**Design of a virtual sensor using machine learning imputation techniques in a wireless sensor network.**

Final Report

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in the Department of Electrical, Electronic and Computer Engineering

University of Pretoria

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| **Part 1. Preamble** |

This report describes the work that I did in designing a virtual sensor for a wireless sensor network using a machine learning technique.

*Project proposal and technical documentation*

This main report contains a copy of the approved Project Proposal (Part 3 of the report) and technical documentation (Part 5 of the report). The latter provides details of the schematics, stripboard layout, and software code. I have included this appendix on a CD or DVD that accompanies this report.

*Project history*

This project does not build on any projects that were completed in previous years. Stripboard design software as well as the circuit error checking software was provided by Fritzing.org, an opensource initiative. The stripboard sensor circuit was designed and soldered by myself. One of the equations I used was adapted from Steinhart [1]. I used the Tkinter python library to implement the graphical user interface. All other work in this report was my own and completed from first principles.

*Language editing*

This document has been language edited by a knowledgeable person. By submitting this document in its present form, I declare that this is the written material that I wish to be examined on.

My language editor was Mr Joseph Henry Mervitz

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*Language editor signature Date*

*Declaration*

I, Michael Matusowsky understand what plagiarism is and have carefully studied the plagiarism policy of the University. I hereby declare that all the work described in this report is my own, except where explicitly indicated otherwise. Although I may have discussed the design and investigation with my study leader, fellow students or consulted various books, articles or the internet, the design/investigative work is my own. I have mastered the design and I have made all the required calculations in my lab book (and/or they are reflected in this report) to authenticate this. I am not presenting a complete solution of someone else.

Wherever I have used information from other sources, I have given credit by proper and complete referencing of the source material so that it can be clearly discerned what is my own work and what was quoted from other sources. I acknowledge that failure to comply with the instructions regarding referencing will regarded as plagiarism. If there is any doubt about the authenticity of my work, I am willing to attend an oral ancillary examination/evaluation about the work.

I certify that the Project Proposal appearing as the Introduction section of the report is a verbatim copy of the approved Project Proposal.

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M. Matusowsky Date

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**LIST OF ABBREVIATIONS**

**TDD**  Test-driven development

**PIC32** Peripheral interface controller 32-bit

**MCU** Microcontroller Unit

**TCP/IP** Transmission control protocol/Internet protocol

**PC** Personal computer

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| **Part 2. Summary** |

This report describes work carried out on the design of a virtual sensor using machine learning in a wireless sensor network with the objective of using the virtual sensor to impute sensor values of a single sensor node, if a sensor node in the network fails, using the other sensor nodes that are still actively transmitting.

**What has been done**

A literature survey was completed on modern wireless communication systems as well as different machine learning implementations. The hardware and software for the sensor nodes and server was then designed and implemented from first principles. communication system was then designed from first principles. At the core of the hardware system is three PIC32 (Peripheral interface controller 32-bit) microcontroller units (MCU) with an ESP8266 WiFi module that includes a transmission control protocol/internet protocol (TCP/IP) framework, and all additional hardware was designed and implemented. A Python program was developed to simulate the system, as well as C code for the PIC32 processor. The system was implemented and tested throughout the development phase using a test-driven development (TDD) process. Four WiFi modules were used in a star network topology whereby one WiFi module acted as the TCP/IP server on the desktop personal computer (PC) and the other three modules acted as TCP/IP clients on the sensor nodes. The neural network for each sensor node was implemented on the server as well as on the corresponding sensor node’s MCU. The main results from one of the test cases is shown in the figures below.

(Add a figure or figures here – this will probably be a figure that also appears in section 4 of the report).

**What has been achieved**

Successful imputation using machine learning was achieved in a wireless sensor network that was deployed in multiple locations. The accuracy of the imputation depended highly on the amount of training data available where it was discovered that a minimum of 5 days of data was required before a sensor node would be adequately trained. Figure X shows a virtual sensor trained with 2 days of data while figure Y shows a virtual sensor trained with 5 days of data.

**Findings**

It was found, while analysing the weights of the neural networks, that the time input in the neural network was much more important than the sensor inputs with regards to imputing temperature data. Another important discovery was that due to glitches within the hardware, the sensed value by the thermistor would sometimes return a ground value and thus a filtering algorithm had to be implemented to account for the glitches. Such an occurrence is shown in figure X below.

**Contribution**

New software that had to be mastered to complete this project was Fritzing. Fritzing is an opensource PCB/stripboard/circuit designing software that undergraduate students would not usually be aware of and has not been covered in any undergraduate module. The Fritzing software was used specifically for the stripboard module to plan, test and implement the circuitry on a stripboard. Further software that needed to be learned was the MPLAB Harmony Framework for PIC32 MCU’s which was extremely useful in configuring the right clock speed as well as the Universal Synchronous/Asynchronous Receiver/Transmitter (USART) and analog-to-digital converter (ADC) modules.

Due to the limited amount of program memory in the PIC32 and the requirement for string handling, some functions usually provided by the standard library for C had to be re-written from first principles due to the overhead in program memory introduced when using functions such as sprint() which would allow data to be converted from integers and floats to strings and then written to the USART buffer.

A server was developed using Python on a PC connected by USB with a WiFi module. The server would act as the communication center to periodically request and transmit readings from the sensor nodes as well as determine if a sensor node is offline. The code for the serial communication was implemented by the student with the use of the pyserial library.

Code for the neural network, including the training algorithms, was developed by the student without reliance on any existing libraries in python. A framework for training neural networks with a minimum of 3 inputs, theoretically unlimited hidden nodes and layers, and a maximum of 1 output was developed from first principles. A friend in a postgraduate course helped provide some clarity on the chosen training method that is used as it was complex and completely new to the student since no undergraduate module covers evolutionary models for training in neural networks. The study leader provided no assistance with regards to the training but did provide some advice regarding the output layer of the neural network as the student originally wanted to have the output be a binarized output layer with multiple output nodes. The study leader advised to use a single output node in the output layer.

There was a strong reliance on an existing python library called csv to deal with reading and writing from the local database.

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| **Part 3. Project identification: approved Project Proposal** |

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| 1. **Problem Statement** |

In this section the problem that is being addressed by the project proposal is described in terms of the motivation, context, technical challenges and limitations of the proposed project.

**Motivation.** Sensors are devices used in everyday objects such as mobile phones, touch-sensitive elevators and self-driving cars. There are innumerable amounts of applications where sensors are used to gather data about the environment and then used in other electronics to monitor or react to the conditions being sensed such as the lighting in a room being adjusted based on the required illumination level. A problem arises in wireless sensor networks (WSN) where, due to the nature of the wireless communication, data can be lost or corrupted during the transmission phase due to external factors such as solar radiation corrupting data from satellites or congestion in a network causing packet loss when transmitting data to other devices. Furthermore, the cost of implementing or needing to replace many physical sensors in a network can become prohibitively expensive.

This project will look at designing and implementing a wireless sensor network that will make use of data imputation methods and machine learning to realise virtual sensors that can completely replace physical sensor nodes and give accurate substituted data in place of nodes with failed sensor modules.

**Context.** The integrity of received information is an important issue in the modern age. Sensors play a pivotal role in electronic devices of all shapes, sizes and function and especially more so in wireless sensor networks where data loss is an expected occurrence [1]. Data imputation and virtual sensors are tools that allow a system to counter-act the effect of this data loss by accurately substituting values that real sensors would most likely return [2]. This then allows the system to still make use of incomplete data rather than completely discarding affected data entries.

The main function of this project will be to ensure the robustness of a wireless sensor network by making sure that damaged nodes in a wireless sensor network can be replaced by virtual sensors using imputation techniques that make use of machine learning algorithms which will allow the system to remain robust in terms of the provided sensor data even when a node malfunctions or is removed from the network thus allowing the system to continue running in real-time while gathering data that closely resembles the affected sensor nodes would-be data.

K-Nearest Neighbours (KNN, lazy learning), multi-layered perceptrons (MLP, supervised learning) and self-organizing maps (SOM, unsupervised learning) are three popular machine learning methods that have been used to great effect in data sets that do not deal with time-series analysis [3,4,5,6] where KNN, MLP and SOM outperform traditional imputations techniques , such as hot-swapping, to significant degrees on multiple data sets including but not limited to a breast cancer detection data set, a seed classifying data set and sonar imaging data set.

**Technical Challenges.** The technical challenges for this project are: (i) Designing and implementing an imputation technique using machine learning algorithms on individual sensor nodes that can act as a virtual sensor. (ii) The algorithm should be robust to ensure the integrity of the data that is being substituted by the virtual sensors. (iii) The algorithm should be efficient enough so that congestion does not occur due to computations taking place which in itself would then cause loss of more data.

**Limitations.** The availability of bandwidth in the network will limit how many readings can be transferred and received per time interval between all nodes and the server. The second limitation is the processing speed and power of the processing unit at each sensor node. Another limitation is the cost of developing the product thus cost-effective hardware is a necessity as well as putting a financial limit on the amount of nodes that can be physically implemented for this project.

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| 1. **Project requirements** |

The main aim of the project will be to create a wireless sensor network that makes use of the machine learning imputation techniques to ensure the integrity and robustness of the data that is transmitted and received over the network.

**2.1 Mission requirements of the product**

The system will need to fulfil the following requirements.

* The system must use machine learning algorithms to implement virtual sensors in the wireless sensor network.
* Communication between nodes in the network must be done using wireless communication.
* The algorithm implemented must be efficient enough so as not to introduce computational congestion in the system.
* The system must detect a malfunctioning node and replace it with a virtual sensor.
* The virtual sensor must be able to replicate data accurately as if they were real sensors.
* The data read by all the sensors must be stored in a database.
* The virtual sensors must be implemented on every corresponding node as well as having a copy of every trained virtual sensor on the server.
* Each sensor node should consist of a power unit, a sensor module and a processing unit.

**2.2 Student tasks**

The following tasks will need to be completed.

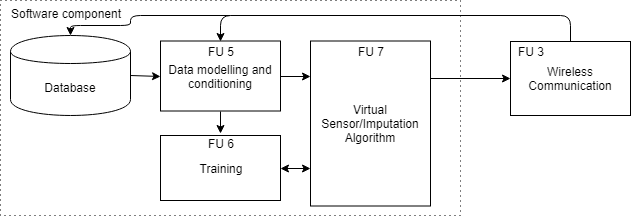
* An investigation of the current machine learning imputation techniques in literature must be done.
* An investigation of where and how virtual sensors have been implemented must be done.
* An investigation of wireless communication interfaces must be done to decide on the best communication interface for the product must be done.
* An investigation for the causes of lost data in wireless sensor networks must be done.
* The imputation algorithms must be designed and implemented with a focus on robustness.
* The algorithms must be trained and tested in MATLAB or Python using data that has been collected from the environment being sensed by the hardware.
* The control algorithms on the processing units for each sensor node must be implemented.
* The circuitry for the sensor nodes must be implemented on stripboard.
* The software and GUI for the server must be designed and implemented on a PC.

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| 1. **Functional analysis** |

This section contains information on the subsystems and each function unit of the system separated into the hardware and software components.

The hardware component, shown in Figure 1, will consist of a sensor module (FU 1) which will sense the characteristics of the environment and be attached to a processing unit (FU 2). These two functional units cover a single sensor node. The processing unit will, at regular intervals, take environmental readings from the attached sensor(s) and package the data for transmission via wireless communication (FU 3) with the other sensor nodes as well as a central server (FU 4) which will contain the database that will store historical data for later use in data modelling and then training the virtual sensors of each sensor node as well as general storage for historical data of the network.

**Figure 1. Overview of the hardware component**



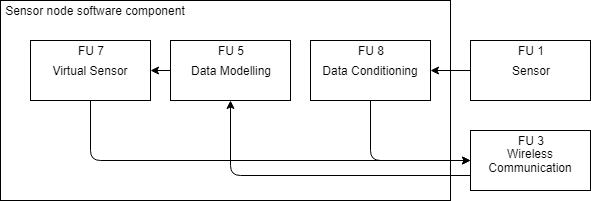
**Figure 2. Overview of the server software component.**

The server software component, shown in Figure 2, will consist of the database and all the software of the server of the system.

When the system is functioning in a manner that all the sensor nodes are active with functioning physical sensor nodes, the server will simply store the sensor readings received from the sensor nodes through a wireless communication link (FU 3) in the local database. This data will then be modelled (FU 5) so that I may be used as offline training (FU 6) data for the machine learning algorithms that will be deployed as the virtual sensors on both the server as well as the processing unit of the sensor nodes.

When the system is functioning in a manner that a sensor node in the network has been taken offline, the incoming sensor data to the server from the remaining sensor nodes will be stored in the database and modelled (FU 5) to be used as an input for the virtual sensor (FU 7) contained on the server that will be activated once it is determined that a sensor node has stopped communicating with the server.

When the system is functioning in a manner that a sensor node is online (i.e. it is communicating with the server) but does not have a functioning sensor module attached, the server will continue to receive readings from the remaining sensor nodes that do have a functioning sensor module attached. These readings will be stored in the database and forwarded to the sensor node without a functioning sensor module to be used as the input for the virtual sensor contained on the sensor module.



**Figure 3. Overview of the sensor node software component.**

The sensor node software component, shown in Figure 3, will consist of two modes of operation.

The first and default mode of operation will consist of the sensor node taking environmental readings using the attached sensor module (FU 1) and using the digital filtering algorithms to reduce noise from the read data (FU 8). This data is then uploaded to the server using a wireless communication link (FU 3) to be stored in the server’s database.

The second mode of operation will consist of the sensor node imputing environmental readings by activating the virtual sensor (FU 7), which itself will use the machine learning imputation method, if the node detects that no sensor module is attached to the processing unit. Readings from the other sensors in the network will be passed to the sensor node by the server through the wireless communication link (FU 3) and then modeled so that the data can be used as input data for the virtual sensor. The imputed sensor data from the virtual sensor is then uploaded to the server for storage in the database.

One of the potential methods of the virtual sensor involves the usage of a self-organising map, an unsupervised neural network, where the neurons are organised in a connected 2-D grid as shown in figure 5 and the correlation in data is learned using the steps in Figure 4.



**Figure 4. The steps of a self-organising map.**



**Figure 5. A self-organising map neural network after 301 iterations.**

The self-organising map initially randomises the positions of all the neurons. A data point is then selected randomly to be used as the reference point to match the neuron that is the closest in proximity to the point. The neuron is then moved closer to the data point. The neighbouring neurons in a certain radius of that neuron are then also moved closer based on how far they were positioned from the data point, with further neighbouring neurons moving less. The moving rate and the radius for the chosen neuron, also known as the learning rate, is then decreased on each iteration. These steps are repeated until the positions of all the neurons has stabilised in a way that significant neuron movement does not occur as seen in Figure 5.

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| 1. **Target specifications** |

This section contains the main specifications of the proposed project.

**4.1 Mission-critical system specifications**

The mission critical systems specifications are given in Table 1 below.

|  |  |  |
| --- | --- | --- |
| **SPECIFICATION**  (in measurable terms) | **ORIGIN**  **(**or motivation of this specification) | **VERIFICATION**  (how will you confirm that your system complies with the specification?) |
| The virtual sensor using the MLP neural network imputation method should impute values, at minimum, within 30% accuracy of the actual observed values for 90% of the data. | [2] and [3] both show that the imputed values from MLP neural network methods are within 30% of the actual observed values on average and within 15% in an absolute best-case scenario. | The imputed values from the virtual sensors will be compared to the physical sensor readings. |
| The virtual sensor using the MLP neural network imputation method should not stray further than 1 standard deviation from the mean values that would be sensed by a physical sensor. | A standard deviation greater than 1 would indicate that the virtual sensor has been improperly trained and will not be of any practical use. [7] suggests a standard deviation of not higher than 1 would provide a good indication of a well-trained system. | Each virtual sensor, both on the server and on the node, will be tested by turning nodes ability to physically sense the environment as well as completely turning off a sensor node to ensure that the server can activate the corresponding virtual sensor. If the virtual sensor can impute data that would be sensed by the physical sensor within the specified standard deviation from the mean, it would be deemed functioning correctly. |
| Imputation of a single value should take no longer than 7 seconds when using the MLP neural network algorithm while running on the server once the physical sensor data from the functioning sensor nodes has been input into the virtual sensor. | Imputation of a single value takes up to 7 seconds in [1] when using the MLP neural network imputation technique and this is due to the computations being done by the processor. To prevent congestion due to server processes taking place, some time must be given for these computations to take place before new values can be imputed. | A timer will be setup between the time that the virtual sensor has been given the input and the time that the virtual sensor gives an output. This will determine the time it takes to impute a value on the server for the given algorithm. |

**Table 1. Mission-critical system specifications**

**4.2 Field conditions**

|  |  |
| --- | --- |
| **REQUIREMENT** | **SPECIFICATION**  (in measurable terms) |
| The sensor nodes must be directly connected to the server. | The connection will need to work over WiFi or Bluetooth |
| The server must run on a computer capable of processing large streams of data for training purposes. | Any modern computer with a CPU speed of at least 2GHz. |

**Table 2. Field conditions**

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| 1. **Deliverables** |

**5.1 Technical deliverables**

Table 3 shows the technical deliverables that will be required to complete the project.

|  |  |  |
| --- | --- | --- |
| **DELIVERABLES** | **DESIGNED AND IMPLEMENTED BY STUDENT** | **OFF-THE-SHELF** |
| Atmospheric (barometric or temperature or humidity) sensor modules for the processing units. |  | X |
| 16-bit or 32-bit microcontroller for the sensor nodes. |  | X |
| Wireless communication modules. |  | X |
| Power supply for the sensor nodes. |  | X |
| Sensor module interface with the microcontroller. | X |  |
| Wireless communication module interface with the microcontroller. | X |  |
| Desktop PC for the server. |  | X |
| Desktop monitor. |  | X |
| Software libraries for accessing the database. | X |  |
| Processing unit sensor control software. | X |  |
| Processing unit communication protocol. | X |  |
| Database on the server to store the data received from the physical sensors. | X |  |
| Server communication protocol. | X |  |
| Imputation algorithm using MLP neural network technique in MATLAB or Python for simulation. | X |  |
| Imputation algorithm using MLP neural network technique on the sensor node processing units. | X |  |
| Imputation algorithm on the server. | X |  |
| Data modelling software on the server. | X |  |
| Data modelling software on the sensor nodes. | X |  |
| Graphical user interface for the PC application. | X |  |

**Table 3. Deliverables**

**5.2 Demonstration at the examination**

1. All the software will be preloaded onto the sensor nodes and the server before the demonstration begins.
2. The physical system will then be demonstrated by switching on all the sensor nodes and the server and activating the system.
3. The graphical user interface on the PC will be used to show the current outputs of the sensor nodes in the network.
4. A software command will be submitted to one of the sensor nodes from the PC to activate the virtual sensor using the MLP neural network algorithm to impute data.
5. The sensor node will acknowledge this command and return the imputed value as well as the sensor reading to compare it values. This will confirm the virtual sensor is functioning correctly using the MLP neural network imputation technique.
6. A software command will then be entered on the server to activate a virtual sensor using the MLP neural network imputation technique on the server that will impute values for the chosen sensor node. The values will again be compared to the values sensed by the sensor node. This will confirm that the virtual sensor on the server is functioning correctly using the MLP neural network imputation technique.

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| 1. **References** |

[1] Y. Li and L. Parker, “Nearest neighbour imputation using spatial-temporal correlations in wireless sensor networks,” *Information Fusion*, vol. 15, pp. 64-79, 2014.

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| **Part 4. Main report** |

**1. Literature study**

* 1. **BACKGROUND AND CONTEXT OF THE PROBLEM**

With the widespread proliferation of sensors in all different types of environments a new use case has come up in recent times called the Internet of Things (IoT) where sensor devices are interconnected to form wireless sensor networks (WSN). WSN have applications in many different fields including but not limited to the mining and aeronautic industry.

Different WSN may use different technologies to achieve the required goals, be it networks that may require low-power usage (LoRa), networks that need to communicate over vast distances at a low cost (Sigfox) or networks that need fast and reliable communication over shorter distances (WiFi).

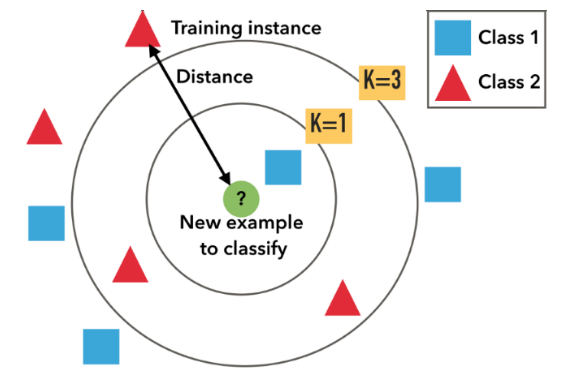
Two problems arise in all these WSN that may cause loss of important data. The first problem deals with the noise level in the environment. If the noise level is high, then it may result in a degraded signal strength and thus performance in the WSN degrades to a point where data packets are lost (packet loss) or corrupted packets being transmitted across the network. These lost or corrupted packets may then cause errors further down the WSN pipeline if the application requires corrective action. The second problem deals with dead sensor nodes in the network. Dead sensor nodes are sensor nodes in a network that have failed or stopped responding and thus the data from these nodes is no longer being collected.

Much of the research based on virtual sensors (VS) has focused on using different machine learning approaches in representing the lost data or in creating new data by finding the relationship between different nodes in a network.

VS systems implementing machine learning can be segmented into three main different types of learning namely lazy learning, supervised learning and unsupervised learning.

***1.1.1 Lazy learning systems***

In lazy learning systems, the artificial intelligence does not require an explicit learning phase but uses an existing database to find the closest matching neighbours to the incoming inputs with *k-*Nearest Neighbours (KNN) algorithm [1], visualised in figure 1, being the one of the most widely used methods.

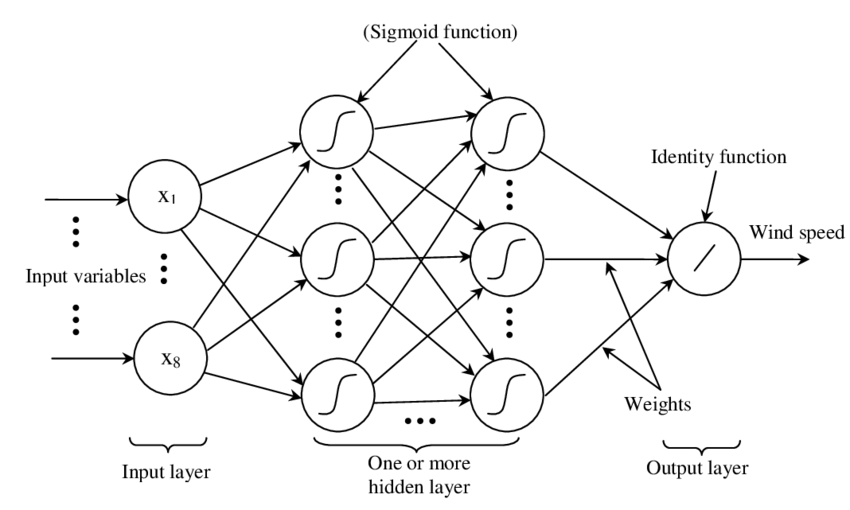


**Figure 1. Visualisation of the KNN algorithm.**

The advantage of these systems is that no time is required to train the artificial intelligence as the generalisation of the training data does not occur until a query is made to the system. One such system using the KNN algorithm in combination with a decision tree, as discussed in [2], was found to be very effective in smartphones that need to detect head movements for a virtual reality device with accuracy only going as low as 90% when using a combination of accelerator, gyroscope and magnetometer sensor readings; however, the data set that is used must be carefully selected beforehand or else the classification accuracy will not have the optimal result. This requirement of acquiring a suitable database beforehand is not feasible in the real-world environment where environmental noise must be accounted for as well in the data set.

***1.1.2 Supervised learning systems***

In supervised learning systems, unlike the lazy learning systems, the artificial intelligence requires a training phase to generalise data so that queries can be made to the system. Learning is supervised in the manner that training targets are provided to the artificial intelligence for the desired model and parameters are adjusted accordingly over many training epoch cycles until a desirable model emerges. The most famous of these supervised learning systems is the artificial neural network (ANN). There are differing types of ANN namely feed-forward neural networks (FFNN), recurrent neural networks (RNN) and convolutional neural networks (CNN) being just a few, with each having their own field of applications in artificial intelligence. Multiple layered perceptron (MLP), figure 2 [3], are a form of FFNN which have a minimum of three layers namely the input layer, the hidden layer of which there may be more than one and finally the output layer. In the case of MLPs there are various differing training methods in the literature that are covered later in this section.



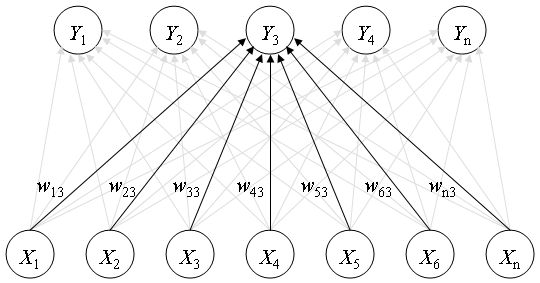
**Figure 2. Structure of a MLP with multiple inputs and hidden layers and a single output node.**

As shown by [3], MLPs are universal function approximators which allow them to create mathematical models through regression analysis as well as being useful in the field of classification problems which is another case of regression. VSs can be implemented using MLPs as was done in [4] where a virtual Infrared Radiation (IR) sensor based on a conventional visual (RGB) sensor is used to estimate thermal IR images for terrain classification. Mean Squared Error is used as the loss function during training and is defined as

where *C* is the number of channels, and are thermal values at each pixel (*i*, *j*) of a ground truth thermal image and an output thermal image **.** Training was done using genetic algorithms instead of the widely used backpropagation algorithm. The results of the work in [4] using the MLP method were promising where the MSE and standard deviation of the temperature difference was 1.8 degrees Celsius and 3.7 degree Celsius respectively.

***1.1.3 Unsupervised learning systems***

In unsupervised learning systems the artificial intelligence requires a training phase but, unlike supervised learning systems, there are no corrections made in terms of requirements in terms of the training targets i.e. no backpropagation or similar algorithm is used to correct the error of the artificial intelligence. The Kohonen map, figure 3, described in [5], otherwise known as a SOM is a widely used type of FFNN with an input layer and an output layer each which has multiple nodes associated with the layer. The SOM works by first being initiated to a state with random weights and then training occurs by forward propagating a dataset over several epochs.



**Figure 3. A Kohonen Map with n inputs and outputs, fully connected from the input layer to the output layer.**

With each forward propagation the nodes within a certain range of the desired output value move closer to the target output where the closer nodes move more than the further nodes. The amount that the nodes may move towards these target values decreases with each epoch by an amount set beforehand. The goal of the SOM is to organise the neural network outputs in such a manner that the target data is mapped accurately. This requires the output layer have enough nodes to cover as many data points as possible which may not be immediately clear during experimentation and would require iterating several times before an optimal number of nodes is found for the relationship between input data and output target data. A SOM is used in [6] for the localisation of sensor nodes in a WSN. Each sensor node is represented by an output node in the SOM and is initially trained based on the received signal strength from the nodes to then triangulate a precise location for the node. It was found that the number of nodes heavily influenced the accuracy of the data and that an increase in output nodes leads to less accurate localisation in some cases for certain sensor nodes. This VS proved to be less accurate than the triangulation method with which it was tested against.

***1.2.1 Supervised learning algorithms***

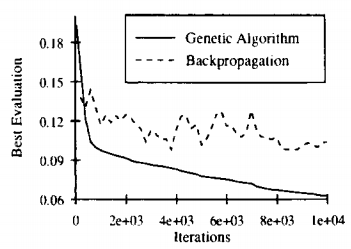
Within the supervised learning systems there are many different methods used in training these systems. The most widely used training method makes use of the backpropagation algorithm but in recent genetic algorithms (GA) have found their uses in training MLPs.

*1.2.1.1 Backpropagation algorithm*

The backpropagation algorithm [7] calculates the output error in an MLP then assigns fault to each weight in the MLP after the initial forward pass of inputs. There are various supplementing algorithms used, the most basic being simple gradient descent and more recent algorithms using the Levenberg-Marquardt [8, 9] method to calculate a gradient. The only requirement for using the backpropagation algorithm is that the activation function of a neuron in the MLP must be differentiable. The main issue with the backpropagation algorithm is that the weights in the MLP may be trained in a way that an optimum solution may be found for the desired input-output relationship, but it may not be the most optimal due to the algorithm regressing to a local optimum instead of a global optimum. Another issue is that the backpropagation algorithm does not perform well if plateaus are present during the training phase. Thus, the performance of an MLP trained using backpropagation is affected by the initial randomised weights of the MLP before training is performed and so more research is being done in other methods of training MLPs especially with the increase in computational power.

*1.2.1.2 Genetic algorithm*

GA work on the idea of natural selection where only the fittest in a population will pass on their genes. This is known as neuro-evolution. There are many different versions of the GA where different properties are used to determine genes and phenomes that would be crossed over to generate new populations from the fittest sample size. In MLPs, GAs generally use the weights as the genes but there are other implementations that combine the weights as well as the number of nodes and hidden layers [10]. The way a GA is used in training neural networks is that a population of neural networks are initialised with random weights. The dataset is then forward propagated through the network with target outputs and an error is calculated based on some pre-determined loss function, the simplest of which is based on the Euclidean distance. The fittest candidates in the population are then selected based on the calculated error and are known as the parent nodes. Through various differing methods of selection, parent nodes are paired and their genes crossed over to form new child nodes, some of which may be mutated using some random process to avoid stagnation in the population, until the population reaches the original population value and the process restarts. The advantage of this system is that, due to the randomly initiated state of the first population, there is less likelihood that the global optimum solution would not be found using neuro-evolution. The disadvantage is that the computational power required is much greater than for backpropagation; however, in [11] it was found that training FFNN using GAs shows that this method outperformed the backpropagation algorithm both in the final evaluation and in the time to train as well as never having an increase in error as the number of training iterations increased seen in figure 4.



**Figure 4. Training error of GA and backpropagation**

* 1. **APPLICATION OF THE LITERATURE**

This project is largely concerned with the identification of the relationship between sensor nodes in a sensor network using data that has been collected by the sensor network hence many of the above algorithms are applicable to the proposed scenario. The fact that multiple sensor nodes will be deployed to generate training data results in an interesting case where each sensor node will require its own virtual sensor. It is assumed that a user of this system will have collected the required training data for each sensor node prior to activating a virtual sensor. The algorithms were carefully considered with their advantages and disadvantages kept in mind and the most suitable algorithm was chosen for the problem based on modern trends in machine learning.

Machine learning is by far the most integral part of the project since the relationship that must be modelled by the system between all the sensor nodes in the network is incredibly important to the functioning of the virtual sensors. GA was chosen due to experimental evidence showing that the training method converges much faster than the backpropagation algorithm which would lessen the amount of training time required as well as not falling into the potential trap of local optimums which may require a reinitialization of the training due to stagnant results. GAs have multiple different approaches that can be used when finding the fittest population and then repopulating so plenty of experimentation may be done to find the most optimal MLP topology during training whereas the backpropagation would need to be iterated through using a grid search.

A star topology was chosen for the sensor network that would make use of WiFi communication technology where the sensor nodes would communicate with a central server. Low power usage is of no concern in this project and the project is concerned with sensor networks where distances from each node are not too far apart from each other (<50m) which would mean that expensive technology such as ZigBee and LoRa are not required.

The database of the system will be stored locally by the server and used as training and test data for the VS once enough data has been gathered. A separate database will collect the VS outputs for comparison to real sensed data once training is complete.

**2. Approach**

The solutions to the engineering problems provided by this project were carefully studied and approached in a manner that enough consideration was given to alternative designs with respect to each design’s trade-offs. All the available tools were utilised to aid in the design and implementation of the project as well as an engineering approach to solve the problem. Below each entity in the functional analysis as in the project proposal (**Part 3)**, **Section 3** is described systematically.

**2.1 TEMPERATURE RECORDING, FILTERING AND CONVERSION**

The temperature that must be recorded by each sensor node is one of the most important steps in the system as without this recording mechanism no data can be acquired to train the VSs that accompany the system. Since the ambient temperature where the sensor nodes would be deployed is not expected to change too quickly under normal conditions, a sampling rate of 1 sample per 30 second interval was chosen. The sensor node was designed from first principles instead of using an off-the-shelf solution as cost was taken into consideration. No scaling circuit was designed as the modified Steinhart-Hart equation [12] was deemed a better software solution than using hardware to deal with converting voltages to degrees Celsius. It was found during testing that a filtering algorithm was required for the incoming values as a small bit of noise was experienced in the form of temperature anomalies due to hot air pockets moving through the buildings as well as hardware glitches that resulted in ground values being returned on very rare occasions. A mean filter, median filter and a scalar Kalman filter (SKF) was designed and implemented in software on the server to deal with these anomalies and it was found that the SKF performed much better in terms of dealing with the anomalies than the other two methods as well as being computationally simple and was chosen as the final filtering algorithm.

Temperature is recorded when the server sends a query to a sensor node requesting a temperature sensor reading. The sensor node analog-to-digital converter (ADC) converts the voltage values to a 10-bit digital value and packaged in a byte array and sent to the server. This procedure is performed two more times for the other sensor nodes and the values are then stored in a CSV file along with a timestamp which forms the database.

**2.2 VIRTUAL SENSOR ALGORITHM**

For the virtual sensor algorithm, only the MLP methods were considered while SOM and KNN were discounted due to the lack of ability for the SOM algorithm or KNN algorithm to perform or otherwise find a regression model. An algorithm was implemented to iterate through various topologies based on number of hidden nodes as well as hidden layers to determine an optimal middle ground where an acceptable accuracy was reached by the MLP while taking training time into consideration. Iterations took the average final error over 20 tries per topology and the optimum topology was then used for the final MLP. All algorithms were designed, implemented and tested in Python.

**2.3 VIRTUAL SENSOR TRAINING**

The database for training the VS consists of a minimum of 5 days’ worth of data which equates to roughly 14400 collected sensor readings. This data is split up into a training set and a test set of roughly 60% training data and 40% test data. Before training can begin, the data is first normalised to values between 0.0 and 1.0 by finding the maximum and minimum in the data then scaling it down by using the scaling equation defined as

(2.1)

Where is the current value being scaled, is the lowest value in the dataset and is the largest value in the dataset. An initial population of randomly initialised neural networks is instanced with the above normalisation kept in mind.

***2.3.1 Forward propagation***

Forward propagation in the MLP consists of giving the appropriate input nodes the correct input values and then propagating these values forward through the MLP through a series of nodes and layers where each node sums all incoming inputs then activates by using an activation function defined in this project by the Softsign function as

(2.2)

until ultimately arriving at the output node with the predicted value. The Softsign function was chosen due to its faster computation speed as compared to the sigmoid activation function and tanh activation function.

***2.3.2 Loss function***

The loss function for the neural networks was adapted from the literature, the loss function described by [11] was of specific interest as they are low cost computationally and give enough information regarding the error percent of the neural network. The error was calculated by adding the error of each prediction and dividing by the total predictions made during each epoch.

***2.3.3 Fittest population selection and mating***

Following on from the error calculation, the fittest neural networks are selected for breeding. Parents are then randomly selected, irrespective of which parent is the most fit in the fittest population, for breeding. Weights are randomly selected across both parent’s weight arrays to complete a child neural network’s weight array with a small chance to completely randomise a single weight in the array to act as a mutator until the original population size is reached. This is repeated over a specified number of epochs until a candidate neural network emerges for a specific VS.

**2.4 VIRTUAL SENSOR IMPLEMENTATION**

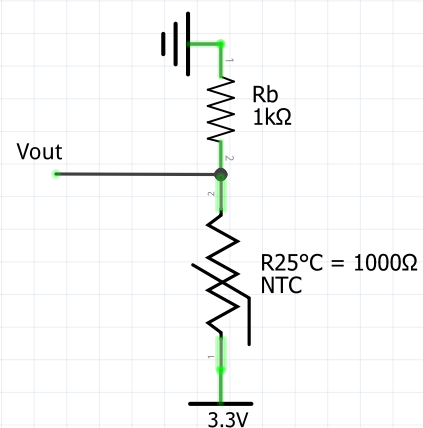
The VSs are deployed on both the server and the sensor nodes, applying the weights that have been found through the training phase. As such, the readings from the VS on the sensor node should not differ much or at all from the VS deployed on the servers. The system will identify if a sensor node is not communicating with the server and use the appropriate VS to take over sensing operations until the sensor node is able to reconnect to the network. Otherwise the sensor node will send both VS data and actual sensed data back to the server.

**3. Design and implementation**

The design approach adopted is a top-down design making use of the functional decomposed blocks of the functional block diagram detailed in figure 1, figure 2 and figure 3 in the project proposal (**Part 3**). Each major functional block is discussed in terms of the design, simulation, performance, evaluation and optimisation where applicable.

**3.1 TEMPERATURE SENSOR**

The sensor circuit is implemented using a thermistor to realise a temperature sensor. From the PIC32MX220F032B (PIC32) microcontroller datasheet (**Part 5**), the maximum input voltage to the ADC is 3.3V. Taking this into consideration, an NTC thermistor with R25°C = 1000Ω was chosen as the sensing component and a 1000Ω resistor used for the voltage divider bias resistance. This ensures that the room temperature would always be half the maximum input voltage as seen by the ADC terminal of the microcontroller. The circuit schematic is shown in figure 3.1.



**Figure 3.1. Voltage divider for the sensor node.**

The conversion equation from voltage to an unsigned integer is defined as

(1)

Where the resolution of the ADC is taken from the PIC32 datasheet and is 1023, the system voltage is 3.3V, the ADC Reading and Analog Voltage Measured are the desired values. From the TTC05 thermistor datasheet (**Part 5**), the lowest possible resistance is 0.031Ω for a temperature of 130°C and the highest possible resistance is 10556Ω for a temperature of -30°C. Using the equation for a voltage divider output defined as

(2)

where the bias resistance, , is 1000Ω and is 3.3V, the lowest and highest

expected values by the ADC in terms of voltage are:

* Lowest voltage when temperature is high with : 0.001V
* Highest voltage when temperature is low with : 3.014V

This indicates that the sensor would not make use of the full scale of the ADC by not utilising the highest 9.13% possible but is still deemed acceptable without needing to implement a scaling circuit.

Based on the calculated values above, the highest and lowest converted values to be expected as well as the room temperature converted value are shown below in table 3.1 by re-arranging equation 3.1 as

(3)

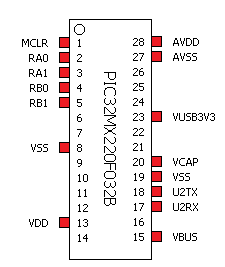
|  |  |  |
| --- | --- | --- |
| **Temperature** | **Input voltage** | **ADC Reading** |
| 130°C | 3.014V | 935 |
| 25°C | 1.65V | 512 |
| -30°C | 0.001V | 1 |

**Table 3.1. ADC Readings based on input voltage from temperature sensor.**

Two voltage divider circuits were implemented with the outputs connected to different analog input pins on the microcontroller meaning two temperature sensors were implemented per sensor node. This was done for redundancy since components may have slightly different tolerances than specified in the datasheet.

**3.2 MICROCONTROLLER**

Due to the low power usage of this microcontroller (100mA on average when running at 80MHz), having software support in the form of the Harmony framework as well as being a well-stocked microcontroller solution available locally in South Africa the PIC32 was chosen as the processing unit for the sensor node. The pins that were chosen to be used are indicated in figure 3.2 and their function detailed in table 3.2. All power pins were attached with a 10uF tantalum capacitor to ground as was suggested in the PIC32 datasheet to protect against current surges.



**Figure 3.2. PIC32 pins used.**

|  |  |
| --- | --- |
| **Pin number** | **Function** |
| 1 | Required to program PIC32 |
| 2 | Analog Sensor Input 1 |
| 3 | Analog Sensor Input 2 |
| 4 | Required to program PIC32 |
| 5 | Required to program PIC32 |
| 8 | PIC32 Voltage Ground Supply |
| 13 | PIC32 Voltage Power Supply (3.3V) |
| 15 | PIC32 Voltage Power Supply (3.3V) |
| 17 | USART Receive pin |
| 18 | USART Transmit pin |
| 19 | PIC32 Voltage Ground Supply |
| 20 | Voltage Capacitor 10uF |
| 23 | PIC32 Power Pin |
| 27 | ADC Voltage Reference (3.3V) |
| 28 | ADC Voltage Ground |

**Table 3.2.**

**3.3 WIFI MODULE**

For the wireless communication there was a choice between using Bluetooth technology or WiFi. WiFi was chosen as TCP/IP was the preferred method of message transmission in the network as well as allowing for a relatively simple implementation of a star network topology. The ESP8266 WiFi module was chosen due to the low power options available on the ESP8266 microcontroller as well as for the ability to communicate through USART. Four ESP8266 WiFi modules were implemented in the project, one to serve as the server’s communication device and the other three to be used on each sensor node. The firmware version installed on each module is 1.5.1 and is available in **Part 5** as well as the instructions and hardware setup required to flash the firmware.

***3.3.1 Server module***

The module used to act as the server’s communication interface requires communication through USB to transmit all received data to the server on the desktop PC. A serial-to-TTL device was required. Power to the module is provided through the USB port to both the serial-to-TTL device as well as the ESP8266 module which has a maximum current draw of 350mA on startup and 150mA on average while transmitting or receiving data. It was found that the desktop PCs USB ports were able to supply the required power and no external power source was required. The baudrate of the module was set to 115200bps as this was the maximum baudrate possible from the desktop PCs communication link which translated to 14.4kB/s maximum transfer rate, well above what is required to transmit and receive data without losing any packets.

The following commands in table 3.3 must be sent to the ESP8266 module through a terminal interface, such as Termite or PuTTY, to set it to server mode.

|  |  |
| --- | --- |
| **Command** | **Description** |
| AT+CWMODE=2 | Set the module to station and access point mode. |
| AT+CWSAP= “ESP Access Point 1” | Set the SSID of the module to be accessed via WiFi |
| AT+CIPMUX=1 | Set the module into multiple access mode so that multiple devices (maximum 8) can connect to the server |
| AT+CIPSERVER=1,333 | Start the TCP/IP server on port 333 and begin accepting TCP client connections. |

**Table 3.3**. ESP8266 server mode setup commands.

***3.3.2 Client module***

The modules used to act as the client’s communication interface requires communication through USART to transmit all received data to the microcontroller as well as transmit data over WiFi when data is received through USART from the microcontroller. 10uF tantalum capacitors were placed between power and ground due to the high current draw at startup. The baudrate of the module was set to 115200bps as this was the maximum baudrate possible from the microcontroller’s communication link, well above what is required to transmit and receive data without losing any packets.

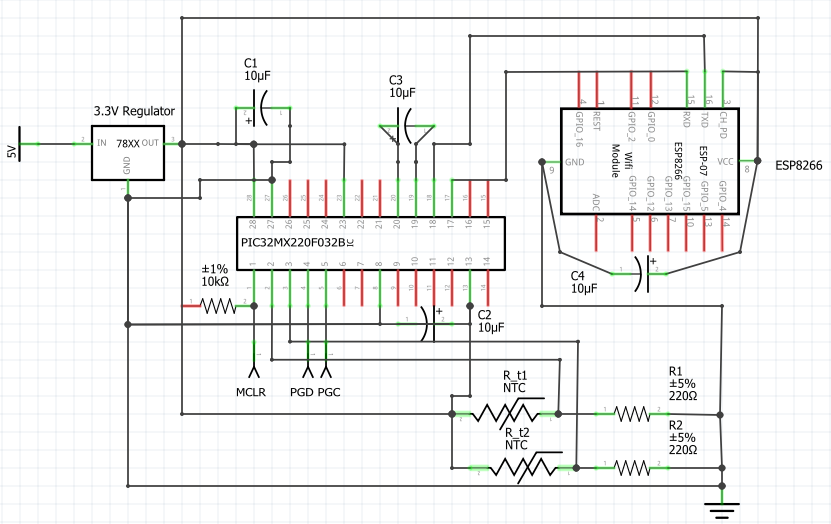
The following commands in table 3.4 must be sent to the ESP8266 module through the USART interface by the microcontroller to set it to client mode prior to attempting to connect to the server.

|  |  |
| --- | --- |
| **Command** | **Description** |
| AT+CWMODE=1 | Set the module to access point mode. |
| AT+CWJAP= “ESP Access Point 1” | Set the module to automatically seek out the server’s specified SSID and connect to it if found. |

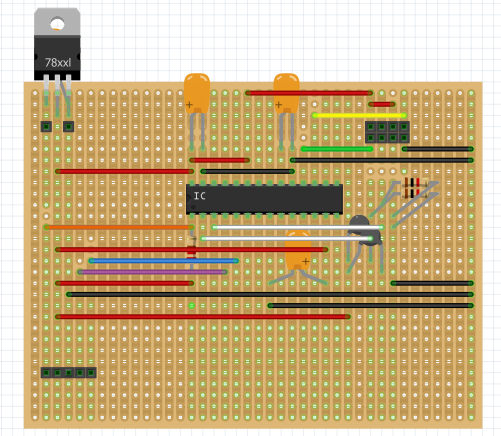
**Table 3.4.** ESP8266 client mode setup commands.

**3.4 FINAL SENSOR NODE CIRCUIT**

The circuits were implemented on a stripboard although PCB was available at a greater cost. Due to USB power supplies having a standard output voltage of 5V, a 3.3V voltage regulator was used to bring down the voltage as both the microcontroller and WiFi module have a maximum voltage tolerance of 3.6V. The schematic is shown in figure 3.3 and the stripboard design, done in Fritzing, in figure 3.5. There is a single power line and ground line shared between all components in the circuitry.



**Figure 3.3. Full circuit schematic of the sensor node.**

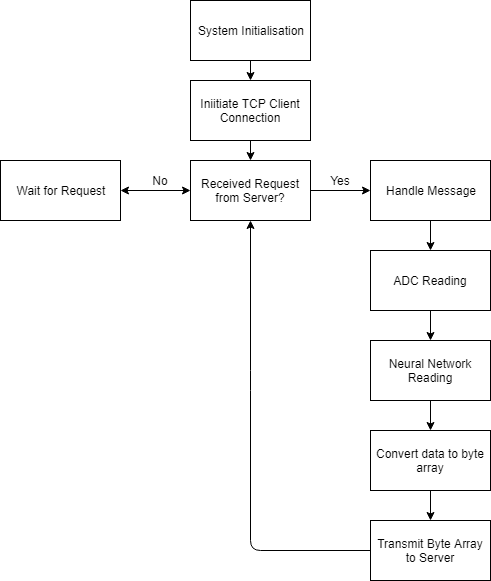
****

**Figure 3.4. Stripboard design of the sensor node done in Fritzing**

Due to the Fritzing software not including an ESP8266 WiFi module it must be noted that the 8 pin holders in figure 3.4 in the top right section that are in a 4x4 configuration of the stripboard were reserved for the pins of the ESP8266 WiFi module. The five pins in the bottom left are reserved for the PICKIT3 programming device that is required to program the PIC32.

**3.5 MICROCONTROLLER SOFTWARE**

The Harmony framework was used to initialize the clock speed and peripherals to the required states to perform specific operations, specifically USART communication and PLL clock required for the ADC. The ADC was configured manually using information provided by the datasheet. A workflow engine was considered but due to the unpredictability of peripheral interrupts interrupting the program flow, a state machine was implemented to ensure no important functions would be interrupted during important functions. The design of the state machine is shown in figure 3.5.



**Figure 3.5. Microcontroller State Machine.**

***3.5.1 System Initialisation***

The microcontrollers initial state involves initializing all data structures that were used as well as the system clocks and pin configurations. The Harmony framework was used to set the pin configuration of the system shown in table 3.4

|  |  |
| --- | --- |
| **Pin number** | **Function** |
| 2 | Analog Input 0 |
| 3 | Analog Input 1 |
| 18 | USART Transmit 0 |
| 19 | USART Receive 1 |

**Table 3.4. PIC32 pin configuration.**

The following settings were used in setting up the USART communication with the PIC32 microcontroller:

* Static driver implementation
* Interrupt Mode
* Byte model support
* Baud rate: 115200 (required for communication with ESP8266 WiFi module)
* Interrupt priority level: 1
* Operation mode: normal USART operation mode
* No handshake protocols
* Line control: 8 data bits, no parity bit, 1 stop bit (8-N-1)

The following settings were used in setting up the ADC for sensor data acquisition:

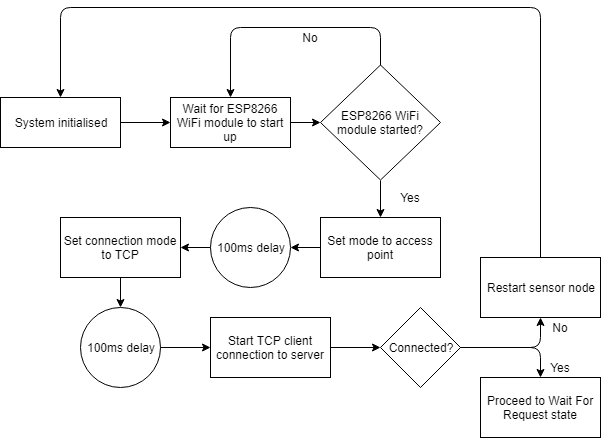
* Pin2 and Pin3 set to analog
* Pin2 and Pin3 set to input
* Internal counter set to 16
* Set voltage reference to Pin27 and Pin28
* Set acquisition time to 3.841us (based on PIC32 datasheet suggestion)
* Enable ADC

***3.5.2 Initial TCP Client Connection***

The sensor node must start an initial client connection to the server. The commands in table 3.5 are sent from the microcontroller through USART to the ESP8266 WiFi module to initiate the TCP client connection. Due to the ESP8266 WiFi module having a start-up time, the microcontroller waits before sending the commands at startup as seen in the figure below, figure 3.6. There is a mandatory 100ms waiting time between each command so that the ESP8266 WiFi module can process and execute the commands.

|  |  |
| --- | --- |
| **Command** | **Function** |
| AT+CWMODE=1 | Set the WiFi module to access point mode. |
| AT+CIPMODE=0 | Set the WiFi module to TCP connection mode. |
| AT+CIPSTART=”TCP”,”192.168.4.1”,333 | Initiate a TCP connection to a specified IP Address and port number. |

**Table 3.5. Initial commands required to initiate a TCP client connection.**



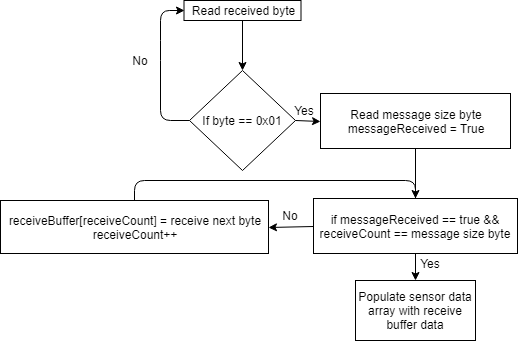
**Figure 3.6. Design of the initial connection state.**

***3.5.3 Message handling***

When a message is received through WiFi it is communicated to the microcontroller through USART. The bytes received must be handled and assigned to the relevant data structures to be used in the rest of the program. An interrupt handler was used to deal with incoming bytes. A byte message will consist of the following attributes:

* Header byte [1 byte]
* Message size [1 byte]
* Data bytes [6 bytes]
* Tail byte [1 byte]

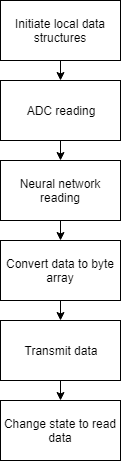
The data bytes consist of the raw sensor data that the server receives from the other sensor nodes in the network as well as the seconds that have passed since midnight in byte format. The design of the message handling is shown in figure 3.7.



**Figure 3.7. Read data from USART buffer.**

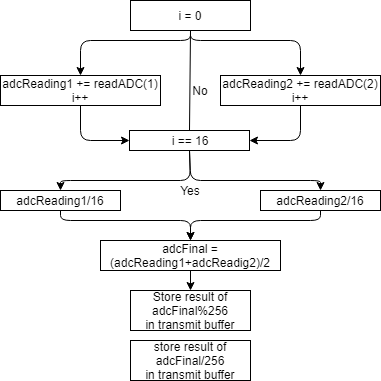
***3.5.4 ADC and neural network reading***

After the data has been received from the server the system changes state to transmission mode. The block diagram in figure 3.7 describes the general process before the transmission of the data to the server occurs.



**Figure 3.7. PIC32 transmit process.**

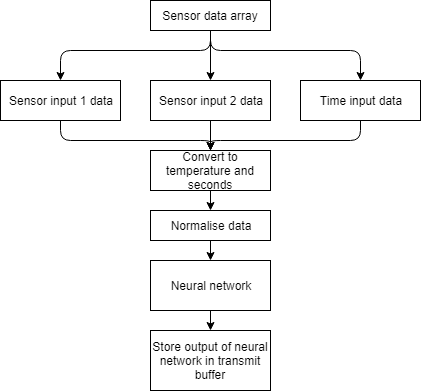
**ADC reading**



**Figure 3.8. ADC reading and averaging.**

From figure 3.8 above it can be seen that two ADCs were used. The average reading over 16 cycles was used from both temperature sensors and then summed together and divided by two to get a final average reading. This was done to minimise the effect that small differences in the thermistor element could have due to the manufacturing process. The result, due to each byte in the transmit array only being able to handle integer values up to a maximum size of 256, is split into a low and high byte by first taking the modulus256 of the original value and storing it as the low byte value then dividing the value by 256 and storing the result in a high byte.

**Neural network reading**

****

**Figure 3.9. Neural network reading.**

Figure 3.9 above, shows the steps associated with extracting the sensor and time data received from the server then converting it to a format that can be normalised and used as input to the neural network. Conversion involves the usage of the Steinhart-Hart equation as

(4)

where:

* T is the temperature in Kelvin
* a, b and c are the Steinhart coefficients
* R is the resistance of the thermistor divided by the bias resistor

By setting and taking making , where is the room temperature and setting , where B is a Steinhart parameter found in the thermistor datasheet (**Part 5**) and is equal to 3800, the equation simply becomes

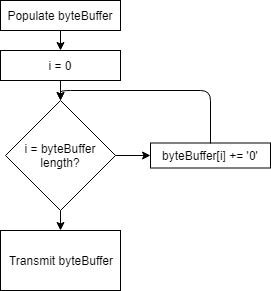
(5)

This is a less computationally complex adaptation of the Steinhart-Hart equation since only one logarithmic function needs to be calculated with minimal loss in accuracy.

After the conversion is complete, the values are normalised using equation (2.1) to be used as inputs into the neural network. Once the neural network forward propagates the input values and produces an output, the output is stored in the transmit buffer.

***3.5.5 Conversion to byte array and transmission***

During experimentation it was found that the built-in C library function that could convert integers to character strings so that the USART could transmit the values introduced a significant overhead (12% program memory was added for every call to the function) to the program memory. A solution was found, figure 3.10, that reduced the overhead significantly and allowed the accurate transmission of the required characters by adding the ‘0’ character to each integer. By hardcoding an integer-to-character conversion, the byte array to be transmitted was populated with the sensor data and neural network data then transmitted to the ESP8266 WiFi module after the send command was given. Transmitting messages is a two step process where the first step requires a message length be specified and the second step is transmitting the message to be sent. The commands required are listed in table 3.6



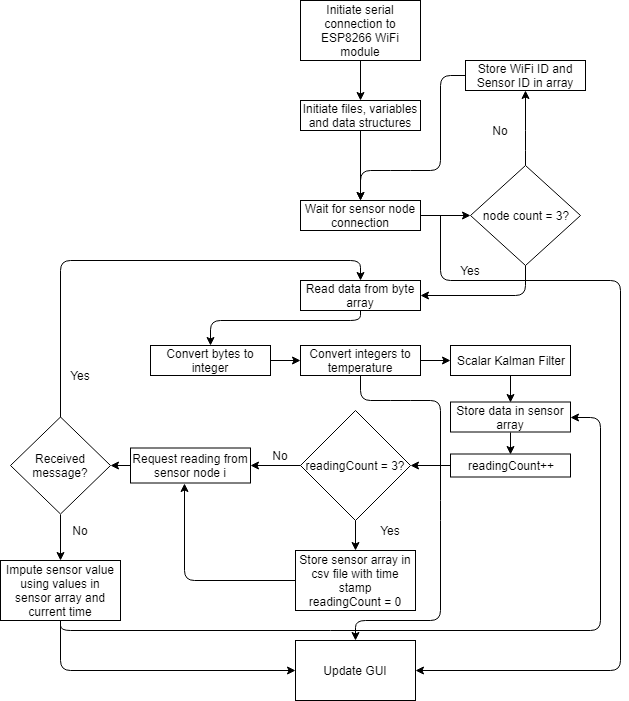
**Figure 3.10. Manual conversion of integers to character bytes.**

|  |  |
| --- | --- |
| **Command** | **Function** |
| AT+CIPSEND=<length of message> | Specifies the length of the message to be sent over WiFi to the server. |
| <message> | The message to be sent after CIPSEND command has been transmitted. |

**Table 3.6. Required steps to send a message to the server from the microcontroller.**

**3.6 SERVER SOFTWARE**

The software programmed in Python for the server contains all the data structures, GUI and algorithms regarding controlling the flow of the system as a whole. The VSs for all the sensor nodes in the network are contained in separate states as well as a WiFi re-identification system for the sensor nodes in cases where a sensor node re-establishes communication after being disconnected from the network. The architectural design of the server system is shown in the block diagram of figure 3.11.

****

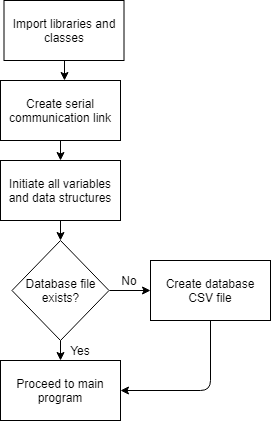
**Figure 3.11. Architecture design of the server.**

***3.6.1 Server initialisation***

The pyserial library is used to communicate with the serial COM ports available through USB communication on the desktop PC. This is a requirement to transmit data through the USART communication channel to the connected ESP8266 WiFi module. The following settings were used to establish a working connection:

* Port: COM3
* Baud rate: 115200
* No parity bit
* No stop bits
* Byte size: 8 bits
* Timeout: 3 seconds

When the serial connection is established, the server is started using the commands listed in table 3.7. All variables and data structures, discussed in section **3.9 Data design**, are then created and initialised. The file to store the collected data is also created if it has not already been created. The block diagram of these steps is shown in figure 3.12.



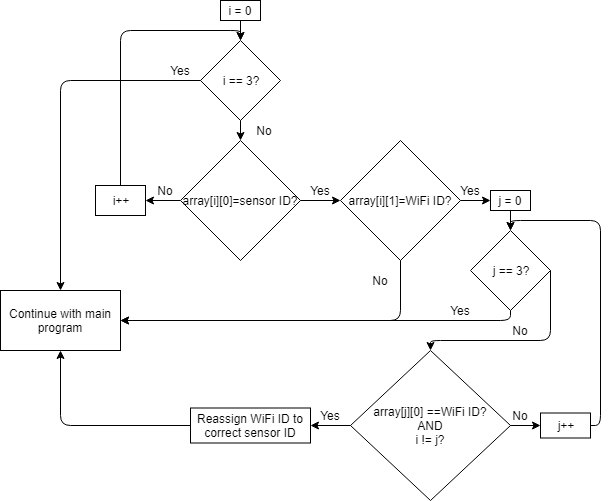
**Figure 3.12. Server initialisation procedure.**

|  |  |
| --- | --- |
| **Command** | **Function** |
| AT+CIPMUX=1 | Allow multiple incoming connections (maximum 8) |
| AT+CIPSERVER=1,333 | Start the server on port 333. |

**Table 3.7. Required commands to start the server.**

***3.6.2 WiFi re-identification system***

Each sensor node contains information that identifies itself with the server. The server ESP8266 WiFi module also automatically assigns a TCP client number to each sensor node that expires and is re-assigned if a sensor node disconnects from the network. A WiFi identification system was implemented to ensure that no sensor node would be mistaken for a different sensor node due to duplicate TCP client numbers that have been previously assigned but have not yet expired after a sensor node disconnects. If no changes are required the program proceeds as before. The block diagram of this function is shown in figure 3.12.



**Figure 3.12 Wifi re-identification procedure.**

***3.6.3 Sensor data filter***

During experimentation it was found that there is a rare glitch in the system that occurs when a sensor node reconnects to the network where ground values are received instead of the expected sensor readings, figure 3.13. A SKF was designed and implemented to filter out the glitches as well as to smooth out the received readings. The noise analysis of the SKF was done using gathered data and scaling up the noise covariance. Through observation from the simulations, the covariance noise value was determined and chosen to be 0.1 as minimal loss of data was experienced and the glitches were successfully filtered out. The flow diagram of how the SKF functions is shown in figure 3.13. The scalar Kalman filter consists of the following equations:

Prediction: (6)

Prediction error: (7)

Kalman gain: (8)

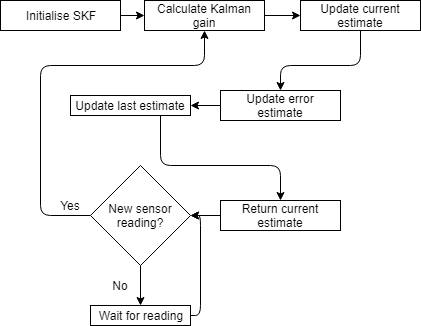
Correction: (9)

Update error: (10)

Where:

* is the current sensor reading
* S[n] is the prediction
* M[n] is the error associated with the prediction
* K[n] is the Kalman gain associated with the prediction
* is the covariance noise in the system

The initial system state is assumed to be a room temperature of 25°C.

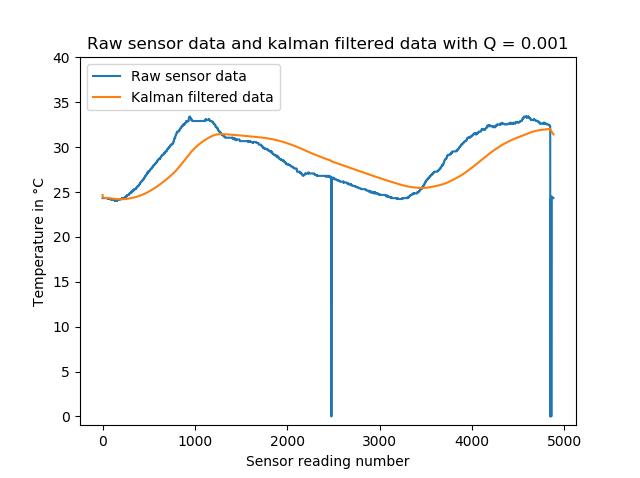


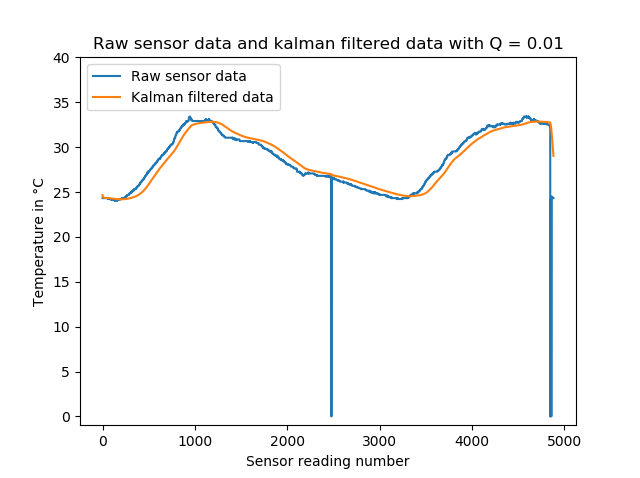
**Figure 3.13. Scalar Kalman filter function.**

**Simulations**

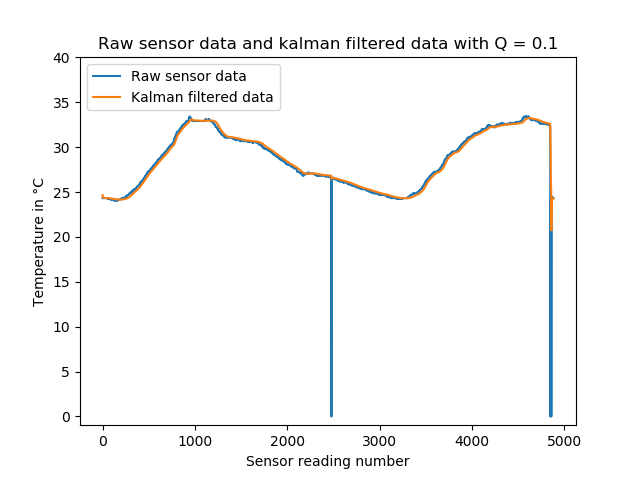
The simulations to determine the covariance noise, or Q, are shown in figure 3.14 to figure 3.17. Two glitches are visible in the plotted data.

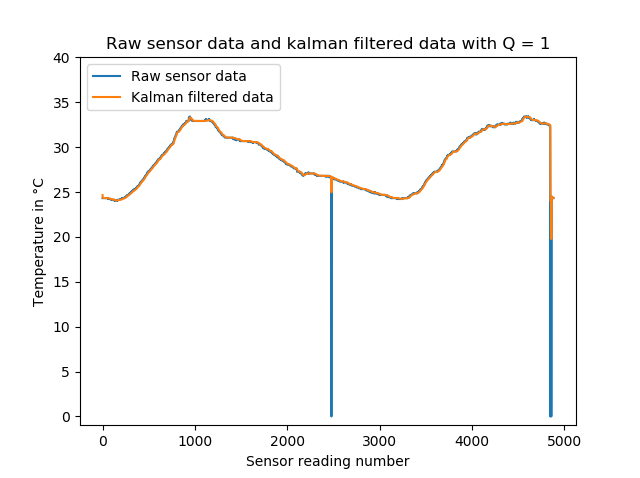
* Aim: The aim of this experiment is to demonstrate the performance of the SKF with different Q values.
* Data size: 5000 individual sensor readings
* Kalman filter parameters: R = 25, Q = 0.001, 0.01, 0.1, 1.0
* Platform: Python.



**Figure 3.14. Scalar Kalman filtered temperature with Q = 0.001**

**Figure 3.15 Scalar Kalman filtered temperature with Q = 0.01**



**Figure 3.16. Scalar Kalman filtered temperature with Q = 0.1**

**Figure 3.17. Scalar Kalman filtered temperature with Q = 1.0**

The covariance error that is decided upon is a Q value of 0.01 as the overall shape of the data does not vary as much from the origin as with the Q value of 0.001 while being able to filter out the glitches more effectively than with a Q value of 0.1 while smoothing the incoming data. A Q value of 1.0 was deemed not effective in filtering out the glitches.

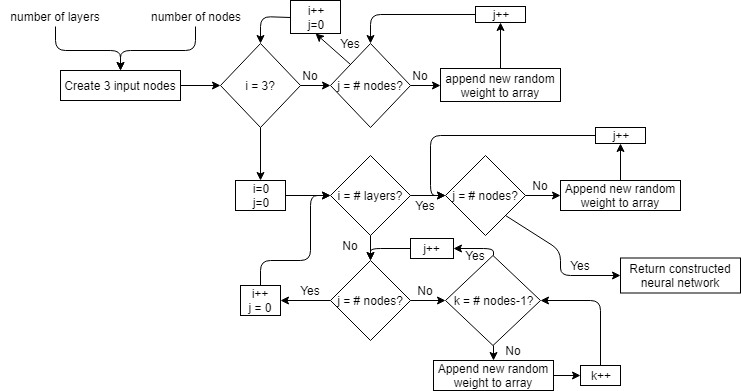
**3.7 IMPUTATION WITH NEURAL NETWORK**

The MLP neural network is the core feature required to implement the VSs in the WSN. The design and implementation of the chosen training algorithm, neural network as well as the simulations to choose an optimal MLP topology in terms of training time and accuracy are described in this section.

***3.7.1 Architectural design***

The MLP class design is illustrated below in figure 3.18. Each layer, including all hidden layers, is constructed individually until the output layer is reached. Once the neural network is constructed with random weights applied, it is returned to the program that called the neural network constructor. It takes two parameters to determine the hidden topology of the neural network which will always have 3 input nodes and 1 output node:

* The number of hidden nodes
* The number of hidden layers



**Figure 3.18**. **Neural network construction block diagram.**

The output can be described mathematically as the sum and products of the inputs, weights and activation functions. The mathematical model is described as:

For each node in the input layer:

(11)

where:

* is the resulting output after an input has been put through the softmax activation function.
* is the normalised input to the input node.

For each node in the hidden layer:

And

(13)

where:

* is the resulting output after the inputs have been summed and multiplied with the weights then put through the softmax activation function.
* is the result of the sums of the inputs multiplied by the weights.
* is the weight associated with the input.
* is the resulting sum.
* not including the bias node if it is the first hidden layer.

For the output node in the output layer a linear activation is used and thus:

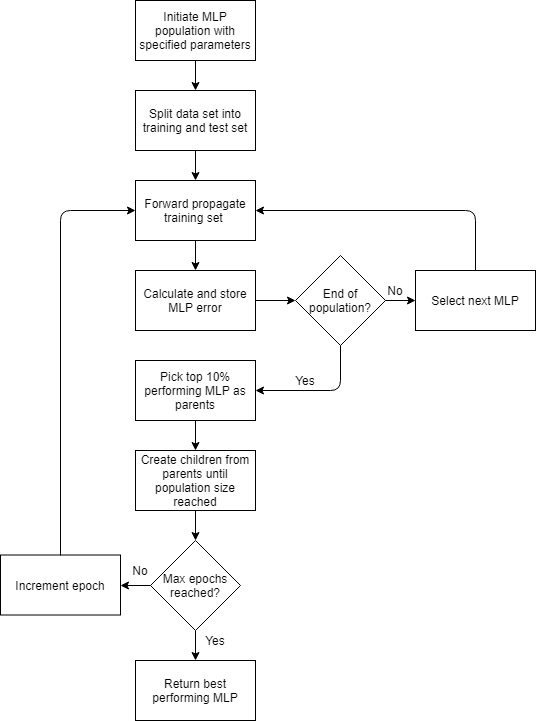
where:

* is the resulting output after the inputs have been multiplied with the weights and summed together. is the number of hidden nodes in the previous layer.
* is the weight associated with the input.
* is the number of nodes in the previous layer including the bias node.

In addition to the above, the input layer and every hidden layer has a bias node included that is not connected to the previous layer. This is implemented to increase the flexibility of the model to fit the data and to allow the network to fit data if in the unlikely scenario all the input features are equal to 0. The output from the bias node will always be equal to 1.0.

***3.7.2 Training design***

The genetic algorithm designed and implemented for neuro-evolution of the MLP is described in figure 3.19. There are four main steps in the genetic algorithm, namely the forward propagation, prediction, error calculation, parent selection and finally repopulation which are described in more detail in this section.

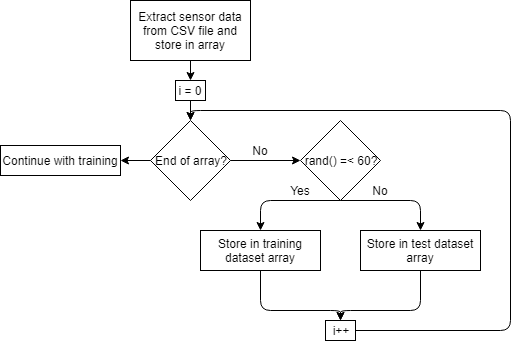


**Figure 3.19. Genetic algorithm training block diagram.**

The input parameters of the training algorithm are

* The number of MLPs to initiate in the population
* The number of hidden nodes per hidden layer in each MLP
* The number of hidden layers per MLP
* The number of training epochs
* The sensor dataset that must be used

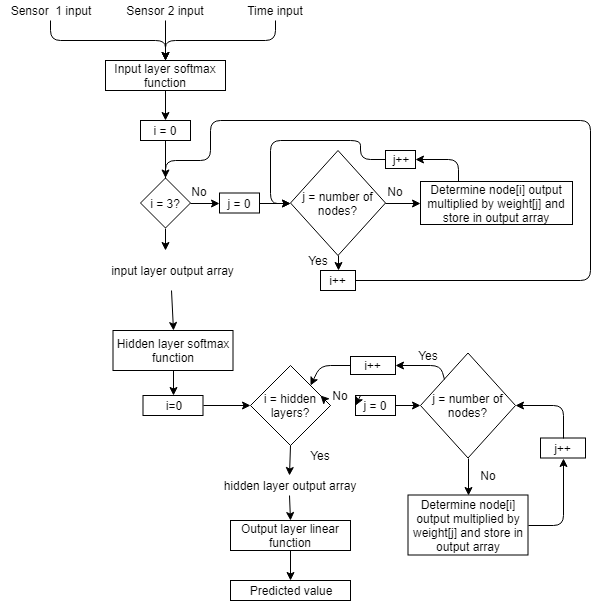
The dataset used for training the MLP is previously collected sensor data from the implemented WSN. The dataset is randomly split into 60% training data with targets and 40% test data with targets using the algorithm described in the block diagram of figure 3.20.



**Figure 3.20. Splitting data into training and test data.**

**Prediction**

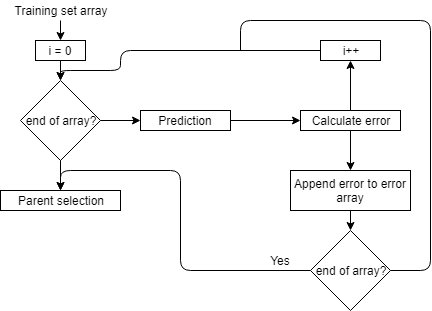
The prediction of a value involves an initial forward propagation described by figure 3.21 and equations 11-14.

****

**Figure 3.21. Prediction block diagram.**

Each prediction is based on three input parameters which are the other two sensor node inputs in the WSN and the time that those data points were collected during the day. The prediction value aims to emulate the value that the sensor it is associated with in the WSN would sense.

**Forward propagation**

****

**Figure 3.22. Forward propagation block diagram.**

**Error calculation**

The error of each MLP is calculated using the mean absolute error (MAE) as

(15)

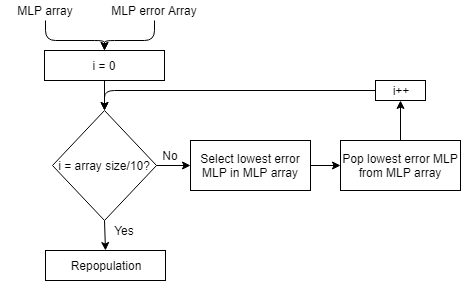
where:

* MAE is the mean absolute error of an individual MLP
* N is the amount of training points
* is the predicted value by the MLP
* is the target value associated with the inputs to the MLP

MSE was an alternative error function that was considered. However, the MAE is robust to outlier values as it does not make use of the square as in the MSE. Furthermore, outlier values are not expected in the training dataset.

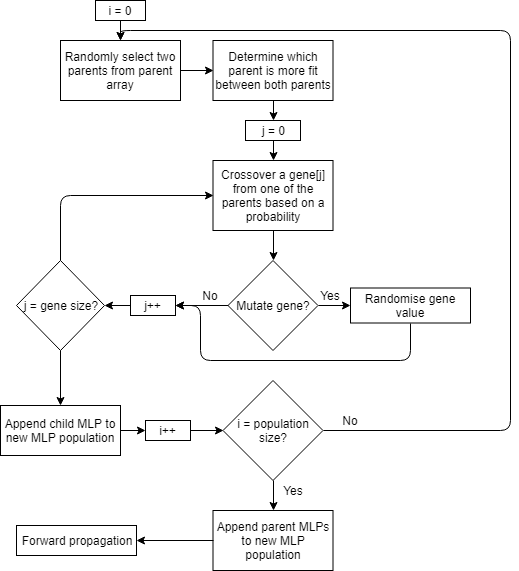
**Selection**

The selection of parent MLPs is done immediately after the last MLP in the population has had its MAE calculated after forward propagation of the entire training dataset is complete. The top 10% of the population is chosen to breed new MLPs. The block diagram description of the selection process is shown in figure 3.23



**Figure 3.23. Parent selection block diagram.**

**Repopulation**

****

**Figure 3.24. Repopulation using most fit parents block diagram.**

With the top 10% parent MLPs selected, breeding of child MLPs commences. For each child, two parents are randomly selected from the parent pool. The probability that a gene is copied over to the child MLP is calculated using the error associated with both parents using the probability equation

(16)

where is the error associated with the first parent, is the error associated with the second parent and is the probability of the first parent copying over a gene from its gene array to the child MLP gene array. Accordingly, the probability for the second parent to copy over a gene is

(17)

which allows the fitter parent a higher likelihood to copy over weights that are more desirable.

To avoid stagnation in the population as the training epochs increase, every gene, when copied, has a small probability (<=2%), to be completely randomised instead of copied over from the parent MLPs. This ensures that there is always some diversity in the genetic pool of the MLP population.

Once the old population size has been reached by repopulating the new population with child MLPs, the process is repeated beginning with the forward propagation step until the specified epoch number has been reached.

**3.8 DATA DESIGN**

**3.7 Design summary**

This section summarises the project tasks and how they were implemented (see table 1).

|  |  |  |
| --- | --- | --- |
| **Task** | **Implementation** | **Task completion** |
| Design of a PCB for the main electronics | The PCB design was completed, using the PCBCAD package. This was done from first principles. | completed |
| Development of optimization routine | Optimization was completed in Matlab, but the Optimization Toolbox was used, and while some code was developed from first principles, numerical methods for optimization were taken off the shelf. | incomplete |

**Table 1**

**Design summary.**

Ensure that your table lists all of your tasks (technical design tasks, not including things like “write report”, or “bind report”). These would include student tasks in sections 2.3 and 2.5 of the Project Proposal.

**4. Results**

Commence this section on a new page

**Super important! The compulsory table mentioned in Appendix 4 of the study guide should appear here.**

**The following is just an example.**

**4.1 Summary of results achieved**

|  |  |  |
| --- | --- | --- |
| **Description of requirement or specification**  **(intended outcome)** | **Actual outcome** | **Location in report** |
| **Mission requirements of the product** | | |
| The system should provide continuous AC power to a household | The system could provide continuous power during daytime hours when grid power failed. | Section 4.2.6 |
| Motor speed should be controlled. | Stable feedback control of the motor speed was achieved. | Section 4.2.2 |
| Fuel consumption must be kept to a minimum. | Fuel consumption was slightly higher than expected. | Section 4.2.7 |
| Bit error rate (BER) should be low. | The measured BER was high. | Section4.2.1 |
| Delivered power should be adequate for the load. | The system could not deliver the required power into the load. | Section 4.2.3 |
| **Field conditions** | | |
| The system should supply power and actual environmental conditions (sunshine or rain; day or night) | The system was never tested under rainy conditions. The system could not supply power under any conditions other than bright sunlight. | Section 4.2.6 |
| The system should use actual real-time data, corrupted by noise, arriving over a noisy wireless link. | The system could work error-free for at least one hour under these actual field conditions. | Section 4.2.1 |
| **Specifications** | | |
| BER should be below 1E-6. | The BER was measured as 10 bit errors in 1000 bits. | Section 4.2.1 |
| The motor should reach 50 rpm. | 46 rpm was measured. | Section 4.2.2 |
| 2 kW should be delivered to the load. | The system could deliver 800 Watts into the load before overheating. | Section 4.2.3 |
| **Deliverables** | | |
| DC-DC convertors had to be designed and implemented by the student. | The student completed the design and implementation. | Section 4.2.8 |
| The inverter had to be designed and implemented by the student. | The student did not complete the inverter. The design was completed and simulated, but the implementation in hardware did not work correctly. | Section 4.2.8 |

**TABLE 2**

**Summary of results achieved.**

**4.2 Qualification tests**

**4.2.1 Qualification test 1: testing of communication distance**

4.2.1.a Qualification test

*Objectives of test/experiment*

*Equipment used*

*Experimental parameters and setup*

*Experimental protocol (experimental steps)*

4.2.1b Results and observations

*Measurements*

*Description of results*

*Statistical analysis*

**4.2.2 Qualification test 2: measurement of bit error rate**

4.2.2.a Qualification test

*Objectives of test/experiment*

*Equipment used*

*Experimental parameters and setup*

*Experimental protocol (experimental steps)*

4.2.2b Results and observations

*Measurements*

*Description of results*

*Statistical analysis*

**5. Discussion**

**See the study guide – this section is very important. You need to show that you can stand back and be critical of your own work. The worst possible thing that you can write here is “everything works perfectly”. There is no perfect design, and you as (aspiring) engineer should be able to point out the shortcomings of your design and/or results.**

**Tip: Use the headings in the study guide. These are *not* compulsory, but will help you to organize your thoughts, and the headings actually tell you some of the things that you are required to comment on.**

Commence this section on a new page

**6. Conclusion**

Commence this section on a new page

**6.1 Summary of the work**

**…**

**7. References**

**Here you need to be extremely honest about what you achieved, and did not achieve.**

**Conclusions need to be technical and MAY NOT relate to your personal experience (e.g. “I learnt a lot” would be a good example of what NOT to write).**

**[1]** N. S. Altman, “An introduction to kernel and nearest-neighbour nonparametric regression”, *The American Statistician*, vol. 46, no. 3, pp. 175-185, 1992.

**[2]** M. S. Astriani, G. P. Kusuma, Y. Heryadi, E. Abdurachman, “Smartphone sensors selection using decision tree and KNN to detect movements in Virtual Reality Application”, in *2017 International Conference on Applied Computer and Communication Technologies (ComCom)*, IEEE, 2017.

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[8] K. Levenberg, “A Method for the Solution of Certain Non-Linear Problems in Least Squares”, *Quarterly of Applied Mathematics*, vol. 2, pp. 164-168, 1944.

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[11] D. J. Montana, L. Lawrence, “Training feedforward neural networks using genetic algorithms”, *Proc. of the 11th international joint conference on Artificial intelligence*, pp.762-767, IJCAI, 1989.

[12] J. S. Steinhart, S. R. Hart, “Calibration curves for thermistors”, *Deep-Sea Research and Oceanographic Abstracts*, vol. 15, no. 4, pp. 497-503, 1968.

|  |
| --- |
| **Part 5. Technical documentation** |

This main report is supplemented with technical documentation. This provides more detail on the software that was used in the experiments, including program listings, a user guide and circuit designs. This section appears on the electronic medium that accompanies this report.

The CD (or DVD, or flash disk) is organized into the directories listed below.

*Main report*

**Use this text**

*Part 5: Technical documentation*

*Software*

*References*

*Datasheets*

*Author*

**indicate the actual directories on your CD here. The minimum required directories are listed in Appendix 4 to the study guide.**

*Datasets/Raw*

*Datasets/Final*