The impact of data prediction schemes on the reduction of the number of transmissions in sensor networks

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Abstract

Future Internet of Things (IoT) applications will require that billions of wireless sensors devices, including smartphones and home appliances, transmit data to the cloud frequently. In such scenarios, the energy consumption at the sensor device side is no more the only key problem to solve, as the high contention for the spectrum resources in the uplink may be also the system bottleneck. Fortunately, both issues can be minimized by simply reducing the number of data transmissions from the sensors, which not only diminishes the energy consumption of the sensor nodes, but also keeps the spectrum utilization low. In this work, we present a sensor network model that uses statistical theorems to describe the expected impact of aggregating and predicting the data generated by sensors in Wireless Sensor Networks (WSNs). We aim to provide a foundation for future works by characterizing the theoretical gains of processing the sensed data and conditioning its transmission. Our simulation results show that the number of transmissions can be reduced by almost 85% in the sensor nodes with the highest workload, and we detail the impact of predicting and aggregating the transmissions according to the parameters that can be observed in average scenarios.

Keywords: sensor networks, data science, predictions, data reduction, model

1. Introduction

Wireless sensor nodes (sensor nodes, for brevity) are small computer devices with a radio antenna. They are often equipped with sensors that are capable of sensing one or more environmental parameters. As an example, temperature and relative humidity sensors are some of the cheapest and smallest sensor chips available, and are commonly used in real world applications. Sensor nodes are usually organized as a Wireless Sensor Networks (WSNs) in which the Gateways (GWs) are responsible for managing their operation and collecting their measurements. In the last years, several works addressed their constrained energy resources as one of the biggest challenges for embed applications [1]. A potential problem of having a sensor node running out of battery in a WSN is that the exact data they could produce would not to be available anymore. Such an impact can be better understood if we consider that most of the WSNs are data-oriented networks, i.e., the data that the sensor nodes can produce is their most valuable asset [2]. In case a sensor node is responsible for providing a communication bridge between its neighbors, its absence can—in the best case—make the other sensor nodes consume more energy trying to find new routes to the GW. However, occasionally, their role will be essential to keep the full connectivity in the WSN.

Besides the latest researches showing that the new technologies may be able to harvest energy from solar, mechanical and thermal energy sources [3, 4], Internet of Things (IoT) application scenarios will combine new services and dramatically increase the number of sensing devices, such as, among others, tiny sensors, smartphones, home appliances and vehicles [5]. In such situations, the efficient use of spectrum resources, as well as the energy consumption of the sensor nodes, is one of the key challenges that also affects the next generation of wireless networks, for instance, WLANs, 4G and 5G networks [6, 7, 8].

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In order to handle both challenges, we present a sensor network model for monitoring applications, based on the sensor nodes’ connectivity and their maximum distance to the GW in number of hops. Based on this model, we use statistical theorems to draw conclusions about how efficient is to shift one computing solution to the sensors nodes (i.e., both wireless sensor nodes and other IoT sensors): the data prediction. Our goal is to provide a sufficiently strong background on which future applications can rely to create smarter and more complex systems. In the next sections, we will evaluate the gains that can be obtained by reducing the number of transmissions and compare with the costs of choosing a certain prediction model, considering its expected (in)accuracy and the correlation between the measurements made by different sensor nodes.

We anticipate that object tracking and event detection applications are not under the scope of this work, because they usually have other requirements than those we assume in this model, such as higher reliability or lower delays [9].

The rest of the paper is organized as follows: Section 2 shows the current state of the art, giving a wider perspective and highlighting the contributions of this work; Section 3 details how we model the data using Normal distributions, which is fundamental for understanding the assumptions we will make further; Section 4 describes the network model; Section 5 describes the applications covered in this study; Section 6 models the transmissions and the energy consumption expected when adopting the data aggregation or the data prediction methods; Section 7 presents the experimental study and the simulation results; and Section 8 shows our conclusions and ideas for future work.

2. Related Work

Several works applied prediction techniques based on the data retrieved by the sensor nodes to substitute their communication. In the dual prediction schemes (firstly presented in [10, 11, 12]), the adoption of prediction models is made both in the GW and in the sensor nodes, based on the strong assumption that the energy necessary to execute an instruction is of some orders of magnitude smaller than the energy required by the radio transmissions in WSNs (which is shown in [13, 14, 15]). Such characteristics forces the applications to give a certain level of autonomy to the sensor nodes to compute their decisions locally, based on the available historical data, instead of transmitting every measurement to the GW. Once the sensor nodes can reproduce the same “a priori” knowledge as the GWs and locally compare the measurements with the predictions, they are able to decide whether the actual measurements will be transmitted to the GWs or not, based on the difference between the predicted and the measured values.

As soon as the dual prediction scheme was established, different prediction methods started to be tested in the sensor nodes, such as constant predictions, moving mean and exponential smoothing models in [16]. Within time, sensor nodes became less energy constrained and able to compute more powerful algorithms, and some works started to consider the use of more sophisticated prediction models, showing the transition from the first generation of wireless sensor nodes to the new generation of IoT devices. For example, in [17], the authors chose the traditional ARIMA as the method for making the predictions, which represents a higher computational cost to the sensor nodes in change of an increase in the predictions’ accuracy. In [18, 19], the authors deployed a real WSN using a dual prediction scheme and compared the energy saved by using different prediction methods, such as constant prediction models, weighted moving averages, ARIMAs and exponential smoothing. In their tests, the constant prediction models showed the best trade-off between accuracy and energy savings.

Nowadays, the works tend to increase the computational complexity of the predictions to improve their accuracy. For that, in [20], the authors suggested the use of an ANN model when the predictions using ARIMA fail. More recently, in [21, 22], the authors gave to the sensor nodes the ability of taking decisions locally using Gaussian Processes and stochastic gradient descent regression, which require much higher computational power than the traditional methods. Following the trend of adopting complex prediction methods in sensor networks, in [23], the authors incorporated information theory in their analysis and described a method that can accurately predict and evolve their prediction models.

Apart from the quality of the predictions, there are other variables that can impact the efficiency of the dual prediction schemes. For example, the number of transmissions required to distribute the prediction
models and/or their parameters, the power required to compute them, and the bit error rate and the quality of the channel used. So far, most of the works present a deductive reasoning, i.e., after describing their experimental results, the authors infer conclusions about how the network behaves. The model presented in this paper only assumes a dual prediction mechanism in which predictions can be computed both in the GW and in the sensor nodes and that, after a measurement, each sensor node is able to compare the measured values with the ones provided by the model and transmit them only when the prediction has failed. Our reasoning is based on mathematical theory that supports the analysis of the data observed in these scenarios.

The work presented in [24] was the first one to introduce statistical methods to choose which prediction model better fits to a certain environment. It considers the percentage of transmitted measurements \( r \) and the user desired level of accuracy \( \alpha \). Later, in [18], the authors designed an extended model for the Prediction Cost (PC), which is more generic and also considers the computational costs of executing each algorithm in the sensor nodes with respect to their memory footprint \( \text{Ec} \):

\[
\text{PC} = (\alpha f(e) + (1 - \alpha)r) \text{Ec}
\]  

where \( e \) is the measure of the predictions’ accuracy (e.g., mean squared error, root-mean-square deviation or symmetric mean absolute percentage error) and \( f(e) \) is the accuracy according to the measure chosen. The approach presented in [25] calculates whether it is worth to make predictions in the sensor nodes or not, based on the relation between the predictions’ accuracy, the correlation between measurements and the error tolerated by the user. It takes the parameters observed at a given moment as input in order to adapt the behavior of the nodes, which can vary among: (i) being in the sleep mode (and making no measurements); (ii) making measurements and transmitting every measurement done; and (iii) making measurements, transmitting them to the GW whenever the prediction differs by more than an accepted value, and updating the prediction model parameters when necessary.

To the best of our knowledge, this is the first work that models generic dual prediction schemes in sensor networks and show their potential as a whole class of applications.

3. Data model

A Normal distribution is characterized by its probability density function whose pattern is often encountered in several types of observations. According to the Central Limit Theorem, the sampling distribution of the mean of any independent random variable tends to be Normal, even if the distribution from which the average is computed is decidedly non-Normal. In [26], for example, the authors showed that environmental readings—such as temperature, light and humidity—done by outdoor WSNs can be approximated to normal distributions, if properly managed.

In this work, we will assume that a sensor network is composed by a set of sensor nodes \( S \) and each sensor node \( i \) (such that \( i \in S \)) is responsible for measuring a certain parameter from the environment, such that the set of observations follows a Normal distribution with mean \( \mu_i \) and variance \( \sigma^2_i \). By convention, this is represented as \( Y_i = N(\mu_i, \sigma^2_i) \). A prediction \( \hat{y}_i \) (for example, \( \hat{y}_i = \mu_i \)) can be calculated by the sensor node \( i \) and the GW. We define the accepted threshold \( \varepsilon_i \), i.e., the prediction is told to be correct if the real observation \( y_i \) is in the interval \( [\hat{y}_i - \varepsilon_i, \hat{y}_i + \varepsilon_i] \).

Assuming that the data is normally distributed, the chances of observing a new value inside the accepted interval can be calculated by normalizing the value of \( \varepsilon_i \), i.e., rewriting it in terms of the variance \( \sigma^2_i \) as

\[
z_i = \frac{\varepsilon_i - \hat{y}_i}{\sigma_i}
\]  

Thus, in this case, the accuracy of the predictions \( \alpha_i \) can be calculated based on the cumulative distribution function of the normal distribution \( \Phi \). Again, according to the Central Limit Theorem, we assume unbiased predictions and errors normally distributed. Thus, the percentage of observations that will fall outside the accepted interval is represented by the two-tailed Z-test (i.e., \( 2\Phi(-|z_i|) \)), and \( \alpha_i \) is

\[
\alpha_i = 1 - 2\Phi(-|z_i|). 
\]
By substituting the Equation 2 into Equation 3, we can observe that
\[ \alpha_i = 1 - 2\Phi\left(-\frac{\bar{y}_i - \bar{y}}{\sigma_i}\right), \] (4)
which shows that the accuracy of the predictions depends on the accepted threshold, on the mean and on the variance of the data.

Finally, based on the Law of the Large Numbers, in the next Sections we will describe a system’s behavior as a model using mathematical equations and assume that the average of the results obtained in random scenarios will be similar to our calculations.

4. Network model

Langendoen and Meier [27] presented a ring model for WSN topologies to describe a multi-hop network based on the average number of neighbors \( C \) of a sensor node and on the number of hops from the GW to the furthest nodes \( D \). The distance from the GW also defines in which ring a sensor node is placed. That is, since transmissions made by a component (either the GW or a sensor node) can reach neighbors that are up to 1 unit of length from it, to reach the GW from ring \( d \), a sensor node has to make a \( d \)-hop transmission. Therefore, assuming an uniform node density on the plane and defining it as \( C + 1 \) nodes per the unit disk, the first ring will contain \( C \) nodes, and subsequently the number of nodes \( N_d \) in ring \( d \) can be calculated based on the surface area of the annulus:

\[ N_d = \begin{cases} 0, & \text{if } d = 0 \\ Cd^2 - C(d - 1)^2 = (2d - 1)C, & \text{otherwise} \end{cases} \] (5)

The number of nodes in the sensor network is equal to \( CD^2 \) and, given that the first ring has \( C \) sensor nodes, it is expected \( C \) branches with \( D^2 \) sensor nodes each. In this work, each branch will be referenced as a sub-tree. As Langendoen and Meier also described, the expected number of direct children of a node in ring \( d \) (defined as \( I_d \)) does not depend on the value of \( C \):

\[ I_d = \begin{cases} 0, & \text{if } d = D \\ \frac{2d + 1}{2D - 1}, & \text{otherwise} \end{cases} \] (6)

---

1The region bounded by two concentric circles.
Figure 1 shows an example of a sensor network based on this model with $D = 3$ and $C = 5$. In this work, we will use a similar structure to derive the number of transmissions and the energy consumption models, based on the nodes’ positions. First, we define the set of children nodes of a node $i$ as $H_i$. Its expected cardinality does not depend on $C$ and can be calculated based on which ring the sensor node is located ($d$). Therefore, we define the expected size of $H_i$ as $K_d$, where $d$ is the ring in which the sensor node $i$ is. The value of $K_d$ is the number of direct children times the expected number of their children plus one (representing themselves):

$$K_d = \begin{cases} 0, & \text{if } d = D \\ I_d(K_{d+1} + 1), & \text{otherwise} \end{cases}$$

(7)

Note that, since the expected number of sensor nodes is $CD^2$ and the first ring is expected to have $C$ nodes, the expected number of children of the nodes in the first ring (i.e., $K_1$) is always $D^2 - 1$.

The sensor nodes in the first ring have the highest workload, i.e., they handle the highest number of transmissions. Because of that, in cases where the sensor nodes’ energy resources are constrained, those in the first ring are first to run out of battery, which can lead to the end of the communications in the sensor network.

As we mentioned in Section 2, some works have already shown that the energy necessary to execute an algorithm is of several orders of magnitude smaller than the energy required to make a radio transmission (either transmitting or receiving) in WSNs. Therefore, we assume that the number of transmissions and receptions made by the sensor nodes are the major concern in WSNs, not only due to the challenges to access the medium, but also due to the energy required for the external communication. Although these challenges are commonly observed in real-world irregular topologies, they are often neglected by other models (as we could observe in [26]), due to their complexity. Having said that, we highlight that the main advantage of this model is its simplicity to identify and describe the operation of the bottlenecks in a sensor network, i.e., the sensor nodes in the first ring. In the following, we carefully describe the number of transmissions and the energy consumption of an homogeneous sensor network based on it.

4.1. Energy levels

Supposing that no communication is made, a sensor node will consume the minimum energy ($E_{MIN}$) during a time unit, which consists on the average energy required for the minimum operation of each sensor node. In case of either transmitting or receiving, a sensor node will consume an extra amount of energy, respectively defined as $E_{TX}$ and $E_{RX}$. Such values may vary according to the hardware, the chosen MAC protocol and other (internal and external) factors.

We will assume that the GW has neither energy nor memory constraints, i.e., its energy resources and storage capacity are unlimited or, at least, significantly larger than in the sensor nodes. Hence, it is able to run compute-intensive algorithms without compromising the sensor network lifetime. Thus, the total energy consumed in a sensor network is proportional to the sum of the amount of extra energy used to transmit and receive the data from the sensors (disregarding the GW). It is modeled by the following equation:

$$E_{SN} = S_{SN}E_{TX} + R_{SN}E_{RX} + CD^2E_{MIN},$$

(8)

where $S_{SN}$ is the number of transmissions and $R_{SN}$ the number of receptions that occur in the sensor network during the considered period. Their values are proportional to the frequency of measurements ($f$) and the observed time period ($T$), and can be calculated based on the size of the network ($D$) and its node density ($C$).

4.2. Node-to-GW transmissions

In monitoring WSNs, sensor nodes transmit their data in a pre-defined interval that can vary from few seconds to hours. In the simplest approach, measurements are transmitted right after their creation, and
we use them as the baseline in our further comparisons. However, these transmissions, which we call node-to-GW, may not necessarily happen right after a measurement, in case the sensor nodes aggregate the data received from other sensor nodes or past measurements.

Given that sensor nodes must forward the information from their children towards the GW, the number of transmissions during a period of $1/f$ seconds in a sensor node in ring $d$ is $|K_d| + 1$ and the number of receptions is $|K_d|$. Thus, in $T$ seconds, the total number of transmissions and receptions of a sensor node in ring $d$ are:

\[ S_d = (|K_d| + 1) fT \quad (9) \]
\[ R_d = |K_d| fT \quad (10) \]

and its energy consumption is equal to

\[ E_d = S_d E_{TX} + R_d E_{RX} + E_{MIN} \quad (11) \]

Based on (7), we can affirm that $|K_1| > |K_d|$, if $d > 1$. Applying this inequality to (11), we mathematically show that, if $d > 1$, then $S_1 > S_d$, $R_1 > R_d$ and therefore $E_1 > E_d$, which shows that, in an homogeneous sensor network, the sensor nodes in the first ring run out of battery earlier than the others, reducing the network coverage and eventually limiting its lifetime. Therefore, we focus on modeling the number of transmissions and the respective energy consumption of the sensor nodes in the first ring in the following.

4.3. GW-to-node transmissions

GW-to-node transmissions are those initiated by the GW, for example, in order to change a configuration or update the software of the sensor nodes. Assuming one unicast transmission per packet, the sensor nodes in the first ring will receive and forward every GW-to-node transmission to their children. In case of transmitting a packet to every sensor node in the sensor network, the number of transmissions made by the GW to a sub-tree is $D^2$, i.e., the number of nodes in each sub-tree. Therefore, the number of receptions and transmissions required by a sensor node in the first ring to forward the transmissions from the GW to its children is

\[ R^* = D^2 \quad (12) \]
\[ S^* = D^2 - 1 \quad (13) \]

Thus, the extra energy consumed by such transmissions can be represented as

\[ E_{GW-to-node} = R^* E_{RX} + S^* E_{TX} \]
\[ = D^2 E_{RX} + (D^2 - 1) E_{TX} \quad (14) \]

If the packets of the same sub-tree are aggregated or if the GW uses broadcast (or multicast) transmissions, the sensor nodes in the first ring will receive only one packet that will be split before being retransmitted to the direct children in the second ring. In such cases, the extra energy required for the GW-to-node transmissions

\[ E_{GW-to-node} = E_{RX} + I_1 E_{TX}, \quad (15) \]

where, from [6], $I_1 = 3$, if $D > 1$. 

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Parameter | Description
---|---
f | Number of measurements per time slot
T | Time interval between the generation of new prediction models
C | Expected number of neighbors of each sensor node
D | Expected number of rings/hops of the sensor network
\( \rho \) | Correlation between the measurements in a certain sub-tree
\( \alpha \) | Expected accuracy of the predictions made by the GW

Table 1: Parameters taken into account to calculate the number of transmissions and receptions using the model.

5. Prediction schemes

In this work, we consider dual prediction schemes such that, in order to reduce the number of transmissions from the sensor nodes to the GW, the predictions are compared with the measurements in the sensor nodes, and the measurements are transmitted to the GW only in case of inaccuracy. This kind of scheme exploits the proximity of the sensor nodes to the sources of the data, avoiding unnecessary transmissions and handling occasional sensor nodes’ hardware limitations that could reduce the sensor network lifetime.

Figure 2 illustrates step-by-step how a generic prediction scheme works and more details are explained in the following. In summary, a dual prediction scheme has two tasks that may be executed either by the GW or by the sensor nodes, namely the **prediction model(s) generation** and the **prediction model(s) dissemination**, which details are explained in the following.

5.1. Assumptions and limitations

In this work we assume that the Quality of Information (QoI) can be scaled as “acceptable” if the values at the GW do not differ by more than a certain threshold. Since the sensor nodes can compare the predictions with the real measurements locally (without making any transmission), no transmission will be required if the prediction is accurate and does not differ by more than an accepted threshold from the measured value. Figure 2c shows both cases: the green points are inside the accepted threshold and, even though they are not exactly the same as the predicted value, the sensor node does not have to make any transmission. On the contrary, the red points fall outside the accepted threshold and must be reported by the sensor node in order to inform inaccuracy of the predictions.

In some cases, the system has no information about the statistics of the data which is going to be retrieved by the sensor nodes. Thus, it may be needed a learning phase before beginning to make predictions that also includes, for example, schemes that use advanced prediction methods, like Artificial Neural Networks (ANNs), which require larger amounts of data to find stable models, due to their high complexity and the large number of parameters to estimate [28]. We do not include this phase in this model, because we assume that the GW has no energy constraints.

Moreover, in our work, we do not expect distributed algorithms, i.e., the sensor nodes do not have to synchronize with their neighbors. However, this can be easily extended given the number of expected neighbors of each sensor node.

5.2. Prediction model(s) generation

A prediction method is a class of algorithms used to compute predictions given a set of parameters and the historical data as input [29]. Each set of parameters defines a prediction model, which is a deterministic function that depends only on the historical data to compute its output. In other words, it is possible to create different prediction models using the same prediction method. In our case, the prediction models are used to predict which values will be measured by the sensor nodes in the next period. Examples of prediction methods widely used are the Moving Mean, the AutoRegressive Integrated Moving Average (ARIMA) and the Exponential Smoothing, which are better explained in [30].

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In short, the number of measurements per time unit \((f)\), the interval between predictions \((T)\) and the other parameters shown in Table 1 may vary from case to case. For example, in [2a] we assume that the sensor nodes make one measurement per minute and either the GW or the sensor node predicts all measurements of a day, which means that 1440 measurements are predicted at a time.

In case that the prediction models are generated in the GW, the prediction method used can be chosen after considering the asymmetric resource availability in the sensor nodes. In other words, the extra storage capacity and computing power inherent to the GW can be exploited in this decision. For instance, ANNs are examples of prediction methods that are able to provide a higher accuracy, but they may not fit to the sensor nodes constraints, because they require a computation intensive training phase over a large amount of data. Simpler models, such as the average inside an hour-interval through a set of days, can also require a large amount of memory without providing good results if computed in the sensor nodes.

Finally, a decision about adopting a prediction model to summarize the future measurements can be done based on the expected amount of energy that can be saved. In the end, each sensor node can transmit or receive a message informing the prediction model parameters, if a model is expected to provide substantial energy savings, or otherwise a notification about the absence of prediction models.

5.3. Prediction model(s) dissemination

We assume that the prediction models can be either calculated in the sensor nodes or in the GW. In case that they are calculated in the sensor nodes, the GW must receive the parameter values and, in some cases, also the prediction method selected. On the other hand, if the GW is responsible for computing the prediction models, it must also inform the sensor nodes about the parameter values. We expect that the efficiency a prediction scheme depends on how many transmissions are required for this task, which is proportional to the number of hops between the sensor nodes and the GW. Therefore, from now, we will refer as dissemination to the process of transmitting the prediction model (either from the sensor nodes to the GW or from the GW to the sensor nodes) and it will be taken into account in our evaluation.

Assuming that the dissemination of a prediction model is made through an unicast transmission, the sensor nodes in the first ring will receive and forward every transmission to their children towards the proper destinations. That is, if the prediction models are calculated in the sensor nodes, their final destination will be the GW. Otherwise, if the prediction models are generated in the GW, they must be forwarded to the nodes’ children. Thus, given that the number of children of a sensor node in the first ring is \(D^2 - 1\), this will be the number of transmissions required for the dissemination when the prediction models are calculated in the GW and the sensor node in the first ring will receive \(D^2\) packets. Therefore, the extra energy required by the sensor nodes in the first ring to disseminate the prediction models to the GW can be represented as

\[
E_{\text{DIS-GW}} = R_{\text{DIS-GW}} E_{\text{RX}} + S_{\text{DIS-GW}} E_{\text{TX}}
= (D^2 - 1) E_{\text{RX}} + D^2 E_{\text{TX}}
\]  

(16)

In case that the prediction models are calculated in the sensor nodes, the sensor node in the first ring will make \(D^2\) transmissions to the GW and receive a total of \(D^2 - 1\) prediction models. Thus, the extra energy required by the sensor nodes in the first ring to disseminate the prediction models to the sensor nodes can be represented as

\[
E_{\text{DIS-SN}} = R_{\text{DIS-SN}} E_{\text{RX}} + S_{\text{DIS-SN}} E_{\text{TX}}
= D^2 E_{\text{RX}} + (D^2 - 1) E_{\text{TX}}
\]  

(17)

If packets to the same sub-tree are aggregated or if the GW uses broadcast (or multicast) transmissions, the sensor nodes in the first ring will receive only one packet that will be split before being retransmitted to the direct children in the second ring. In such cases, the energy required for the disseminations is

\[
E_{\text{DIS-GW}} = I_1 E_{\text{RX}} + E_{\text{TX}},
\]  

(18)
(a) The data that will be measured by a sensor node can be predicted either in the GW or in the sensor node.

(b) The prediction model can be a time series method [31]. In this example, we assume a simple model such that the parameters are the points in which the slope signal got inverted.

(c) Based on the prediction model, the sensor node and the GW are able to compute the same predictions. In this example, we interpolate the values to predict the other measurements.

(d) The sensor node can compare its measurements with the predictions locally. If a measurement falls outside the accepted threshold, it is transmitted to the GW.

(e) Only the measurements wrongly predicted (in red) are transmitted to the GW. The green points are not transmitted, because they are inside the accepted threshold. Here, the accuracy is around 0.8.

Figure 2: A dual prediction scheme.
where, from (6), \( I_1 = 3 \), if \( D > 1 \).

The prediction models must be transmitted from the sensor nodes to the GW or vice-versa. Such extra transmissions, besides generating traffic, may consume an extra amount of energy that may turn the prediction scheme into an inefficient option. Hence, either the sensor nodes or the GW can calculate whether adopting prediction models is really efficient given the extra transmissions provoked by the transmission of the prediction models and the expected number of wrong predictions.

5.4. Reporting measurements to the user

Figure 2b shows a set of parameters that could be used to predict the other values during a time interval. Once the parameters have been disseminated, the GW is able to provide information about their measurements to the user (or to an application attached to it). In order to keep the consistency, the GW must compute the same values as the sensor nodes, as illustrated in Figure 2c. Measurements eventually received from the sensor nodes take the place of the predictions once they fix the predictions’ inaccuracy.

Furthermore, when the GW receives a measurement (informing that the prediction was wrong), it can increment a local counter that would be used to assess the accuracy of the predictions and to decide whether to recalculate and retransmit the prediction model to the respective sensor node. This procedure is repeated until the time interval is over and a new cycle with new predictions is started (as explained in Section 5.2).

6. Transmissions and energy consumption

As described before, adopting a data prediction scheme can benefit the network not only by reducing the number of transmissions, but also its energy consumption, which may extend its lifetime. In this Section, we develop a formula to calculate the number of transmissions and the energy consumption in homogeneous networks, based on different possible approaches, one with no data aggregation in the intermediate nodes and another in which sensor nodes are able to aggregate transmissions and reduce the traffic load of the network.

6.1. Case 1: No data aggregation

Let us assume that \( \alpha_i \) is the accuracy of the predictions in sensor node \( i \), i.e., \( \alpha_i \) is the probability that a measurement of \( i \) matches to the prediction and does not have to be transmitted to the GW, and \( \alpha_i^c = 1 - \alpha_i \). Therefore, the expected number of transmissions and receptions made by the sensor node \( i \) is respectively \( (\alpha_i + \sum_{j \in H_i} \alpha_j^c) \) and \( (\sum_{j \in H_i} \alpha_j) \) during a time interval \( 1/f \) (i.e., between two measurements). Hence, the number of transmissions and receptions in a sensor node \( i \) during the observed time \( fT \) is represented by \( S_i' \) and \( R_i' \) as

\[
S_i' = \left( \alpha_i^c + \sum_{j \in H_i} \alpha_j^c \right) fT, \tag{20}
\]

\[
R_i' = \left( \sum_{j \in H_i} \alpha_j^c \right) fT \tag{21}
\]

and its energy consumption is

\[
E_i' = S_i' E_{TX} + R_i' E_{RX} + E_{DIS} + E_{MIN}. \tag{22}
\]

Notice that a low accuracy in the predictions used in the sensor nodes that are far from the GW has higher impact in the total number of transmissions and in the energy consumption of the network than a low accuracy in the predictions from sensor nodes in the first rings. However, in terms of number of
transmissions, the bottleneck is still in the nodes in the first ring. Therefore, let us define the minimum average accuracy \( \alpha_{\text{min}} \) which would make it possible to reduce the number of transmissions, according to the size of the network and its number of rings. This value can be used to define the maximum number of transmissions \( S'_{i,\text{max}} \) and receptions \( R'_{i,\text{max}} \) in a sensor node \( i \) in ring \( d \):

\[
S'_{i,\text{max}} = (1 - \alpha_{\text{min}}) + \sum_{j \in H_i} (1 - \alpha_{\text{min}}) = (1 + K_d) (1 - \alpha_{\text{min}})
\]

and

\[
R'_{i,\text{max}} = \sum_{j \in H_i} (1 - \alpha_{\text{min}}) = K_d (1 - \alpha_{\text{min}})
\]

As explained in Section 4, \( K_d = |H_i| \), for a sensor node \( i \) in ring \( d \). Finally, the use of predictions will reduce the number of transmissions and the energy consumption if \( E'_{i,1} < E_{i,1} \). After some mathematical development shown in Appendix A, we arrive at the following expression for the minimum average accuracy of the predictions:

\[
\alpha_{\text{min}} > \frac{E_{\text{DIS}}}{(D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) f T}
\]

In conclusion, a prediction scheme requires a minimum accuracy to ensure the reduction in the number of transmissions. As explained before, the values \( E_{\text{TX}} \) and \( E_{\text{RX}} \) may vary according to the hardware, the MAC protocol and the operational system, but usually they are not changeable after the deployment. Hence, the minimum accuracy is a lower bound that depends only on the network layout (i.e., the number of rings \( D \)), the frequency of the measurements \( f \) and the time between two predictions \( T \). If the accuracies of the predictions do not reach this limit, there will exist two actions to improve the network operation, either to set new values for \( f \) and \( T \), or to turn the prediction scheme off.

6.2. Case 2: With data aggregation

Additionally to prediction scheme explained in Section 5, it may be possible to adopt an aggregation scheme in the sensor nodes, making them able to aggregate the data received from their children and transmit only after making their own measurement. Thus, we model an aggregation scheme which will be used as a reference for comparison of the efficiency of the prediction scheme and that can also be adopted to enhance the gains provided by the predictions. First, we introduce a scenario with only two sensor nodes in order to clarify the normalization of the data and its application. Later, we extend the model to a more complex scenario with \( D \) rings.

6.2.1. Network with two sensor nodes

Let us consider a section of the sensor network with the GW and a sensor node \( i \) with a single child \( j \). We assume that their measurements follow the Normal distributions respectively represented by \( Y_i = N(\mu_i, \sigma_i^2) \) and \( Y_j = N(\mu_j, \sigma_j^2) \), which represents a Multivariate Normal (MVN) distribution and can be defined based on their correlation, i.e., the relationship between each pair of distributions. An illustration of the MVN distribution containing \( Y_i \) and \( Y_j \) is shown in Figure 3. Due to the sensor network topology, the transmissions from sensor node \( j \) can reach the GW only through the sensor node \( i \). Thus, every \( 1/f \) seconds, \( i \) may transmit to the GW if its prediction has failed or if it had happened to \( j \).

Assuming that the predictions are not biased, we may also approximate them to normal distributions and label an outcome as incorrect whenever a measurement falls outside the interval defined by the accepted
Figure 3: Values of $Y_1$ and $Y_2$ are correlated ($\rho = 0.7$), and each line represents a different density of points.

threshold $\varepsilon_j$. In such case, the probability that the sensor node $j$ will transmit (including its own measurement) after $1/f$ time units is $1 - \alpha_j$. Thus, after a period $fT$, the expected number of transmissions is

$$S_j'' = (1 - \alpha_j)fT,$$

which is the same number of receptions in $i$ ($R_i''$). The energy consumption of the sensor node $j$ can be calculated as the energy to transmit with no additional energy required for reception:

$$E_j = S_j'' E_{TX} + E_{MIN} + E_{DIS}$$

(27)

Similarly, sensor node $i$ will transmit if the prediction about its measurement fails (i.e., it falls out of the accepted threshold $\varepsilon_i$) or if the prediction in sensor node $j$ had failed and the real measurement has been received. In other words, there will be an transmission if at least one of the two predictions fail.

Given that the node $i$ is able to aggregate the transmissions, its total number of transmissions is not a simple sum as in the case without aggregation, because it depends on the correlation of their measurements. Let us assume that the correlation between $Y_i$ and $Y_j$ is defined by the Pearson correlation coefficient and represented by $\rho_{i,j}$. Therefore, to model the probability of having at least one wrong prediction, we must calculate the correlation matrix ($\Sigma$). It is defined as

$$\Sigma = \begin{bmatrix} \sigma_i^2 & \rho_{i,j} \sigma_i \sigma_j \\ \rho_{i,j} \sigma_i \sigma_j & \sigma_j^2 \end{bmatrix}$$

(28)

Finally, given the lower limits

$$l_i = \bar{y}_i - \varepsilon_i \text{ and } l_j = \bar{y}_j - \varepsilon_j,$$

(29)

the upper limits

$$u_i = \bar{y}_i + \varepsilon_i \text{ and } u_j = \bar{y}_j + \varepsilon_j,$$

(30)

and the correlation matrix ($\Sigma$), it is possible to calculate the following MVN probability:

$$F(y_i, y_j) = \frac{1}{\sqrt{|\Sigma|(2\pi)^2}} \int_{l_i}^{u_i} \int_{l_j}^{u_j} e^{-\frac{1}{2} \theta^T \Sigma^{-1} \theta} d\theta$$

(31)
Figure 4: The hashed rectangle in the center illustrates the points in which both predictions are correct.

The value of \( F(y_i, y_j) \) represents the probability that both predictions (in \( i \) and \( j \)) are correct and can be illustrated by the density inside the crosshatched rectangle in Figure 4. Thus, the probability that at least one prediction fails can be calculated as \((1 - F(y_i, y_j))\), and the value of \( S_i \) as \((1 - F(y_i, y_j))\). Finally, the energy consumption in sensor node \( i \) is modeled as

\[
E_i = S''_i E_{TX} + R''_i E_{RX} + E_{DIS} + E_{MIN},
\]

which may determine the sensor network lifetime.

### 6.2.2. Larger networks

Now, we will extend the example above to larger sensor networks. The correlation matrix \((\Sigma)\) of several data distributions can be calculated as

\[
\Sigma = \begin{bmatrix}
\sigma_a^2 & \rho_{a,b} \sigma_a \sigma_b & \cdots & \rho_{a,z} \sigma_a \sigma_z \\
\rho_{b,a} \sigma_b \sigma_a & \sigma_b^2 & \cdots & \rho_{b,z} \sigma_b \sigma_z \\
\vdots & \vdots & \ddots & \vdots \\
\rho_{z,a} \sigma_z \sigma_a & \rho_{z,b} \sigma_z \sigma_b & \cdots & \sigma_z^2
\end{bmatrix},
\]

and similarly to the two-dimensional model, the expected number of transmissions made by the sensor node \( i \) (represented by \( S''_i \)) depends on the probability of all predictions being correct (including its own), which can be calculated as

\[
S''_i = 1 - F(i, a, b, \ldots, z),
\]

where \( \{a, b, \ldots, z \in H_i\} \), and the function \( F \) is the MVN probability function integrated from the lower accepted limits to the upper accepted limits over the \( k = K_d \) distributions:

\[
F(a, b, \ldots, z) = \frac{1}{\sqrt{|\Sigma|} (2\pi)^{k/2}} \int_{L_a}^{U_a} \int_{L_b}^{U_b} \cdots \int_{L_z}^{U_z} e^{-\frac{1}{2} \theta^T \Sigma^{-1} \theta} d\theta,
\]

which can be efficiently calculated with the use of Monte Carlo methods for higher dimensions [32].

The number of receptions at the node \( i \) \((R''_i)\) is slightly different from the previous example, since now the sensor node may have several children in the next ring and their transmissions happen independently. Let
us define \( H'_i \) as the set of direct children of \( i \), which expected size is \( I_d \), as explained before. The expected number of receptions can be calculated as

\[
R''_i = \sum_{j \in H'_i} S''_j,
\]

and its energy consumption is defined by

\[
E''_i = (S''_i E_{\text{TX}} + R''_i E_{\text{RX}}) f T + E_{\text{DIS}} + E_{\text{MIN}}
\] (37)

Even though the function \( F \) has no closed formula, it is possible to set a lower bound based on a case when there is absolutely no correlation between the values measured by \( i \) and its children. When the correlation is equal to zero, the expected number of transmissions and receptions in sensor node \( i \) are the maximum possible:

\[
S''_{i, \text{max}} = 1 - \alpha^{1+K_d}
\] (38)

\[
R''_{i, \text{max}} = I_d (1 - \alpha^{K_d/I_d})
\] (39)

We claim that

\[
E''_i \leq (1 - \alpha^{1+K_d}) E_{\text{TX}} + I_d (1 - \alpha^{K_d/I_d}) E_{\text{RX}} + E_{\text{MIN}} \] f T + E_{\text{DIS}},
\] (40)

which means that a mechanism that aggregates the data is able to save more energy than the one that only makes predictions. Comparing (40) with (22), we have that for any \( \alpha \in [0, 1] \) and \( K_d \geq 0 \), it can be shown based on the proof detailed in Appendix B that \( (1-\alpha^{1+K_d}) \leq ((1+K_d) (1-\alpha)) \) and, hence, \( S''_{i, \text{max}} \leq S'_{i, \text{max}} \). Moreover, \( R''_{i, \text{max}} \leq R'_{i, \text{max}} \) and \( I_d (1 - \alpha^{K_d/I_d}) \leq K_d (1 - \alpha) \), which can be similarly proved to be true, since \( (K_d/I_d) \geq 1 \) when \( K_d > 0 \) and \( \alpha \in [0, 1] \). In case of being in the last ring, since there are no children \( (K_d = I_d = 0) \), no reception is made.

For now, we did not distinguish the energy consumption to transmit and receive aggregated transmissions from the case without aggregation. In a real implementation, they could be the same if we adopted simple aggregation functions, such as the maximum, minimum and the average of the measurements. In the next Section, for the simulations, we incorporate a different packet length and show that the mechanism the energy consumption can still be modeled in such cases.

7. Results

The model presented before can be used to calculate the expected behavior in a sensor network given the parameters shown in Table 1. The observed results can be used to draw conclusions about the effects of adopting a prediction or an aggregation scheme in a sensor network in terms of number of transmissions and energy consumption levels. In this Section, we show how the number of transmissions vary from scenario to scenario and finally compare the results obtained in simulations with those calculated using the model in order to corroborate its applicability.

7.1. Number of transmissions

As one can notice, the number of transmissions and the energy consumption in this model are highly attached to the correlation of the measurements made by the nodes in a sub-tree and the accuracy of their predictions. Assuming normally distributed values, the expected number of transmissions and receptions rely on the cumulative density functions of MVN distributions to calculate the probability that no transmission is made in a group of \( n \) nodes measuring data with correlation \( \rho \), as illustrated in Algorithm 1. Based on
Data: $n = \text{number of nodes}, \, \alpha = \text{accuracy}, \, \rho = \text{correlation}$

Result: $P(n, \alpha, \rho) = \text{probability that no transmission happens}$

if $n = 0$ then
    return $P \leftarrow 1$
else
    $q \leftarrow |\Phi^{-1}\left(\frac{1-\alpha}{2}\right)|$
    $Q \leftarrow \{q, q, \ldots, q\}_{1 \times n}$
    $Y \leftarrow \{Y_1, Y_2, \ldots, Y_n\}$
    $\Sigma \leftarrow \begin{bmatrix}
    1 & \rho & \cdots & \rho \\
    \rho & 1 & \cdots & \rho \\
    \vdots & \vdots & \ddots & \vdots \\
    \rho & \rho & \cdots & 1
    \end{bmatrix}_{n \times n}$
    return $P \leftarrow \Phi(Y, \Sigma, Q)$
end

Algorithm 1: Algorithm to calculate the probability that no transmission will be made.

These values and considering that the bottlenecks of a sensor network are in the nodes in the first ring, we calculate the number of transmissions in a sensor node $i$ in ring 1 as

$$S_i'' = \left( (1 - P(K_1, \alpha, \rho) f) + I_1 \right) T,$$

the number of receptions as

$$R_i'' = (1 - P(K_1, \alpha, \rho) f) I_1 f T,$$

which can also be used to calculate the energy consumption in the other cases, when predictions or aggregations are adopted.

In Figure 5a, we show how different values of $D$ can impact the number of transmissions in the first ring if the other parameters are not changed. In these simulations, sensor nodes make one measurement per minute and the GW predicts their measurements once a day during three days ($T = 3$). Therefore, 4320 measurements are expected, which 1440 ($= f$) happen between each model generation. Finally, GW-to-node transmissions were aggregated. We assume that the connectivity between the sensor nodes does not vary when the size of the sensor network changes, following the proposed model.

Let us categorize the tests into two sets:(i) with (some) prediction and no aggregation; and (ii) with aggregation, but no prediction. The results show that the number of transmissions does not depend on the density of sensor nodes ($C$), but on the number of rings ($D$). Furthermore, the number of transmissions increases exponentially (as well as the number of sensor nodes) when new rings are added, if the aggregation is not adopted. On the other hand, the number of transmissions is constant and independent of the number of rings, if the transmissions are aggregated. When the predictions are highly accurate and the number of rings is small ($D \leq 4$), the aggregations are not enough to significantly reduce the number of transmissions, if compared with the scenario with high accuracy (0.9), as highlighted in Figure 5b. However, for larger sensor networks, the use of aggregation reduces the number of transmissions to a level that cannot be achieved even in the case of the highest accuracy considered (0.95), as shown in Figure 5a.

Similar results were observed by the authors of [33], but they did not realize that the predictions had less impact in the final savings and concluded that such optimal achievements happened due to the high accuracy of the predictions. However, as we can observe here, the aggregation scheme plays a major role in the results. To detail the power of the aggregation scheme, we considered a sensor network with 5 rings in which the aggregation scheme produces nearly the same number of transmissions observed in the scenario with the most accurate predictions. In Figure 6, we highlight the gains obtained by adopting both schemes. First, we observe that the number of transmissions can be reduced to 15% of its maximum in the best scenario, where the predictions are highly accurate and the measurements in the sub-tree are highly correlated. Additionally,
(a) The aggregation reduces the number of transmissions from quadratic to linear order.

(b) When number of rings is small ($D \leq 4$), the use of predictions can lead to less transmissions than the aggregation scheme.

Figure 5: The impact of the network size in the number of transmissions.

we did not observe any significant gains when the predictions are less accurate (around 0.5) nor when the predictions are more accurate (around 0.7) and the correlations are less than 0.7. Finally, increasing the accuracy from 0.5 to 0.9 with an average correlation (0.5) reduced around 30% of the transmissions, while increasing the correlation from 0.5 to 0.9 with an accuracy of 0.5 reduced only in 6.5% the number of transmissions, which illustrates that the impact of making accurate predictions is much higher than having a high correlation between the measurements.
7.2. Energy consumption

The energy consumption in the sensor nodes in the first ring is addressed as the bottleneck of some sensor networks’ lifetime and it was the one considered in the plots. Thus, in order to show the potential of this model, we simulated 3 days of a homogeneous sensor network with the same topology described in Section 4.1 with $D = 5$ and $C = 3$, which sums up to 75 sensor nodes plus the GW. The efficiency of the aggregation scheme explained in Section 6.2 depends on the correlation between the measurements in a sub-tree. In order to show their differences, we simulated different correlations among their measurements: $\rho \in [0.1, 0.2, \ldots, 0.9]$ and $\rho = 0.95$.

In our simulations, we calculated the extra energy necessary to make transmissions and receptions in a WSN, based on TelosB nodes [34] simulated using a TDMA-based MAC protocol in OMNET++ [35]. In the MAC protocol adopted, each sensor node has a reserved slot to transmit. Therefore, we do not expect collisions during the transmissions and there is no overhearing. We point out that other MAC protocols may obtain different results, due to concurrent transmissions, although similar gains could be expected.

In the model, the number of children is used to define how many distributions will be used, which means that decimal values cannot be considered. Hence, we rounded all of them up to the next integer, which resulted on an upper bound for the number of transmissions in the simulations. We highlight that the aggregation scheme may require larger packets to accommodate all the aggregated information in a transmission, which would mean higher values of $E_{\text{TX}}$ and $E_{\text{RX}}$ in comparison with the non-aggregated transmissions. In our simulations, we used packets with 8 times the payload of the normal packets.

In Figure 6, we can see that simply adopting the aggregation scheme (without making predictions) reduces the extra energy consumption to 60% of the total, yet larger packets are used. The greatest gains, nonetheless, are obtained after adopting the predictions and the aggregation scheme: they can save up to nearly 92% of the energy consumed by the transmissions. As explained before, the accuracy of the predictions are more significant and have higher impact than the correlation between the measurements in a sub-tree. Hence, a very low correlation ($\rho = 0.1$) with highly accurate predictions ($\rho = 0.95$) gives better results than a high correlation ($\rho = 0.9$) with an average accuracy ($\rho = 0.5$).

Regardless of the values shown in the plot, the amount of energy saved depends on the hardware of the sensor nodes, their operational system and the chosen MAC protocol, besides other configurations. Nonetheless, it is mainly driven by the relation between the minimum energy necessary to keep them making...
8. Conclusion and Future Work

In this work, we presented a mathematical framework to calculate the gains and benefits of adopting a data prediction scheme, in terms of number of transmissions and energy consumption in a sensor network. Our model relies on theoretical statistics and can be used to exploit the characteristics of the sensor networks to adopt predictions to improve the use of the channel resources by a sensor network and its lifetime. Differently from most of the works about this topic, we base our assumptions on the statistical theory to develop a framework for the future applications that will be build on the top of the sensor networks and rely on their efficiency.

The model shows that, in terms of transmissions, the benefits of adopting an aggregation scheme are greater than using only predictions, and that combining both leads to the highest savings. For example, as observed in Figure 7, the energy consumed by making transmissions and receptions in the bottlenecks (i.e., the sensor nodes in the first ring) can be reduced by nearly 85%. This result is achieved when accurate predictions are made by the GW and the intermediate transmissions are aggregated in the nodes. Moreover, our simulations also show that the accuracy of the predictions impacts more than the correlation between the measurements made by the sensor nodes.

Considering that this model has been designed to represent different types of sensor networks, there are some challenges to set up the best parameters for each use case. From our experiments, we expect that the critical points to calculate such values for a real scenario may vary between: (i) finding the precise correlation of the measurements; (ii) approximating the measurements to normal distributions, since it may require some data analysis in advance; (iii) having restrictions about changing the operation of some sensor nodes, because they may be fundamental for the sensor network connectivity and its QoI; and (iv) calculating the energy necessary for each step (i.e., transmission, reception, etc.), since details in the software and hardware implementations may influence such values.

On the other hand, the model provides means to endorse the adoption of predictions to reduce the number of transmissions in sensor networks and extend their lifetime. The backbone of the model consists of an application of two statistical theorems: (i) the central limit theorem, which supports the normalization of the data measured by the sensor nodes; and (ii) the law of large numbers, that allows the extrapolation to average scenarios.
We plan to include this model in a larger system that is able to improve the accuracy of the predictions made by the GW after consulting external sources of information. In the future, a more complete system will be able to choose the best mechanism to evaluate the QoI provided by a sensor network. Finally, all these features make it possible to run self-managed systems that adapt the sensor network’s operation according to their surroundings (and not only based on the observed environment) in order to achieve the best results, i.e., the highest QoIs and the lowest energy consumption possible.

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Appendix A. Minimum average accuracy

Let us suppose that a sensor node \( i \) is in ring \( d \). The minimum average between the accuracies of its children (\( \alpha_{\text{min}} \)) necessary to decrease the number of transmissions using a dual prediction scheme must satisfy the following equation:

\[
S'_i + R'_i + S^* + R^* < S_i + R_i \\
(K_d + 1) \alpha_{\text{min}}^c + (K_d \alpha_{\text{min}}^c) fT + < (K_{i,d} + 1) fT - (S^* + R^*) \\
\alpha_{\text{min}}^c (D^2 + (D^2 - 1)) fT < (D^2 + (D^2 - 1)) fT - (D^2 + (D^2 - 1)) \\
\alpha_{\text{min}}^c < \frac{(D^2 + (D^2 - 1))(fT - 1)}{(D^2 + (D^2 - 1)) fT} \\
\alpha_{\text{min}}^c < \frac{fT - 1}{fT} \\
\alpha_{\text{min}}^c < 1 - \frac{1}{fT} \\
\alpha_{\text{min}}^c > \frac{1}{fT} \\
\alpha_{\text{min}} > \frac{1}{fT} \\
(A.1)
\]

Furthermore, the minimum average between the accuracies of its children (\( \alpha_{\text{min}} \)) necessary to make the mechanism save energy must satisfy the following equation:

\[
S'_i E_{\text{TX}} + R'_i E_{\text{RX}} + E_{\text{DIS}} < S_i E_{\text{TX}} + R_i E_{\text{RX}} \\
(K_d + 1) \alpha_{\text{min}}^c E_{\text{TX}} + (K_d \alpha_{\text{min}}^c) E_{\text{RX}} fT + E_{\text{DIS}} < (K_{i,d} + 1) E_{\text{TX}} + K_d E_{\text{RX}} fT \\
\alpha_{\text{min}}^c (D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT < (D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT - E_{\text{DIS}} \\
\alpha_{\text{min}}^c (D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT < (D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT - E_{\text{DIS}} \\
\alpha_{\text{min}}^c < \frac{(D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT - E_{\text{DIS}}}{(D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT} \\
\alpha_{\text{min}}^c < 1 - \frac{E_{\text{DIS}}}{(D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT} \\
\alpha_{\text{min}} > \frac{E_{\text{DIS}}}{(D^2 E_{\text{TX}} + (D^2 - 1) E_{\text{RX}}) fT} \\
(A.2)
\]

where the value of \( E_{\text{DIS}} \) depends on where the prediction models are generated and may be modeled by (16), (17), (18) or (19).
Appendix B. Proof of $1 - \alpha^x \leq x \ (1 - \alpha)$

Let us assume two values $\alpha$ and $x$ such that $\alpha \in [0, 1]$ and $x \geq 1$. We want to show that $1 - \alpha^x \leq x \ (1 - \alpha)$:

\[
\begin{align*}
1 - \alpha^x &\leq x \ (1 - \alpha) \\
1 - \alpha^x &\leq x - \alpha x \\
-\alpha^x - 1^+ &\leq x - \alpha x \\
\alpha^x &\geq 1 - x + \alpha x \\
\alpha^x &\geq 1 + x (\alpha - 1) \\
\end{align*}
\]

(B.1)

When $\alpha = 0$ or $\alpha = 1$, we can easily observe that the affirmation is true, because $x \geq 1$ by definition.

For the other values of $\alpha$, we can use the Bernoulli’s inequality [36]:

\[ (1 + i)^j \geq 1 + ij, \quad (B.2) \]

where $i > -1$, $i \neq 0$ is a real number and $j \geq 2$ an integer value. Substituting the values of $\alpha$ and $x$ in Equation [B.1] respectively by $i + 1$ and $j$, the claim is proved.