

Detection of False Data Injection in open wireless sensor networks using subjective logic

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Abstract

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1 Introduction

1.1 Motivation

1.2 Problem Statement

2 Preliminaries

2.1 Subjective logic

2.1.1 Definition

Subjective logic is a logical mathematical framework that extends the probabilistic logic. Subjective logic preserves the capability of probabilistic logic to form logical statements and arguments while adding the capability to represent second-degree uncertainty. For further elaboration in probabilistic logic, we can represent the possibility of each outcome of an experiment as a value $\epsilon[0, 1]$. However, it ignores the reliability of the sources and sufficiency of the information we had before drawing the conclusion about these possibilities. The point where subjective logic extends probabilistic logic to handle is this second degree of uncertainty when we are not just lacking the certainty in the outcome of the experiment we also lack the certainty in the possibilities of the outcome of our experiment. In subjective logic, we can represent our belief in those possibilities making it very powerful tool in representing systems with uncertainty such as trust networks which we are using in our work.

2.1.2 Opinions

Subjectivity in the real world sprouts from having incomplete information, for the purpose of this work we will refer to information as evidence from now on, and draw opinions based on this evidence. Naturally, the chosen building block of subjective logic is the opinion. Opinions can be either binomial having only two possible outcomes, multinomial having multiple possible outcomes or hypernomial which having composite output consisting of many single simple possible outputs. In the work done in this thesis, we are only using binomial opinions. A binomial opinion is represented by a 4-tuple $\omega_X^A = (b, d, u, a)$. Where ω is the opinion statement. A is the opinion holder. X is the statement the opinion subject. The b is the belief in the opinion statement. The d which is the disbelief in the opinion statement. Then we have u the uncertainty about the statement. And a which is the base rate of our the probability of the statement being true without regard to the amount of information we have. The additivity requirement for an opinion is.

$$b + d + u = 1 \quad (2.1)$$

As clear from this from the chosen components of the opinion especially the belief, disbelief and uncertainty we can represent the main factors that affect subjectivity specifically

2.1.3 Projected Probability

In the context of binomial opinions, we can simply define projected probability as the probability that the opinion statement is true by taking into consideration our belief and the uncertainty in our the opinion statement. This clear from the equation to calculate his probability.

$$P(x) = b_x + a_x u_x \quad (2.2)$$

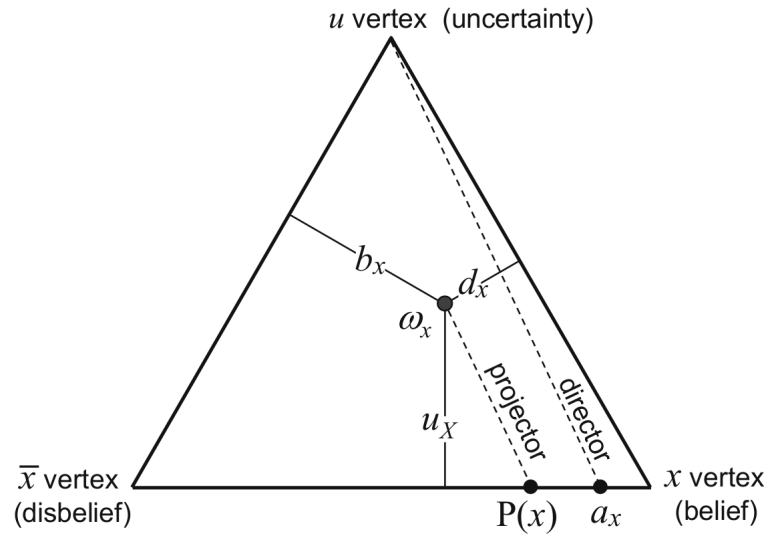


Figure 2.1: Barycentric triangle visualisation of binomial opinion [13]

2.1.4 Belief

While in literature belief calculation can differ according to the system according to the cause and the intended use, There are some formal methods of calculating belief including using evidence for and against the truth of our statement. Where r_x represents evidence for. s_x represents evidence against and W represents the non-informative weight; which is used to represent the element of uncertainty by putting a weight for it against the weight of the evidence [13].

$$b_x = \frac{r_x}{r_x + s_x + W} \quad (2.3)$$

2.1.5 Cumulative operator

There are many operators in subjective logic to be able to be able to operate on opinions and help make decisions. One essential operator for our work is the cumulative operator which is used when we have multiple opinions about the same statement from different independent sources to fuse these opinions and form one new more trusted opinion. The symbol for the cumulative operator is \oplus .

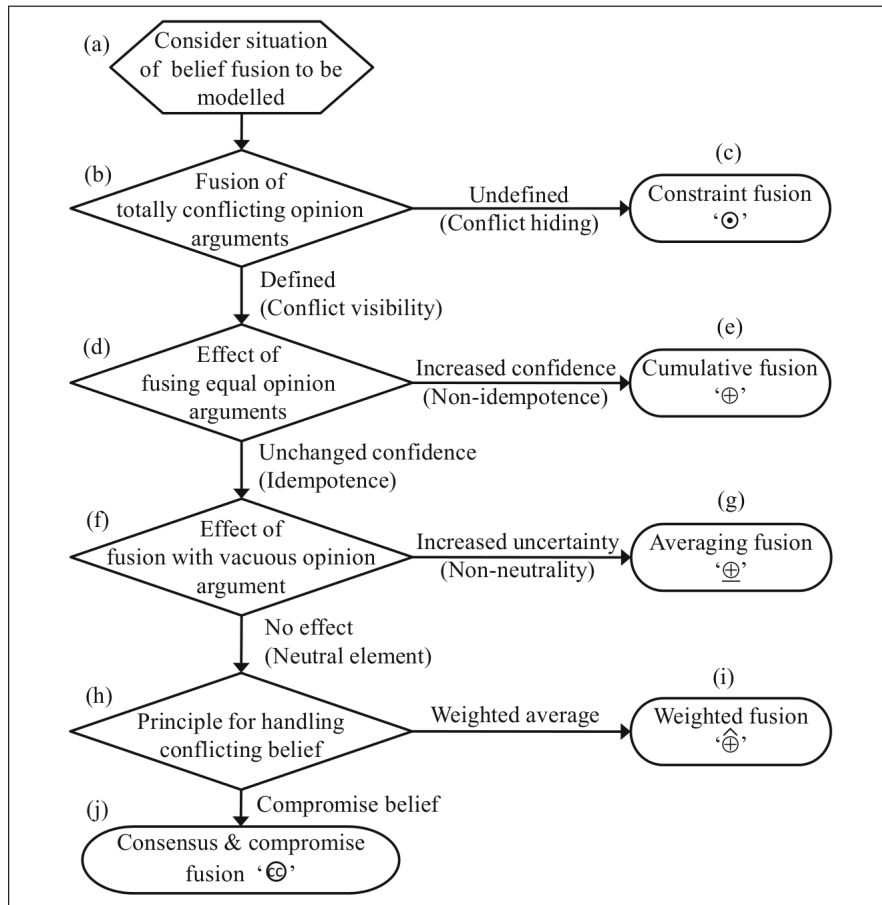


Figure 2.2: Procedure for selecting the most adequate fusion operator [13]

2.1.6 Transitivity operator

Transitivity operator is used for trust discounting. First, we explain two types of trust functional trust and referral trust. Functional trust is due to direct interaction with the subject of trust while referral trust comes from the subject of trust being referred to the trusting entity by an intermediate entity. so we use the transitivity operator to discount

the intermediate entity's trust in the subject of trust according to the end entity's trust in the intermediate entity to create a derived functional trust which is a direct trust link between the end entity and the subject of trust.

One good example to explain this using by [13], is if Alice just moved to town and needs to go to the mechanic but she does not know any good mechanics. However, her co-worker Bob has his car in a good condition. So, she asks Bob for a good mechanic and he refers her to Eric. Now, there are two people who trust Eric with different levels. The first is Bob's functional trust in Eric because he maintains his car. And, the second is Alice's referral trust in Eric because Bob referred him to Alice so normally this trust is affected by how much Alice trust Bob.

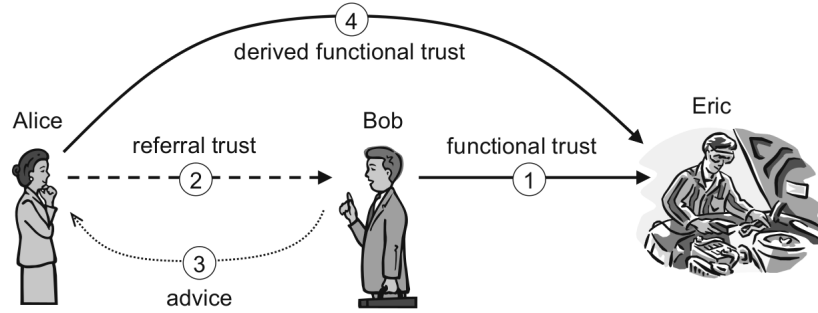


Figure 2.3: Transitive trust principle [13]

2.2 Particulate matter

2.2.1 Definition

Particulate matter or more commonly known as fine dust, are small particles of dust that exists in the air. The existence of particulate matter in high concentrations is considered polluting to the air. As people being exposed to high concentration of particulate matter causes many health complications over time. Particulate matter is classified into three categories according to their size being $PM_{0.5}$, $PM_{2.5}$, PM_{10} where the suffix number signifies the particle having a diameter of the suffix or less. In 2008, the European Union issued a directive stating the standards of air quality and the allowed concentrations of air pollutants [7]. In the mentioned directive, it was stated that $PM_{2.5}$ should be limited to an average concentration of $25\mu g/m^3$ annually later reduced to $20\mu g/m^3$. And in the extension for this directive in 2011, it was stated that PM_{10} should be limited to an average concentration of $48\mu g/m^3$ annually and $75\mu g/m^3$ daily permitted to be exceeded only 35 times per year. In this thesis, we work on forming an estimation of particulate

matter level within a certain area. There is a body of work that tried to develop a mathematical model to predict levels of particulate matter. Some examples are the work done by Tian et al. in [20] and that done by Yanosky et al. in [21]. However, Sensors are more interactive and can provide information about real-time unexpected events that can not be included in a mathematical such as construction work.

2.2.2 Sensor

We decided to use gp2y1010au0f sensors because it is the best cheap option according to [2]. First, we have to clear that this a sensor that reads the amount of dust in the air. The sensor does not have the ability to distinguish between different particle sizes [3]. However, this sensor can be calibrated to read both PM2.5 and PM10 by deriving calibration coefficients [3]. The results of testing the sensor were meaningful in terms of accuracy and precision. However, there are some problems that should still be fixed such as in cases of high-level humidity or any other light scattering problems which leads to reading bigger particle diameter than the one measured. In conclusion, noting in our prototype we only care about how much an attacker can change the actual readings and assume normal weather normal conditions and with careful deployment and careful calibration, this sensor can give us readings with high levels of accuracy and precision enough to test our security system on.

2.3 Open Networks

2.3.1 Definition

Our Definition for the term open network here is a network where anyone can participate and make use of its resources, for example in the work done in this thesis we develop an application that monitors fine dust concentration in the air by taking sensor reading at different points and produces a reliable estimation of the fine dust in the area. The term opens means that if anyone wants to deploy a sensor and send readings to the application to make the application's output more reliable they can easily do that without having to contact anyone or going through any kind of procedures.

2.3.2 LoRa and LoRaWan

LoRa and LoRaWan make us capable of creating our open network easily. According to the LoRa alliance in [1]. LoRa is a physical layer technology that is capable of long range communication. One LoRa gateway can cover hundreds of square kilometers. While LoRaWan is the communication protocol built on top of it to optimize battery lifetime of Internet of things nodes, usage of network capacity and maximize the quality of service. To summarize, using few gateways we could create low power wide area network

-LPWAN- which is a perfect for wireless sensor networks as the sensors operate with low power and send small chunks of data at a time.

2.3.3 TheThingsNetwork

TheThingsNetwork utilized all of this to create an actual open network [18]. On TheThingsNetwork, anyone can use the existing network resources from gateways and backend servers. This is done by deploying your own sensors and send them to your own application without needing to deploy network resources. While this approaches our definition for open networks it does not completely fulfill it. Because you can not simply deploy a sensor and extend the application to your area by registering the sensor. However, this can be simply achieved by simply publicly sharing the application key so anyone can register their sensor to the application. We also have to mention that security measures such as an end to end encryption are taken within TheThingsNetwork so that the network or the data traveling in it are not comprised [19]. In conclusion, the open network as we explained is already implemented and we are currently looking in how to secure the application functions within it.

2.4 Attacker Model

We consider that our attacker has full access to all information sent by the sensor and can change it freely according to his will. This data includes the position of the sensor. However, we do not consider any case where the attacker changes the sensor's position because we consider sensor readings as an estimation of particulate matter level within a certain area. Accordingly, where does the sensor position exactly within this area is irrelevant to our work. Noting that determining that the best way to divide large landscapes into smaller pieces will be left to future work. Also, attacks where the attacker changes the time-stamp are not considered because the data has to be real-time data. In conclusion, the work done in this thesis only consider attacks where the attacker the actual level of particulate matter or the battery level of the sensor.

3 Related Work

As mentioned in the introduction in chapter 1, the work done in this thesis has two connected goals. The first is detection and mitigation of false data injection attack in our system. The second is investigating the capability of subjective logic to deal with the previously explained conditions of the system to achieve the first goal. Our literature review focused on the work done to detect false data with that have similar features and those who tried to use subjective logic to guarantee the data quality.

Our literature review started with looking into work done in the detection of false data injection attack with some similarities in the system. A lot of work has been done in the mitigating the effect of false data injection attack, especially in Smart grids. Smart grids systems are similar as some of the hardware sending the measurements could be completely controlled by an outside party. However, some differences exist such. As mentioned by Hao et al. [10] there are two approaches to deal with false data injection attack in general. The first is the protection against it by protecting some of the data sources. Protecting the data sources is completely not feasible in our open network. The reason for that is we need our application to be extendable easily in new areas. However, requiring some nodes to be secured first will hinder the extension and complicate the procedures. The second is to detect the injected false data then choose a way to handle them either correcting them or choosing to exclude them from the system analysis. The main method of detection in smart grids according to Rahman et al. [17] and Hao et al. [10] is residue test. However, the used method is inapplicable in our case because of the amount of data about the system needed to implement them and the usage of state estimation. As mentioned in the work proposed by Rahman et al. in [17] they use the information from both directions of the buses which are the input and the output. And in the work done by Cui et al. [6] they mentioned using state estimation to perform the residue test. Though, we try to use prediction model to estimate some readings as a reference we do not want it to be the only one because prediction can not consider unusual event which is why we went with the sensing network in the first place.

While in the work done by Sencun Zhu et al. [23], they developed a scheme to make sure that you need to compromise more than $t+1$ nodes, where t is a design parameter, to be able to inject false data. As the $t+1$ nodes would have to agree on the report so it could be taken into consideration. However, this will not work in our network model because their network is not an open one where anyone can join. So, having a design parameter related to the number of nodes for the scheme to work is not a realistic ap-

proach. And also our network is a sparse network, while the nodes here try to reach a consensus. However, our nodes report estimations for fine dust in an area but we do not expect them to send the exact same readings as each other.

In the work presented by Przydatek et al. [16], they have aggregator nodes that construct Binary Merkel hash trees where the leaves are the actual sensors. In the cluster, the hashing of the children node in the tree should get you the parent value. In this work, they pointed out that they can not work on every value. In our system that would be possible because we only view readings every hour. In this work, they consider the median of the random samples they get. And though the median value has a high robustness against false data, it has a high robustness cost as it does not use most of the available data. We adopted the concept of fusing the data but we decided to use subjective logic instead of normal statistics as subjective logic is more powerful tool as explained in the previous chapter 2.

In the paper written by Huang et al. [12], they have a noise mapping participatory sensing application in an office. In this paper, they chose an another approach to deal with false data injection. The approach is to minimize the effect of the false data in the system behavior using robust statistics. We chose this paper because participatory sensing is similar to our concept of having an open network. Their System is divided into three stages. The first is the watchdog module which accepts the readings and feedback from the reputation module, that will be explained later. The watchdog module uses the input and an outlier detection algorithm to calculate cooperative ratings for the readings. The second stage is the reputation module which uses the previously calculated cooperative readings as an input to build long term trustworthiness using Gompertz function. While in the third stage they use these reputations to get statistics summary about the noise level in the office where the usage of the reputations eliminates the effect of outliers. In this work contrary to most of the other reviewed work did expect the sensors to provide different data. However, they still used consensus based outlier detection algorithm because noise level within a closed area such as an office should nearly agree. In conclusion, we adopted the architecture of the detection system in this work which consists of three components that work sequentially. The outlier detection in a single time step. A module to build trustworthiness over a long time. Using the calculated trust to produce the final output.

Also in the work done by Burke et al. [4] to ensure data integrity in participatory sensing application, though they did offer some novel problems to ensure the security of the data and make it feasible to protect nodes. By offering special hardware with hardware-based cryptography hardware for the sensing output so it can not be manipulated. And having in accessible parts of the applications software vouch that no tampering happened to the software. However, we chose to try a different approach because we see that this might slow down the expansion of our open network.

Some works decided to use subjective logic such as work done by Gomez et al. [8]. They decided to have a broader look at the wireless sensor networks systems. They considered intentional and unintentional injected false data. They also considered bogus data and problems with injecting during data processing. However, we did not consider problems with data processing in our work. The reason is they defined different states for their data and defined the processing to be happening during the routing. While as explained in our network the data goes from the sensor to the gateway to the backend directly without any kind of processing and all the processing is done in the application. The part we focused on is bogus sensor data. We adopted from this work their approach to consider unintentional data due to exhausted batteries. They decided to test their system on a herd control application to monitor the health and well being of the cows. Their test case is very different from our system so we can not adopt their methods of calculating belief in the data values. They also had some related work in [9].

4 Implementation

4.1 System architecture

In figure 4.1, We explain the complete architecture of our system. As clear from the figure, our system consists of four modules, has one time of input and Some output. The only input type to the system is packets with node's ID, node's location, PM level Reading and battery percentage. Clearly, Some of the packets components are missing in the figure. The reason for that is, we only included the components that are constantly used in the figure to give more focus on them. The desired output from the system is a final estimation of fine dust in a certain area and a subjective opinion about it. However, we have some other different outputs that were added for testing results and will be discussed in the testing chapter 6. The modules of the system are the virtual sensors, Statistical summary module, outlier detection in a single time step module and long term trustworthiness module. The latter two modules were discussed in details in the Reputation System chapter 5. Thus, we will focus only on the first two modules and the overall system behavior in this chapter.

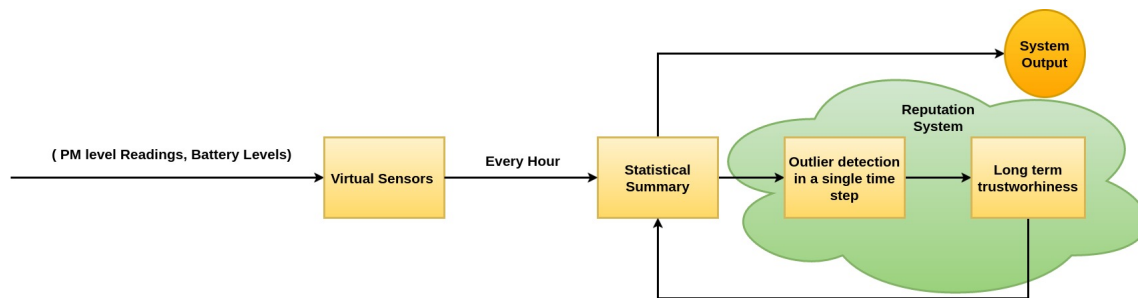


Figure 4.1: System architecture

4.2 Data Fusion

Before discussing the system modules, We need to explain the method operations are carried out on the data and the opinions. For this, we need to clarify That every reading is paired with an opinion of some entity about this opinion.

4.2.1 Data Operations

The operations that are done on the data is fusing data together when they represent the same thing. This is done by calculating a weighted average or weighted deviations. The weights for every reading in these operations is the expected probability of the opinion paired with these readings.

4.2.2 Opinions Operations

While there is more variety in operations done on opinions accompanying the data. The operations on opinions help update opinions during transition periods for the actual data. The two operations done are opinions cumulation together and opinions discounting by other opinions.

Cumulation of opinions is used when we fuse data together to get a weighted average, We at the same time cumulate the opinions using a cumulative operator to form an opinion about the weighted average.

Discounting the opinions when we have referral opinions this happens in two cases. The first case when the node has an opinion about its reading but it also has an opinion about itself, this will be explained later, we then discount the first opinion about the reading by the opinion reading about itself using the transitivity operator. The second case is when we have the node's opinion about its reading and the server's opinion about the node, and we need to know the server's opinion about the reading. In this case, we discount the node's opinion about the reading by the server's opinion about the node to get the server's opinion about the reading.

4.3 Virtual sensor

We delegate all of the data processing to the application to ensure a higher level of security. This was done by registering all of the real sensors in the application as corresponding virtual ones. The virtual sensors can save the readings and all useful information until we need to use the data.

4.3.1 Registration

Registering the node requires saving the node's ID and the node's location. In addition to that, the virtual sensor stores the real sensor reading and the opinion it has about this reading. Whenever a real sensor sends a reading, the application checks if the sensor already registered or not. If the sensor is not registered, the application registers

the sensor by creating virtual sensor save it in the list of sensors and create a vacuous opinion about it in the reputation list.

4.3.2 Self Opinion

The sensor forms an opinion about itself according to the battery level that is received with any reading. The purpose of this opinion is as mentioned in the work done by Gomez et al. [8] is to mitigate the effect of unintentional This opinion is referred to as $\omega_{battery}$. The components of the equation to form the opinions are explained in details in equation 4.1. This equation was taken directly from the work done by Gomez et al. in [8]. The $\alpha_{battery}$ mitigates the impact of the remaining battery on its own trust evaluation [8]. The $battery$ is the remaining percentage of the battery's charge level from 0 to 100%. While $batteryuncertainty$ represents the uncertainty we have about the battery level. We set the $batteryuncertainty$ to 0 in our work. Next, we explain in detail how the input packets are handled.

$$\omega_{battery} = (b, d, u, a)$$

$$\text{where } \begin{cases} b = (battery/100) - \frac{100 * \alpha_{battery}}{battery} \\ d = 1 - b - u \\ u = batteryuncertainty \end{cases}$$

(4.1)

4.3.3 Handling received readings

The received reading itself is handled the same whether it is the first every time or not. The reading is simply paired with a dogmatic opinion. We chose a dogmatic opinion because normally a sensor would be 100% of its own reading. Then this opinion is discounted by the self-opinion created using the battery reading.

After this, we check if this is the first reading received during this hour. If it is, we simply store the reading and the opinion associated with it as the sensor's reading and the opinion about it. If it is not, We fuse the reading with the previously stored one and cumulate the opinion with the previously stored one. The results of the fusion and cumulation are our new reading and opinion for the current hour.

Finally, every hour all of the virtual sensors sends their reading for the current hour to the Statistical summary module for processing. And after the module is done processing

the data the virtual sensor throws away its reading and opinion about the reading.

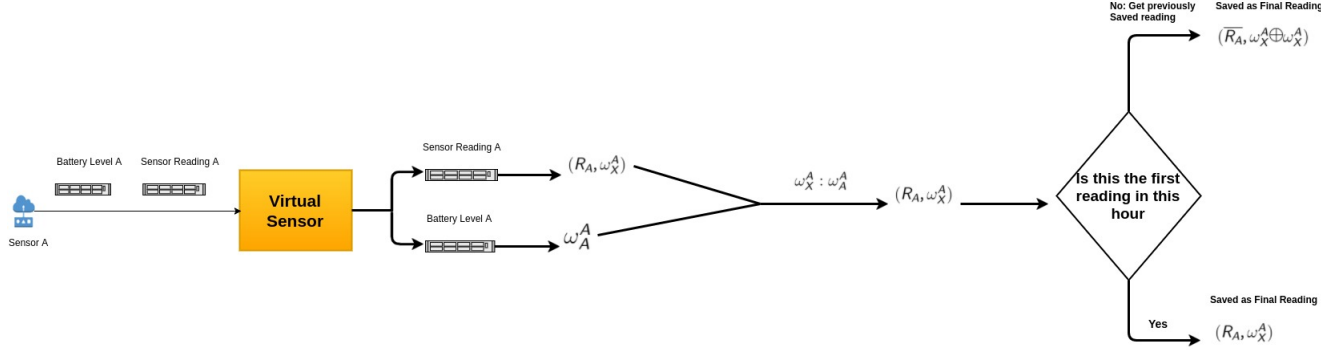


Figure 4.2: Input Readings Handling

4.4 Statistical summary module

The Statistical summary module is the module that produces the final output of the system. At first, when implementing this module, we thought about implementing an alarm that triggers when the PM level exceeds a certain level to simulate the real life application. However, since our implementation is a prototype designed with proof of concept as its goal, we decided to just produce a final estimate of the PM level in the area and an opinion about this estimation. We took this decision because it gives us more freedom to analyze the data and the behavior.

Every hour, the statistical summary module pulls the reading and opinion pairs from all of the virtual sensors. We take the opinion out of the sensors. The server keeps opinions about each sensor to represent their reputation. How these opinions are formed will be explained in the Reputation System chapter 5. Then we discount the opinions of the virtual sensors about their readings by the opinions of the server about the virtual sensors. Next, we fuse data together and cumulate opinions. The result of the data fusion is the final estimate for fine dust in the area. And the result of this cumulation is the final opinion about this data.

4.5 Challenges

4.5.1 Environmental Model

The environmental model could not be implemented. Though, reviewing the literature revealed that a decent amount of work was done in the field of particulate matter levels.

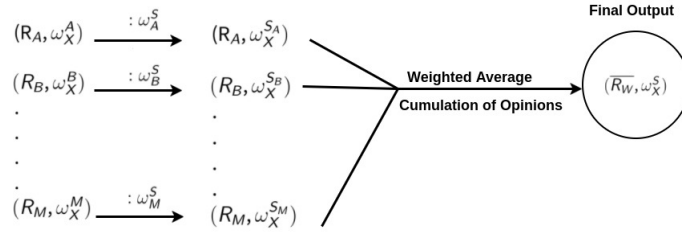


Figure 4.3: Input Readings Handling

However, for their implementation by us is not possible because of missing parameters and lack of knowledge in the environmental sciences.

Such as in the work proposed by Yanosky et al. [22] they had the variable $g_t(s_i)$ accounting for residual monthly spatial variability, $g_t(s)$ accounting for time-invariant spatial variability and $Z_{i,t,1}$ and $Z_{i,t,P}$ for time varying covariates.

And in the work done by Henderson et al. [11], they developed a model for predicting the yearly average of PM2.5 level in the area. We thought of might for a way to manipulate the model to predict data in smaller intervals. However, the lack of variables such as the size of commercial and industrial areas in the city. And our lack of understanding for environmental science made us shy from using this approach.

4.5.2 Hardware

The hardware could not be implemented in the specified time frame for this project. The hardware implementation involved two components getting the backend to receive data on TheThingsNetwork servers. And having a microcontroller with a LoRaWan transmission module and the sensor of our choosing connected to it sending data to the backend application.

The first part we got the project to configure and run on our server making sure there is no problem with how it is written. However, the second part we were not able to get it running because of incompatible hardware. The problem is the developers of TheThingsNetwork provide a software development kit (SDK) for handling data sending when using Arduino microcontroller with few lines of code without handling any configurations in the network stuff. However, the available hardware for us was waspmote microcontroller.

Although, waspmote can understand Arduino code it still has its own integrated development environment (IDE) and few differences between it and the Arduino code. This makes waspmote incompatible with some of the third party libraries. These incompat-

ibilities included the SDK developed by TheThingsNetwork. The problem is the calling of *<Arduino.h>* file in one of the classes and this file does not exist in waspmote. So, we have two solutions.

The first solution is reprogramming the library and changing the functions called from the *<Arduino.h>* file by functions that exist in the waspmote. Before discussing the second solution, we should point out that waspmote contains a lot of previously implemented libraries to handle LoRaWan. So, the second solution would be to get the configuration for the LoRa channels used by the TheThingsNetwork. We performed a quick search for someone who already implemented this but none could be found. The solution was to do more research to be able to configure it. However, our research question could be answered without this. At the end, we decided to spend more time in analyzing the data rather than implementing this but we believe this can be surely implementable.

5 Reputation System

Recalling that one of the main purposes of this work is testing how effective is subjective logic in creating a reputation system. The reputations of nodes are kept as a list of opinions. Where the server has an opinion about every node that represents the trust of the server in the node.

5.1 Concept

5.1.1 Outlier detection in a single timestep

As mentioned in chapter 3, when explaining the work proposed by Huang et al. [12]. The architecture of their system was adopted. This consisted of three stages. The first was detecting outlier in single time steps. The second is forming the trustworthiness over time using these single time steps results. The third is forming a statistical summary where the low trust nodes have minimal effect on the system. The third stage is the output of the system after forming the reputation and it is not a part of the reputation system. Thus in this chapter, we will focus on the first two stages.

For the first stage, We are aiming to detect outliers in a single time step. To achieve our goal, we had to research the properties of particulate matter to be able to distinguish illogical readings. We decided to use the statistical distribution of particulate matter to determine the outliers.

According to the work done by Henderson et al. [11] they mentioned that PM2.5 in the 25 sites they tested at were normally distributed. This was supported also by the paper published by Cameletti et al. [5] where they were trying to develop a spatiotemporal model for particulate matter levels prediction. It was also backed by the work done by Tian et al. [20] as they mentioned that the data from the Moderate Resolution Imaging Spectroradiometer (MODIS) for PM2.5 showed to be normally distributed.

To verify this we chose a random sample of 50 hours of readings. Then at each time step, we fitted the readings of all of the sensors into a normal distribution. Next, we performed the Kolmogorov–Smirnov test of 5% significance level to make sure that the fitted distribution does represent the data. Our hypothesis was only refused once out of

fifty.

Further investigation proved that this occurred at an instance where one of the sensors sent very high readings during this time step as it raised the average of the readings to nearly 244% of its value when we exclude this sensor. Such readings are possible but they indicate unusual events happening near the sensor such as fireworks, actual large fire or construction work.

To summarize, there are two main properties that we use which are particulate matter is normally distributed over space and unusual events distort that normal distribution. In figure 5.1, we can find a visual representation of the comparison between the empirical CDF of the data and the CDF of normal distribution resulting from fitting the data in one of the time steps.

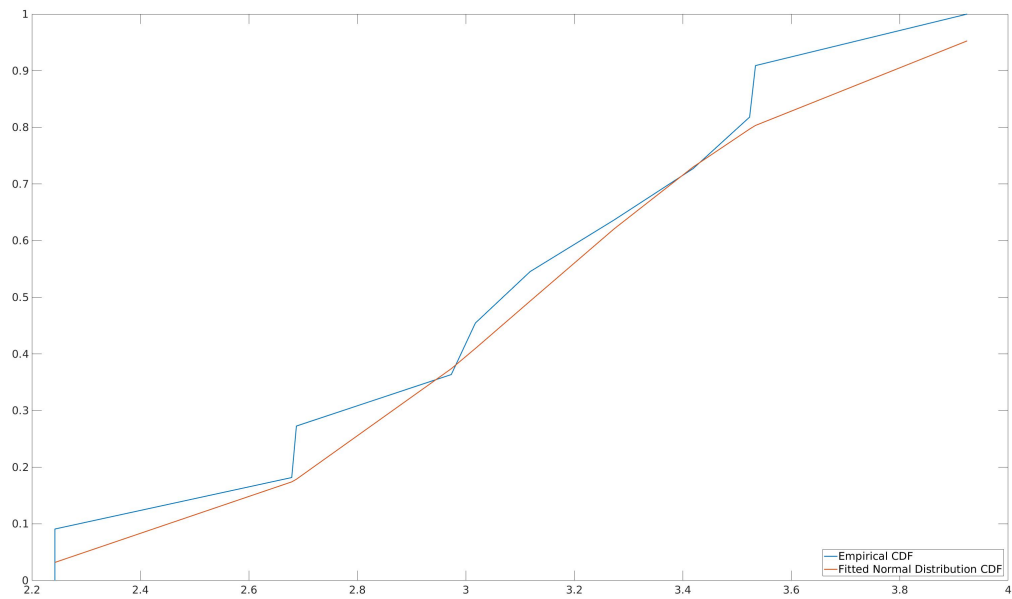


Figure 5.1: Visual comparison between Empirical and Fitted distributions

We tried to use the aforementioned information that we found to detect outliers in a single time step. Firstly, as previously mentioned we consider the reading of any of the nodes as an estimation of the PM level in the area, not as the exact reading at node's location. In addition to that, we suppose that we have a mathematical environmental model that is able to provide a prediction for the particulate matter level in the area.

For testing the honesty of a certain node, we fit all of the other nodes readings and the prediction of the environmental model into a normal distribution. Then we judge if the reading of the node belongs to the same distribution or not. This system uses both of the aforementioned properties. The normal distribution property which is clear in fitting the data to the distribution.

The unusual events property here is dealt with by considering as an attack because they lead to a false estimation of particulate matter within the area. So the effectiveness comes is that every distribution with false data will be distorted which makes it harder to get evidence from it, this will be explained later. While the better-fitted distributions result in more evidence.

Assuming we have one attacker, we will have one completely correct distribution that we gather evidence from. This will result in quickly completely distrusting the attacker. While the number of attackers increases all of the distributions will be ruined. However, the more attackers while forming one distribution the less evidence taken from that distribution and vice versa.

In conclusion, we try to figure out does a reading comes from the same distribution as all of the other nodes or not. An example of this in figure 5.2. Where R_A is the reading of node A. $\omega_X^{S_A}$ is the server's opinion about the reading of node A. While M represents the environmental mathematical model.

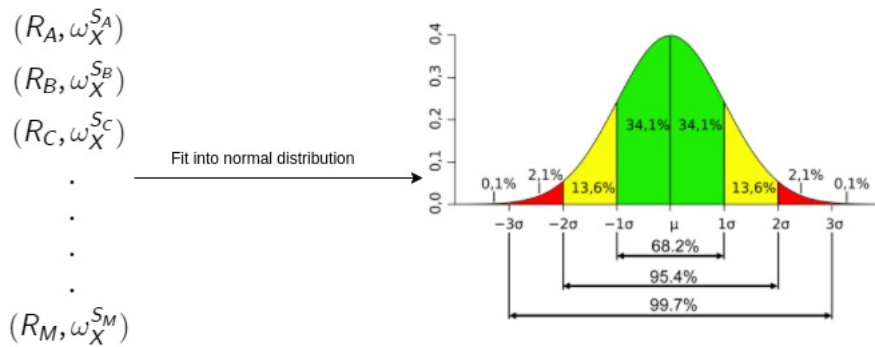


Figure 5.2: Outlier detection test for node Y

5.1.2 Trustworthiness over time

The method we devised for implementing the first stage proved perfect to use in the second stage. As for the second stage, we try to form trustworthiness over time. For this, we use subjective logic. Recalling equation 2.3 for calculating belief. This equation needs a

numeric value to be plugged into the equation as the value for the evidence for and evidence against. The method for getting the numeric values will be elaborated later. The evidence of each time step is aggregated with previous time steps to update the opinions. The more recent the evidence is the more weight they hold.

5.2 Implementation

5.2.1 Outlier detection in a single timestep

When fitting the data into normal distribution we faced a problem. As explained in 5.1, when we have unusual readings that do not belong to the system due to unexpected events or due to attacks the normal distribution is distorted. As shown in figure 5.2 we use the readings and the opinions about the readings to perform the distribution fitting.

Noting that a normal distribution has only two defining parameters. The first is its location parameter which is the mean. The second is its scale parameter which is the standard deviation. So, we use the expected probabilities of the opinions as weights for the readings to calculate a weighted average and a weighted deviation. This helps us avoid the distortion of our distribution. Thus, it ensures that we have a more accurate distribution for judging the node currently under test.

The next step would be to extract numeric data to plug into the belief calculating equation. For performing that the simplest method would have been to calculate the distance from the mean or the median value and calculating a threshold for the allowed distance from the mean. The problem with this is its naivety as only through careful studying of the relation between PM levels variation with space can this threshold be determined.

Even then the problem mentioned earlier with the environmental model will exist. The problem was that such an approach would not take into account the unusual events that may cause juristic changes in the PM levels readings. However, this possible in our case because the data follows a normal distribution. By using the property mentioned in figure 5.2 that a reading belonging to this distribution should lie at a maximum distance of two standard deviations from the mean with a probability of 0.954. And in the case of the unusual events, both the mean and the deviation will change appropriately.

So, what we did at first is determine the number of deviations allowed by fine tuning using some elementary tests results and we found out the best value to be 1.5 of the deviation. The amount of data included within a distance of 1.5 deviations is around 86% of the data belonging to the distribution.

An example of the method is explained in figure 5.3. The figure includes two scenarios. The yellow markers represent the reading in each of the scenarios. In the first scenario, The reading is between the 1.5 deviations away from the mean and the actual mean. So, the distance between the 1.5 deviations away from the mean and the reading itself is calculated as evidence for. In the second scenario, the reading is even further than 1.5 deviations away from the mean. So, the distance between the reading and the 1.5 deviations away from the mean is calculated as evidence against.

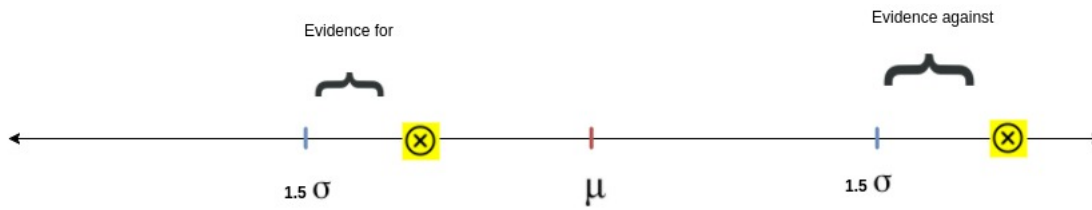


Figure 5.3: Evidence calculation in a single time step

During the full testing of the system, this method did not yield the best results. So, we decided to tweak the approach a little bit.

First, We point to the fact mentioned before that the existence of attackers distorts the distribution. Even if we managed to mitigate the effect of this from greatly distorting the distribution, the deviation value among our data was very high. So, We decided against having a constant marker at 1.5 deviations.

Instead, we implemented a moving marker that ranges from 2 deviations to 0.5 deviations. The decision of where to put the marker is based on the ratio between the deviation and the mean as explained in equation 5.1. Noting that if the equation produced a number less than 0.5, we will take 0.5 instead. In the work done by Monn et al. [15], they said that the PM2.5 levels might be uniformly distributed as they were discussing small scale spatial variations. This meant that we have to be more tolerant with our markers in case of the readings were more concise and nodes were in an agreement. In the aforementioned case, one sensor that lies on a road with high traffic would be distrusted quickly because of slight disagreement. That is why we increased our upper limit to 2. And now since the marker is a moving one. We can afford to do that because we can be more strict whenever we have a wider distribution where the nodes are not agreeing. The lower limit was obtained through fine tuning as lower numbers just ended up distrusting everyone.

Noting that, with this approach the larger the readings the larger the evidence. This could be changed by standardizing the normal distribution. However, we decided against standardization and decided to keep it as it is. Because this makes the system more sensitive when we have higher levels of particulate matter in general which is a more dangerous situation for people involved. Thus, it makes sense to keep the system as is.

To conclude this part, evidence collected in a single time step is collected according to the position of a reading with respect to the distribution of the other readings. If it is within the area between the markers, then the distance between it and the nearest marker is considered evidence for. If it lies outside the nearest marker the distance is considered evidence against. The markers are moving according to how wide the distribution is. And we call evidence for collected in one time step r_{x_t} and evidence against collected s_{x_t} . A comparison between the constant marker approach and the moving marker approach is can be found in the testing and evaluation in chapter 7.

$$marker = 2\sigma * (1 - \frac{\sigma}{\mu}) \pm \mu \quad (5.1)$$

5.2.2 Trustworthiness over time

For forming long term trustworthiness with the more recent data holding more weight for the system to be adaptive and interactive. Before starting to explain how our system work, we define our starting point. We are designing an adaptive system. The system starts from the point of complete uncertainty about the node whether it is an attacker or not. This kind of opinion is called a vacuous opinion [13]. A vacuous opinion with 0 belief, 0 disbelief and 1 uncertainty as in equation 5.2. We do that with every new node joining the system.

$$\omega_X^{S_A} = (0, 0, 1, 0.5) \quad (5.2)$$

As mentioned before, we use equation 2.3. In this equation, there are 3 variables non-informative weight W , evidence for r_x and evidence against s_x . The non-informative W is set to 2 as this the convention when you need to create a vacuous binominal opinion at the beginning. While evidence for and evidence against are the aggregations of evidence for and evidence against in single time steps.

However, aggregating over all of the time the system has been running is not realistic because it will reach a point where new evidence is insignificant. This will greatly affect the response speed, one of the metrics used to evaluate the system performance, of the system.

To fix this we thought about implementing a sliding window approach. However, implementing a sliding window approach is more complicated, requires more storage and does not introduce a solution for the problem of the necessity of having more weight for more recent evidence. While all of this can be fixed with a decay factor approach. Where we just multiply the old evidence with a factor $\alpha < 1$ so old evidence will get smaller over time. This is easier to implement, requires less storage and fixes the necessity of having more weight for recent evidence. The equations to implement this are equations 5.3 and 5.4. Noting that in all of this thesis the term decay factor represents the factor by which we multiply the old evidence at each time step. Hence, when we say later that the decay factor decrease, this means having smaller weight for the old evidence as the factor multiplied by the old evidence decrease.

$$r_x = \alpha * r_x + r_{x_t} \quad (5.3)$$

$$s_x = \alpha * s_x + s_{x_t} \quad (5.4)$$

6 Testing Setup

6.1 Overview

The testing is done by simulation. We have data that represents the reading of a real network. The readings represent the particulate matter levels in the city of Ulm, Deutschland. The data is plugged into the application prototype. Thus, we only changed few lines in our code to handle the different input format from the actual sensors readings being sent in a message.

6.2 Data

The data is obtained from the archives of LUFTDATEN SELBER MESSEN [14]. It is collected by the people of Ulm. The application to collect the data is a project of the Open Knowledge Foundation Germany (specifically the OK Lab Stuttgart). They also link to the official daily average from the environmental office of the state government.

The data is saved in CSV files. This data is saved as a CSV file for each sensor in each day. The file contains the longitude, latitude, timestamp of the reading, PM2.5 level reading and PM10 level reading. We implemented our system using PM2.5 level. We took this decision because we were still investigating the possibility of using the work done by Henderson et al. [11] as an implementation for the environmental model. And in their work, they focused on the PM2.5 level. And we do not expect to need any modifications in the system for as the only required property we have is that the data follows a normal distribution which is true for both PM2.5 and PM10 as explained in chapter 5.

6.3 Attackers Classification

We have two classifications for the attacks done. According to the first classification, the attacker could be either random attacker or clever attacker. Random attackers inject random readings. Clever attackers try to change to the final reading in a certain direction by constantly increasing or decreasing the reading. According to the second classification, the attacker could be either Continuous or periodic attacker. Continuous attacker when they start injecting wrong readings they do it consistently for every reading. However, periodic attackers inject false data in a certain period then stops for a

while to regain some trust and then perform the attack again. Thus, we have four possible combinations and attacker would be one of them. The four types of attackers are continuous clever, continuous random, periodic clever and periodic random.

6.4 Output

As we previously discussed, the main outputs that we are keeping track of our final estimation of the particulate matter level in the area and the final subjective opinion about the estimation. We also keep track of the reputation list containing the trust of every node during the run of our system. We were recording this to help us better analyze the results. However, we do not discuss this extensively in our evaluation chapter 7. The reason for doing this is because the information we need to present is implicit in our final opinion. As we do not really focus on the blocking parameter. The output data are written in CSV files.

6.5 Attack Scenarios

6.5.1 Overview

At the beginning of the run, all of the nodes start reporting honest readings. No nodes join midway through the runs. All of the nodes stay honest for 50 hours after that the attacking nodes start attacking. All of the attacking nodes start injecting their false data at the same time. We took this case because that is the critical point where the attacking node is a trusted one at the beginning of the attack. And it is most effective when all of the nodes attack at the same time.

Every attack is tested for different attackers node to total number of nodes. The different ratios $\in \{1/11, 2/11, 3/11, 4/11, 5/11, 6/11\}$.

6.5.2 Random Continuous attacks

In the random continuous attack, our attackers injected random false data instead of the actual readings. They did that continuously after the 50 hours at the beginning we use to stabilize the system, meaning they do it for every single reading. The tested random readings $\in [0, 50]$. We chose 50 because it is double the permitted value for PM2.5 by the European Union in their directive [7].

6.5.3 Clever Continuous attacks

Clever continuous attack behaves nearly in the same way as the random continuous attack. The difference is that the clever attacker tries to move the reading in a certain direction instead of just injecting random readings. They do that by taking the correct reading and adding a certain value to it.

The added values $\in \{5, 10, 15, 50, 200\}$. The first three values in the previous set are chosen to see the effect of small changes. This is tested to view the effect when the particulate matter is already high and the person wants to push it over the threshold stated by the authorities. The latter two values in the set are used to test injecting greatly shifted readings where these values occasionally or rarely exist in a real system. Noting that when we say occasionally and rarely happens we mean occurring as an average reading of a sensor over a full hour because that's the chosen time step.

6.5.4 Periodic attacks

Periodic attacks have nearly the same implementation. The difference is that we do not inject false data every single time. Instead, it injects data for a certain period and repeats the same process with a certain frequency. Our frequency will be referred to as the number of attacks per day. The period length $\in \{1, 2, 3, 4, 5\}$. For example, And the frequency $\in \{4, 2, 4/3, 1\}$. For example, period length of 2 and frequency of 4 means we attack for 2 hours every 6 hours.

Though periodic attacks are nearly similar in implementation. However, we chose to only focus on the effect of their combination with significant shifting clever attacks. We have done this as we needed to focus more on something because of the output size that we got when we needed to exclude some of the output we got so we can perform a more thorough analysis. And marginal shifts with periodicity will hardly affect our system. Thus, we chose to focus on significant shifts which can affect the system. And

6.5.5 Decay Factor

As explained in chapter 5, we have a decay factor for old evidence by which we let their effect on our opinions decay over time. On the time of testing, we were not able to argue choosing a certain decay factor. Thus, instead of choosing one decay factor in our implementation, we decided to test on more than one and observe our results. Therefore, the results that will be presented in the next chapter 7 will contain a comparison between the behavior of the system using different decay factors that $\in \{0.975, 0.9, 0.8, 0.7, 0.6, 0.5\}$. Finally, as mentioned earlier in chapter 5 the term decay factor represents the factor by which we multiply the old evidence at each time step. Hence, when we say later that

the decay factor decrease, this means having smaller weight for the old evidence as the factor multiplied by the old evidence decrease.

7 Evaluation

7.1 Metrics

We have three main metrics to evaluate our system based on them. Obviously, since we try to detect and mitigate the effect of false data injection attack our most important metric would be the impact of the attack on the final reading. We chose the root mean square error (RMSE) to represent the impact of the attack. However, we also care about the mitigation speed. Therefore, we chose the response speed as our second metric. Finally, we expected all of this to be reflected in our opinions, meaning whenever the RMSE was low, we will have low belief in our reading. Therefore in the case, that mitigation was not possible, we will know that we have a non-trustworthy reading.

7.2 Injecting random data

Random attacks were used for the initial evaluation of the system and are not the main focus of our work. Note that the discussed results in the random attacks do not have the same seed. Thus, this does not provide the best comparison between different decay factors. However, we depended on the fact that we have 50 possible values for the injected value. And one of the defining factors of a good pseudorandom generator is that it goes through the whole or most of the cycle of the possible numbers. And we used the Random object on java which uses a *Linear Congregational* algorithm to produce 50 values. And it is known that *Linear Congregational* algorithm is a good pseudorandom generator algorithm when provided with a seed that follows certain conditions. In conclusion, we decided that for an initial evaluation the difference is not that huge that we need to go through the trouble of choosing our seeds manually.

As we suggested our first target was to evaluate the impact of the attack on our results. This going to be done mostly through graphs similar to figure 7.1. Thus, we decided to start discussing the evaluation by explaining Figure 7.1 first. First of all this graph was produced from running our system 5 times. Each time lasted for 50 hours. And each run started at the same point in time for all decay factors. As clear from the graph the x-axis represents the ratio of the number of attackers to the total number of nodes. And the y-axis the RMSE of the reading. The graph includes a comparison between the constant marker and variable marker approaches discussed in chapter 5. While the markers are

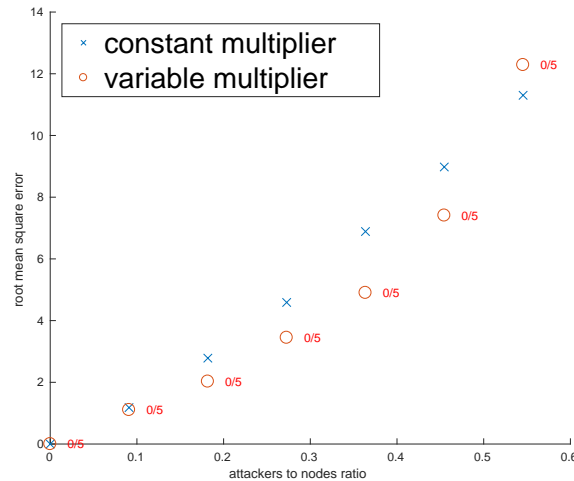


Figure 7.1: Random attack with decay factor of 0.975

called multipliers in the graph owing to the value multiplied by the standard deviation as that was the exact point that needed to be changed in the actual code. The fractions besides the red scatter points represent the number of times the system completely broke and could not function properly out of the five performed runs. The cases where the system breaks down are not included in the graph and only represented in the text that states their number. If the system breaks in all the runs no red point will be drawn. Next, we explain what is meant by the system breaking down.

The system breaking down is an observation we had when running the system multiple times. However, this observation was expected before implementing the variable marker approach. The explanation for this observation is that the measures taken to stop the distortion of the distribution are not enough. Therefore, when the distribution

is too distorted the mean becomes in the middle between everyone and with very high deviations the markers just close up on the mean. Thus, all the nodes just start accumulating evidence against. This at the end leading to all the nodes being distrusted and they become blocked and no readings are accepted from any of the nodes. Therefore, the system breaks down completely.

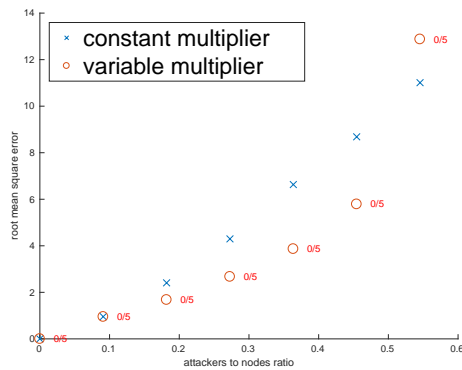


Figure 7.2: Random attack with decay factor of 0.9

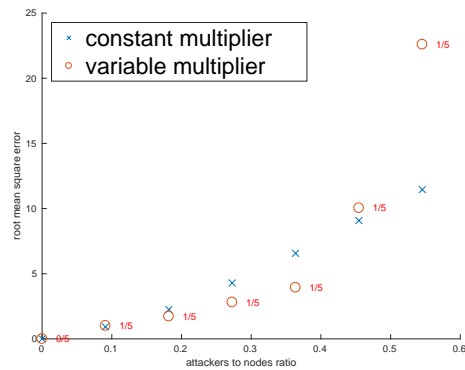


Figure 7.3: Random attack with decay factor of 0.8

The set of graphs shown in figures 7.2-7.5 help us prove and visualize the first three observed relations. The first relation is that increasing our decay factor helps the system becoming more stable and more resilient against being broken. The second relation is that the more added stability due to increasing our decay factor helps us deal with higher attacker ratios. The third relation is that the less the decay factor the less RMSE we have

The first relation observed in the first set of graphs could be easily interpreted. As we explained before in chapter 5 we formed the system so that more evidence will accumulate against outliers even when all the distributions are distorted. Therefore, having a higher decay factor allows the old evidence to have more weight which gives the system

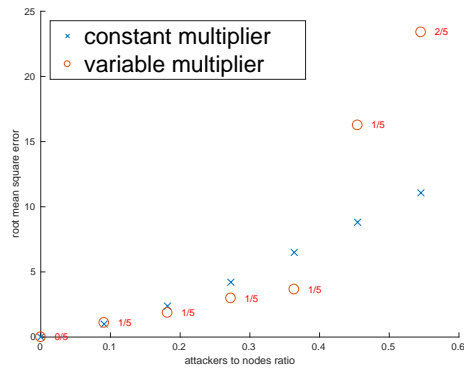


Figure 7.4: Random attack with decay factor of 0.7

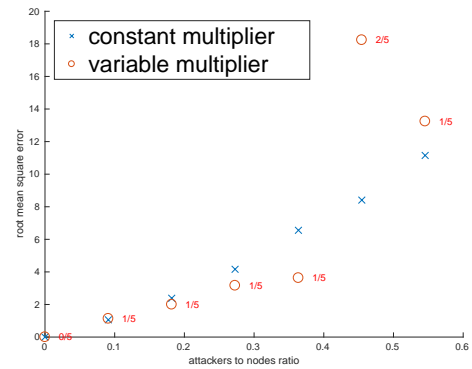


Figure 7.5: Random attack with decay factor of 0.6

more time to accumulate new evidence to even out in the weight against the old ones. This allows the system the required time to accumulate enough significantly larger evidence against the outliers to make their weight insignificant and even block them. Then the system starts reverting to normal with excluding the outliers and honest nodes start accumulating evidence for.

The third relation can be explained that the less the decay factor is, the less evidence retained from the past and the more weight given to recent observation which contains the false data. Making our system more responsive. This should be supported by our analysis of the response speed.

While in figures 7.6 and 7.7, we can observe how the system performance improve over time by viewing the RMSE for the system at different points in time. While the visible difference between the RMSE after 50 and 30 hours is very small and can be deemed as insignificant. There is a considerable difference when looking at the RMSE after only 10 hours. Thus, we can conclude that to some extent after 30 hours the system stabi-

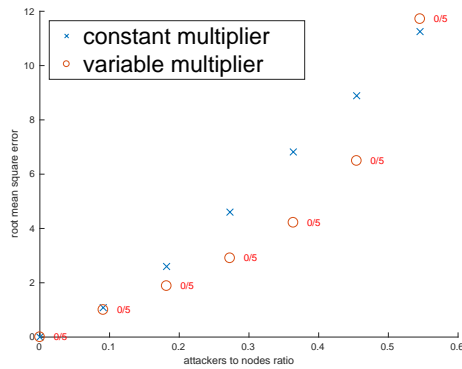


Figure 7.6: Random attack with decay factor of 0.9 in 30 hours

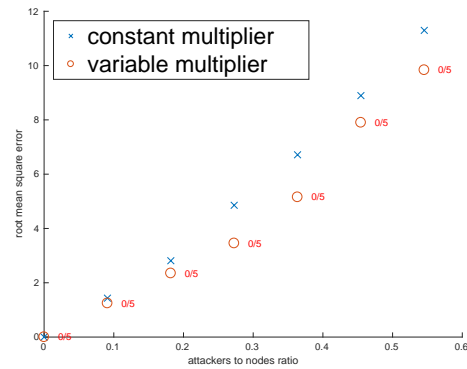


Figure 7.7: Random attack with decay factor of 0.9 in 10 hours

lizes meaning the RMSE after a certain point that precedes the 30 hour mark is generated from the difference of information source as in the attackers case, we have a significant weight for the honest nodes information, while the others are either excluded or have insignificant weight. However, in the "attackers absent" runs all of the 11 nodes we have report honestly. In conclusion, RMSE decreases as more time passes. However, it comes at a point where it stabilizes due to the difference in the number of information sources.

Also comparing the graph in figure 7.9 with the previously mentioned one in figure 7.7, we can find our fourth observed relation which is the response speed improves with the decrease of the decay factor. This was highly expected especially after the third relation in which the overall performance is actually better for smaller decay factors. As both happen due to the fact we explained earlier that the higher the decay factor, the bigger weight old evidence has and the harder to even it out using new evidence and change the belief values.

We further elaborate the response speed and connect the opinions role, to the rest of the metrics, in judging the data through the graphs in figures 7.10 and 7.11.

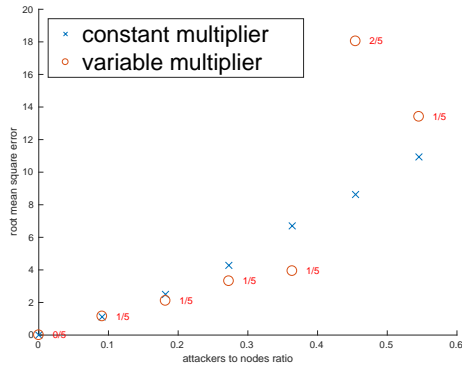


Figure 7.8: Random attack with decay factor of 0.6 in 30 hours

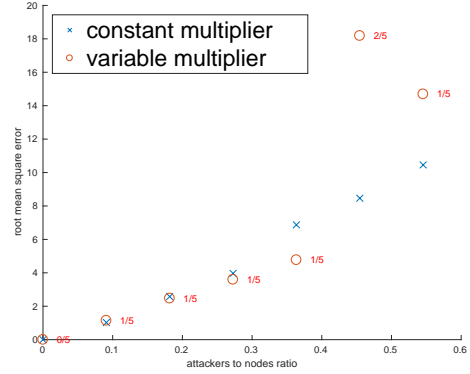
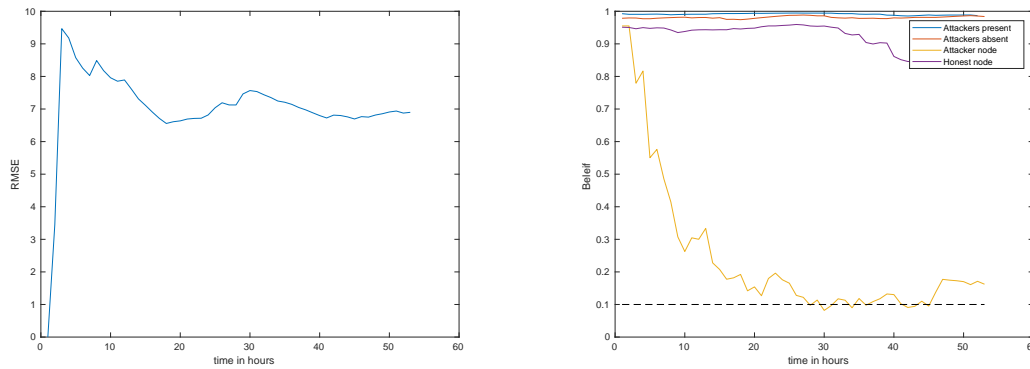


Figure 7.9: Random attack with decay factor of 0.6 in 10 hours

First, we start by explaining what do these graphs represent. Both figures have the same graphs but at different decay factors. Therefore, explaining 7.10 as an example of both would suffice. In the left subfigure 7.10a we can see how does the RMSE changes over time. While in the right subfigure 7.10b, we see the changes that happen to the final opinion about the final estimation in an environment that has attackers once and environment that attackers are absent from once. Continuing in the same subfigure, we see the changes to the trust in an honest node and attacker node in an environment where attackers are present. Noting that, these set of graphs were chosen as examples and are produced from a single run for our system.

By comparing the graphs in the figures 7.10a and 7.11a, It does not really support the third relation concluded earlier. Noting that, In these figures, we could observe that for the decay factor of 0.9, the RMSE stabilized close to the 7 and for the decay factor of 0.6, the RMSE stabilized close to the 6. Though there is a difference, it might be deemed as insignificant. However, we decided that this was produced from a single run using random attacks. Which can not outweigh the first set of graphs that were produced from aver-



(a) RMSE change over time

(b) Opinions change over time

Figure 7.10: Random attack with decay factor of 0.9 and attackers ratio 4/11

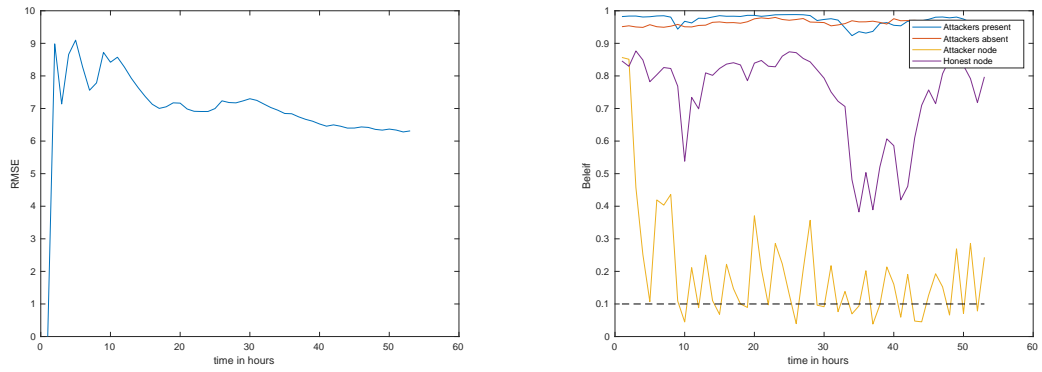
aging the results of 5 runs. However, we can also observe the fifth relation here which is the smaller the decay, the more expressive power the opinion has. And that perfectly follows the expectations we had as the decay factor decreasing makes the opinion more sensitive to change.

Next, we compare all of the graphs in the figures 7.10 and 7.11. We can easily observe the response speed by observing the slopes of the curves in figures 7.10a and 7.11a. Where in figure 7.11a, it stops being steep after 17 hours since the start of the run. While for figure 7.10a, it stops being steep after 26 hours since the start of the run. This suggests that the response speed is higher for smaller decay factors. This is also reflected in the figures 7.10b and 7.11b, where the belief in the attacker node in 7.10b falls slower than it falls in the 7.11b. All of this supports our fourth observed relation.

We can also observe from figures 7.10 and 7.11, that there are more rapid fluctuations in the belief of single nodes in figure 7.11b. This suggests the system instability which leads to the system breaking down. Therefore, these graphs support our first observed

relation.

Our final observation is the dips in the final opinion and the honest node in 7.11, while both do not exist in 7.10b. This can be interpreted to support our fifth relation. However, it can be also be interpreted from another perspective that our system is too quick in its reactions as an honest node should not be distrusted and particulate matter is not a time sensitive application that we need to have such high sensitivity. We chose to go with the first interpretation simply because we used subjective logic for its expressive power in dealing with such cases. And Some doubt should be present for a while when the system discovers an outlier. And such a doubt does not exist in 7.10b.



(a) RMSE change over time

(b) Opinions change over time

Figure 7.11: Random attack with decay factor of 0.6 and attackers ratio 4/11

In conclusion, we observed five very important relations. The decay factor is inversely proportional to the RMSE which is the indicator of the impact of the attacks, to the response speed and to the expressiveness power of our opinions about the current events in the system. However, the decay factor is directly proportional to the stability of our system. And whenever our system becomes too unstable it becomes susceptible to breaking down completely. Also, increasing the decay factor provides better results with

higher attacker ratios.

7.3 Injecting significantly shifted data

7.4 Injecting marginally shifted data

7.5 Periodic Injection of data

8 Conclusion

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