. 6, the discriminator loss against time is presented when no interfering traffic is introduced. We can notice that a steady performance is achieved while few spikes happen due to the stochastic nature of the wireless channel. When interfering traffic is introduced, the discriminator loss in Fig. 7 has more time instances at which the discriminator loss deviates from the steady performance of the no interference case. Note that in this case, we do not have a labeled version of the data so these spikes on the discriminator loss curves cannot be compared to the physical variation of the channel but the increase on the number of these spikes in the case of interference reflects the expected more randomness on the wireless link when impaired by the interfering traffic.

Finally, in Fig. 8, we present the cumulative density function (CDF) for the discriminator for the cases of the leader-follower testbed performance with and without interference. The CDF is used to statistically compare the population of stochastic samples. In this case, the impact of interference on the performance is demonstrated by shifting the CDF curve to the right such that the discriminator loss is higher compared to the no interference case. It also shows that in this case, the deviation in performance due to the interference is not large in this case.

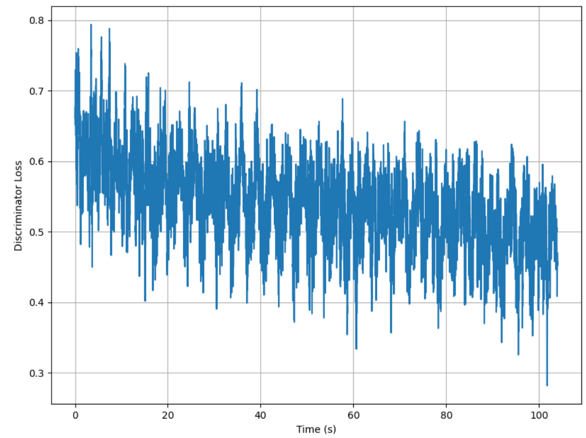

FIGURE 7: THE DISCRIMINATOR LOSS AGAINST TIME FOR WIRELESS TRANSMISSIONS WITH INTERFERENCE OF 48 MBPS

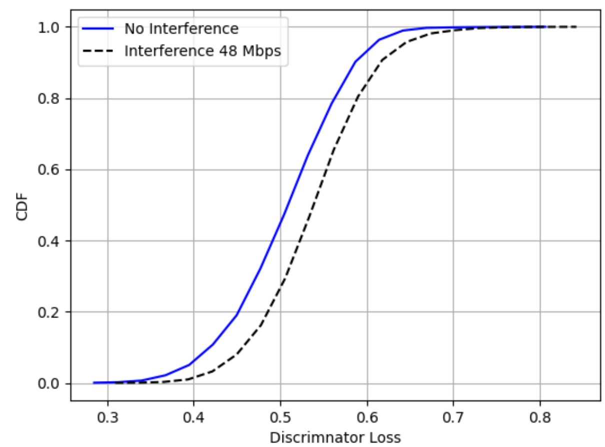

FIGURE 8: THE CDF OF THE DISCRIMINATOR LOSS FOR WIRELESS TRANSMISSIONS WITH AND WITHOUT INTERFERENCE

5. CONCLUSIONS

This work presents the initial prototype of the use of deep learning to study the system performance of an industrial wireless system. We deployed a GAN to model the behavior of the industrial system in order to use the discriminator loss to identify the deviation of the performance in different features when deploying various wireless communications scenarios. We have shown that the discriminator loss of a trained GAN can provide insights about the wireless communications state within an industrial use case. We plan to extend this work to identify and characterize industrial wireless systems through the inclusion of various operational, network, and spectrum features. Moreover, other post-processing metrics that use the discriminator loss time series are to be defined to identify the operating modes of the system.

DISCLAIMER

Certain commercial equipment, instruments, or materials are identified in this paper in order to specify the experimental procedure adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

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