Sensitivity Analysis of Predicting Wireless Channels within an Indoor Factory Floor

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***Abstract*—Industrial floors are becoming more reliant of wireless networks. These wireless networks must perform with strict requirements under harsh environments, such as heavy interference from machinery of high mobility in case of moving robots. This results in a high variation in the SNR of the wireless channels involved. Traditional means of determining the SNR rely on measuring periodically, thus this information becomes old in between measurements. Research into predicting the SNR of wireless channels has already been performed for regular wireless networks, but not for industrial applications. In this research the possible gains for prediction of throughput and reliability within an industrial wireless network have been investigated. This is done using a simulation of an industrial wireless network under realistic factory conditions. From the measurements of the throughput and packet loss of prediction methods and the state of the art, it was found that the theoretical throughput gain in some scenarios lies above 100% and even for a variance of around 5 Decibels in prediction level, a positive gain in both throughput and reliability was measured.**

1. Introduction

The industry is adopting more wireless networks for communication on the factory floor. This change is part of the 4th industrial revolution or Industry 4.0. The communication between machines is increased, and wireless sensors can be placed anywhere to improve the monitoring of factory floors. Robots are moving materials around and performing other complex task requiring a lot of communication between different parts of the factory. Such a network differs from consumer networks (GSM, 3G, LTE, etc.) in the fact that it should be a lot more reliable because inadequate communication might lead to property damage or even death of personnel. Apart from the stricter requirements, these networks also have to deal with a harsher environment (high temperature, metallic environment, etc.). Factory floors often deal with large amounts of interference caused by the heavy machinery and some connections might have a high mobility as robots move around. However, these connections are often required to be very reliable.

Furthermore, different applications within the factory floor require different network optimizations. A logging machine might only care about bandwidth, while a robot would require low latency and reliability as well. One of the ways to possibly increase stability and throughput of a wireless network is to have a better indication of the channel quality, which would result in more efficient use of the channel. As the industrial machinery which causes interference often operates on a known schedule, this could be used to guarantee reliable operation within harsh environment by scheduling communication of different application intelligibly. Before creating such algorithms which identify; predict and schedule communications, it would be beneficial to know the impact that these algorithms would have.

Therefore, this paper will focus on the research question: What is the performance gain for different fundamental networking aspects when applying interference prediction? two categories of fundamental aspects have been investigated, namely: reliability and throughput. Previous research has been done already on this subject [2], however this has not been adapted specifically to industrial floors yet.

Within this paper, we will look at the throughput and packet loss (reliability) for different mobility speeds, and how they will be affected by different levels of channel quality prediction. This is done using a single user system, where the transmission between a base station and a single end node is considered.

This paper is divided into 5 sections. In section 2, different research that relates to this subject will be reviewed to provide a background into this subject. In section 3, the strategy for answering the research question is discussed. In section 4, the different outcomes of the experiments are shown and discussed. and finally in section 5, a conclusion is drawn towards these results and further options are discussed.

2. Related Works

Wireless networks can have different data rates, depending on the Signal to Noise Ratio (SNR) of the wireless channel. A higher SNR allows for a higher bitrate without information loss. To estimate the SNR of a channel, an SRS

(Sounding Reference Signal) packet is being transferred periodically from the User Equipment (UE) to the Base Station (BS), which is then processed to estimate the SNR [1]. The time between SRS packets and the necessary processing delays cause a difference between the estimated SNR and the actual SNR, or SNR aging [2]. This mismatch in SNR leads to less than optimal use of the channel. Therefore researchers are trying to estimate the SNR as well, in order to get a more accurate match. The estimation of SNR is often based on predicting the mobility of users, as this has a large and predictable effect on the channel quality [3]. The result is that other sources of interference are not taken into account. As factory floors have multiple different sources of interference and the underlying mechanisms causing interference are not only based on mobility, new research needs to be done with a different prediction approach, specifically aimed towards factories.

SNR predictions in [2], [3] and [4] are based on gaussian distributions. As multiple researches use this strategy, it was decided that the research in this paper should also use a normal distribution to determine different levels of prediction, as explained in Section 3.4.1.

3. Methodology

To perform different measurements for the throughput and packet-loss, a simulation has been written in MATLAB using QUADRIGA (explained further in section 3.1). In there, an entire factory floor is simulated where different measurements are performed (explained further in section 3.2). There will be different controlled environment variables that will be controlled during this research (see section 3.3). Within this simulation, throughput and packet loss will be evaluated based on different methods to determine the SNR of the channel (see section 3.4). The State of the Art methodology (SOTA) will determine the SNR by sending SRS packets periodically to determine the SNR for the channel during that period. The prediction method will employ a normal distribution around the actual SNR value with varying variances and means, this will be further explained in section 3.4.1.

3.1. QUADRIGA

In order to generate realistic channels, QUADRIGA [5] is used. This is a quasi deterministic radio channel generator. With this tool, a channel response can be generated based on real measurements. This tool supports 3GPP indoor factory channel models based on real measurements and observations.

3.2. Simulation set-up

Within the simulation, a 50 by 50 meter factory floor with a height of 6 meter is simulated. A base station is placed at the ceiling in the center of the factory floor. For the simulation, QUADRIGA will be set up using an NLOS

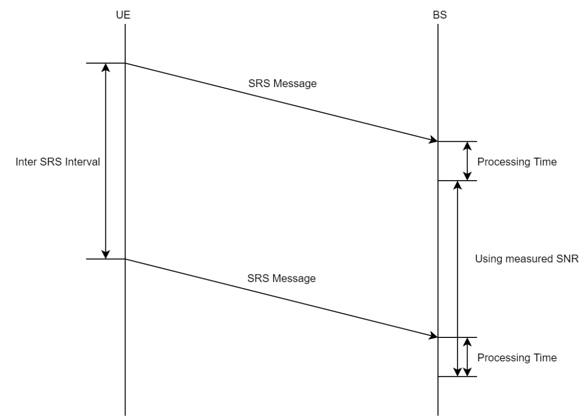


Figure 1: An overview of Inter SRS Intervals within the SOTA

(Non line of sight) configuration. The connection between a single user and the base station is considered. The channel response of this connection is generated by QUADRIGA with realistic background noise for factory floors, which is used to calculate a corresponding SNR for the connection.

3.3. Control parameters

Within the experiment different parameters will be varied to determine their effect on throughput and packet loss. The variables that will be evaluated are:

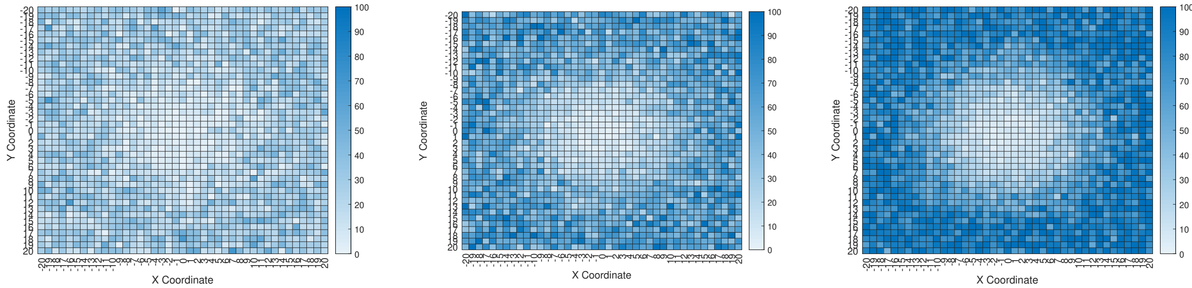
- Location dependence
- Mobility speed
- Level of prediction
- Length of Inter SRS Interval

The location dependence will be investigated by placing the user at different positions within the factory. For each position, the throughput and packet loss will be measured to find correlations. The mobility speed will be investigated by having the user move around its designated position. Users will move in circles around their determined position and the speed in which they walk these circles will be altered. The third variable that will change is the level of prediction. In this case that means that the variance of the prediction will change where a lower variance correlates to a better prediction. The exact details of this prediction can be found in Section 3.4.1. The fourth variable is the ‘inter SRS time’. This is the period between SRS packets that the SOTA will use to determine the channel SNR.

3.4. Output Parameters

The first and most important output parameter is the thoughput gain. The second is the packet loss.

3.4.1. Throughput gain. To determine the throughput gain, the throughput is determined for the SOTA as well as the



(a) The gain of 100% prediction vs the state of the art using an inter SRS time of 40ms and a mobility of 0.33m/s

(b) The gain of 100% prediction vs the state of the art using an inter SRS time of 40ms and a mobility of 1m/s

(c) The gain of 100% prediction vs the state of the art using an inter SRS time of 40ms and a mobility of 3m/s

Figure 2: The gain of 100% prediction vs the state of the art using an inter SRS time of 40 ms and different mobility speeds

prediction method. Both methods will send 1000 transmissions with 1ms in between to determine the total throughput. To determine the SNR of the channel, the SOTA will normally send a SRS message, process this for 4 ms and then use that until the next SRS message is received and processed. For an inter SRS interval of 20 ms, this would mean that the SOTA will select a new SNR value every 20 ms and this value is always 4 to 24 ms old. An example of this can be seen in Figure 1. This SNR value is then used to determine an appropriate 'Modulation Coding Scheme' (MCS) to determine the bit rate that the connection can handle. After which a successful transmission will be determined by combining the chosen MCS against the actual current SNR to calculate the chance that the packet was sent successfully and simulating this chance. By doing this for all 1000 transmissions, we can determine a throughput value by taking the successful transmissions and their corresponding bitrates.

For the prediction method, this works almost the same. The difference is that in this case the used SNR will be determined by a random distribution around the actual SNR. For different levels of prediction, different variances will be used. As with normal distributions, 50% of the results will lie above the actual SNR, compensation for this might be neccesary, therefore there should be a compensation within the offset of the mean [4]. As the SNR is in decibels, this offset can be added to the mean. Thus

$$predictedSNR \sim \mathcal{N}(SNR + offset, \sigma^2)$$

where the σ^2 or variance is used to express the level of prediction, higher values mean worse predictions. A perfect prediction, or a prediction level of 100% would mean a variance of 0 Decibels and as there is no case of overestimating when doing a perfect estimation, an offset is not required. For both the SOTA methodology and prediction methodology, throughput values are measured. In the results (section 4) the gain between the throughput for the SOTA and the throughput for the prediction method will be shown and discussed.

As an example, the actual SNR might be -5 Decibels at a certain moment. When selecting a variance of 2 Decibels, and an offset of 0, this would mean that the predicted SNR would be $\mathcal{N}(-5, 2^2)$ distributed. This would mean that half of the estimations would lie above -5 Decibels and would therefore select a higher bitrate than possible and result in packet loss. Thus a $\mathcal{N}(-6, 2^2)$ distribution might perform better at a true SNR of -5 Decibels.

3.4.2. Packet Loss. For the same situation, as the throughput, the packet loss will also be measured. Thus using the same strategies for determining the througput gain, the number of successful transmissions is noted down. As the packet loss can be decreased by systematically choosing a lower bitrate for each transmission, the most important consideration here is the tradeoff between throughput and packetloss. Thus for the experiment, we will mostly look at the packet loss for high throughputs. In practise this means that the packet loss, for the same variances and mean offsets as the maximum throughput gain will be measured.

4. Results and Discussions

We will first consider the impact on just the throughput of the prediction methods and afterwards discuss trade offs between both low packet-loss high throughput.

4.1. Throughput

4.1.1. Throughput gain for perfect predictions. We start by measuring the throughput of the SOTA against a perfect prediction of the SNR. This will show the maximum improvement that can be gained by prediction algorithms. In figure 2b we can see that the gain increases as we move away from the base station. This is expected as the signal is more stable close to the base station, thus the fact that the SOTA, which has a 4-44ms delay, as explained in Section 3.4.1, has less of an impact. figure 2a and 2c also show how different levels of mobility impact the throughput gain. When looking at the three different mobility speeds measured, it can be seen that a higher mobility increases the throughput gain. This is due to the SOTA being influenced by the mobility speed and a perfect prediction is not. As the SOTA performs worse under higher mobility because its measured SNR ages faster, the gain would increase

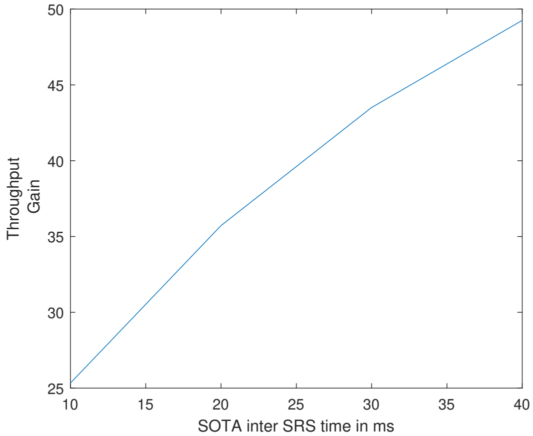


Figure 3: The average gain for all locations of 100% prediction vs the state of the art for different SRS intervals

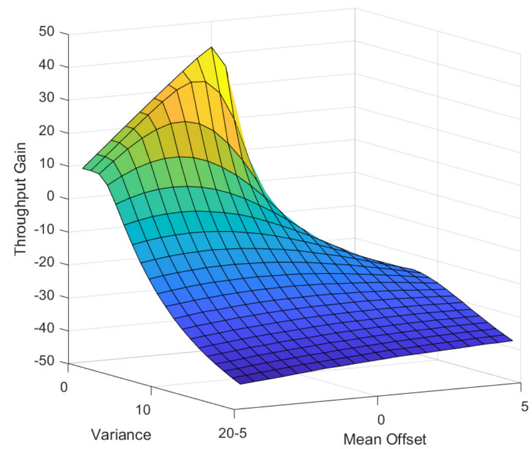


Figure 4: The gain of different levels of prediction over the state of the art for 40ms inter SRS interval

as the mobility would increase. However a non perfect prediction algorithm would most likely also experience reduced performance under higher mobility, depending on the algorithm. Therefore it is not possible to state that prediction is preferred under high mobility environments. In the following presented results, the gain will always rise for higher mobility as the variance of the prediction method is controlled and is therefore not influenced by the mobility. Normally a higher mobility would result in a higher variance of the prediction method, however as this paper does not include explicit prediction algorithms, the relation between the mobility and the variance of these algorithms is unknown.

The average gain within the entire factory floor for a 40ms inter srs interval is measured to be **49.25%**. In Figure 3, it can be seen that as the inter srs interval increases, the SOTA performs significantly worse, which is expected as it will rely on older information for its SNR estimation.

4.1.2. Decreased level of prediction. All results above have been collected using a 100% prediction level. The next results will show the gain in throughput using the methods described in Section 3.4.1 with different variances. In Figure 4 the gain for 40ms inter srs interval against varying levels of prediction is plotted. The purpose of this plot is to demonstrate that when selecting a different variance not equal to 0 (perfect prediction), an offset < 0 is required to achieve the highest throughput. For the sake of simplicity, in the next graphs, the offset will no longer be plotted but instead, the offset with the highest throughput will be selected for each step in variance.

4.1.3. Different Inter SRS Intervals. In this part different inter SRS intervals are evaluated. When taking the maximum throughput for each offset, with different levels of inter SRS intervals in the SOTA, this results in Figure 5. In this graph it can be seen that for an inter SRS interval of 40ms, a variance of around 4 Decibels already results in a positive gain in throughput with respect to the SOTA. This data is however for the entire factory, and as seen before, locations close to the base station experience less gain then locations further away.

4.1.4. Distance from Base station. The distance from the base station has a huge influence on the gain as was seen earlier in Figure 2. Therefore it is important to measure the gain of different levels of prediction, also for different locations. When looking at Figure 6a to 6c, it can be seen that the achieved gain can be much greater when moving away from the base station however, when the predictions get worse, the loss is also a lot greater. Therefore when implementing such a prediction algorithm, it must perform sufficiently, otherwise the results would be counterproductive. This tipping point seems to be around a variance of 5 decibels, however it increases slightly as the user moves

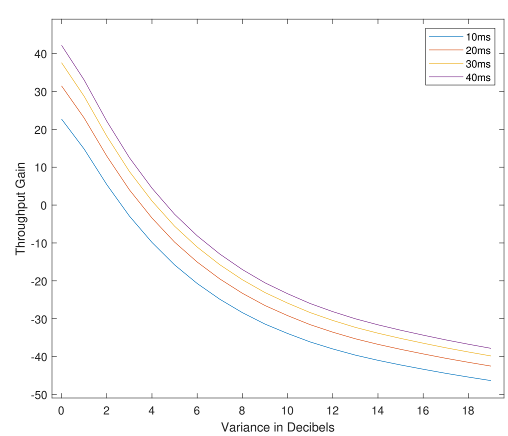
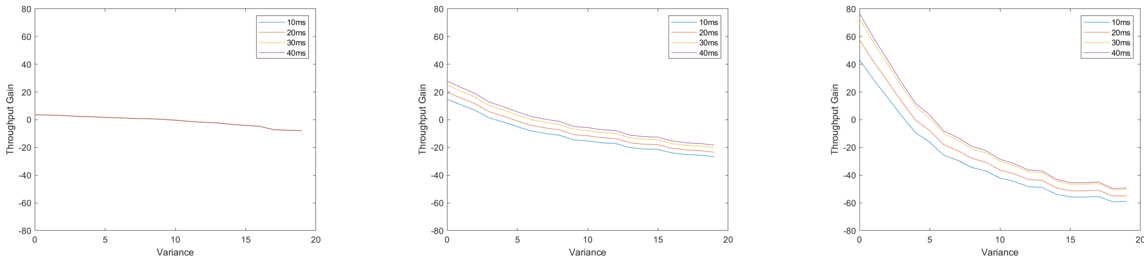


Figure 5: The gain of different levels of prediction vs the state of the art for different inter SRS intervals



(a) The gain of different levels of prediction vs the state of the art for different inter SRS intervals at 1 meter from the base station

(b) The gain of different levels of prediction vs the state of the art for different inter SRS intervals at 10 meters from the base station

(c) The gain of different levels of prediction vs the state of the art for different inter SRS intervals at 20 meters from the base station

Figure 6: The gain for different levels of prediction vs the state of the art for different inter SRS intervals and distances from the base station

closer to the base station.

4.2. Packet Loss

In this subsection, Packet loss will be discussed. Before this is done, it is important to realise that packet loss on its own is not an informative metric. As the channel bit rate could be decreased, it would be easy to get zero packet loss on any channel. Therefore packet loss should be discussed together with throughput in this case. Difference in packet loss for the same throughput would be much more informative. Secondly there are multiple ways to view packet loss. If a 1000 packets were sent of which one method successfully transmits 450 and the other method 900, one could state that the second method is twice as good. However when looking at packet loss, this results in 55% vs 10% packet loss, and suddenly the second methods seems 5.5 times better.

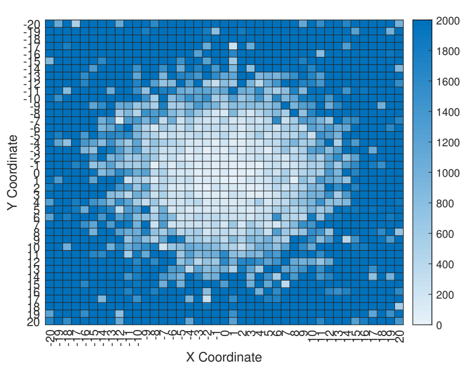


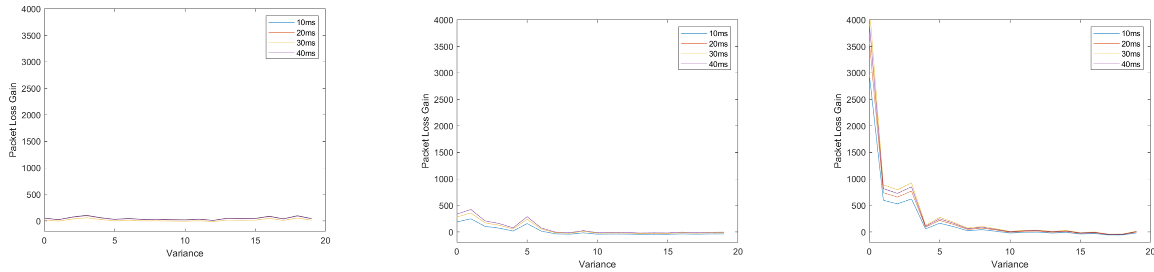
Figure 7: The gain in packet loss of the SOTA against 100% prediction for different positions in the factory.

4.2.1. 100% prediction. Again first the 100% prediction is discussed to estimate the theoretical maximum improvements that could be made. In Figure 7 the gain for the packet loss can be seen. A higher gain means that the SOTA loses more packets than the prediction method. This figure is generated for the same packets as the throughput in figure 2b, which means that a 100% prediction gives a great increase in the reliability of the channel, while also having a huge increase in throughput. This is to be expected for a perfect prediction, therefore it is also important to look at less than perfect predictions.

4.2.2. Decreased level of prediction and location dependence. In Figure 8a to 8c we have the same graphs as seen before in Figure 6a to 6c, but this time for packet loss. The most important notion for these figures is that instead of selecting the mean offset with the highest packet loss gain, the highest throughput gain is still selected. Therefore this data reflects the occurred packet loss corresponding to the throughput in Figure 6a to 6c. In this packet loss data, it can be seen that when predicting well and being further away from the base station, the reliability of the wireless channel could improve a lot.

5. Conclusion

This research aimed to find the performance gains within throughput and packet loss (reliability) when applying interference prediction. The results reflect that with a 100% prediction rate, gains in both reliability and throughput are possible (**49.25%** gain for throughput on average and over **2000%** gain in reliability for those same packets). From the different control parameters that were varied in the research, it can be concluded that all of them (Location dependence, mobility speed, level of prediction and length of Inter SRS Interval) have an influence on both packet loss and throughput. It was found that locations further away increase the gain of both throughput and packet loss. A higher mobility speed also results in a higher gain. The level of prediction has to be precise enough for the prediction method to outperform the SOTA (tipping point is located around 5 Decibels variance in the results). And as was known already, the length of the Inter SRS Interval has a huge influence on the performance of the SOTA, and therefore on the gain of both throughput and latency. The previously mentioned results indicate that a prediction



(a) The gain for a distance of 1m from the base station

(b) The gain for a distance of 10m from the base station

(c) The gain for a distance of 20m from the base station

Figure 8: The gain in packet loss of SOTA vs Prediction for different levels of variances and inter SRS times, seperated by distance to Base station

algorithm for the SNR on a factory floor could provide increased throughput and reliability, and thus research into these algorithms (specifically for factory floors) should be pursued.

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