

Empirical temperature modelling for fresh produce logistics during transit in southern Africa

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ABSTRACT

The need to constantly ameliorate Cold Chain Logistics (CCL) can no longer be ignored. This industry has grown in size with significant positive impact on the GDP of economies globally. Amidst great opportunities vested in this industry, it stills struggles with ills such as poorly managed service level agreement, no or inadequate chain visibility and cargo losses. Such losses are mainly caused by lack of real time information about the current status of cargo as well as lacking insight into the possible impact of supply chain incidents on cargo quality.

This work presents an empirical temperature modelling for fresh produce logistics during transit in southern Africa. It describes the characterization of cold chain processes and the development of predictive neural network models based on data that were collected using off-the-shelves temperature sensors.

Extensive literature studies were conducted on: containers, RFID, cold chain and logistics operations, the needs of the industry in southern Africa, state-of-the technology in the industry, the intelligence and communication capabilities for an improved cold chain monitoring system, temperature modelling and neural networks,

Cross-border field tests were conducted during normally cold chain logistics operations from Johannesburg (South Africa) to Lusaka (Zambia) and sufficient experimental data were gathered. These results were analysed using MS Excel and Matlab and numerous visualization explanations were generated for various temperature profiles behaviours experienced in reefer containers during transit.

Artificial neural network models were developed by first training using the Levenberg-Marquardt backpropagation, Bayesian regularization backpropagation and Scaled conjugate gradient backpropagation with number of neurons based on the rule of thumbs in order to select the best and fastest achieving function. Predictions, multi-step predictions and step-ahead prediction beyond targets were generated and visualised for delays events, offloading events and the complete events during a fresh produce cold chain logistics operation at set points of 2°, 5° and both. The ANN step-ahead prediction beyond targets predicted five cargo temperatures from a minimum number of five sensors in the trailer (inputs). The prediction horizon was (5 timestamps), (20, 50, 100 timestamps) and (300 timestamps) all at 5min intervals for offloading events, delays during transits and complete trips events respectively.

The models performances were evaluated using the correlation between the target and the predicted values also known as regression (R) and the model prediction error (MSE). Both showed values close to 1 and 0 respectively indication of good model results.

Deployable components of the models were built as DLL files to be deployed and incorporated on the cold chain management software tool created that runs on Microsoft visual studio platform.

A cost benefit analysis model was generated as published in appendix H comparing the average value of cargo lost per trip, total value of cargo lost per trip, annual turnover per truck and total annual turnover relating to 2%, 5%, 15%, 35%, 40% and 50% fractions of fruits and vegetables impacted by cold chain losses.

Key words: Cold chain logistics, Temperature modelling, RFID, Temperature Monitoring, Artificial neural network, Temperature Prediction, Cost benefit analysis.

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“Avoid the trap of looking back unless it is to glorify God for what He has done”. TB Joshua

CHAPTER 1

1 Introduction

1.1 Background and Motivation

There is an increasing international trend towards the containerization of freight [1]–[4] . This results from the increasing globalization of the economy and the need to effectively move freight between different modes of transport from area of production to distribution centres. Intense international competition in the agricultural, manufacturing, logistics and retail industries requires high levels of efficiency across the entire value chain. Much focus has been placed on the transportation element of global value chains, as this area has suffered from significant inefficiencies in the past [5]–[7].

There are several reasons why the transport leg of global value chains offers several difficult challenges. Firstly, this activity normally involves the service of a third party that does not have a direct interest in the cargo, as would be the case for the seller and the buyer of the goods. Transporters may tend to be more concerned about the utilization levels of their assets than about the goods they are transporting. Secondly the international transport process normally involves a number of independent players, most of whom are managing infrastructure and services that are essential for the completion of the transport cycle but who are not directly affected if something goes wrong along the way. This includes: roads operators, customs authorities, ports operators, rail operators and others. It can therefore easily happen that cargo is either mistreated, get delayed or is subjected to inappropriate services during the transport process. Such deviations from the planned process can result not only in costly delays in the overall value chain, but more importantly in damage to the cargo itself. This is of specific importance to fresh produce.

In the case of fresh produce the transport activity forms a very big portion of the overall landed cost of the goods [8], . This results from the fact that the goods have limited shelf life, that there is usually a large distance between areas of production and consumption, and that specific

conditions must be maintained during the entire transport process to ensure that the quality of the goods is retained until delivery to the customer. A reduction in quality leading to the downgrading of the product has a huge impact on the value of the delivered product or can even cause it to be scrapped [9].

Technology based solutions have found increasing levels of application in the transport industry in recent years [10]–[12]. The most widely known is the use of GPS technology, in combination with wireless networks (typically GSM networks) to provide real-time traceability of freight vehicles. Initial applications of GPS focused on vehicle recovery, fleet management and driver management. In specialized transport applications, e.g. cash-in-transit applications, technology is also used extensively to provide visibility of the status of cargo in transit. The transport of goods required to be cooled while in transit resulted in the deployment of a special kind of container, called a reefer container, that is equipped to provide temperature and humidity controlled conditions using on-board equipment.

Existing solutions for the management of cargo in transit still suffer from specific limitations:

- Information from on-board sensors are usually not easily accessible from a remote management office;
- The hardwiring of on-board equipment results in lack of flexibility to do measurements where they are needed – e.g. in the case of fruit products it is necessary to also know the temperature where the product is situated inside the refrigerated container, not on the periphery of the container;
- If an incident occurs that may cause damage to the goods (either a shock or a temperature that is exceeded) there is normally no immediate alarms when this incident happens. In many cases it will still be possible to salvage the cargo if action is taken soon enough (e.g. when the allowed temperature is being exceeded but the goods have not suffered damage as yet).
- If an incident occurred that caused damage to the goods, there is normally no record of exactly when it occurred. If the goods were handled by multiple third parties, it is then the problem of the cargo owner or his insurer to claim damages in terms of an existing service level agreement (SLA).

Apart from using sensor data to protect the quality of the goods, such data can also be used to determine if the cargo is being taken through the desired sequence of transport operations. By

the time of dispatch of goods, it is normally known within which geographic boundaries the goods must be transported, between which modes of transport the goods must be exchanged and at which geographic locations, what environmental conditions should be maintained during this process and at which location(s) the container should be opened. If there is a deviation from the initial plan it is normally only discovered long after the fact (which may be several weeks), by which time significant economic damage may have been suffered by the cargo owner. If immediate notifications can be generated in case of deviations from the planned cargo operation and these alarms can be communicated to the relevant stakeholders, it will be possible to take more timely action either to implement corrections or to try and salvage the goods before it is lost.

1.1.1 Cold chain logistics overview

Cold chain logistics involves the transportation of temperature sensitive products by means of refrigerated trucks, commonly called reefers, along a supply chain through thermally controlled and refrigerated packaging methods. The transportation of chilled and/ or agricultural products in reefer containers has grown to become a large and steadily growing business in Southern Africa and the world at large[13].

The South African fruit industry is a significant employment generator; it employs approximately 460 000 people who have two million dependents[14]. The industry accounts for 50% of all agricultural exports in South Africa [15], with an annual export value of approximately R12 billion [14]. Unfortunately, a huge amount of this profit and commodities are lost due to poor quality of these products before they reach their target destinations.

A significant fraction of perishable goods is lost or damaged during transportation, partly due to ineffective cold chain logistics practices. Approximately 35% of fruits and vegetables are lost in cold chain logistics [16]; such losses represent a significant portion of loss in profits generated in food supply chains, and hence justify improved management practices. The internal biological and chemical process of fresh produce, such as respiration, continues after harvesting. This implies that the product absorbs oxygen and releases carbon dioxide and ethylene. This results in the liberation of heat energy. Lowering the temperature reduces the respiration and consequently the heat considerably, hence avoiding deterioration due to high concentrations that may be caused by these latent activities. Refrigeration is basically removing heat by evaporation. Farm produce in the cold chain are refrigerated for the sole purpose of prolonging their shelf life [17] , state and quality thereby avoiding cold chain ruptures. Maintaining the required in-transit

temperature and humidity is of key importance in actualizing this goal. The required temperature in cold chain mainly depends on the cargo type. Fresh fruits and vegetables are usually transported between 0°C to 8°C, Meat and cold chilled products at a temperature below -18°C, dairy products like margarine and butter usually between -8°C to 7°C, frozen foods and ice cream are usually transported at -24°C to -18°C while chocolate at -8°C to -18°C and pharmaceutical products usually between 2°C to 8°C.

The delivery of these cargo types in good conditions from point of production to point of distribution or consumption has been an issue for all players directly involved in the supply chain (the growers or producers, the logistic service provider and other transport companies, and the final consumer). Efficient monitoring of the temperature of these cargoes at a reasonable cost is the cry-for-help of these stakeholders.

1.2 Research Problem

Against the above background information and overview, the research work will focus on the development of improved concepts to support the management of fresh produce in transit. The research problem is broken down into the following elements:

1.2.1 Determining the needs of the fresh produce industry:

An in-depth study will be undertaken of the industry to quantify the specific needs of the fresh produce industry regarding the need to determine if goods in transit are subjected to environmental conditions that may lead to the downgrading of the goods. The state of the cargo while in transit will be monitored and investigated. The study will focus on those goods for which the required conditions to be maintained are the most stringent during cross border operations like fruits (apples, oranges, peaches, strawberries), vegetables (green peas, broccoli, etc.) and mixed cargoes

1.2.2 Establishing the current state of technology in the cold chain industry:

The extent to which the above industry needs are satisfactorily addressed by existing systems will be established. More specifically it will be determined in which areas there are the biggest needs for improvement in terms of the accuracy of sensing, and if the ability exist to generate alarms intelligently on the on-board device and to communicate such information to a central office at any stage during a trip.

Currently available technologies being used for cold chain logistics (CCL) and the respective architectural designs of such systems will be determined, i.e.:

- at what point in the system is the raw data being processed,
- how intelligent are the algorithms that are applied to the data to correctly generate events?
- how is data communicated between different elements of the system and
- at what level decisions are taken.

1.2.3 Defining the level of intelligence and the communication capabilities required by an improved system:

Temperature data for different scenarios and at different points within the trailer and also embedded within the cargo will be captured and processed. The nature of the decisions to be taken and the information required to correctly make such decisions will be defined (e.g. GPS location may be used in combination with sensing data to determine if an event is acceptable or not). Furthermore, it will be determined what information needs to be communicated between which points in the system to enable the relevant people to take corrective action.

1.2.4 Experimental work:

Various experimental methodologies will be designed and implemented. The required set of experiments will be conducted to generate sufficient data to understand temperature distributions, variations and profiling within the trailer. These sets of experiments will be conducted within representative operational environments. This will include amongst others:

- laboratory setups for the initial characterization of equipment and measurement techniques,
- access to operational infrastructure (i.e. relevant cargo within its normal operating environment that will allow the capturing of data representative of operational conditions);
- Cross border experiments carried out within the SADC region;
- sensing and data collection equipment (that may include equipment collecting data to be retrieved after a trip or data to be communicated in real time);

- Spatial temperature profiles at the periphery of the trailer and inside actual consignment during transportation will be extracted from the experimental data sets in required formats. These will further be analysed in order to characterize the temperature behaviour of different cargo types.

The above set of experiments will then be completed and the required data collected. This will be utilized to select the most suitable sensing techniques and develop improved monitoring methodologies.

1.2.5 Development of an intelligent sensing algorithms:

Mathematical, statistical and signal processing techniques will be applied to the collected temperature data during the various experiments to accurately and reliably generate defined events from the raw data collated and to predict future events allowing preventative action to be taken before damage to cargo has occurred.

As it is not always practically possible to measure the temperature of the cargo itself, there will be value in a model that can predict the cargo temperature, now and in future, based on the temperatures measured around the periphery of the trailer where sensors can be more easily mounted. This will involve compiling linear or non-linear regression as well as neural network models to determine expected temperature values inside cargo as function of temperature values on the periphery of the container.

1.2.6 Conclusions:

Conclusions will be reached on the following issues:

- Can the identified needs of industry for more accurate sensing techniques be solved in a cost-effective manner?
- What deployment of sensors is required to support such techniques?
- Which algorithms are required and how accurately can they perform the required task?
- What is the most elegant architectural design of an envisaged solution, taking into account cost, ease of deployment, accuracy, flexibility and ease of operation?
- What is the best approach to take for industry to exploit the proposed techniques, given the current state of industry?

Recommendations on an improved concept for cold chain logistics will be proposed.

1.3 Research objectives

The following research objectives have been defined:

1.3.1 Specific objectives

- Firstly, the extent of the cold chain logistics (CCL) problem for typical cold chain operations in Southern Africa must be quantified. As more detailed monitoring implies higher system costs it is necessary to determine what will constitute an optimal level of monitoring to prevent losses while keeping costs at a reasonable level. For this purpose, data will be gathered from cargo owners, research groups and organizations, and service providers involved within the industry.
- Secondly a monitoring methodology will be designed to characterize cold chain operations with sufficient accuracy to pinpoint problem areas.
- Various configurations based on off the shelf instrumentation will be used in monitoring temperatures during transportation, including standalone temperature sensors with built-in data loggers (that require manual downloading of data) and RFID based temperature loggers (that can support wireless and real-time downloading of data). Experiments will be set up by placing the data loggers in various configurations inside reefer containers (including on all the internal sides of the reefer container and the doors except the floor) as well as inside the cargo. These loggers will be configured to detect thresholds being exceeded based on the required transit temperature.
- Accurate spatial temperature profiles and cargo conditions within a reefer container loaded with different kinds of perishable cargo will be generated based on which it can be determined how many monitoring points are actually required.
- Using the above experimental setups data will be collected to characterize actual cold chain operations for a representative set of actual trips, including different types of cargo and trips to different destinations.
- Temperature data of the cargo will be collected from the different tiers of the container where the loggers are installed. These will be used in a temporal temperature prediction model based on neural networks.

- It will be demonstrated how such models can be used to prevent cargo losses by predicting how long it will take for cargo temperatures to exceed allowed thresholds once an unforeseen event occurs, e.g. if the doors are opened in an unauthorised location.
- A detailed databank will be developed containing a representative set of data for different kinds of cold chain operations. Such a databank can be used to design more effective cold chain logistics processes in order to protect the quality of the goods, and to create cold chain performance benchmarks.
- Lastly an optimal approach will be designed to conduct cold chain monitoring on an on-going basis as part of standard operations, finding a balance between sufficient accuracy of monitoring and the cost of the monitoring system.
- The sum total of the above research will enable the development and deployment of optimal cold chain monitoring solutions customized to the end-user's problems, needs and budget.

1.4 Research contribution

This Research will benefit:

1. North West University: This work will make the way for further research at a higher level; hence papers will be published adding to the body of knowledge of the institution as well as adding to its academic influence worldwide.
2. Industries:
 - Tracking companies and Logistics service providers: Tracking companies providing solutions in private vehicles, small fleet to large fleet, asset tracking and workforce cross border tracking in the SADC region will greatly benefit from the results of this research.
 - Insurance Companies: The results obtained can be used to more accurately and intelligently measure the risks in insured containerized freights. This would minimize the possibility of giving lower or higher premiums than the risk demands.
 - Cargo Owners and freight insurance companies: Possible losses arising in containerized freight will be minimized. The benefits of insurance service providers having a better risk assessment has a rippling effect which is felt by companies providing logistics services i.e. transporting goods from one point to another. Like the general public, they will be charged more realistic premiums. Furthermore, possible losses will be minimized with

cargo tracking as opposed to just vehicle tracking. They will be able in a better position to implement corrective measures. These cases can be divided into real time deviations and future deviations. For future deviations, present trends can be compared with previous cases and disasters can be stopped before they happen.

- Retailers and Consumers: retailers and consumers will be provided with evidence on the state and status of fresh produce before purchase. They will have the choice to demand proof that the cargo met all requirements for transit. Such can be reports generated from the monitoring site or real time monitoring feedbacks.

1.5 Dissertation structure

The dissertation is organised in the following way:

Chapter 1 introduces the topic of the research, explains the background information and motivates the importance of this study. The purpose of the study, the problem statement and the methodology employed are covered in this chapter.

Chapter 2 lays out the theoretical dimensions of the research. It carries out a complete and comprehensive literature study and review on the study topic, published and previous works on temperature modelling, cold chain logistics technologies, containers and refrigerated trucks, cold chain operations and improved methods for cold chain logistics operation.

Chapter 3 provides a comprehensive description of the experiments carried out in the research. In addition, materials, methods, surveys and experimental procedures are explained in detail.

Chapter 4 discusses the observation and analysis of the empirical investigation results with respect to the impact of temperature on the goods within the trailer.

Chapter 5 describes the development of models based on data gathered from the experiments and provides an interpretation of the results, including the verification of the results.

Chapter 6 concludes the dissertation and offers recommendations for future studies.

*“Fear not – Those who are with us, fighting for us
Protecting us, are more than those who are against
us to destroy us. the angels unspeakably more
numerous; God infinitely more powerful” TB Joshua*

CHAPTER 2

2 Literature Review

2.1 Introduction

This chapter lays out the theoretical dimensions of this research. It carries out a complete and comprehensive literature study and review on the study topic, published and previous works on temperature modelling, cold chain logistics technologies, containers and refrigerated trucks, cold chain operations and improved methods for cold chain logistics operations.

2.2 Cargo Containers

A cargo container also known as freight container; shipping container or container is a reusable steel box of definite measurement used for secure storage and movement of materials and products within global containerized intermodal freight transport (from one mode of transport to another e.g. from ship to rail to truck).



Figure 2-1: A cargo container

2.2.1 Types of cargo containers and their uses

There are about sixteen types of shipping containers. There are grouped into two broad groups:

General Cargo containers and Specific Cargo Containers. Figure 2-2 below illustrates their classification. These containers comes in various sizes. Table 2-1 below shows the various types.[18]

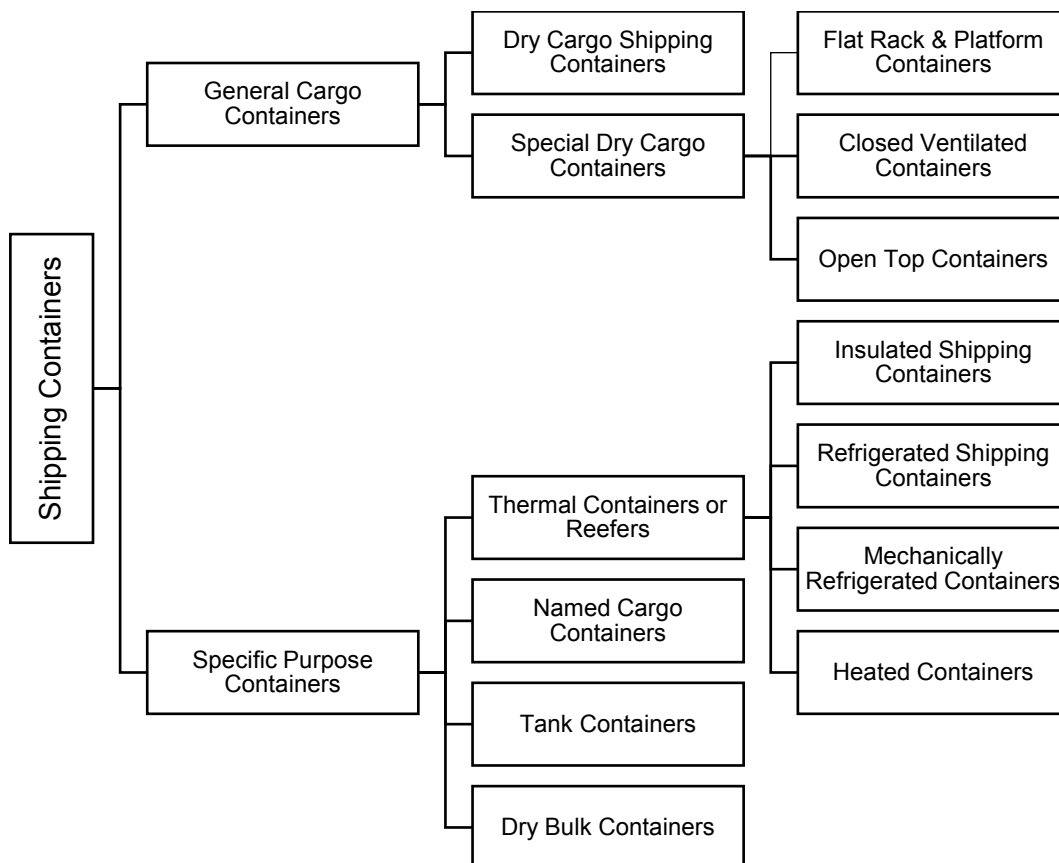


Figure 2-2: Cargo Containers Classifications

Appendix A , page119 gives a breakdown of all the various types of containers.

Table 2-1: Cargo Container Sizes

	20' Container		40' Container	
	Metric	Imperial	Metric	Imperial
Length	6.198 m	20'4"	12.192 m	40'0"
Width	2.438 m	8'0"	2.438 m	8'0"
Height	2.591 m	8'6"	2.591 m	8'6"

The container sizes in Table 2-1 above are by no means exhaustive, as specialised containers do exist, but container widths are fixed.

2.2.2 Refrigerated containers

Among all the various types of containers refrigerated containers are the primary focus of this research. Refrigerated containers, commonly referred to as reefers, require a power source to maintain the container's environment at a specific temperature. This requirement imposes both time and location restrictions on the transportation of these containers. Obviously the constant refrigeration of these containers is of critical importance to the goods being transported.



Figure 2-3: A refrigerated container (Reefer) connected to a temperature controlled loading dock

2.2.3 Reefer container operations and user requirements during cold chain operations

Reefer containers are expected to provide regulated temperature and humidity and, in most cases, a controlled atmosphere as well, for the transportation of perishables commodities, including fruits, fish, meat and flowers.

Refrigeration is essentially the removal of heat through the process of evaporation. Fruits and vegetables are refrigerated in order to prolong their shelf life [17]. Humidity plays a vital role in the state and quality of commodity transported. Technically, the internal biological and chemical process of fresh produce, such as respiration, continues after harvesting. This means that the product absorbs oxygen and releases carbon dioxide and ethylene. This results in the liberation of heat energy. Lowering the temperature reduces the respiration and consequently the heat considerably. Therefore, temperature is the most important factor when prolonging the practical

shelf life. As high concentrations of carbon dioxide and ethylene can deteriorate the commodities, these gases must be removed and replaced with fresh air through the ventilation system. Ethylene production is especially high in fresh produce such as apples, peaches, apricots, avocados and pears. The delivery of these cargoes in good condition from point of production to point of distribution or consumption is very important for all those involved in the cold chain - the growers or producers, the logistic service provider and other transport companies, the retailer and the final consumer. The major challenge is to ensure required product temperature and a continuous cold chain from producer to consumer in order to guarantee prime condition of such goods.

Local temperature deviations can be present in almost any transport situation. Temperature deviation refers to the amount the actual temperature has deviated from a standard temperature. It can also be referred as the difference between the standard temperature expected at a given point and the real measured temperature. Studies have shown deviations of 5°C or more. Deviations of only a few degrees have led to spoiled goods and thousands of rands in damages [17], [19], [20]. A recent study shows that refrigerated shipments rise above the optimum temperature in 30% of trips from the supplier to the distribution centre, and in 15% of trips from the distribution centre to the stores [17]. Roy *et al.* analysed the supply of fresh tomatoes in Japan and quantified product losses of 5% during transportation and distribution [17].

Thermal variations during transoceanic shipments have also been investigated [17], [20]–[22]. The results showed that there was a significant temperature variability both spatially across the width of the container as well as temporally along the trip and that it was out of the specification more than 30% of the time.

In those experiments monitoring was achieved by means of the installation of hundreds of wired sensors in a single container, which makes this system architecture commercially non-viable [17], [20]–[22].

[17], [20]–[22] reveals that temperature in reefer can rise very quickly if the cooling unit malfunctions or fails.

2.2.3.1 Cargo Inspection

The pulp or product temperature of chilled fruit and vegetable cargoes and core temperatures of frozen cargo must always be measured, where possible, before a reefer unit is stuffed. Fruit and vegetables should also be checked for pre-cooling damage, mould, wilt, dehydration, shrivel, discolouration, soft spots, skin break and slip, bruising, chill damage and odour. Frozen cargoes should be checked for dehydration, desiccation, fluid migration, odours, black spot, colour and flavour changes, and should also be examined for signs of any upward temperature deviation and subsequent re-freezing [23], [24]. Cartons, trays and other packaging should be scrutinised in respect of their suitability to protect the cargo during a long sea transit.

2.2.3.2 Cargo Pre-treatment

The condition of products before they are stuffed plays an important role in their condition upon arrival. Hence it is essential that all products are treated correctly prior to stuffing. Even though the temperature, ventilation and humidity are all optimal during the entire voyage, products will only arrive in perfect condition if the pre-treatment has been performed correctly. Successful shipping begins at the product sourcing area.

2.2.3.3 Cargo Pre-cooling

The proper pre-cooling of products will have a positive effect on both shelf life and out turn, compared to products that have not been pre-cooled. Reefer containers are built primarily to maintain the temperature of the products hence products should always be pre-cooled to the required carriage temperature prior to being loaded into the container.

2.2.3.4 Reefer Pre-cooling

Pre-cooling of the reefer container itself should never take place because once the doors of a pre-cooled container are opened; hot ambient air will meet internal cold air, resulting in a large amount of condensation on the interior surfaces. As a result, condensed water may drip from the roof of the container and cause stains and weaken the structure of the boxes. Therefore, condensed water must be removed through the evaporator located inside the reefer machinery. Heat that enters the container during stuffing, combined with heat that is constantly generated by the “respiring” cargo, must also be removed through the evaporator. As soon as water and heat

pass the evaporator, ice is formed and the machinery enters a short defrost mode. Consequently, there will be less capacity available for cooling the cargo.

In a tropical climate (e.g. other Southern African countries) with excessively hot and humid air, any pre-cooling of the container is likely to cause problems and damage the products.

Pre-cooling of the reefer container is only allowed when the container is connected to the cold store and the temperatures are identical. The connection is achieved by the use of a “Cold Tunnel” – a tight duct between the cold store and the container, which prevents ambient air from entering.

2.2.4 Cargo handling and loading into reefer container

The stuffing and placement of cargo will directly affect the flow of air. Heat, water vapour, carbon dioxide and other gases produced by the respiration process from chilled fresh products may damage the product and should therefore be removed. The stuffing should allow the refrigerated air to circulate through the packaging material and throughout the entire load. When frozen cargos are stuffed in this manner, the cold air flows around the cargo thereby blanketing the cartons and removing any heat that enters the reefer container through the walls.

2.2.4.1 Never run a reefer with open doors

When the ambient temperature is warmer than the cargo, operating the reefer with the rear doors open will not cool down the cargo. Rather, the introduction of hot ambient air will heat up the cargo. When hot humid air enters the reefer, moisture condenses on the cold cooling coil and turns to ice. Cooled air escapes through the rear door, and the cycle continues. Once stuffing is complete and the doors are closed, the reefer could run for hours with a partially iced-up cooling coil. This would reduce its cooling effect and put the cargo in danger until the unit completes a defrost cycle.

Furthermore, the generator set should be stopped during stuffing, due to the risk of exhaust gas reaching the fresh cargo.

2.2.4.2 Cargo damage prevention

To avoid cargo damage, the reefer must operate within the following set of rules:

- Avoid running unit with rear doors open.

- Do not stuff cargo beyond the end of the T-floor. The cargo must be stowed correctly into the container. No cargo must be loaded beyond the horizontal ceiling and vertical door red Lines.
- No openings between pallets must be present because this will cause short circuiting of cold air resulting in warm cargo temperatures.
- Do not plug channels at the end of the T-floor
- Do not put reefer set point at a temperature below what is required for the cargo because this will not expedite the cooling process.

2.2.4.3 Blocking and bracing

Wood is usually the preferred material but one should not nail wood to the container. Covering the floor with filler between pallets will help force air through the cargo. Also covering the ends of the last two pallets will force air up and through the cargo.

2.2.4.4 Packaging requirements

Packaging plays an important role when it comes to protecting the cargo. The packaging material must be able to support a stacking height of up to 2.4 metres (7'10"). The material should be able to withstand humidity without collapsing, and should allow the passage of an adequate vertical airflow through the cartons in order to maintain the desired temperature. As the air comes from the bottom of the container, optimal air circulation can be achieved if each carton has symmetrical holes at both the top and bottom. The number, placement, size and shape of the air holes are determined by the product being packaged. Furthermore, the wrapping material used should be sufficiently secure to prevent any blockage of the evaporator fan.

2.2.4.5 Reefer container relative humidity level control

Controlling the relative humidity level is also important when it comes to controlling the quality of product being transported. The relative humidity level affects many products, particularly the shelf life of fruits and vegetables – and thus their condition upon arrival. If the humidity is too high, mould and or fungi may develop. If the humidity is too low, it may result in a higher weight loss causing products to wilt and or shrivel. For many products, it is therefore important to be able to control the relative humidity level during transport.

2.2.4.6 Controlled Atmosphere (CA)

Atmosphere control is another crucial variable in securing the quality of your cargo. When fresh perishables are shipped to distant markets, they require a precisely controlled transport environment. It is well known that harvested fruits and vegetables continue to live and breathe until they are consumed or destroyed by decay or desiccation. Under normal circumstances, these factors dictate the life span of individual products. The life span can, however, be prolonged by keeping the commodities at their optimal temperature, combined with the supply of the most effective blend of oxygen, carbon dioxide and nitrogen. By transporting products under Controlled Atmosphere, the applied environment will slow down the ripening process and extend the shelf life of the products

2.2.4.7 Cold treatment

The purpose of Cold Treatment is to exterminate insects and larvae by maintaining a sufficiently low temperature for a pre-determined period of time. The period of time and temperature required are defined in protocols established by phytosanitary authorities of the importing countries. If the temperature rises above the established requirements, the entire Cold Treatment process will fail and must either be extended or started over again depending on the protocol. Applying Cold Treatment eliminates the need to fumigate cargo using insecticides, such as methyl bromide, which is illegal in many countries. Cold Treatment is primarily applied to various types of citrus fruits, such as oranges, grapefruit and clementine. However, kiwi fruit, apples, pears, grapes, litchis, loquats, etc. can also be carried under Cold Treatment. In order to reap the maximum benefits from the Cold Treatment process, several factors are absolutely essential. These factors include the correct pre-treatment, proper pre-cooling of the products, optimal packaging and stowage, as well as the constant monitoring at the terminals and on board the vessels.

2.2.4.8 Reefer cargo checklist

When preparing for a refrigerated shipment, before and during stuffing, the following must be in place:

- the optimal temperature requirement
- the fresh air ventilation requirement (in cbm/hour)
- the humidity requirement
- the transport time

- the practical shelf life of the product
- the volume of cargo
- the packaging materials and cartons used
- the recommended stowage pattern
- the required documentation, including legislative requirements.

2.2.5 Reefer container malfunctioning

Should a refrigeration unit cease to operate; the chart or logger will register a gradual but steady rise in temperature to the point where eventually the ambient temperature is recorded and the data will not accurately reflect the true status of the cargo itself.

2.3 Temperature monitoring

The next vital component of cold chain operation is temperature monitoring [25]. Temperature monitoring is the process of using data logging devices to record temperatures of products in reefer containers. This enables stake holders to identify, monitor and provide solutions in the supply chain of perishable goods.

A comprehensive temperature monitoring system can assist companies to develop full cold chain performance standards ultimately improving working relationships between supply chain members to exact the ideal outcome of a “consistent quality product out-turn”. Consumer satisfaction correlates with the consistent supply of quality product [26]. The advantage for companies having a dependable cold chain that enables delivery of a reliable product quality is that consumers can relate quality to a product name. Perishable food products by definition are sensitive to temperature and it is of utmost importance that temperatures are maintained to ensure the products remain safe and of sound quality.

2.3.1 Survey of monitoring technologies used in transportation

A considerable amount of literature has been published on technologies for cold chain logistics. In recent years, much international research has focused on the development of an intelligent freight transport system. While a number of supply chain monitoring and tracking tools have been developed most of these focus on non-intermodal transport. Several attempts have been made towards better or upgraded versions:

Jay [27] developed a system for tracking the movement of cargo trailers. A GPS unit provides the location and velocity of the trailer, and a wheel rotation sensor provides the wheel rotation status. Wireless radio communication equipment transmits the trailer movement and wheel information data to a central station. With this information a computer determines the intermodal movement status of the trailer.

Joseph [28] proposed a multi-mode asset tracking and monitoring system that combines a WLAN for monitoring crowded environments (such as on-board a ship) and a WWAN that provides coverage in more dispersed environments. Both networks report events from sensors and tags located in the container.

Robert [29] patented a method and apparatus for securing and/or tracking cargo containers. The security unit comprises a controller and a positioning receiver (this can be a GPS receiver). The controller can be wired or be wirelessly connected to a light sensor, pressure sensor, toxin sensor, vibration sensor, radioactivity sensor, and/or an intrusion sensor.

Unnold [30] developed a computerized system for tracking the real-time locations of shipping containers. In this case a dispatcher workstation with a graphical user interface and a database is proposed. A mobile unit in the yard is attached to the container handling equipment and monitors the container lock-on mechanism. A radio link between the container handling equipment, the container, and the base enables transmission of the real-time position whenever a container is locked onto, moved, or released.

Neil [31] developed a system for tracking and monitoring containers worldwide that uses solar cells, rechargeable batteries, two-way satellite communication, a central processing unit, a variety of sensors, GPS, and a geographic information system (GIS). The apparatus is permanently mounted on the cargo container.

Eddy [32] focused on the development of a “smart container monitoring system” comprising sensors mounted within the shipping container that wirelessly transmit information to an electronic seal mounted on the outside of the container. Moreover, this seal wirelessly transmits information on its status to a remote monitor.

Lee [33] proposed a system for monitoring the electronic sealing of cargo containers during their transport along highways. This involves a wide network of readers mounted along

highways, and electronic seal transponders installed in vehicles and containers. The readers and electronic seal transponders communicate by means of a standardized protocol. The transponders incorporate a unit that analyses and transmits their status to a control centre.

WSNs have been used for the tracking and monitoring of nuclear materials as part of the authenticated tracking and monitor system (ATMS) [34]. The ATMS employs wireless sensors in shipping containers to monitor the state of their contents. The sensors transmit wirelessly to a mobile processing unit, connected to both a GPS and an International Maritime Satellite (INMARSAT) transceiver.

Lau [35] initiated the development of a wireless link between truck and trailer using Bluetooth. The truck uses a SAE J1939 CAN bus while the trailer makes use of an ISO 11992 CAN bus.

Madec [36] have shown that a radio frequency device can be placed in a metal cargo container and that it can still reliably communicate with the outside world. They developed a mesh-network in the 2.4 GHz region, using the 802.15.4 protocol (ZigBee).

Ljungberg and Wang [37], [38] investigated the improvement of animal welfare during handling and transport. In this case, an on-road monitoring system was proposed. A GPS provides the location of the vehicle, while sensors installed in the animal compartment identify the animals and monitor the air-quality, vibration and animal behaviour. A GSM allows on-line data transmission.

Kärkkäinen [39] gives details of how beneficial the combination of wireless sensors and RFID systems in environmental monitoring can be as well as of the monitoring of specific product quality and safety attributes along the supply chain .

Behrens [40] discusses the potential of RFID technology in increasing the efficiency of the supply chain for short shelf life products. He concluded that when RFID is used in recyclable transport containers, investments can be quickly recovered and a range of operational benefits obtained.

Jedermann and Bhero [41], [42] described an autonomous sensor system for intelligent containers combining WSNs and RFID. The proposal includes a miniaturized high- resolution gas chromatography apparatus for measuring ethylene.

Hoffman and Borriello [43], [44] presented an optimised border-post cargo clearance with Auto-ID systems from findings from a study conducted in the SADC region and proposed a combined GPS/RFID system that can provide the required level of visibility to support the problems and inefficiencies experienced in the cross-border operations in the SADC region

Table 2-2: Summary of technologies deployed in transportation

S/No	Technology Type	Deployed for the	Citations
1.	GPS	Intermodal movement status monitoring systems	[27]
2.	GPS, GSM	Monitoring animals during transport	[37], [38]
3.	GPS, WSN,	Tracking and monitoring nuclear materials, Securing and/or tracking cargo containers	[34], [29]
4.	GPS, WLAN	Container tracking systems	[30]
5.	GPS, WWAN, GIS	Tracking and monitoring containers worldwide	[31]
6.	ZigBee	Mesh-network in cargo containers	[36]
7.	RFID	Tracking containers, Monitoring electronic container seals	[40], [33]
8.	RFID, WSN	“Smart packing”, improve traceability, Autonomous sensor systems in logistics	[39][42]
9.	RFID, WLAN, WAN	System and method for asset tracking and monitoring	[28]
10.	WLAN, WSN	Smart container monitoring systems	[32]

Despite these technologies, only a small minority of perishable goods in transit are properly monitored to determine their conditions at any point in time. Current used technologies are mostly geared towards sensing events, like g. door open and close events. While these techniques provide some visibility with respect to activities on the trailer it is still prone to false alarms in respect to the real cargo conditions.

Till present most stakeholders in the cold chain industry are satisfied to only use the conventional trailer monitoring unit. Against the background of our literature research study we propose an improved cold chain logistics monitoring methodology that will assist in reducing the levels of cargo losses that are currently suffered.

2.3.2 Proposed optimised cold chain logistics monitoring

Figure 2-4 below provides a schematic of a proposed system architecture for cold chain logistics monitoring.

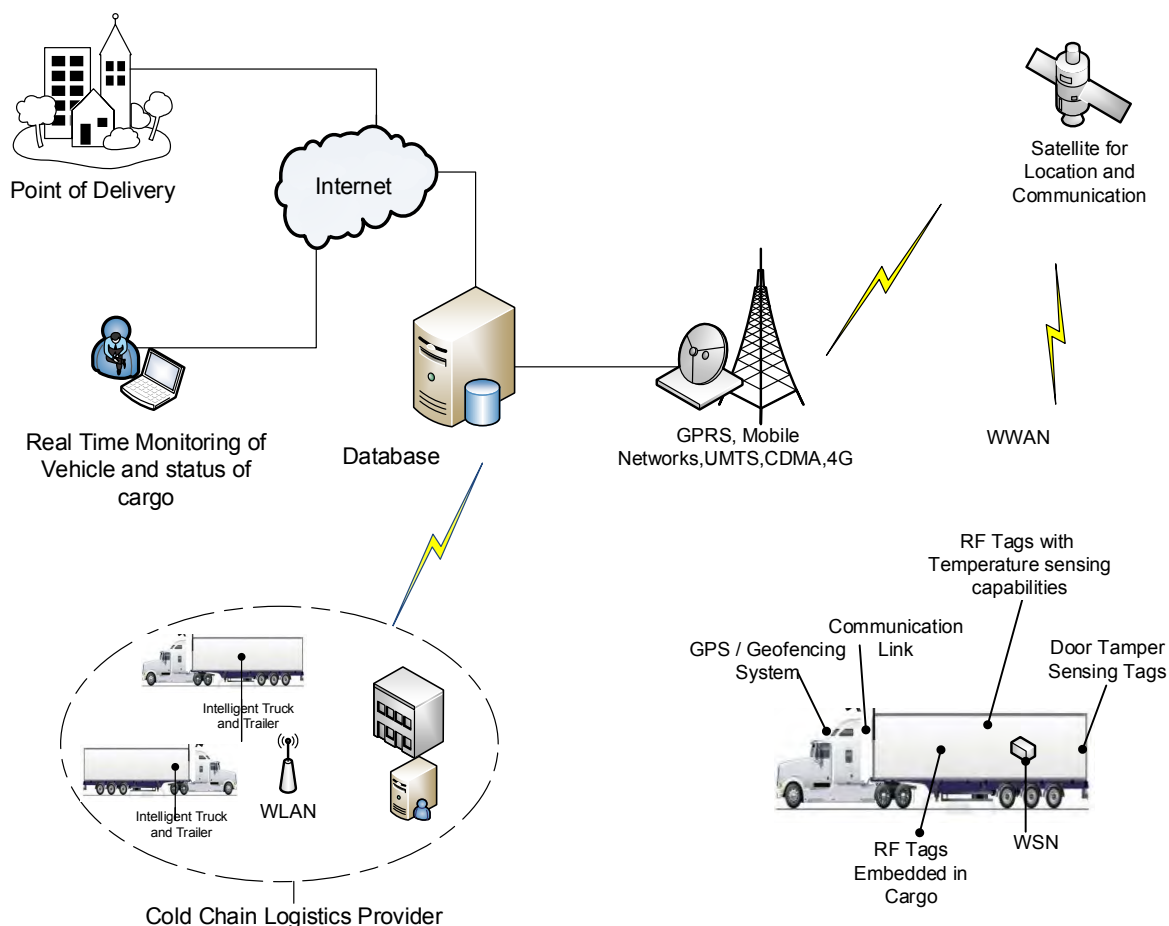


Figure 2-4: An improved cold chain logistics monitoring technology

2.3.3 Temperature data logger technologies

Data logger technology is constantly evolving; currently there are different types of temperature data loggers available, including Radio Frequency Identification Data loggers (RFID), electronic temperature data loggers and graphic (chart) recorders.

2.3.3.1 Radio Frequency Identification (RFID) technology

RFID is the generic term for the technology that uses wireless radio waves to identify people or objects from a distance without requiring line of sight or physical contact [45]. RFID helps to capture real-time information of goods and services. An RFID system consists of an RFID tag, an RFID reader, an RFID antenna, an RFID middleware and a backend system. The RFID tag is the identification device attached to the item (container) to be tracked. The RFID reader and antenna are devices that recognize RFID tags and read the information stored on them. The RFID middleware is a software that facilitates communication between the system and the RFID devices. The figure below shows a typical RFID system and illustrates how the elements communicate with each other

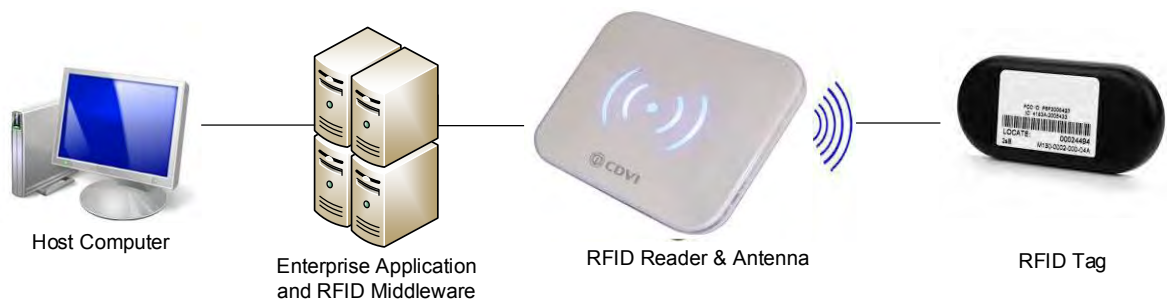


Figure 2-5: A RFID system

An RFID tag mounted on a container may have information about the product/ goods like:

- The total number of items (depending on what the good is)
- Date of loading
- The client's name
- The product identification
- The manufacturer name
- The country of origin
- The country of destination
- The expiration date
- Etc.....

RFID are mainly of three types:

1. Active tags
2. Passive tags
3. Semi active

2.3.3.1.1 Active RFID tags

Active tags are similar to normal mobile radio devices. They require no Direct Current power supply for operation. Active tags contain sensors, integrated circuits (ICs) and possibly a microprocessor. The sensors located on the tag are used to determine environmental parameters like temperature, humidity and pressure. The sensors are also used to detect changes in the operating environment of the container and are able to detect tampering. The range at which active tags transmit depends on the signal strength of the antenna, which is related to the battery's voltage. The batteries have a short life of about some years. Cold or harsh operating environment of the container such as refrigerated containers shortens the batteries life span. The complex nature and size of the active tags make them costlier than passive tags.

The features of active RFID tags can be summarised as follows:

- Programmable IC: Controls device, Software allows customization
- Microcontroller: Collect input from sensors; Process data and output
- Low Power consumption and can last up to 10 years
- Wide temperature range (- 40°C to + 85°C)
- Ultra-High Frequency UHF 300MHz -3Ghz, 10m read range
- High frequency (2.5GHz), long read range and fast read speed



Figure 2-6: An Active RFID Tag

2.3.3.1.2 Passive RFID tags

Passive tags derive their power from the electromagnetic field generated by a reader. Since no battery is required, passive tags have an unlimited lifecycle. They are best used for cost-effective, high volume applications. Their read range is up to about 10 meters. This implies that items to be read need to be located within the read range.

The features of passive RFID tags can summarised as follows:

- Used at pallet, carton level
- Activated by readers, replies using backscatter waves

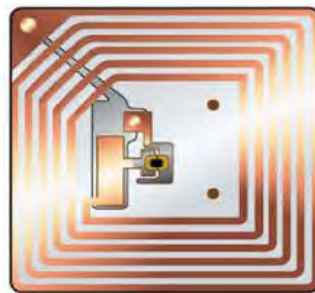


Figure 2-7: A Passive HF RFID Tag

2.3.3.1.3 Battery Assisted Passive (BAP) Tags

A Battery-Assisted Passive RFID tag is a type of passive tag which incorporates a crucial active tag feature. While most passive RFID tags use the energy from the RFID reader's signal to power on the tag's chip and backscatter to the reader, BAP tags use an integrated power source (usually a battery) to power on the chip. If the tag contains sensing devices, they can therefore remain on while the tag is not in the vicinity of a reader. Once within read range all of the captured energy from the reader can be used for backscatter. Unlike transponders, BAP tags do not have their own transmitters.



Figure 2-8: A Battery assisted passive tag

2.3.3.2 Electronic temperature data loggers

An electronic temperature data logger is a device that records data over time either with a built in sensor or via an external sensor. They are based on a digital processor and are usually small, battery powered, portable, and equipped with a microprocessor, internal memory for data storage, and sensors. Some data loggers interface with a computer and utilize software to activate the data logger, view and analyse the collected data, while others have a local interface (touchpad, LCD).

These data loggers are available in a wide range of shapes and sizes, ranging from tiny recorders the size of small buttons to larger heavier duty data loggers. Electronic data loggers are stand-alone devices with their own battery supply. They can be single trip use or multi-trip use data loggers. They may be pre-programmed to start and end at a specific time or started onsite with the press of a button. Various recording intervals for temperature readings can be chosen, with the number of data points the loggers can store ranging from small (only a few thousand recordable data points) to large (tens of thousands of recordable data points). Some loggers may be water resistant or have lights that flash when temperatures have gone outside a set alarm point or just flash when they are turned on. There are many variations of electronic data loggers.

2.3.3.2.1 Single sensor data logger

The single sensor can be either an external or internal thermometer. The external instrument maybe a probe or just a sensor on the outside of the data logger casing. Probes can be plastic or metal, depending on your needs.



Figure 2-9: A Single sensor data logger

2.3.3.2.2 Dual sensor data logger

These temperature data loggers have both an external (probe) and internal sensor, which may be useful for collecting coinciding atmospheric (surrounding vehicle, AV unit or container temperatures) and product temperatures. The external probes can be either metal or plastic depending on the product being monitored. Dual sensors may also be able to measure different functions such as temperature, humidity, pH, voltage, gas concentrations like CO₂, dew point, etc.



Figure 2-10: A Dual sensor data logger

2.3.3.2.3 Multi sensor data logger

You can get multi sensor data loggers, however, if placing loggers in various positions in a load these may be difficult to manoeuvre. Also be aware that if the control unit is misplaced, damaged or lost all data will be irreplaceable.



Figure 2-11: A multi sensor data logger

2.3.4 Motivation and benefits of real time temperature monitoring

Temperature monitoring will identify area(s) that may be leading to disappointing product out-turns and will also identify areas in the cold chain that are effectively maintaining a high cool chain standard. Having access to supply chain information via monitoring will also empower stakeholders to reward good performance or penalize negligence in the supply chain and hence increase profits while minimising losses. The addition of temperature monitoring to perishable product cold chains may be beneficial to supply chains for the following reasons:

2.3.4.1 Market / Customer Requirements

Customers may require their products in the cold chains to be transparent, ensuring any breaks in the cold chain that do occur are identified and dealt with immediately. This is due to the sensitivity of some product types to temperature abuse and fluctuations. Market requirements are often due to food safety or health regulations.

2.3.4.2 Quality Assurance

Temperature monitoring can form part of quality assurance programs in the cold chain operation. It can be a process that is done either regularly or randomly to assure the integrity of the cold chain is being maintained. It may be particularly useful when transporting high risk, high perishability, or high priced products, to have temperature data loggers placed with the load to verify that temperature management is within specification. On-going temperature monitoring can display auditable records or full visibility to clients or even be used as a marketing tool to show customers how reliable a product supply chain can be.

2.3.4.3 Demonstrate Compliance

In order to access certain markets, products must be treated according to specific temperature protocols, particularly for disinfestation of quarantine pests. It is essential that temperature monitoring is carried out to verify that these temperature protocols have been achieved. Monitoring of temperature must be carried out in accordance with the procedures specified in the protocol.

2.3.4.4 Test new supply chains

When establishing new supply chains, temperature monitoring is useful in checking the new cold chain for any breaks or identifying areas that may be susceptible to problems. If everyone in the perishable supply chain is concentrating on maintaining product integrity throughout the chain this will ensure the product reaches its destination with the best quality out-turn possible. Furthermore, if changes are made to a supply chain, e.g. different products moved, new supply chain members, or different markets being serviced, temperature monitoring is useful to ensure the integrity of temperature management in the new supply chain. Ongoing or random temperature monitoring of a chain could identify one or a number of areas in a product supply chain that may lead to an improvement of your supply chain's overall performance. The improvement of cold chain logistics systems could improve product quality and consistency on arrival, which could ultimately lead to a better marketplace position.

2.3.4.5 Troubleshooting or Problem Solving

Temperature monitoring can be used as a tool for searching throughout the supply chain for cold chain handling problems that may be present. It is generally used by the supplier of the product as a checking mechanism after a problem with the product has already been detected, usually by the buyer/retailer. Temperature monitoring of the supply chain in which the product was compromised, allows the supplier to determine whether the problem detected was a once of or due to the general supply chain handling procedures of a member or members in the chain.

2.4 Temperature modelling

2.4.1 Motivation

Previous studies have shown that the set point temperature within a reefer does not always maintain cargoes stacked onto pallets within the required temperature limits, which can then lead to cargo losses [46], [47] .

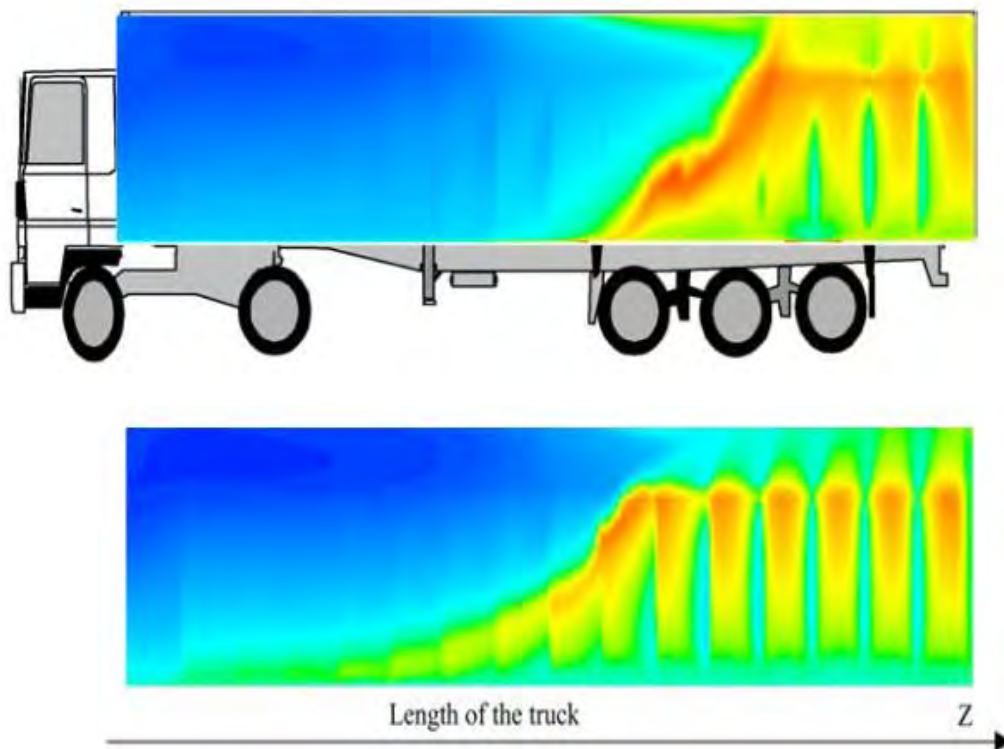


Figure 2-12: Temperature behaviour in a reefer container during transportation

Studies in [48] reveals that deviations of 2°C to 12°C were found inside truck and containers as shown below.

Reefers are normally subjected to different events which may not be regarded as important or may be ignored due to poor visibility of the overall process. This will often involve third parties who have no direct link with the cargo during transportation from distribution centres (DC) to reception centres (RC); their actions may further devalue the quality of fresh produce being delivered. Our field tests conducted within the Southern African Development Community

(SADC), from South Africa via Zimbabwe and Botswana to Zambia, revealed non-trivial scenarios where unexpected temperature behaviour occurs that has significant impact on the cargo.

The above situation can at least be alleviated if the system can detect events with a potential harmful impact of perishable cargo and can then predict at what time in future damage may in fact occur. Such information can be used to communicate alarms to drivers and supervisors to warn them about potential damage before it actually occurs, enabling preventative actions to be implemented. A time temperature prediction model based on neural networks that can assist the prevention of losses during such events will therefore be developed as part of this research.

2.4.2 Events that require the design of a model

The following set of events that may impact the quality of perishable cargo in transit were identified:

- cargo temperatures significantly exceed allowed temperature (set point temperatures)
- changes in temperatures when doors were opened for offloading
- changes in temperatures after doors are opened without authorization
- delays at borders posts due to paper work and/or long queue
- changes in temperature due to refrigeration unit malfunction
- delays due to truck breakdowns, e.g. tyre bursts
- deviations from prescribed operational procedures
- unforeseen circumstances

As the event related to cargo temperature exceeding allowed temperatures due to delays at border posts appeared to be the most common for the trips that were monitored, these type of events will be modelled as part of this research. Others events can be handled in a similar way.

2.5 Artificial Neural Network Literature Survey

This section will give an overview of the operation of biological and artificial neurons, neural network structures, neuron transfer functions and backpropagation learning methods.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large

number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. With proper training, ANN are capable of generalization, the ability to recognize similarities among different input patterns, especially patterns that have been corrupted by noise. [49]

ANNs can be grouped into two major categories: feed-forward and feedback (recurrent) networks. In the former network, no loops are formed by the network connections, while one or more loops may exist in the latter. The most commonly used family of feed-forward networks is a layered network in which neurons are organized into layers with connections strictly in one direction from one layer to another (Jain et al., 1996).

2.5.1 Biological neuron structure

In general, the biological neuron consists of the central body cell, input poles and output poles. The body is called the soma, while the input poles are called dendrites, and the output poles are called axons, as seen in [50]. Electrical impulses are transmitted from the axon terminals to dendrites via synapses which vary in conductivity, thus adjusting the intensity of the signal. The receiving neuron sums the signals received through the dendrites in order to determine its excitation level. If the excitation level exceeds the excitation threshold it transmits its own impulse, propagating the signal [51]. A human brain consists of about 85 billion neurons, with each neuron connected to around 5000 other neurons [52]. This gives a human brain immense processing capacity with advanced predictive, cognitive and classification abilities.

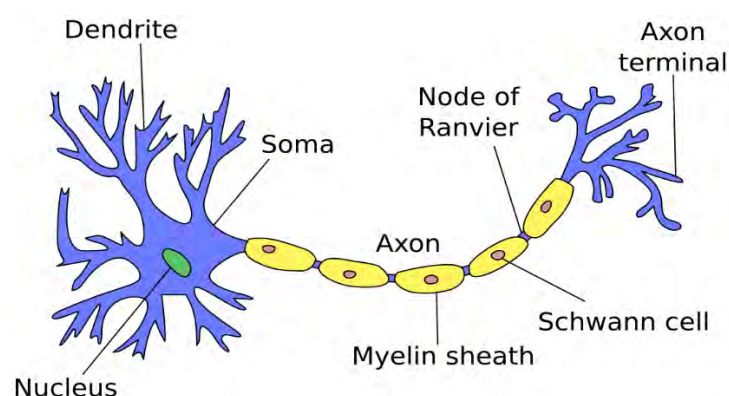


Figure 2-13: Biological neuron

2.5.2 Artificial Neural Networks benefit

Artificial Neural networks, through their extraordinary capability to derive meaning from complex or inaccurate information, can be used to excerpt patterns and distinguish tendencies that are too intricate to be perceived by any individuals or other computer systems. A trained neural network can be understood of as an "professional" in the class of information it has been given to examine. This expert can then be used to run forecasts given new circumstances of interest and answer "what if" queries.

2.5.3 Benefits of Artificial Neural Networks

ANNs have the following benefits over more conventional modelling techniques:

- Adaptive knowledge: A capability to study how to organize tasks based on the information provided for training or original understanding.
- Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
- Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
- Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage. This means that if some of the input data is corrupted and the neural network can still sensibly interpret data from the remaining inputs.

2.5.4 Neural Networks versus Conventional Computers

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do. Neural networks process information in a similar way the human brain does. The

network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to be solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong it is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency

2.5.5 The Neuron

The neuron is the basic building block of the neural network. A neuron is a communication conduit that both accepts input and produces output. The neuron receives its input either from other neurons or the user program. Similarly, the neuron sends its output to other neurons or the user program.

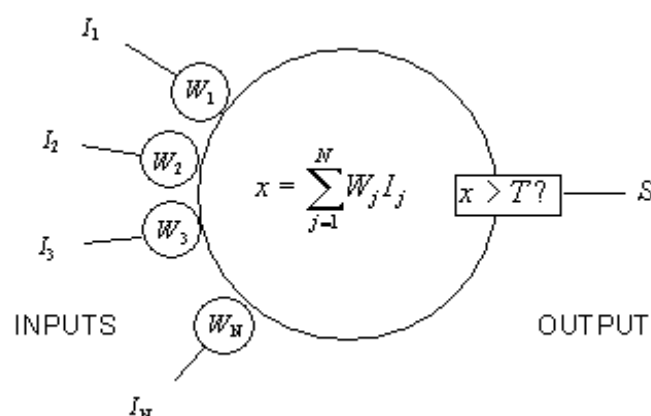


Figure 2-14: Mathematical representation of a neuron

The commonest type of artificial neural network consists of three groups of units: a layer of **"input"** units is connected to a layer of **"hidden"** units, which is connected to a layer of **"output"** units.

- The activity of the input units represents the raw information that is fed into the network.
- The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.
- The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering scheme.

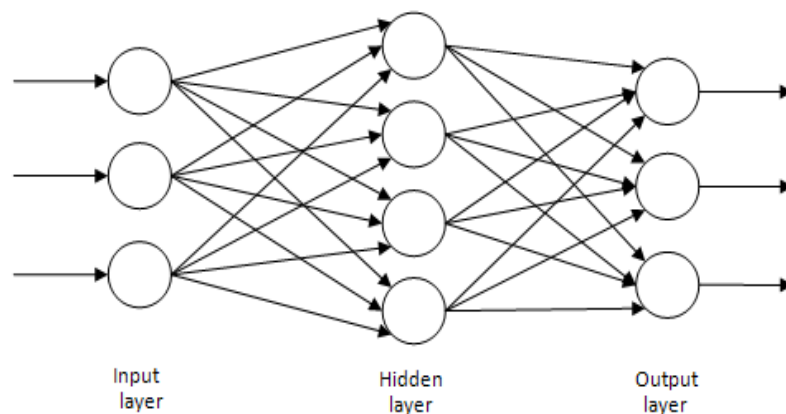


Figure 2-15: A Multilayer Architecture

2.5.6 Neuron Connection Weights

The previous section already mentioned that neurons are usually connected together. These connections are not equal, and can be assigned individual weights. These weights are what give the neural network the ability to recognize certain patterns. Adjust the weights, and the neural network will recognize a different pattern.

Adjustment of these weights is a very important operation. Later chapters will show you how neural networks can be trained. The process of training is adjusting the individual weights between each of the individual neurons until we achieve close to the desired output.

2.5.7 The Learning Process

The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms:

- **Associative mapping** in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units. The associative mapping can generally be broken down into two mechanisms:

Auto-association: an input pattern is associated with itself and the states of input and output units coincide. This is used to provide pattern completion, i.e. to produce a pattern whenever a portion of it or a distorted pattern is presented. In the second case, the network actually stores pairs of patterns building an association between two sets of patterns.

- **Hetero-association:** is related to two recall mechanisms: nearest-neighbor recall, where the output pattern produced corresponds to the input pattern stored, which is closest to the pattern presented, and **interpolative** recall, where the output pattern is a similarity dependent interpolation of the patterns stored corresponding to the pattern presented. Yet another paradigm, which is a variant of associative mapping, is classification, i.e. when there is a fixed set of categories into which the input patterns are to be classified. In **regularity detection** units learn to respond to particular properties of the input patterns and the response of each unit has a particular 'meaning', whereas in associative mapping the network stores the relationships among patterns. This type of learning mechanism is essential for feature discovery and knowledge representation. Every neural network possesses knowledge that is contained in the values of the connections weights. Modifying the knowledge stored in the

network as a function of experience implies a learning rule for changing the values of the weights.

All learning methods used for adaptive neural networks can be classified into two major categories: supervised learning and unsupervised learning.

2.5.7.1 Supervised learning

Supervised learning incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error correction learning, reinforcement learning and stochastic learning. An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights that minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

2.5.7.2 Unsupervised learning

Unsupervised learning uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. Paradigms of unsupervised learning are Hebbian learning and competitive learning. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line.

2.5.8 Transfer Function

The behavior of an ANN depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories: linear (or ramp), threshold and sigmoid. For linear units, the output activity is proportional to the total weighted output. For threshold units the output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations.

2.5.9 Error Calculation

Error calculation is an important aspect of any neural network. Whether the neural network is supervised or unsupervised, an error rate must be calculated. The goal of virtually all training algorithms is to minimize the error. In this section we will examine how the error is calculated for a supervised neural network. We will also discuss how the error is determined for an unsupervised training algorithm. We will begin this section by discussing two error calculation steps used for supervised training.

2.5.9.1 Error Calculation and Supervised Training

Error calculation is an important part of the supervised training algorithm. In this section we will examine an error calculation method that can be employed by supervised training. For supervised training there are two components to the error that must be considered. First, we must calculate the error for each of the training set observations as they are processed. Secondly we must take the average across each sample for the training set. Finally, after all training sets have been processed, the root mean square (RMS) error is determined.

2.5.9.2 Output Error

The output error is simply an error calculation that is done to determine how far off a neural network's output was from the ideal network. This value is rarely used for any purpose other than a stepping stone on the way to the calculation of root mean square (RMS) error. Once all training sets have been used the RMS error can be calculated. This error acts as the global error for the entire neural network.

2.5.10 A Feed Forward Neural Network

A "feed forward" neural network is similar to the types of neural networks that we are ready examined. Just like many other neural network types the feed forward neural network begins with an input layer. This input layer must be connected to a hidden layer. This hidden layer can then be connected to another hidden layer or directly to the output layer. There can be any number of hidden layers so long as at least one hidden layer is provided. In common use most neural networks will have only one hidden layer. It is very rare for a neural network to have more than two hidden layers. We will now examine in detail the structure of a feed forward neural network

2.5.10.1 The Structure of a Feed Forward Neural Network

A "feed forward" neural network differs from the neural networks previously examined. Figure 2-16 below shows a typical feed forward neural network with a single hidden layer

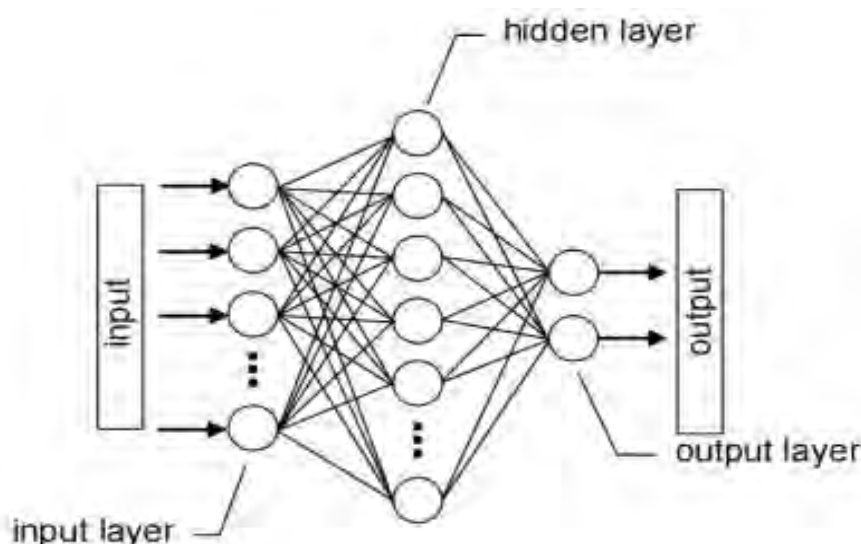


Figure 2-16: A feedforward neural system with a solitary shrouded layer

2.5.11 Choosing the Network Structure

As we saw the previous section there are many ways that feed forward neural networks can be constructed. One must decide how many neurons will be inside the input and output layers. One must also decide how many hidden layers it is going to have, as well as how many neurons will be in each of these hidden layers. There are many techniques for choosing these parameters. In this section we will cover some of the general "rules of thumb" that one can use to assist in these decisions.

2.5.11.1 The Input Layer

The input layer to the neural network is the conduit through which the external environment presents a pattern to the neural network. Once a pattern is presented to the input later of the neural network the output layer will produce another pattern. In essence this is all the neural

network does. The input layer should represent the conditions for which we are training the neural network. Every input neuron should represent some independent variable that has an influence over the output of the neural network. It is important to remember that the inputs to the neural network are floating point numbers. These values are expressed as the primitive Java data type "double". This is not to say that one can only process numeric data with the neural network. If you wish to process a form of data that is non-numeric you must develop a process that transforms this data to a numeric representation.

2.5.11.2 The Output Layer

The output layer of the neural network is what actually presents a pattern to the external environment. Whatever pattern is presented by the output layer can be directly traced back to the input layer. The number of output neurons should be directly related to the type of work that the neural network is to perform. To consider the number of neurons to use in the output layer one must consider the intended use of the neural network. If the neural network is to be used to classify items into groups, then it is often preferable to have one output neuron for each group that the item is to be assigned into. If the neural network is to perform noise reduction on a signal, then it is likely that the number of input neurons will match the number of output neurons.

2.5.11.3 The Number of Hidden Layers

There are really two decisions that must be made with regards to the hidden layers. The first is how many hidden layers to actually have in the neural network. Secondly, one must determine how many neurons will be in each of these layers. We will first examine how to determine the number of hidden layers to use with the neural network. Neural networks with two hidden layers can represent functions with any kind of shape. There is currently no theoretical reason to use neural networks with any more than two hidden layers. Further for many practical problems there's no reason to use any more than one hidden layer. Problems that require two hidden layers are rarely encountered.

2.5.11.4 The Number of Neurons

Deciding the number of hidden neurons in layers is a very important part of deciding the overall neural network architecture. Though these layers do not directly interact with the external environment these layers have a tremendous influence on the final output. Both the number of

hidden layers and number of neurons in each of these hidden layers must be considered. Using too few neurons in the hidden layers will result in something called under fitting. Under fitting occurs when there are too few neurons in the hidden layers to adequately detect the signals in a complicated data set. Using too many neurons in the hidden layers can result in several problems. First too many neurons in the hidden layers may result in over fitting. Over fitting occurs when the neural network has so much information processing capacity that the limited amount of information contained in the training set is not enough to train all of the neurons in the hidden layers. A second problem can occur even when there is sufficient training data. An inordinately large number of neurons in the hidden layers can increase the time it takes to train the network. The amount of training time can increase enough so that it is impossible to adequately train the neural network. Obviously some compromise must be reached between too many and too few neurons in the hidden layers. There are many rule-of-thumb methods for determining the correct number of neurons to use in the hidden layers. Some of them are summarized as follows:

- The number of hidden neurons should be in the range between the size of the input layer and the size of the output layer.
- The number of hidden neurons should be $2/3$ of the input layer size, plus, the size of the output layer.
- The number of hidden neurons should be less than twice the input layer size.

These three rules are only starting points that one may want to consider. Ultimately the selection of the architecture of the neural network will come down to trial and error. But what exactly is meant by trial and error. There are two methods that can be used to organize your trial and error search for the optimum network architecture: the "forward" and "backward" selection methods. The first method, the "forward selection method", begins by selecting a small number of hidden neurons. This method usually begins with only two hidden neurons. Then the neural network is trained and tested. The number of hidden neurons is then increased and the process is repeated so long as the overall results of the training and testing improved. The "forward selection method" is summarized in Figure 2-17 below.

The second method, the "backward selection method", begins by using a large number of hidden neurons. Then the neural network is trained and tested. The number of hidden neurons is reduced and the network is trained and tested again. This process continues until the performance of the neural network starts to degrade.

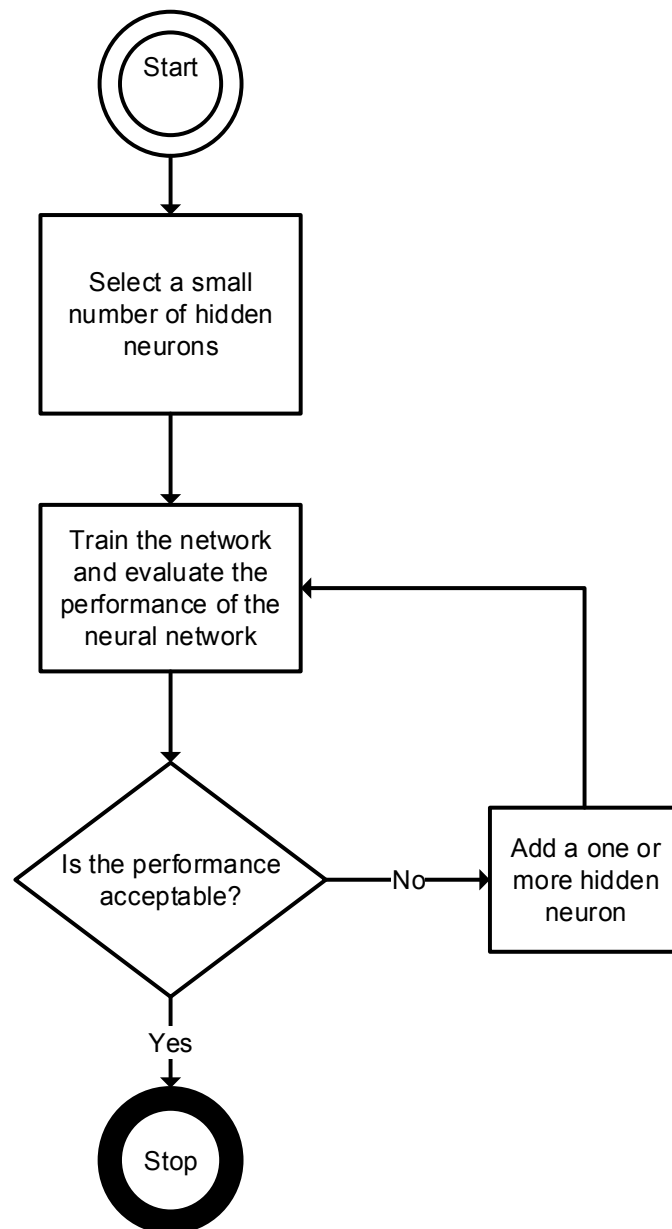


Figure 2-17: Deciding on the wide variety of hidden neurons with forward selection

2.6 In summary

This chapter provided a comprehensive literature study carried out in this research. An elaborated study on containers, its functionalities, types and uses were provided. Reefer container operations, cold chain technologies, cargo handling procedures and an improved method for cold chain logistics operations were also described.

The need for temperature modelling was also motivated and discussed. An overview of Artificial Neural Networks, its components, advantages, architecture, training, learning process, were also described.

"We are Sons and Daughters of LOVE. Let LOVE LEAD" TB Joshua

CHAPTER 3

3 Research Methodology

3.1 Introduction

This chapter describes methodologies used in the research towards data gathering. Experiments performed are extensively discussed. The models involved in executing the research are also underlined.

As mentioned in the research objectives, the extent of cargo losses in cold chain logistics had to be ascertained. It was very pivotal to know what the real issues of importance to industry are. Literature revealed substantive problems. These needed to be confirmed and ascertained in practice.

Cold chain logistics operators were engaged extensively via phone calls, emails, questionnaires, surveys, site visits, meetings and workshops to gather information from them. Experiments were then carried out in cooperation with some of these players.

While the engagements and interactions with industrial partners was not without its fair share of challenges and disappointments, it was eventually carried out successfully.

3.1 Questionnaires and surveys

Cold chain logistics operators and stakeholders contact details were gathered with permission from the perishable products exports control board (PPECB). About five hundred (500) contacts emails were screened and contacted to take part in the research project. They were also furnished with questionnaires.

About 2% of the contacted companies replied positively to the questionnaires. Some obviously were not interested to take part in any form of research for reasons best known to them. Feedback from transporters, cold chain logistics operators and stakeholders revealed the following issues:

- Delays at border posts

- The need for temperature monitoring
- Blame games from parties involved in cold chain
- Cold chain visibility will be greatly beneficial to the SADC region
- The need for private and public sector cooperation
- Poor cold chain practices along some chains
- Temperatures are monitored by on-board cooling system

The invitation to transporters to participate in the study, questionnaires used and some response to those questionnaires are attached in appendix B page 125.

3.1.1 Sites visits and meetings

Subsequent to answers from the questionnaires, meetings were organised by the research group with industrial partners like: Lonrho logistics, Interchain and Sazam freight services for detail discussions. Site visits were also undertaken to get acquainted with cold chain logistics operations at their depots.

3.1.2 Workshops

Workshops were organised by the intelligent freight monitoring group in conjunction with an asset tracking and management company (Techsolutions), a freight logistics consultant and the researchers within the group. The workshops were a platform to keep oneself abreast of the latest trends within the freight industry, report on deliverables and set new tasks to be achieved.

3.1.3 Approvals and paper work

Paper work had to be submitted for visas from the Zambian, Mozambique, Zimbabwean and Botswana consulates in order to be able to carry out the required field tests and cross border experiments. These documents are also found in appendix B page 125.

Table 3-1 below summarises the activities undertaken for the practical understanding of the cold chain practices and experiments undertaken.

Table 3-1: Activities undertaken for data gathering

Date	Activities / Operator visited / Purpose of Visit
04/07/2013	Subgroup meeting with project leader at North West University: Milestones and targets defined
17/11/2013	Lonrho Logistics / Trucks / Dummy experiment installation
20/11/2013	Lonrho Logistics / Trucks / Dummy experiment installation
27/11/2013	Lonrho Logistics / Trucks / Dummy experiment report
16/01/2014	Lonrho Logistics Trucks
27/02/2014 to 27/02/2014	Lonrho Logistics / Trucks / Dummy tags experiment completion, Infrastructure Visit Meeting with Transporter
04/03/2014	Lonrho Logistics / Trucks / LogTags experiment installation
24/03/2014	Lonrho Logistics: Trucks
26/04/2014	Lonrho Logistics / Trucks / Temperature LogTags installation for cross border monitoring to Zambia in the routes
14/05/2014	Lonrho Logistics / Trucks / Temperature LogTags retrievals from trucks for data downloading and analysis
15/05/2014	Lonrho Logistics: 1.) Temperature LogTags retrievals from trucks for data downloading and analysis 2.) Temperature LogTags installation for cross border monitoring to Zambia in the routes:
11/06/2014	Lonrho Logistics: Trucks
10/07/2014	Lonrho Logistics: Trucks
15/07/2014 to 21/07/2014	Lonrho Logistics / Trucks / Cross Border Experiment
18/07/2014	Subgroup meeting with project leader at North West University Determine results from RFID tests and evaluation performed by colleague Design set of experiments and determine parameters to be measured
01/08/2014 to 10/08/2014	Lonrho Logistics: Trucks Cross Border Experiment
20/08/2014 to 26/08/2014	Lonrho Logistics: Trucks: Cross Border Experiment
29/08/2014	IFM workshop North West University
03/10/2014	THRIP meeting North West University
17/10/2014 to 25/10/2014	Lonrho Logistics: Trucks Cross Border Experiment

31/10/2014 to 07/11/2014	Lonrho Logistics: Trucks Cross Border Experiment
04/12/2014	IFM workshop North West University

3.2 Experiments

This section provides a detailed information on experiments conducted to determine multi-point temperature parameters within a refrigerated container. Figure 3-1 provides a description of the experimental methodology.

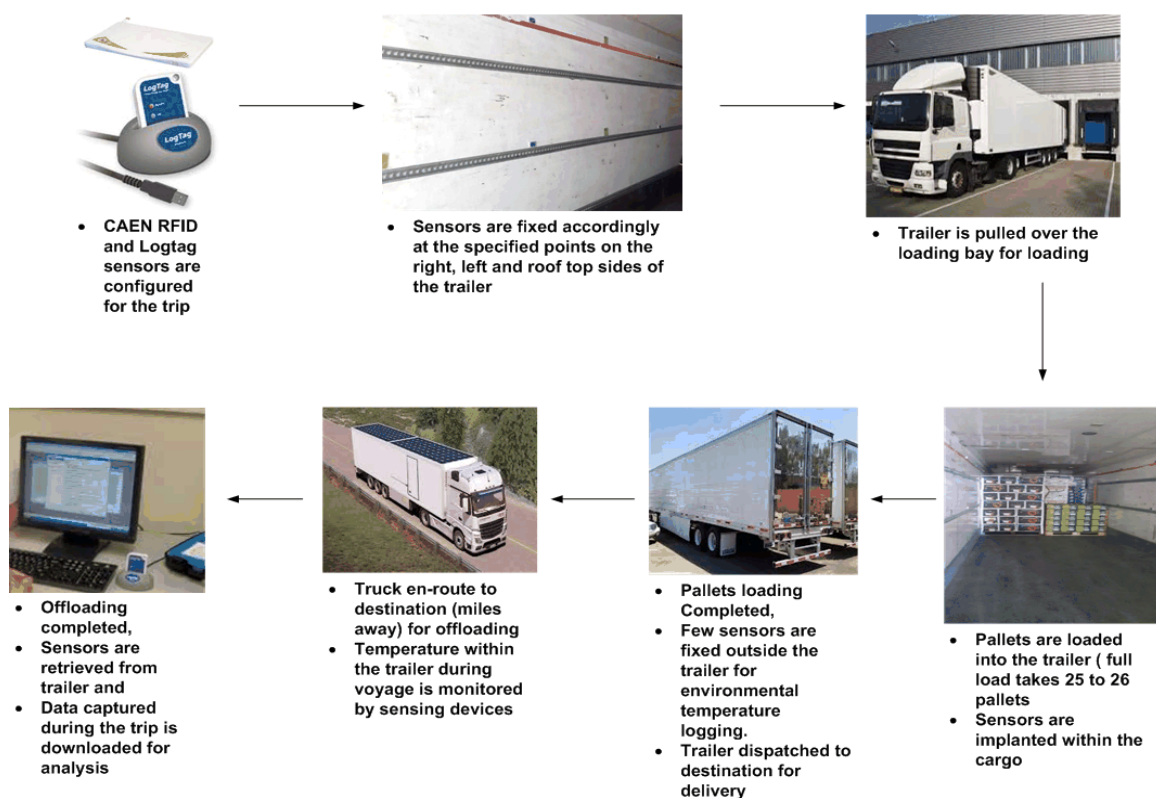


Figure 3-1: Experiment flow diagram for data capturing in a cold chain

3.2.1 Dummy experiments

Due to the cost of the sensors, a dummy experiment was conducted to achieve the following:

1. Determine safety, integrity and recoverability of temperature Logtag sensors during fresh produce shipment.

2. Ascertain possibility of actual LogTags been displaced in the refrigerated container during transportation
3. Determine possible damages that may occur to real LogTags during transportation
4. Define best mounting methods

3.2.1.1 Methodology and results

Sixteen (16) dummy loggers were tagged with passive RFID tags, the IDs were captured with a CSL RFID reader then the dummy loggers were mounted with glue within a 15.4m trailer at different positions (doors, roof and sides) spatially separated from each other. Thereafter, they were scanned with an RFID reader again to confirm RFID readability after being in contact with glue gun glue. The RFID tag on the horse was also captured and the truck was registered on the intelligent freight website.

The experiment was repeated a second time to ascertain the results realised. Results proved that dummy sensors retained their initial positions, none were lost, those mounted on the sides experienced scratches, that was attributed to negligence from loading personnel and pallet placement.

Field test were carried out on the following dates but more than 30% of the sensors were lost. This proved the need for a research staff member to accompany the trailer.

Table 3-2: Field tests conducted without supervision

Dates	Routes	Cargo Types	Sensor installed	Sensors lost
07.03.2014 – 12.03.2014	S.A– Lusaka	Fruits & Vegetables	14	0
14.03.2014 – 17.03.2014	S.A – Lusaka	Fruits & Vegetables	14	0
19.03.2014 – 23.03.2014	Lusaka to S. A	Vegetables	14	0
29.04.2014 – 14.05.2014	S.A - Lusaka	Dry Goods	20	0
16.05.2014 – 20.05.2014	S.A – Lusaka	Fruits & Vegetables	13	5
26.05.2014 – 30.05.2014	S.A - Lusaka	Ice cream	14	0
13.06.2014 – 16.06.2014	S.A – Lusaka	Vegetables	14	0
19.06.2014 – 24.06.2014	S.A - Lusaka	Frozen goods	14	0

3.2.2 Real Cross border experiments

The experiments with dummy loggers being successful and providing enough evidence regarding the integrity and recoverability of sensors, the real experiment was carried out.

3.2.3 Objectives of the experiment

The objectives of the experiment were to capture data and achieve the following:

1. Determine multi-point temperatures at the periphery of the trailer and within embedded cargo
2. Determine the variation within each multi point
3. Determine the differences in measurements at different distances from the airflow
4. Determine the differences in measurements above and below the red line
5. Determine the differences in measurements inside the cargo as compared to on the trailer walls for similar distances from airflow as in 1 and 2 above
6. All the above (1-3) as function of time as from time of departure and after doors were opened
7. Determine the differences for incidents of unexpected doors openings
8. Determine the differences for Incidents of unexpected stops
9. Determine the differences for Incidents of unexpected breakdowns
10. Determine the differences for Incidents of route deviations from planned routes
11. Determine the differences in measurement for different sections of the trailer coupled with positions above and below red line
12. Determine the differences in measurement above the roof
13. Determine the average deviations between actual and required conditions
14. Determine the extreme deviations between actual and required conditions
15. Determine the impact of conditions on status and quality of cargo based on known relationship between ambient conditions and rate of deterioration of specific types of cargo
16. Determine the financial losses if any for a typical a consignment
17. Determine the benefits in practice if required temperatures are maintained
18. Implement a cost benefit model by considering the following scenarios:
 - scenario 1 using tags of which the data is only collected once the truck arrives at the depot;
 - scenario 2 using tags of which the data is communicated in real time to the depot.
19. Determine the average temperature value calculation for different section in container
20. Determine the percentage deviation from set point, above and below this temperature

21. Determine the comparison between averages for different trips.
22. Draw Graph of these average values
23. Establish the average percentage deviation that could be expected for each section of the trailer at a certain height in the trailer; this is determined by comparing the average in each section over all the experiments with the average over all sections in the trailer.

3.2.4 Experimental procedures and set-up

The following procedures were adhered to:

3.2.4.1 Experimental devices

The experimental devices used were 15.3m reefer container, Logtag sensors, Logtag interface, CAENRFID sensors CAENRFID reader and glue



Figure 3-2: Logtag sensor and interface



Figure 3-3: CAEN RFID sensors and reader

3.2.4.2 Tag installation

An important practical consideration is to determine how many tags are required inside a trailer to provide sufficiently accurate temperature monitoring. For this purpose, four tag configuration settings were employed in the experiment:

- Tag configuration A used 14 sensors on the periphery and 5 were embedded within the cargo
- Tag configuration B used 20 sensors on the periphery and 6 embedded within the cargo at different sections within the trailer
- Tag configuration C used 57 sensors on periphery and 13 embedded within the cargo at all five Tiers of the Trailer. 3 sensors were lost.
- Tag configuration D used 45 sensors on periphery and 15 were embedded within the cargo at all five Tiers of the Trailer

Each installation included the following steps:

1. Experiment date was agreed upon with transporter
2. Identification of allocated truck for the experiment
3. Configuration of RFID tags and Logtag loggers at required transportation temperature
4. Selection of tag position configuration (A – D) Figure 3-4 to Figure 3-7
5. Installation of configured tags according to selected configuration

3.2.4.2.1 Tags installation configuration A

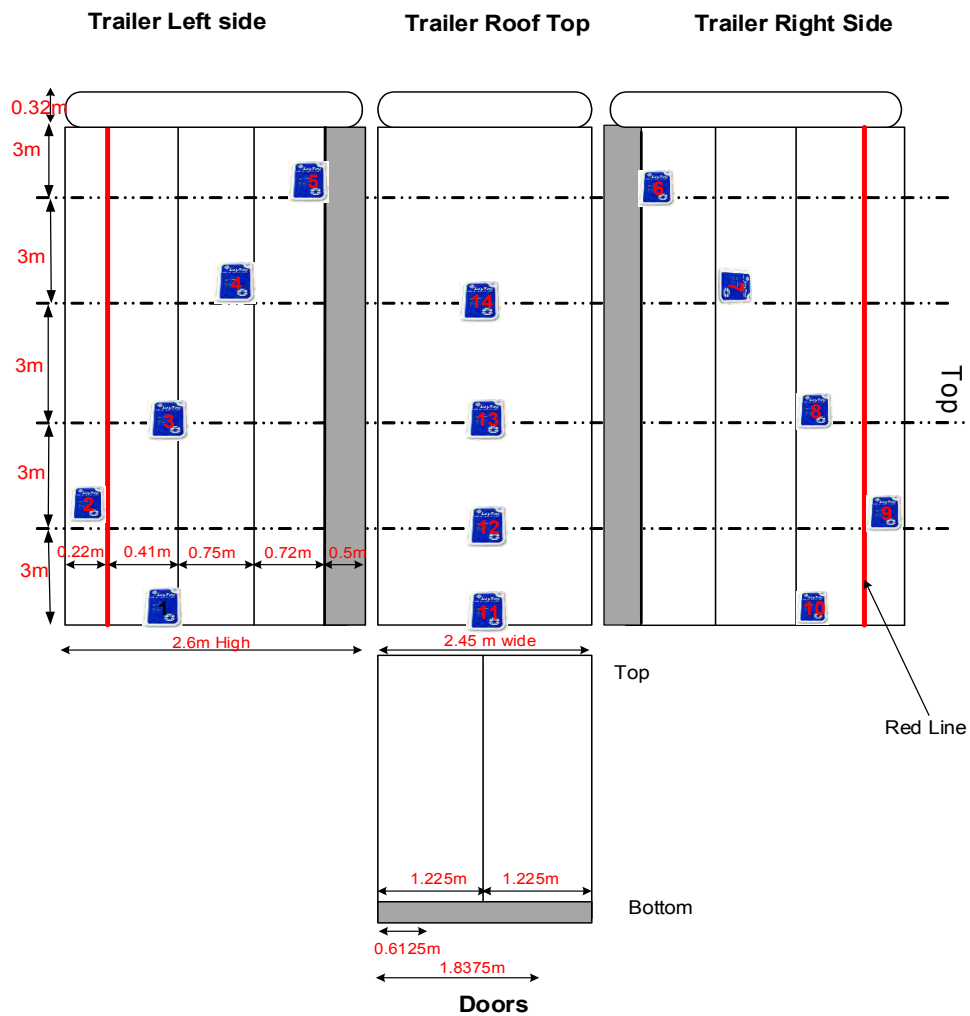


Figure 3-4: Configuration A Sensing tags location in the trailer. Image not drawn to scale

3.2.4.2.2 Tags installation configuration B

20 Logtag sensors were positioned as shown in Figure 3-5 below and 6 embedded within the cargo at different sections within the trailer

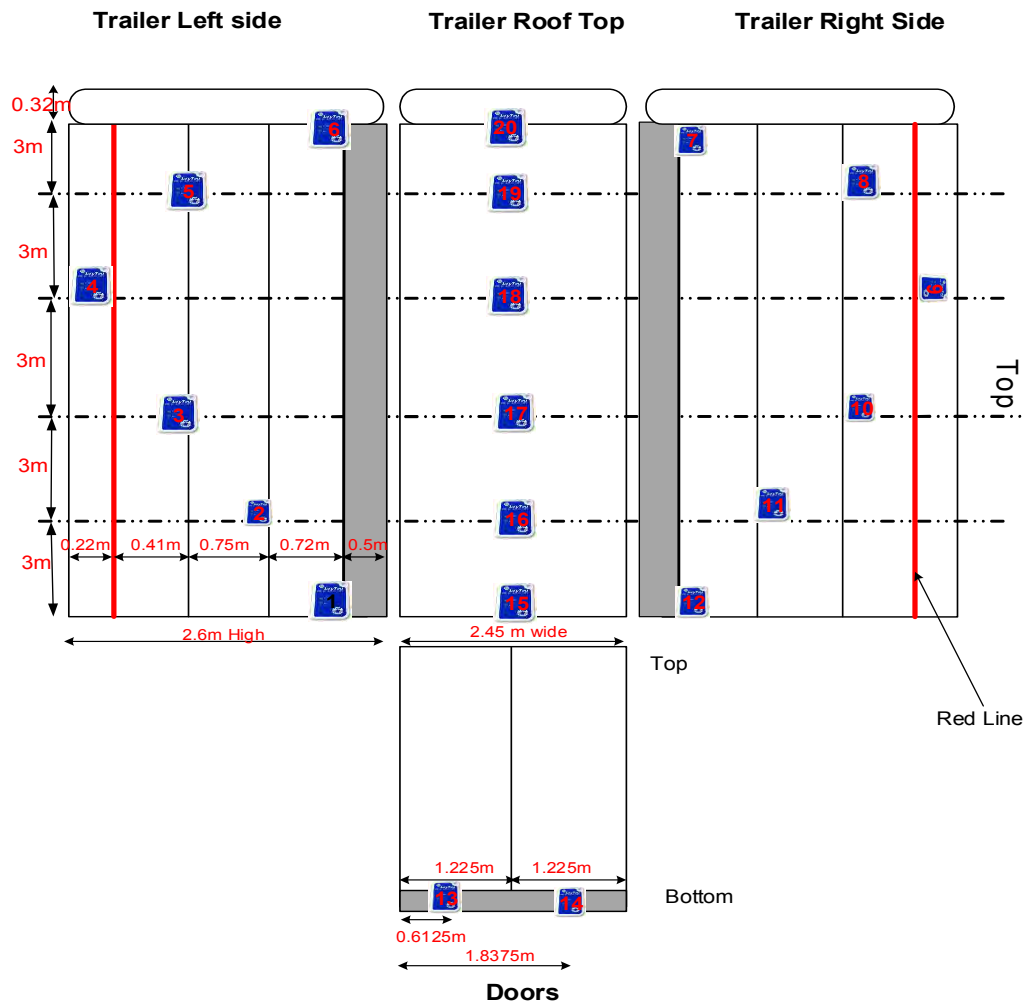


Figure 3-5: Configuration B Sensing tags location in the trailer. Image not drawn to scale

3.2.4.2.3 Tags installation Configuration C

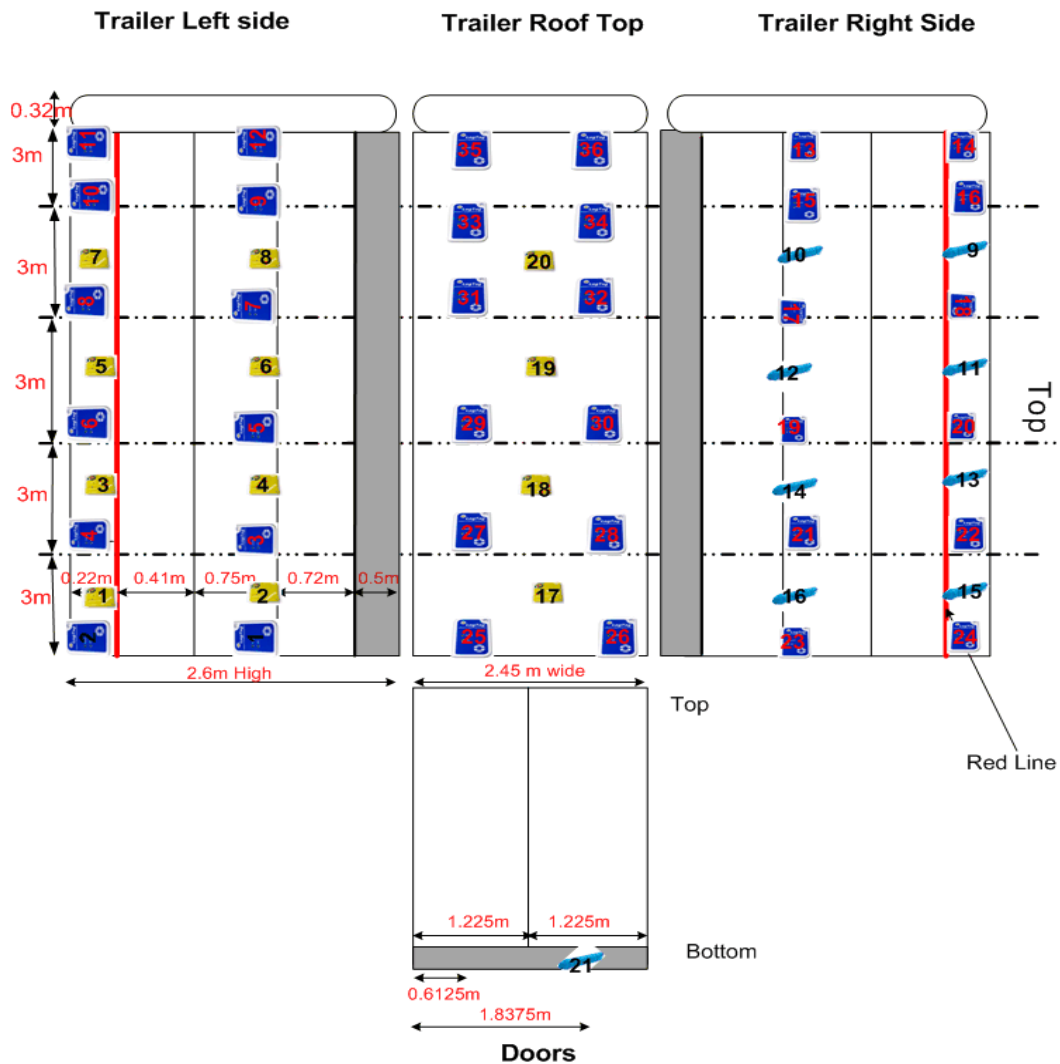


Figure 3-6: Configuration C Sensing tags location in the trailer. Image not drawn to scale

3.2.4.2.4 Tags installation Configuration D

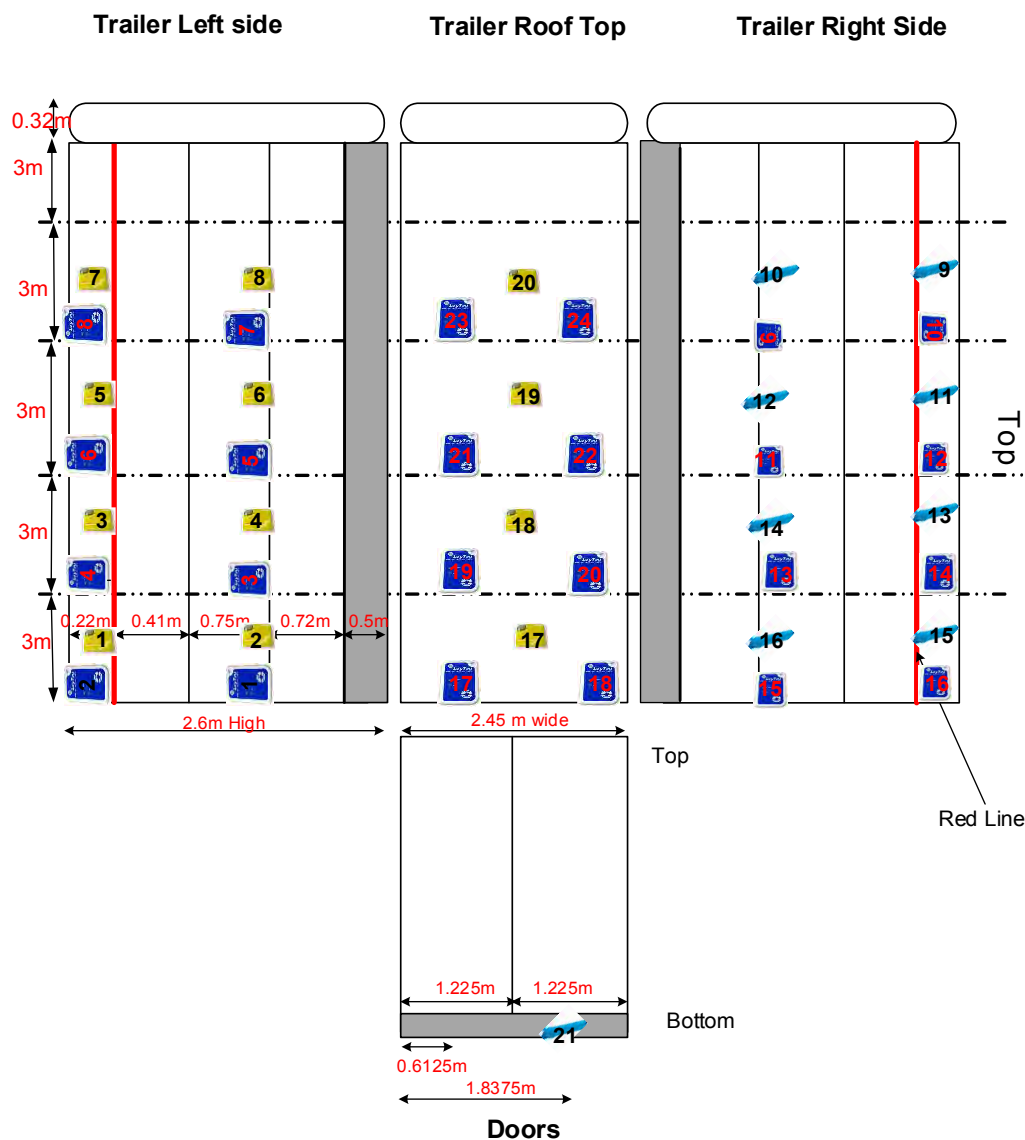


Figure 3-7: Configuration D Sensing tags location in the trailer. Image not drawn to scale

3.2.4.3 Pallet Loading Configuration

The pallet configuration patterns used in industry were identified during the experiment as described in Figure 3-8 not necessarily in this exact order but always in this fashion. The pallets are loaded this way to balance the load on the axles and avoid trailer load above recommended

weights. Failure to adhere to trailer weights can make the transporter liable for fines as much as one thousand US dollars (\$1000) in countries like Zambia.

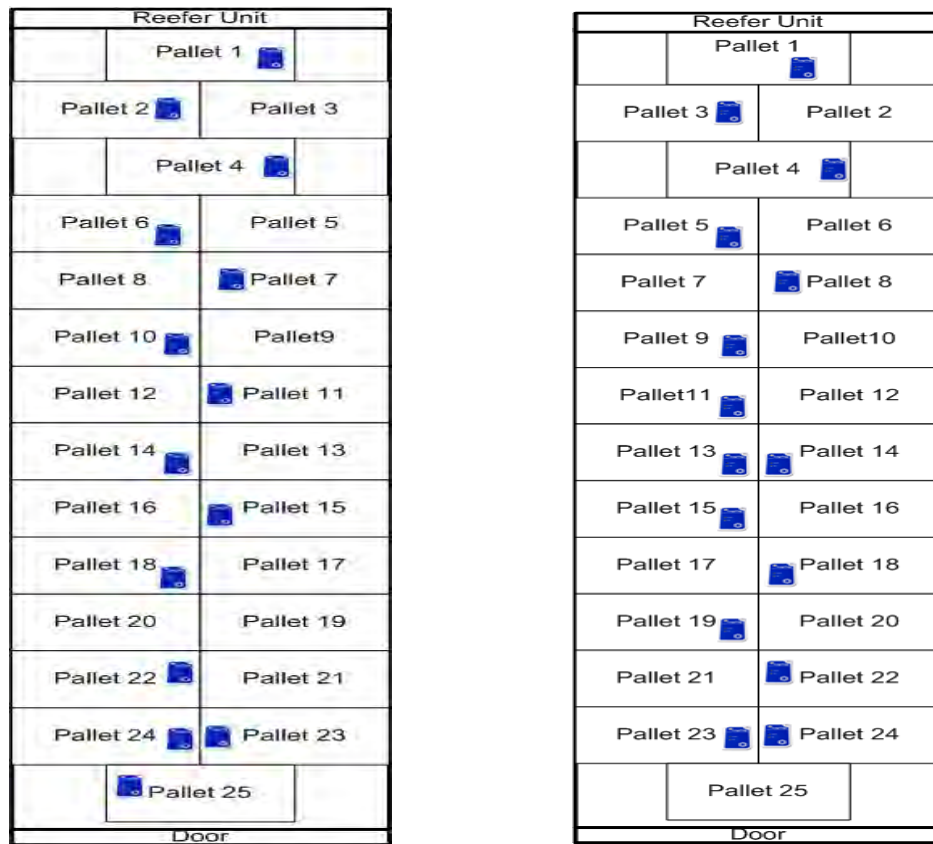


Figure 3-8: Pallet loading configuration adhered to and sensors implants in Test 4 and 5



Figure 3-9: Sensors positions outside on boxes

3.2.4.4 Cargo loading

The following methods were employed during cargo loading to avoid errors and ensure a well-controlled experiment.

1. Accompanying the driver to point of loading
2. Supervision of loading of cargo in order to avoid tags being pushed off their assigned positions
3. Necessary approval was obtained to implant 6 tags in the cargo and ensure they are situated in the first to the sixth tiers of the trailer at different sides of the left, right and centre
4. Approval to tag pallets housing sensing loggers with the designed stickers
5. Supervision of the loading of the cargo into the truck
6. Time recording for every event that occurred when loading started and was completed.



Figure 3-10: Inside a trailer showing installed sensors on sides



Figure 3-11: Inside a trailer showing installed sensors on sides of trailer and pallets been loaded

3.2.4.5 Cargo offloading

The following method were employed during cargo offloading and sensor retrieval in order to ensure a well-controlled experiment:

1. Cargo offloading was monitored closely
2. All tags embedded in pallets were retrieved
3. Times of each tags retrieval and when doors were opened were captured



Figure 3-12: Pallet been offloaded

3.2.5 Temperature requirements

According to the perishable produce export control board (PPECB), all refrigerated produce must be transported at the optimum product temperature with a maximum deviation of + 2°C [53].

3.2.5.1 Natural Value Foods (NVF)

NFV is one of the consignors who requires that their cargoes are delivered according to the following conditions to their client Rosebloom Farm in Zambia:

- (a) Set point temperature of trailer: (3-5 °C) but usually the trailer is set at 5°C both when fruits and vegetables are transported and apples are transported
- (b) Minimum temperature of trailer on during transit = 3°C
- (c) Maximum temperature of trailer on arrival = 5.5°C
- (d) Acceptable deviations: 2°C
- (e) Observed temperature deviation from the set point on the cooling unit meter :1°C

3.2.5.2 Lonrho Fresh

Lonrho fresh requires their cargo to be delivered according to the following conditions:

- (a) Set point temperature of trailer: (2 °C) for fruits and vegetables
- (b) Minimum temperature of trailer on during transit = 2°C
- (c) Maximum temperature of trailer on arrival = 5°C
- (d) Acceptable deviations: 2°C
- (e) Observed temperature deviation from the set point on the cooling unit meter :1°C

3.2.6 Routes

The maps in Figure 3-13 below provides a schematic description of the routes path by the trucks during the experiments.

3.2.6.1 Route mapping and deviations for different field tests

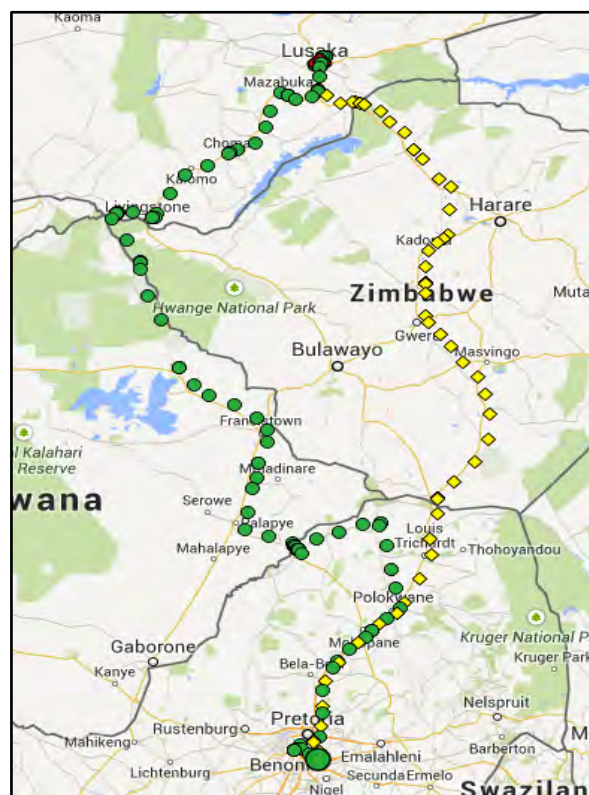
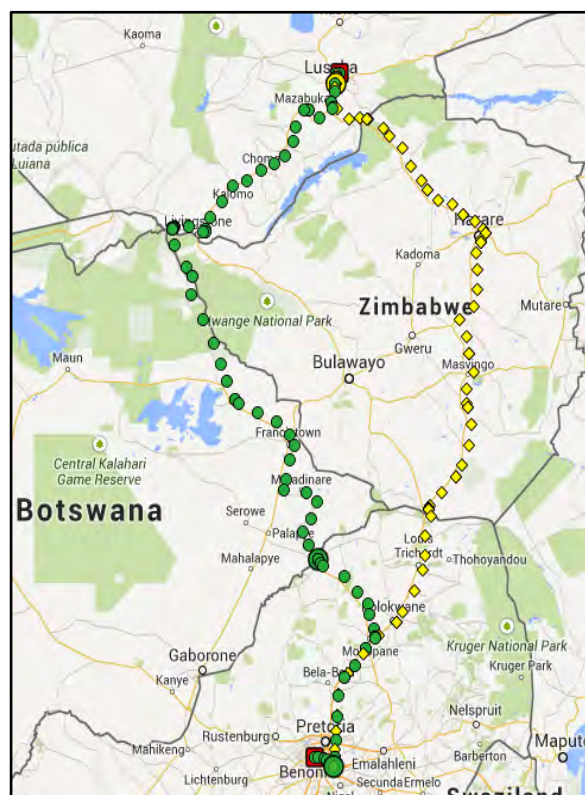
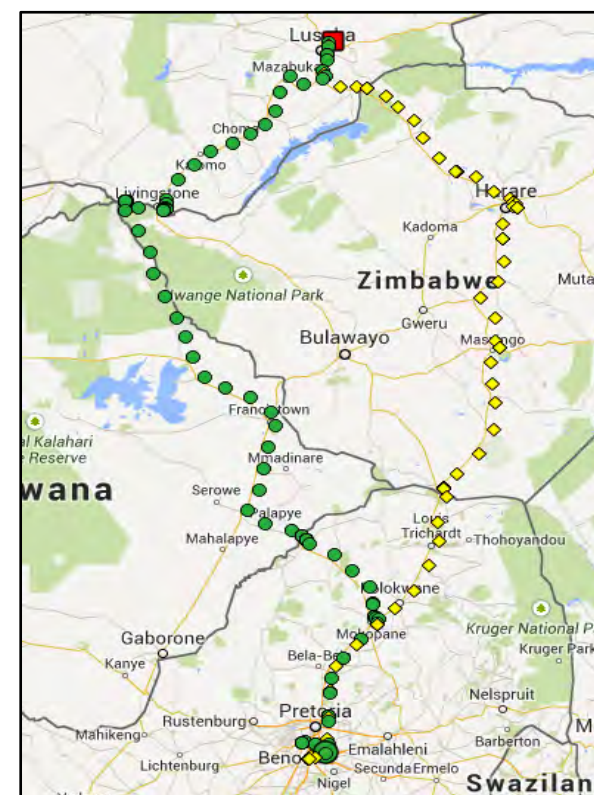
15th – 21st July 20141st – 10th August 201420th – 26th August 2014

Figure 3-13: Route mapping: 15th- 21st July, 1st- 10th August and 20th- 26th August 2014. Green Route maps trip to Zambia while yellow route maps return trip to South Africa

3.2.7 Repetition

Experiments were conducted about ten times. This was vital to ensure a sufficiently large data set to determine the reliability of the results and to collate enough temperature data to characterize the cold chain logistics processes effectively.

3.3 In summary

This chapter provided the methodologies employed in the research's data gathering, mining analysis. This was achieved by means of industrial partners' sites visits, meetings and workshops. Questionnaires and surveys were distributed to numerous cold chain logistics operators and stakeholders.

Repeated cross border experiments across the Southern African Development Community (SADC) were conducted from South Africa to Zambia at 2°C and 5°C. Four sensors tags configuration installation models were used at different times during the experiments. Complete trip data were captured for required data analysis and mining and interpretation.

“...better is not good enough, the best is yet to come...” **TB Joshua**

CHAPTER 4

4 Data Analysis and Results

4.1 Introduction

In this chapter, findings and results from the experiments conducted are presented. Analysis of captured data are also discussed.

Three fundamental goals drove the collection of the data and the subsequent data analysis. Those goals were to determine temperature profiles within a reefer container, characterize such profile, develop a databank about cold chain logistics operations that can be used in future, analyse and interpret collated data and develop a predictive temperature model for cold chain logistics.

Five sets of experiments based on normal cold chain operations were conducted from South Africa (S.A) to Zambia (ZMB) when the 15.32m reefer trailer had a full load and back to South Africa when the trailer was one quarter full. These experiments were conducted from February 2014 to November 2014. The full reefer containers were loaded with 25 pallets of fruits and vegetables each at a set point of 2°C. The duration of each experiment ranged from 6 to 10 days. 53 Logtag Data loggers and 20 CAEN RFID sensors were installed at various points 3m from each other on the periphery of the trailer and some embedded within the cargo as described in the previous chapter. A research assistant accompanied each experimental vessel in order to ensure that sensors were correctly placed and recovered, and furthermore to record events that occurred during each trip. This included the times of loading, sealing, departure, arrival at border posts, duration of interruptions of the journey, time of arrival at destination, time that doors were opened and time when offloading was completed.

Spatial and temporal temperature profiles at the periphery of trailers and inside actual consignments during transportation were captured, collated and extracted from experimental data sets in required formats. These were evaluated and further analysed. The figures below reveal the results that were observed. Temperatures as high as 10°C were experienced at the doors (0.00m) while the lowest temperatures were observed in the region close to the vent (1.7°C – 3.5°C). Analysis from data of set point temperature at 2°C revealed deviation according to Figure

4-1 below. Cargo 5m from the vent were normally within the set point temperatures, while cargo 7m away recorded temperatures around 2.1°C (~5% deviation increase from set point deviation), cargo 10m away experienced 15% temperature deviation (4.15°C) while those 10-15m away experienced up to 40% set point temperature deviation (6.4°C).

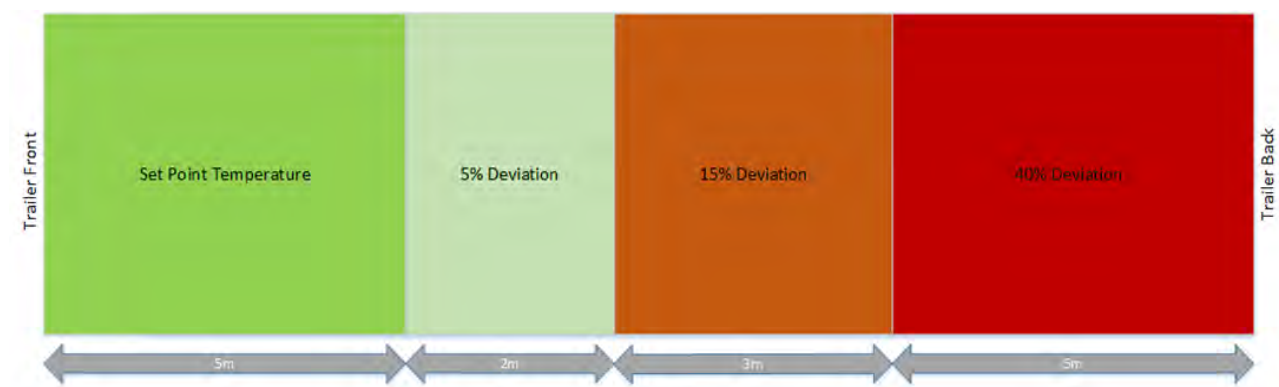


Figure 4-1: Temperature deviation from conducted experiment

These experiments confirmed that the need exist for in-transit temperature monitoring to allow the consignor and consignee to enforce SLAs while allowing the transporter to improve the management of its operation.

4.2 Trailer travelling time

Actual traveling times and delays were ascertained from the experiment and the results are found in appendix C (**Error! Bookmark not defined.**). This confirmed delays highlighted by transporters as a problem through questionnaires and during meetings.

4.3 Experiment 2 Johannesburg to Lusaka 01.08.2014 to 07.08.2014

The experiment was carried out when the trailer was fully loaded and in-transit to deliver fresh produce to Zambia via Botswana and back to South Africa via Zimbabwe. The set point temperature was 5°C for mixed produce (apples, pumpkin, butter nuts, oranges, garlic, papaya, avocado, grape fruits, kiwi fruit, ginger, grapes, melon, pineapples, plums, soft citrus, pears) for the trip up to Zambia and 2°C for vegetables during the return trip back to South Africa. During the field tests the temperature collection time interval was set at 5 minutes. Uneven distribution of the temperature fields was observed and this poses a threat to the goods been transported. Deviations occurred that were above 2°C .

4.3.1 Positions level results and analysis

Results were observed and analysed for the following tag positions within Tiers 1-5:

- sensors embedded within pallets
- sensors attached to the left hand side, right hand side and roof top of the trailer.

4.3.1.1 Sensing tags within pallets at different tiers in the trailer

The figure below shows temperature profile behaviours for sensors tags embedded within the cargoes at the five tiers of the trailer (Tier 1 to 5). Pallet 1 was positioned in tier 1 (close to the Air vent while pallet 6 was positioned in the last tier (tier 5 at the door of the trailer).

The cyclic behaviour shows when the tags where embedded in the pallet within the cargo during loading, when the door was opened for offloading and the return load was loaded at a lower set point temperature of 2°C. Tag installation configuration B was used during this experiment

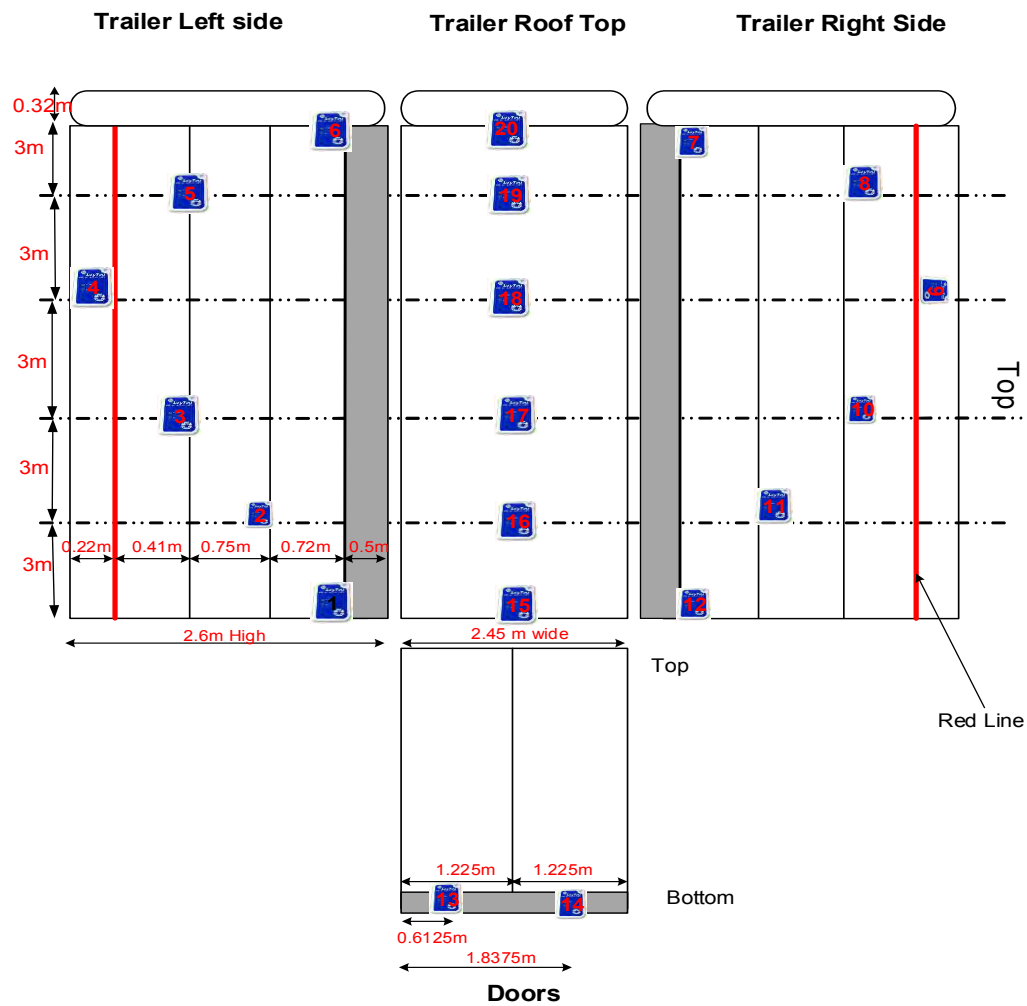


Figure 4-2: Sensing tags configuration B employed for the experiment dated 01 to 07. August 2014

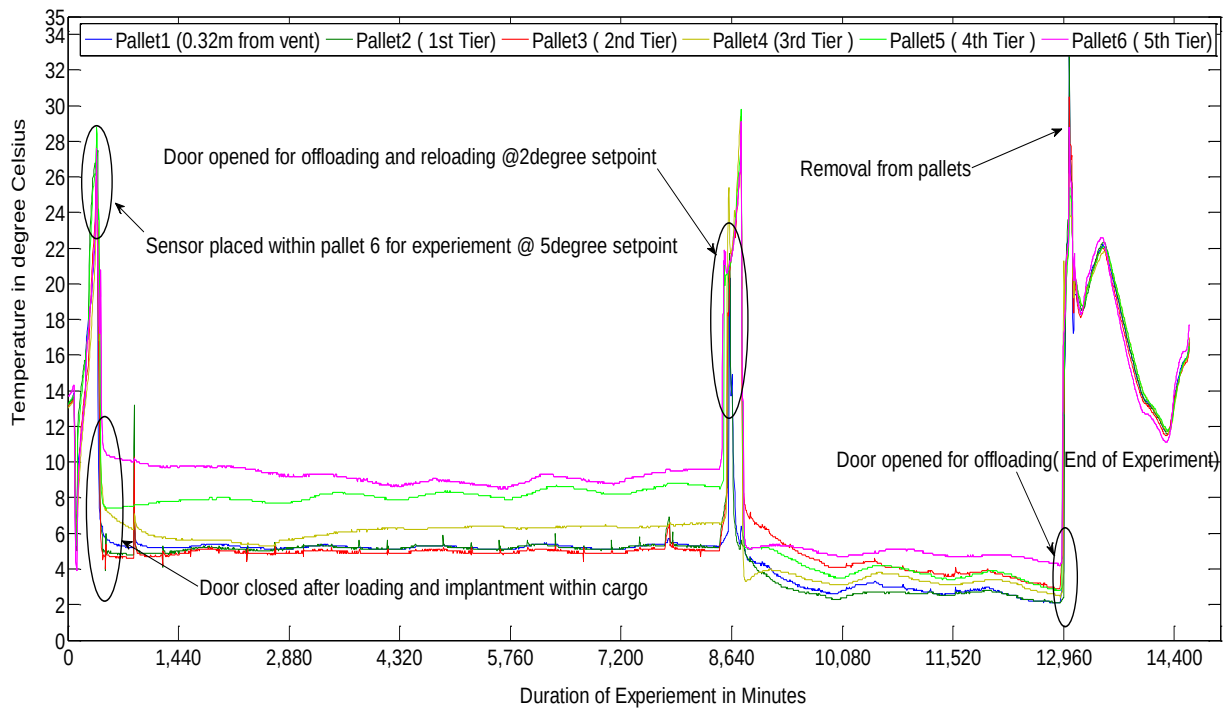


Figure 4-3: Sensing tags within pallets at tiers (1-5) within trailer

The figure below shows the temperature profile zoomed view of the sensors embedded within the cargo in the pallet after the doors were closed after installation during the first leg trip.

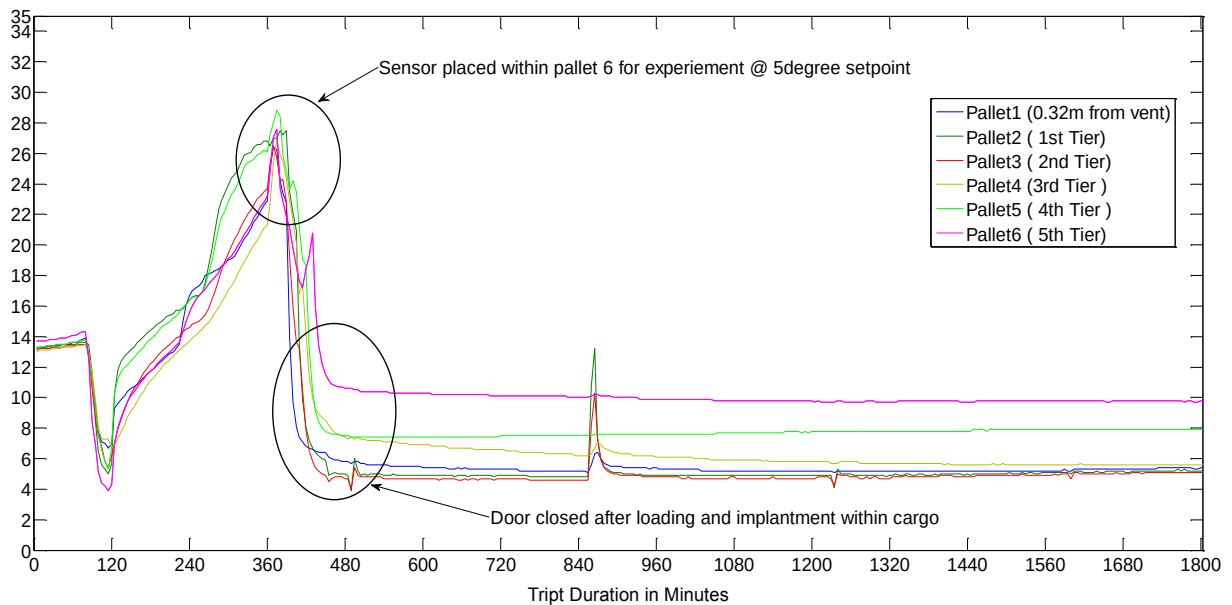


Figure 4-4: Sensing devices within pallets at tiers (1 -5) within trailer zoom view

Overall analysis on sensing tags embedded within the cargo in the pallets:

The set point temperature on the trailer was 5°C and 2°C on the return leg. Deviation greater than 0.5°C was observed by sensing tags placed in the 3rd, 4th and 5th Tier. That is from the middle of the trailer to the end of the trailer on the door side.

4.3.1.2 Sensing tags mounted at periphery left hand side (LHS) of the trailer variation

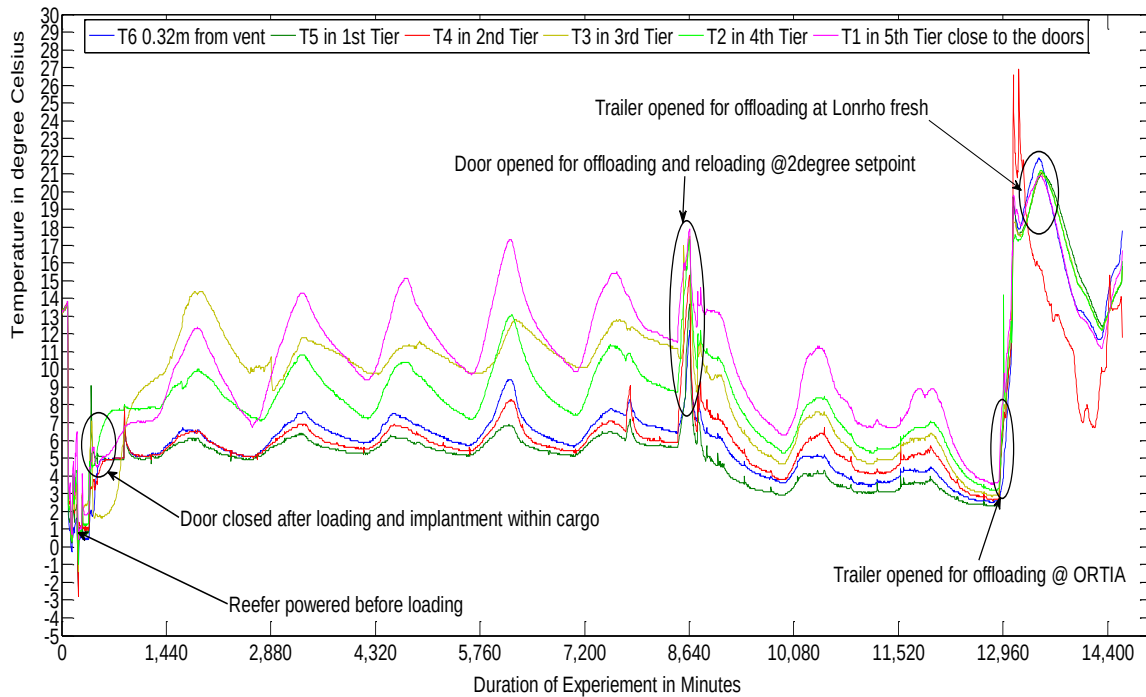


Figure 4-5: T6-T1 sensing devices at tiers 1-5 on LHS of trailer

Analysis:

The set point temperature on the trailer was 5°C and 2°C on the return leg. Deviations greater than 0.5°C were observed by sensing tags placed in all tiers but more on the 3rd, 4th and 5th Tier. That is from the middle of the trailer to the end of the trailer on the door side.

4.3.1.3 Sensing tags mounted at periphery Right hand side (RHS) of the trailer variations

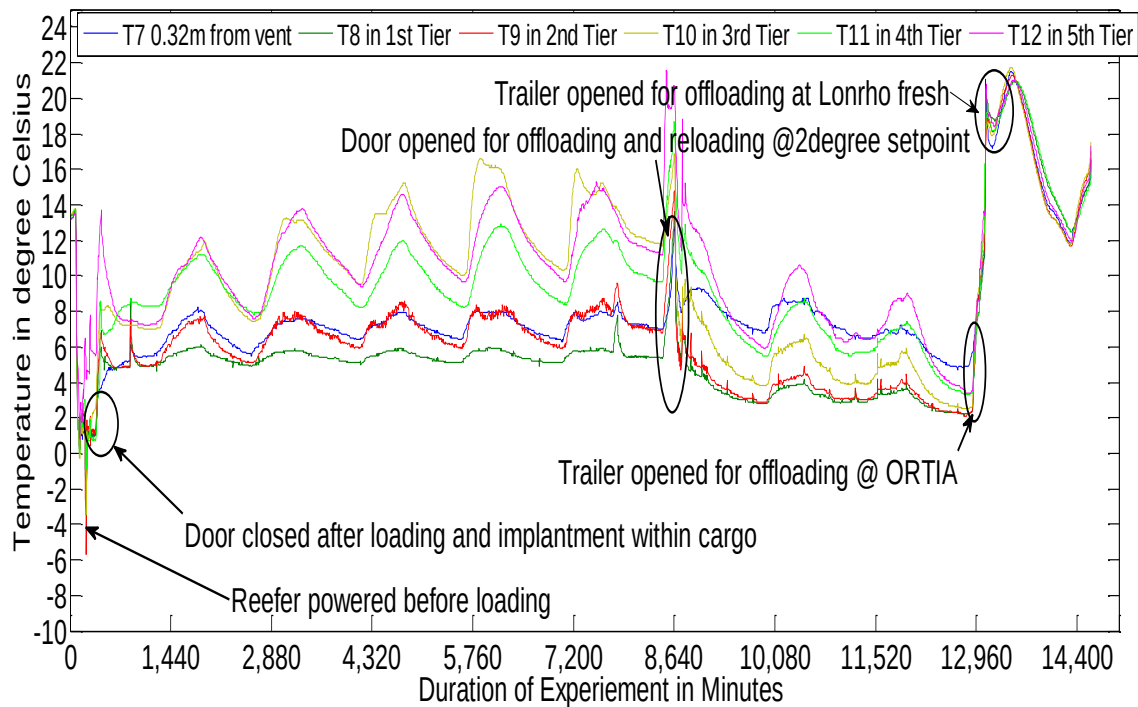


Figure 4-6: T7- T12 sensing devices at tiers (1-5) on Right Hand Side (RHS)

Analysis:

The set point temperature on the trailer was 5°C and 2°C on the return leg. Deviations greater than 0.5°C were observed by sensing tags placed in all tiers but more on the 3rd, 4th and 5th Tier. That is from the middle of the trailer to the end of the trailer on the door side.

4.3.1.4 Sensing tags mounted at periphery Roof Top Centre (RTC) of trailer variations

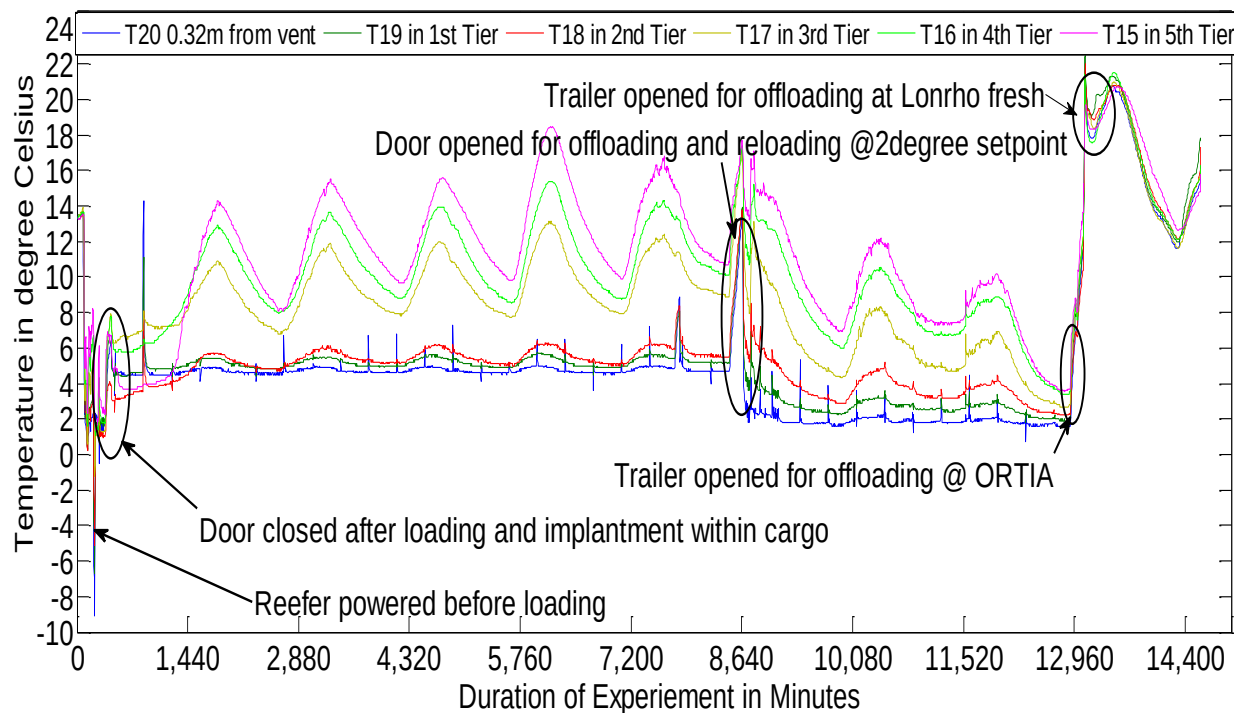


Figure 4-7: Sensing devices at Roof Top Centres at 0.32m from vent and in Tiers (1-5)

Analysis:

The set point temperature on the trailer was 5°C and 2°C on the return leg. Deviation greater than 0.5°C was observed by sensing tags placed in all tiers but more on the 3rd, 4th and 5th Tier. That is from the middle of the trailer to the end of the trailer on the door side.

4.3.2 Tier level results and analysis

4.3.2.1 Sensing tags at tiers level within the trailer 0.32m from the Vent

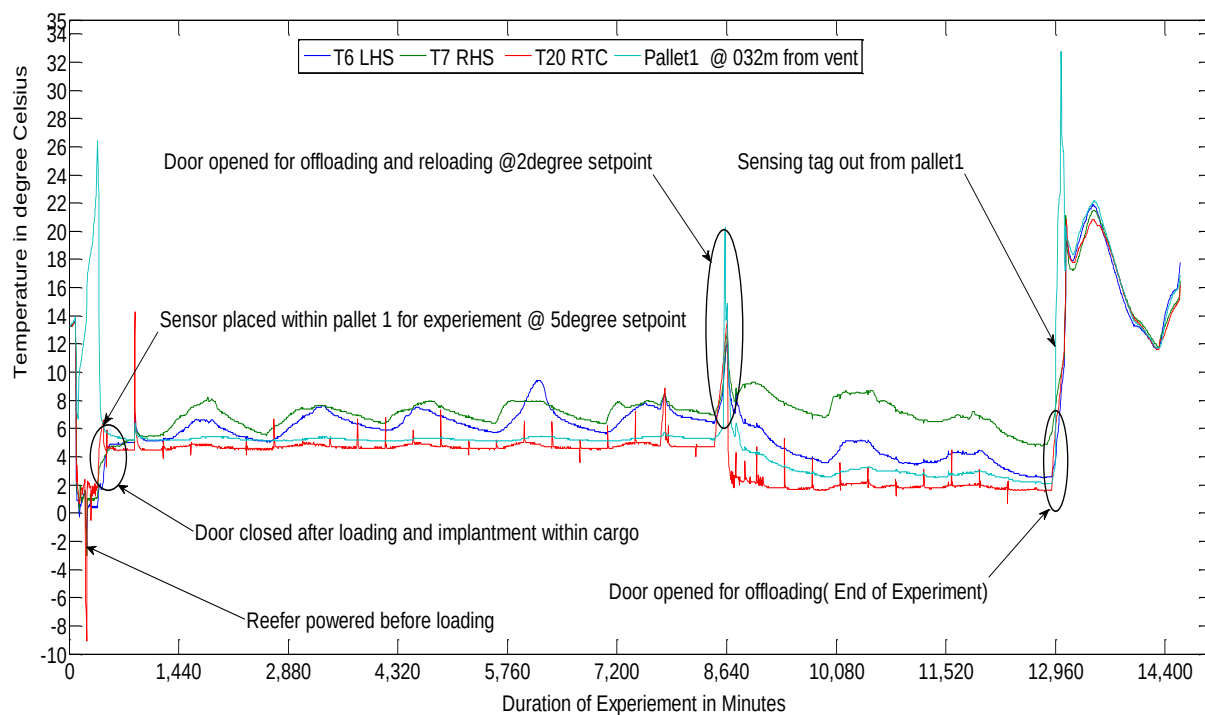


Figure 4-8: Sensing devices 0.32m from vent

Analysis:

Sensing tags within the cargo was within temperature requirements but temperature points on the left and right side of the tiers indicated high temperature deviations above required range.

4.3.2.2 1st tier 3.32m from the vent

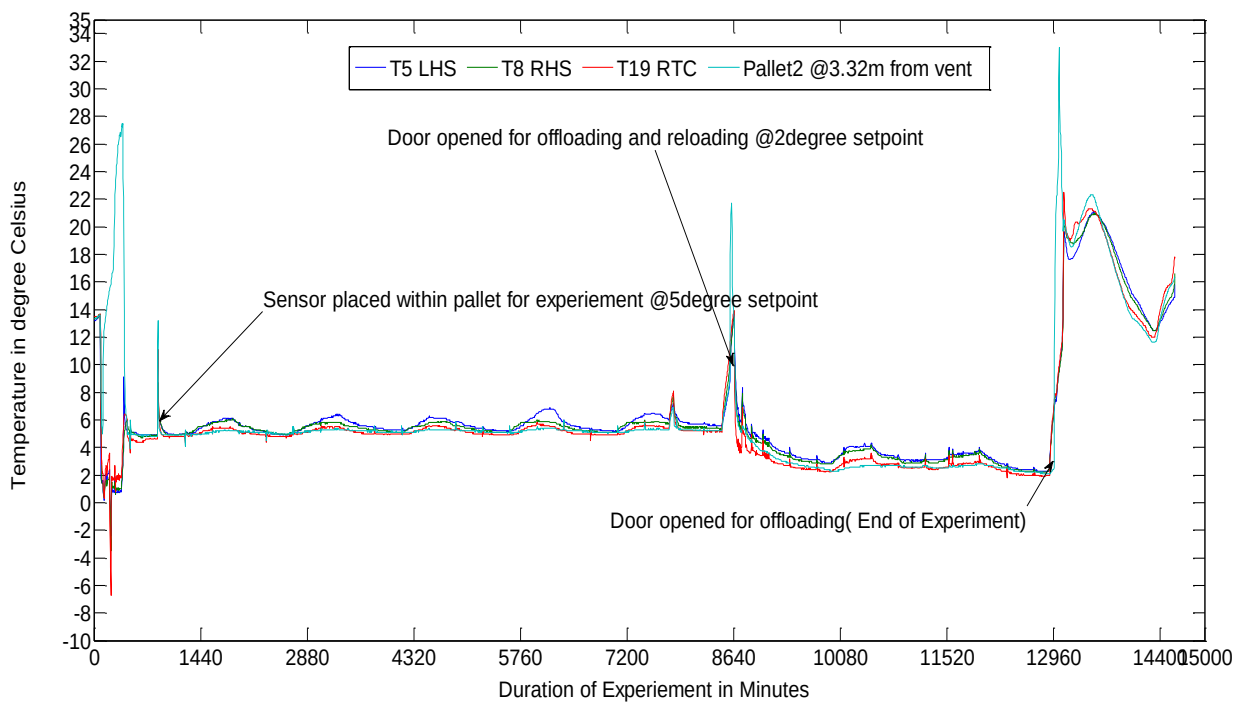


Figure 4-9: Sensors at periphery and within pallet 2 in the 1st Tier (3.32m) from vent

Analysis:

Sensing tags within the cargo was within temperature requirements but temperature points on the left hand side of the tiers indicated high temperature.

4.3.2.3 2nd Tier 6.32m from the vent

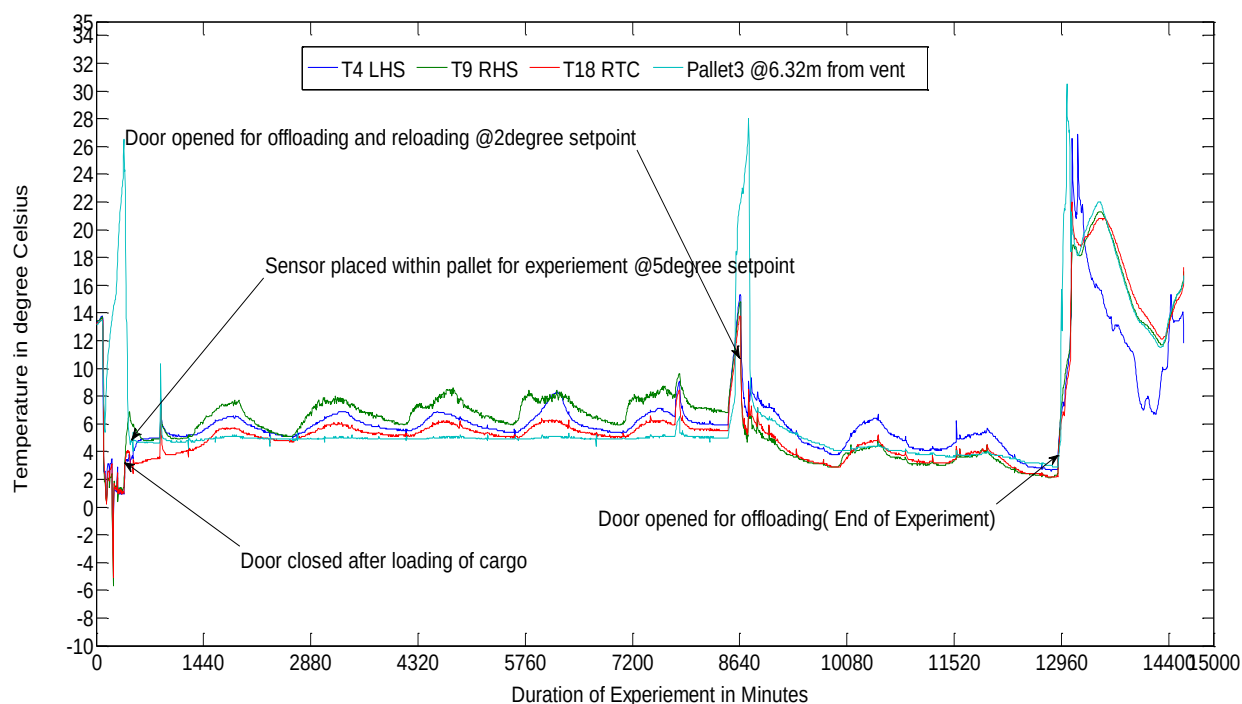


Figure 4-10: Sensors at periphery and within pallet3 in the 2nd tier (6.32m from vent)

Analysis:

Sensing tags within the cargo was within temperature requirements but temperature points on the left, Top and right side of the tiers indicated high temperature deviations above required range.

4.3.2.4 3rd Tier 9.32m from the vent

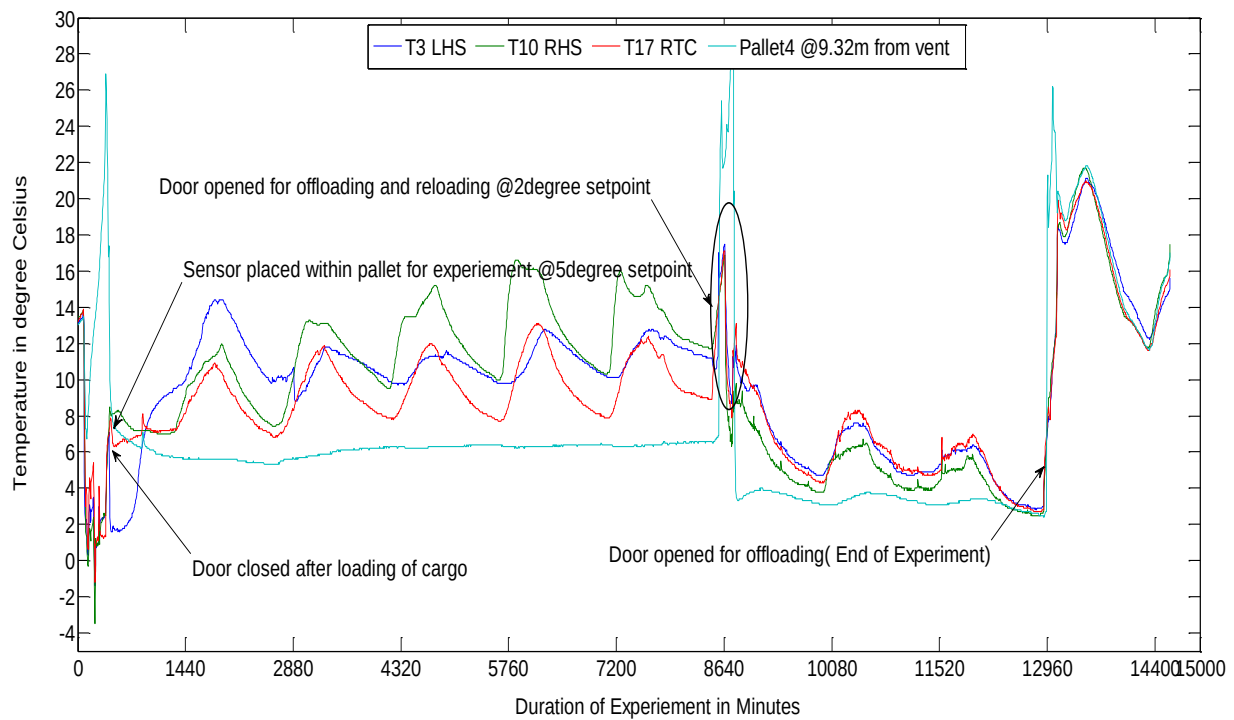


Figure 4-11: Sensors at periphery and within pallet4 in the 3rd tier (9.32m from vent)

Analysis:

Sensing tags within the cargo was beyond temperature requirements and temperature points on the left, Top and right side of the tiers indicated high temperature deviations above required range.

4.3.2.5 4th Tier 12.32m from vent

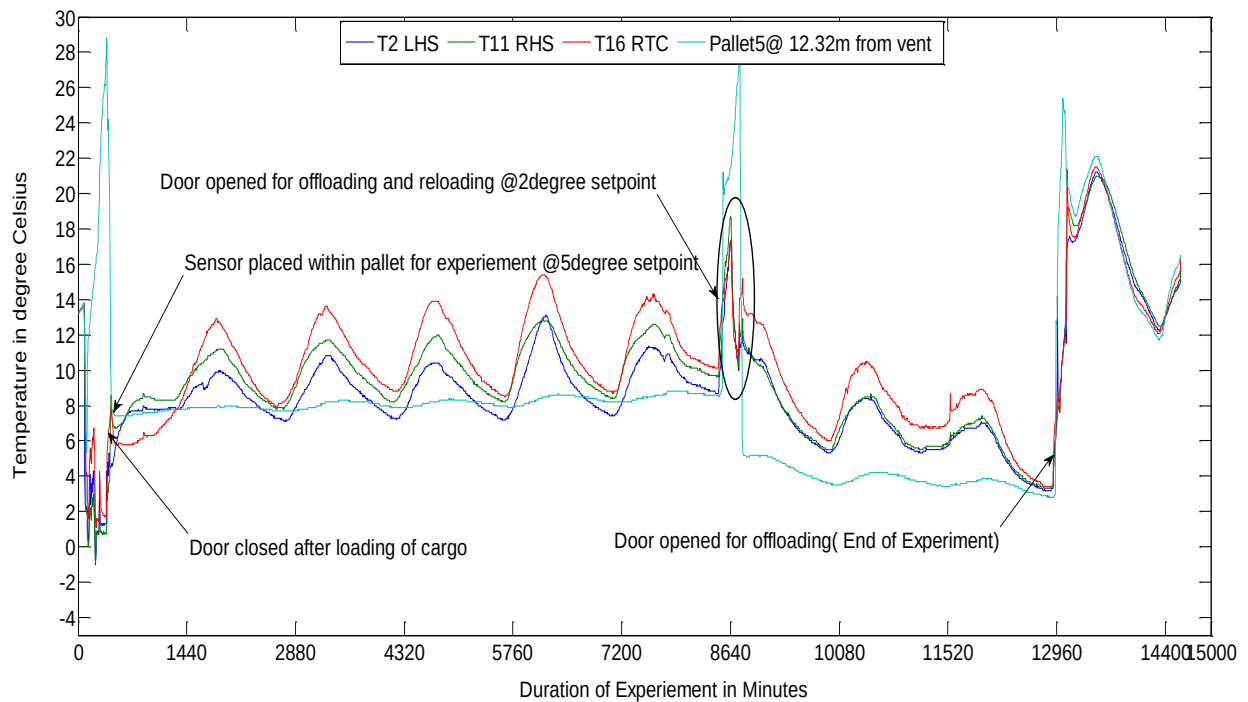


Figure 4-12: Sensors at periphery and within pallet5 in the 4th tier (12.32m from vent)

Analysis

Sensing tags within the cargo was beyond temperature requirements and temperature points on the left, Top and right side of the tiers indicated high temperature deviations above required range.

4.3.2.6 5th Tier 15.32m from vent

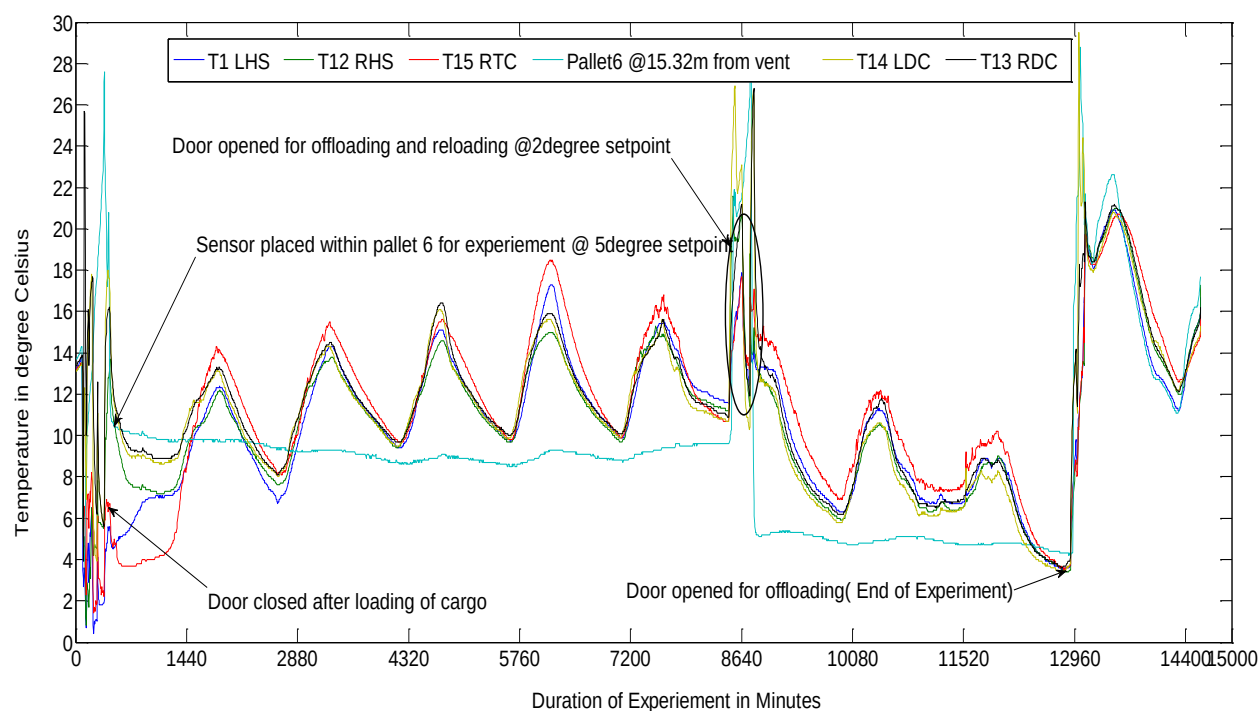


Figure 4-13: Sensors at periphery and within pallet6 in the 5th tier (15.32m from vent)

Analysis:

Sensing tags within the cargo was beyond temperature requirements and temperature points on the left, Top and right side of the tiers indicated high temperature deviations above required range.

4.4 In summary

This chapter provided all the findings and results from the experiments conducted. Analysis of captured data were also presented and discussed. The temperature profiles within the reefer container used were visualized and characterize.

A databank was developed for future reference and purposes in the development of a predictive temperature model for cold chain logistics.

CHAPTER 5

5 Model Development

5.1 Introduction

As explained in the previous chapters the cargo owner is concerned about temperature inside the cargo, but the placement of sensors inside the cargo for each trip is labour intensive and potentially error prone as sensors may be lost. The permanent placement of sensors on the periphery of the trailer will be a more convenient approach for operational purposes.

Over and above having visibility of current cargo temperatures, it will be of additional benefit to know what the expected future temperature profile of the cargo will be, specifically if an unforeseen event should occur (e.g. the trailer doors are opened for inspection at a border post). Such predictions will allow the cargo owner to determine how much time is still available to take corrective action; this will allow the selection of the most optimal line of action to prevent damage to sensitive cargo.

The purpose of the work described in this chapter was to successfully design models to predict cargo temperatures during cross border transportation taking into consideration all possible negative events such as system malfunctioning, unforeseen circumstances or deviations from operational procedures during the voyage.

Real temperature data obtained during the experiments were used to model cargo temperature as function of temperature on the periphery and also to predict future temperature as function of historical temperature.

The work flow for the development of the various models is described in the next section.

5.2 Complete trip model

A complete trip (South Africa to Zambia or Zambia to South Africa) cannot be referred to as an event. A model will be developed from training data representing complete trips and tested on another complete trip.

5.2.1 Data sets collection for model development

Two sets of historical complete trip data were used for model development, one for training and the other for testing.

As the in-cargo temperatures tend to show much less deviation than periphery temperatures, a model for one set of periphery temperatures in terms of another set of periphery temperatures was created, given that worst case cargo temperatures will correspond with periphery temperatures where the cargo is stacked close to the sides.

Distinction between spatial and temporal models was made - for the first, temperatures at some locations were used and modeled for concurrent temperatures at other locations using a narxnet architecture that is trained in open loop mode and tested in closed loop mode. For the temporal models, one variable was used at a time using a narnet architecture, training in open loop and testing in closed loop mode.

Time delays were not implemented (by reading in rows that are displaced in time between input and target values), the input and feedback delays were only used. Matlab then uses the appropriate time delayed values to do predictions into the future.

The complete trips were selected and used in this research work for model development.

5.2.1.1 Importation of the data

The MATLAB function “xlsread” was used to import the data from the saved excel sheet. The data are first grouped in two sets: the training set and the testing set.

The experimental data were retrieved using the necessary software (in this case the software of the logtag analyser) and saved in csv format. The data from various sensors were grouped according to their positioning during the experiment based on tier sections. The data was pre-processed in excel using correlation to identify which sensor data on the periphery is correlated with sensor data within the pallet. In general, the correlations were greater than 0.75 and in many cases 0.99. Depending on the sensor tag configuration, the temperature data was reduced to one variable per each tier. This was achieved by calculating the averages and/or mean kinetic temperature (MKT) for the periphery sensors (INPUT DATA) and the cargo sensors (TARGET DATA).

The pre-processed data was then exported to the Matlab environment for data analysis and neural network modelling.

Data sets were collected as follows:

- By identification of instances when any of the defined events occurred or selection required
- By identification and recognition of time periods when the recorded data reflected the different behaviors as influenced by the specific event, e.g. as from when a truck stopped at a border until the truck has departed and temperatures have returned to normal values.

All the data recorded during each of these time periods were stored in a databank accordingly in the original format, csv format and Matlab files format.

Graphs of temperature behavior during each period were generated. This is to determine if the observed behavior for the different events were sufficiently similar to use a single model for the sets of similar events (e.g. all border crossings).

5.2.2 Graphs of temperature behaviour during different events and experiments

Figure 5.7 – 5.14 below shows visualization from data and analysis in experiment 1. The visualization provides us with an idea and understanding of the relationship with the data.

Appendix D provides additional image plots on other field tests conducted.

5.2.2.1 Experiment 1: temperature behaviour within the trailer at tier levels

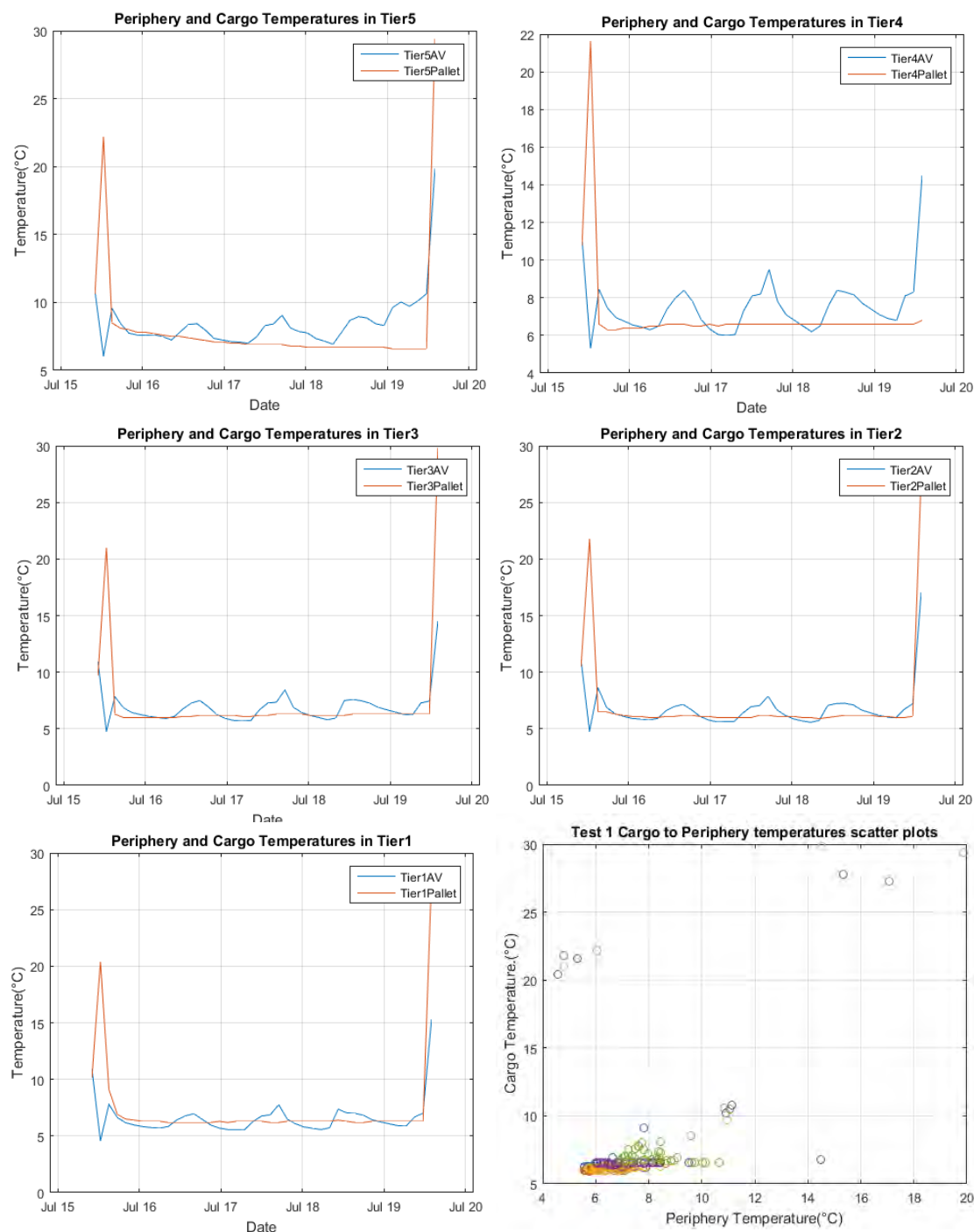


Figure 5-1: Temperature behaviour within the trailer at tier level in test1

The set point temperature was 5°C. The total time delay from the start of the experiment to its end was 29% of the total time duration. The average temperatures per tiers(Tier1-5AV) and per pallets in each tiers (Tier1-5Pallet) are shown in the graphs.

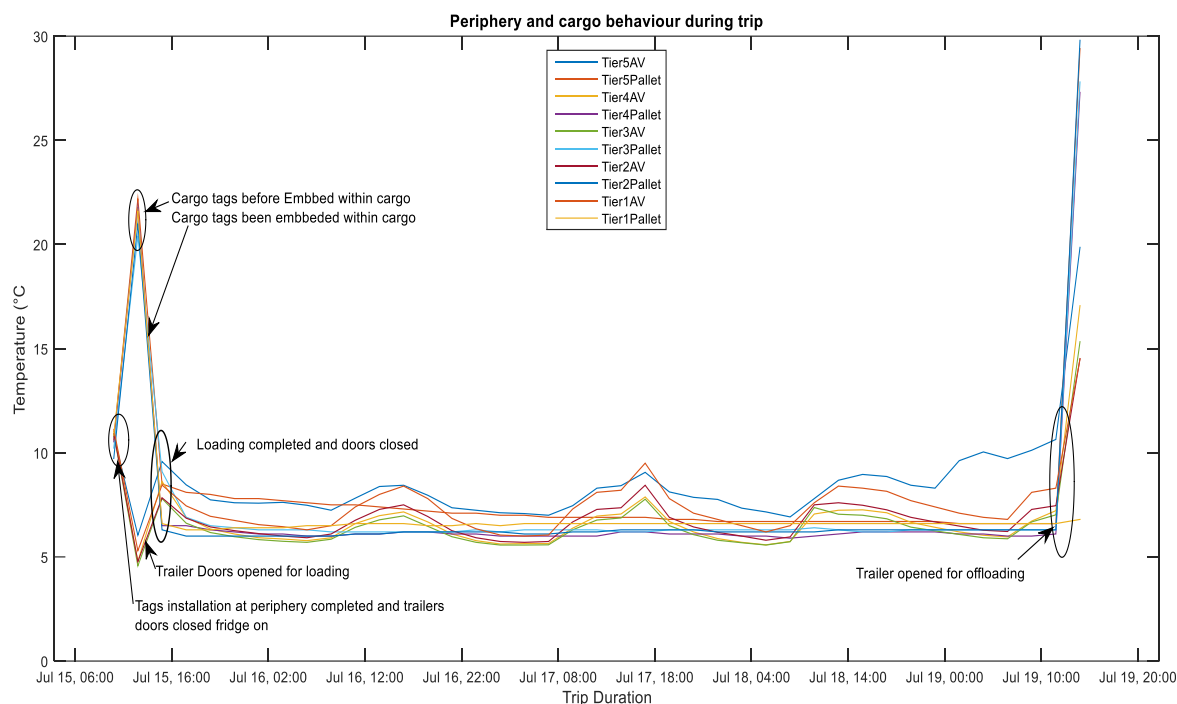


Figure 5-2: Test1 complete trip time based plots

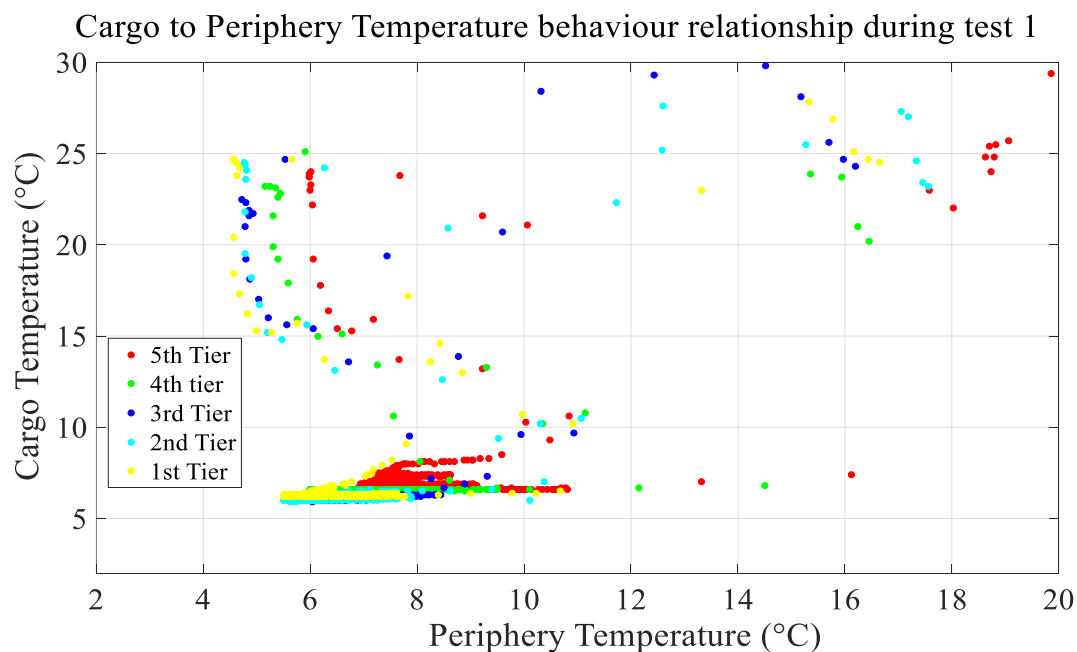


Figure 5-3: Test 1 complete trip scatter plots

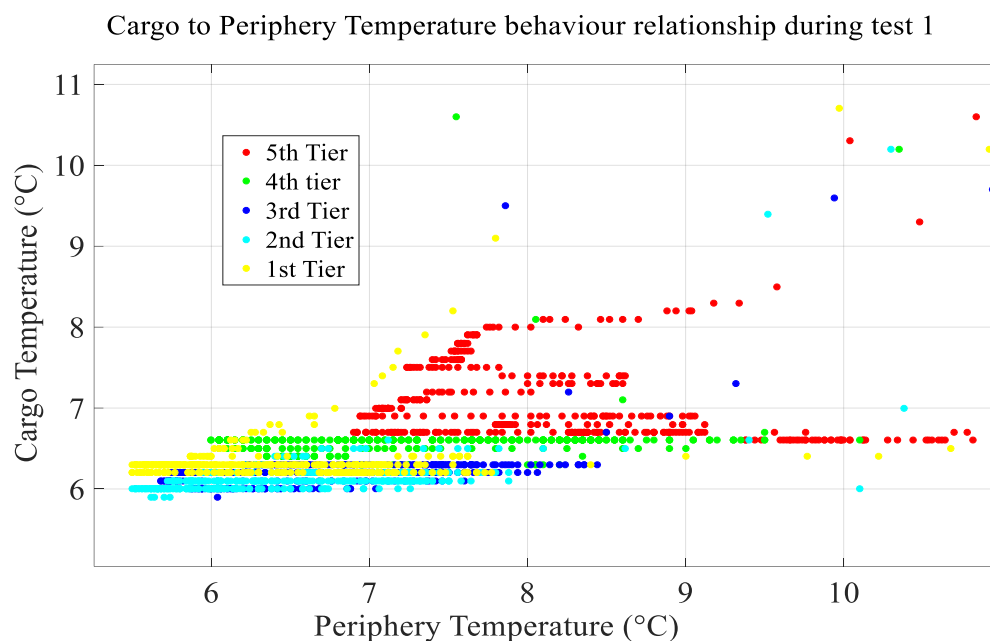


Figure 5-4: Test 1 complete trip scatter plots zoomed in

The scatter plots in addition to time based plots is to determine if there is a significant relationship between two different variables, based on which it can be decided which inputs to use in order to model which outputs.

5.3 Events requiring modelling

The following events have been identified for future work model development:

- Border Delay: When the reefer is stationary for a long time in the middle of the day due to a delay at the border post, at the depot or anywhere else
- Cooling system failure or malfunctioning or truck breakdown
- During cargo offloading (when the doors were opened for offloading).

Models for the above scenarios will be done in the future. Below are graphs for these when they occurred.

5.3.1 Border posts delays events scatter plots

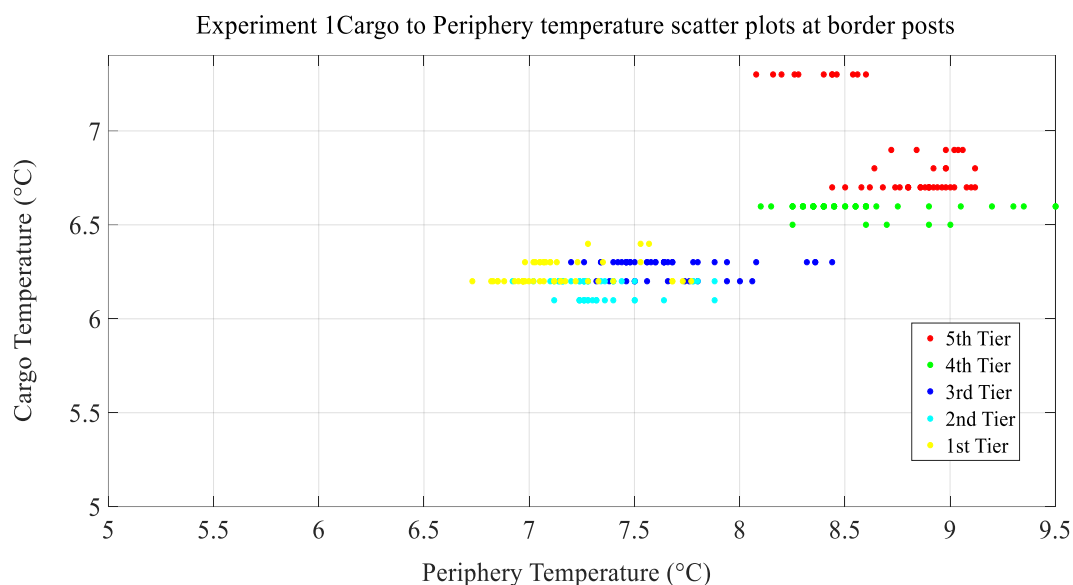


Figure 5-5: Test 1 border crossing delay scatter plots

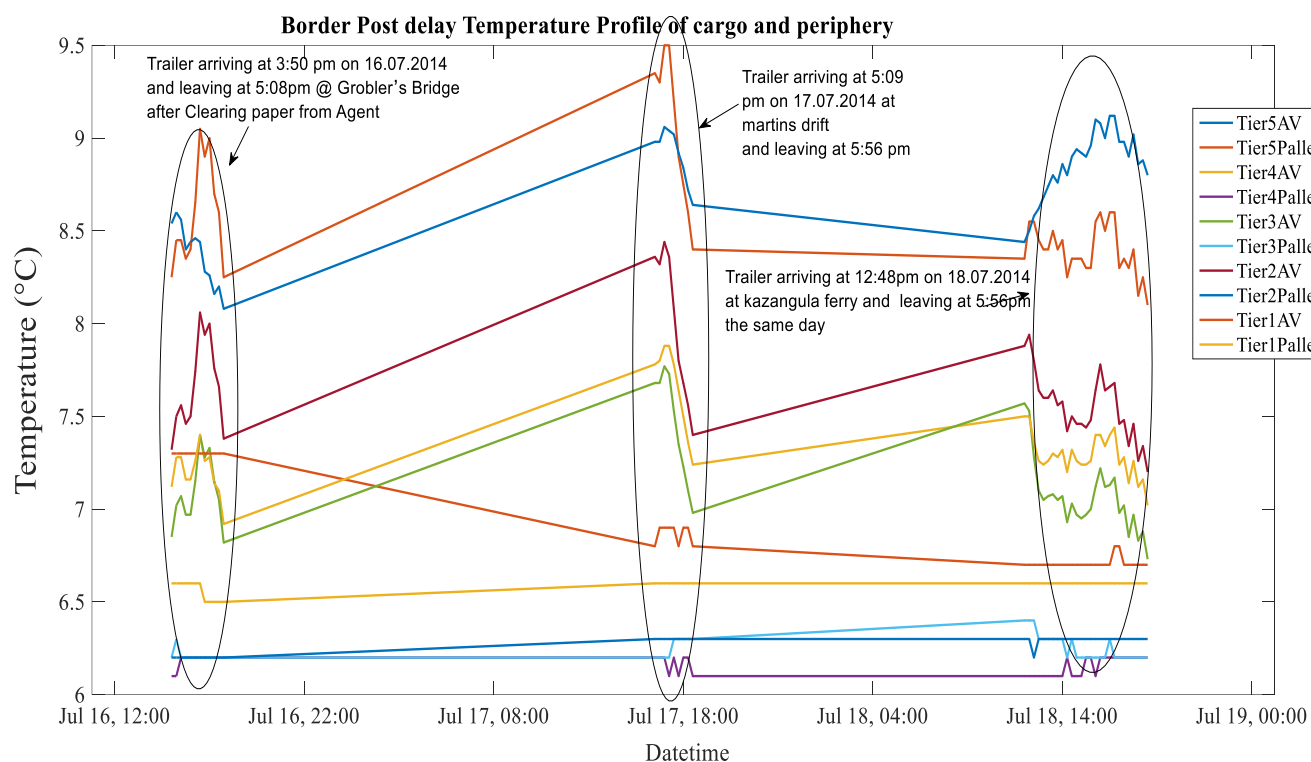


Figure 5-6: Test 1 border crossing time based temperatures plots

5.3.2 Breakdown events

There was a breakdown during test 1 (**Error! Bookmark not defined.**). Figure 5-7 below is the scatter plots and time based plots during the incident. Breakdown can lead to temperature rise which is detrimental to the cargoes. Hence preventive measures should be put in place to avoid and correct such events.

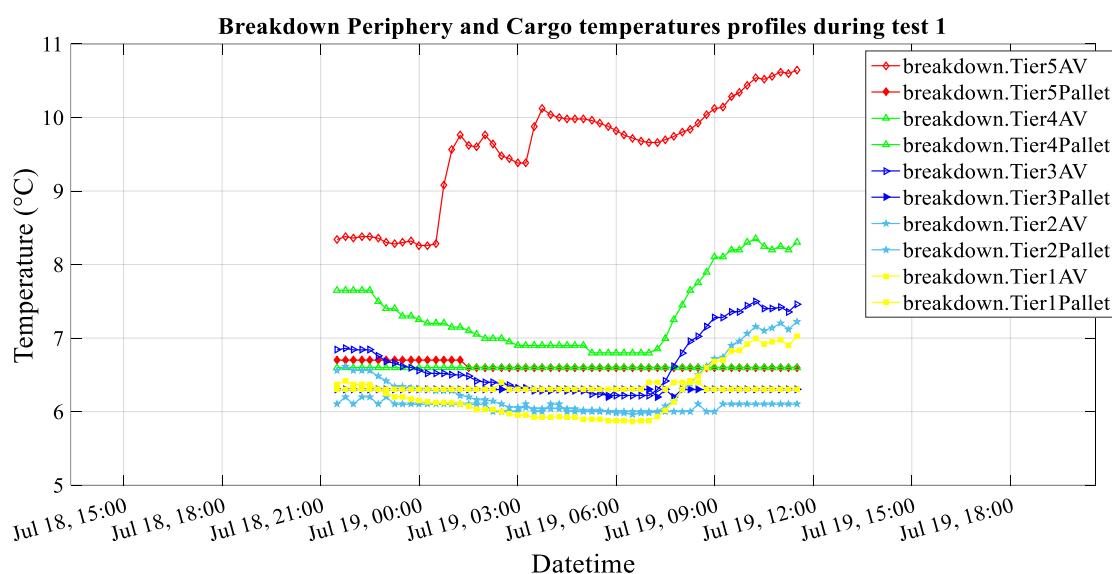


Figure 5-7: Breakdown periphery and cargo time plots

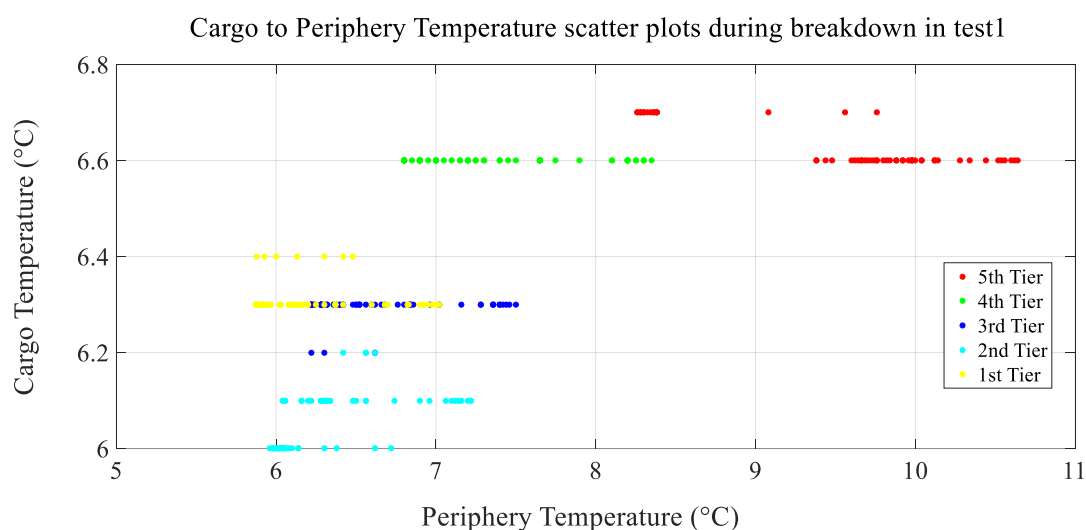


Figure 5-8: Breakdown Cargo to Periphery Scatter plots

5.4 Designing the neural network model

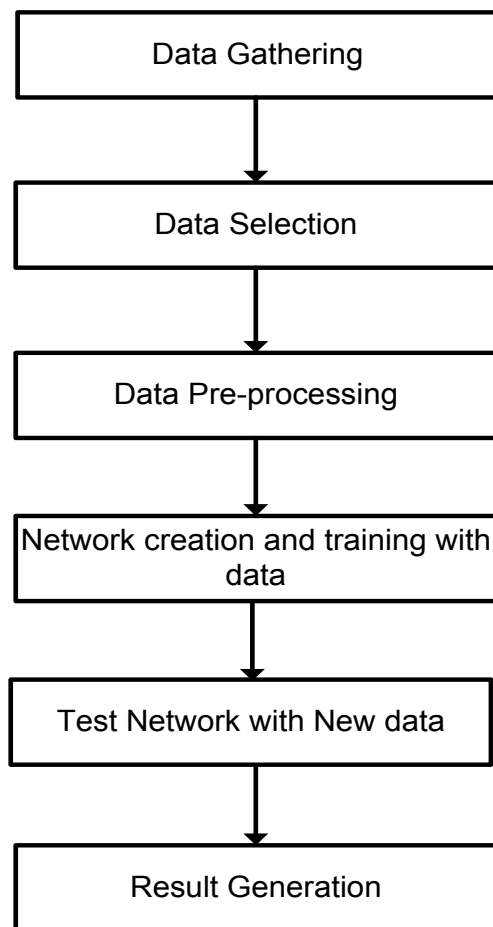


Figure 5-9: Flow diagram for an ANN model creation

The design of a neural network in MATLAB is based on systematic routines. The selection of inputs, the number of hidden nodes and the node transfer functions are of critical importance to the prediction accuracy and reliability of the proposed model.

5.5 Model development methodology

5.5.1 Selection of modelling platform

A modelling technique was required that would allow the extraction of an output value from multiple inputs based on empirical data. At it could not be assumed that the relationships between inputs and outputs would be linear or close to linear, preference was given to a non-linear modelling technique. Neural networks have been widely used for such modelling as it can be shown that neural networks can model non-linear relationships to any degree of accuracy required [54] .

The temperature modelling and implementation was carried out using MATLAB 2015b Neural Network toolbox. The MATLAB neural network toolbox provides a range of functions for modelling non-linear complex systems. This toolbox supports supervised learning with feedforward networks, radial bias networks and dynamic networks as well as unsupervised learning with self-organizing maps (SOM).

MATLAB offers better model development because of its ability in easy matrix manipulations, algorithm implementation, data plotting and easy interfacing with programs in other languages. MATLAB has been recognized as an effective neural network modelling tool and is extensively used in predictive modelling problems. The Neural Network Toolbox function provides varied levels of complexity in which the user is able to produce ANNs.

The toolbox enables the user to set up custom networks and essentially trains the networks by means of specified training algorithms. To train the networks the toolbox divides supplied training data into training, validation and test subsets. These are used to evaluate the network's performance after each training epoch. Once the training is stopped by a specified method or condition, the toolbox can present summarized training information.

The general MATLAB code setup for creating the various network configurations and assigning specific training algorithms and termination parameters is presented in 176 (Appendix G). The presented code was implemented and manipulated throughout the project to derive and train various networks with varied number of neurons according to requirements.

5.5.2 Pre-processing data

In the pre-processing stage, normalization of the data set is applied. This is necessary considering the range of values of the parameters. The inputs and targets datasets are automatically normalized by the following matlab functions

```
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};
```

5.5.3 Network building

The NARX network architecture was employed to develop the models as this allows the combination of inputs consisting of historical values of the target variable as well as external inputs. This tool allows various changes to parameters like the number of hidden layers, the number of neurons in each of these layers, training function, the transfer function, and the performance functions.

5.5.3.1 Maximum number of allowed inputs

We use the rule of thumb that for a linear model the number of inputs should be equal to or less than one tenth of the number of observations, while for a non-linear model the square of the number of inputs should be equal to or less than one tenth of the number of observations [55]. The number of inputs for a neural network must therefore meet the criteria

$$(No\ of\ inputs)^2 \leq \frac{number\ of\ samples}{10}$$

The available number of observations per separate set associated with a different scenario requiring a different model were determined. Table 5-1 below indicates the determined number of observations.

Table 5-1: Maximum number of inputs for each models

Scenarios	Sample period (minutes)	No of observation	Maximum number of inputs
Test 1 complete trip event	15	405	6
Test 2 complete trip event	5	1635	12
Test 3 complete trip event	5	1075	10
Test 4 complete trip event	5	1198	10
Test 5 complete trip event	5	1188	10
Test 1-5 complete trip event	15min, 5min	5589	23
Test 1 border post delay	15	48	2

Test 2 border post delay	5	409	6
Test 3 border post delay	5	57	2
Test 4 border post delay	5	442	6
Test 5 border post delay	5	313	5
Test 1-5 border post delay event	15min ,5min	1269	11

5.5.3.2 The number of hidden neurons

This is a very important consideration for the network architecture as it has a significant impact on the network's performance; a comprehensive discussion on hidden layers and hidden neurons is provided in 2.5.11.3 above:

- too few hidden layer neurons will result in underfitting meaning that the number of neurons is not adequate to model the input-output relationships in the data set.
- the use of too many hidden neurons has its own problems; first, the network will experience overfitting. Overfitting is when a network with high information processing capability is exposed to limited information in the training set that is insufficient to train all the hidden layer neurons. Secondly, it can unnecessarily slow the network training.

The following is a rule-of thumb for selecting the number of hidden layer neurons:

- Select the number hidden neurons to be $\frac{2}{3}$ the size of the input layer, plus the size of the output layer.
- The number of hidden neurons should be less than twice the size of the input layer.

5.5.4 Training and testing the Network

This is the stage where the network is taught how to generalize for the presented data set. For training, a set of data is presented to the network. This data set consists of input-output pairs. The neural network then learns from the input and updates its weights, this is why it is termed supervised learning, since the neural network is taught what the output should be for each of the inputs introduced to it. The updated set of weights is necessary since the main goal of the

training process is to minimize the model error. For feedforward networks, the performance is rated by the value of the mean square error, thus by adjusting the weights, what the neural network is trying to achieve is minimizing the mean square error. Slowly the neural network learns from the training set and improves on its generalization ability so as to later yield reliable results (network output) when it is fed with unseen data (testing input data).

The neural network toolbox in MATLAB splits the data into three different sets: the training set, the validation set and the testing set.

From the training set, the network is able to update the weights of the network during training. The network also utilizes the validation set during the training; this set is not used to determine the required updating of the weights, but the network error when fed with validation data is observed throughout the training. If the validation error increases from its previous minimum value, the training is stopped. When it stops, the network returns the minimum validation error. The test set is used for testing the performance of the trained network. If this set reaches a minimum mean square error at a significantly different number of iterations than the validation set, performance of the neural network will be unsatisfactory.

After training is completed, the network is tested with unseen data and the output is compared with the target (measured result). This is to check how well the network can generalise (predict output from the previously unseen inputs).

The performance is determined using the average model prediction error or mean square error (MSE) and the correlation between the target and the predicted values.

5.5.5 Model architecture selection

The number of inputs and targets were calculated based on the reefer tier level. Knowing fully well that using 53 or 30 or 15 sensors per tier level isn't cost effective, the monitoring accuracy per tier level were compared when 15 sensors, 12 sensors, 5 sensors and 1 sensor were in each tier. A detailed description is provided in 5.6 below.

- Firstly, the cargo temperature was modelled as function of position along the length of the trailer from chiller to doors. The accuracy of this spatial model will determine how many points of monitoring are required across the different tiers to estimate the expected worst case conditions while physically measuring temperature only at a limited number of positions. This scenario assumes that the cargo is in a stable state and that time fluctuations do not play a significant role.

- Secondly the temporal behavior of cargo temperature was modelled in order to determine how long it will take for cargo temperature, which may currently be within the allowed range, to drift out of this range. This is specifically applicable once an external event has occurred (e.g. a border post stops or the opening of the doors) that could be expected to impact cargo temperature. This temporal model will provide early warning if such an event has occurred, even before cargo temperatures are outside of the limits.

5.5.6 Evaluation of model performance:

The model performance is evaluated using the average model prediction error called mean square error (MSE) and the correlation between the target and the predicted values (Regression R).

5.5.7 Model development procedure

The following steps were implemented to train a model: First call the neural network environment fit for the problem to be solved. In this research, the non-linear autoregressive model with external input (NARX) was used.

The screen shots below show the sequence used in the development the model

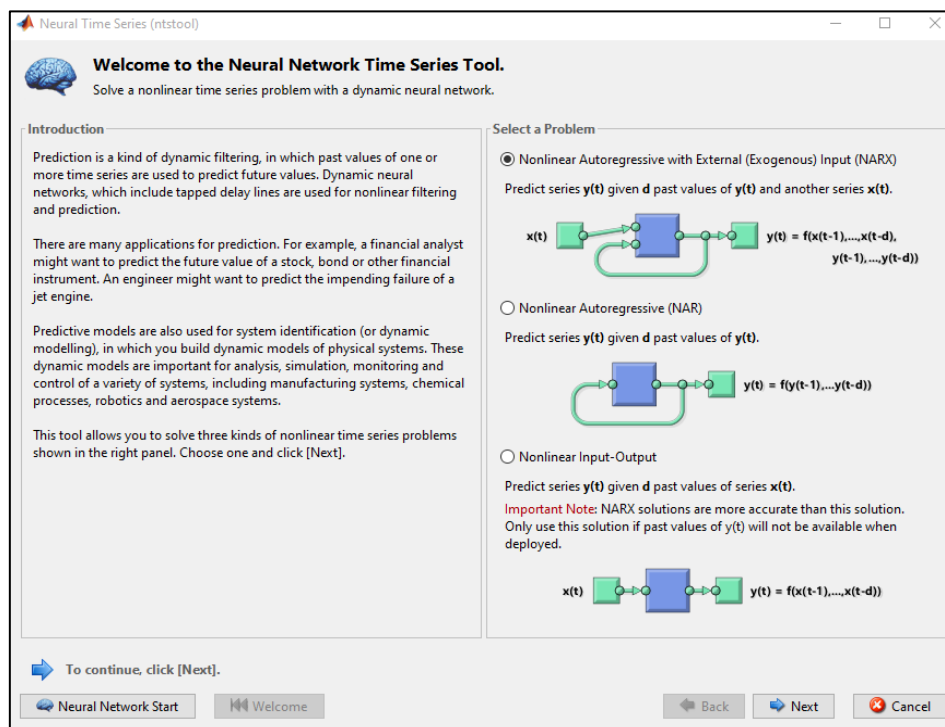


Figure 5-10: Selection of the type of problem to be solved

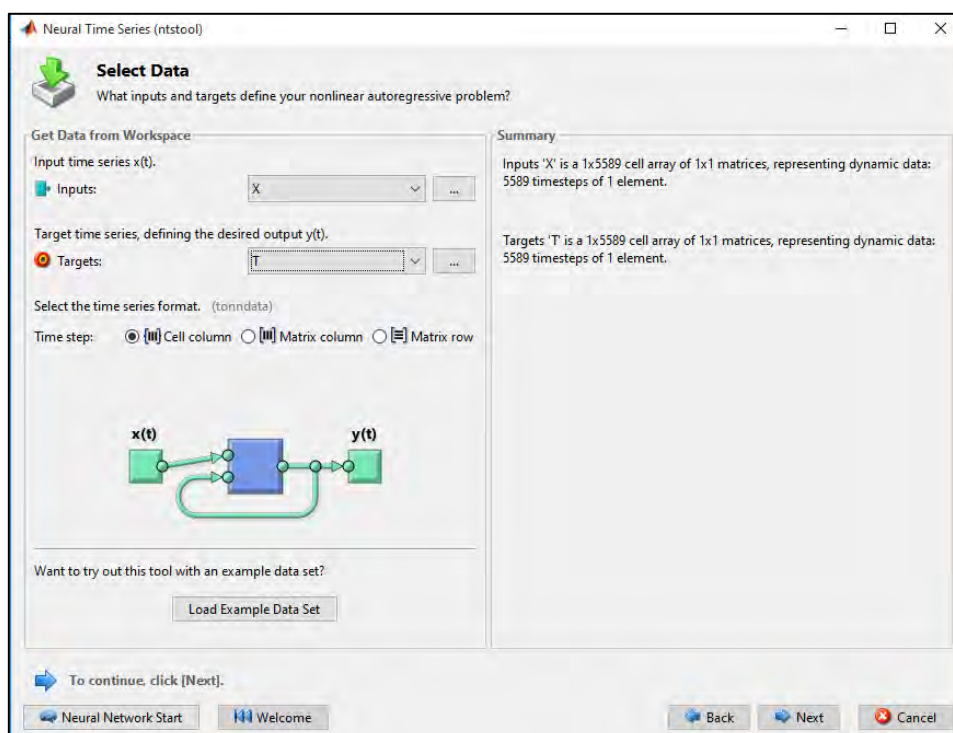


Figure 5-11: Input and target data selection. The data was selected in this window

Then a training window follows suit where the data division function, training method and performance function are selected to train the network. The progress of the training is constantly updated in this window.

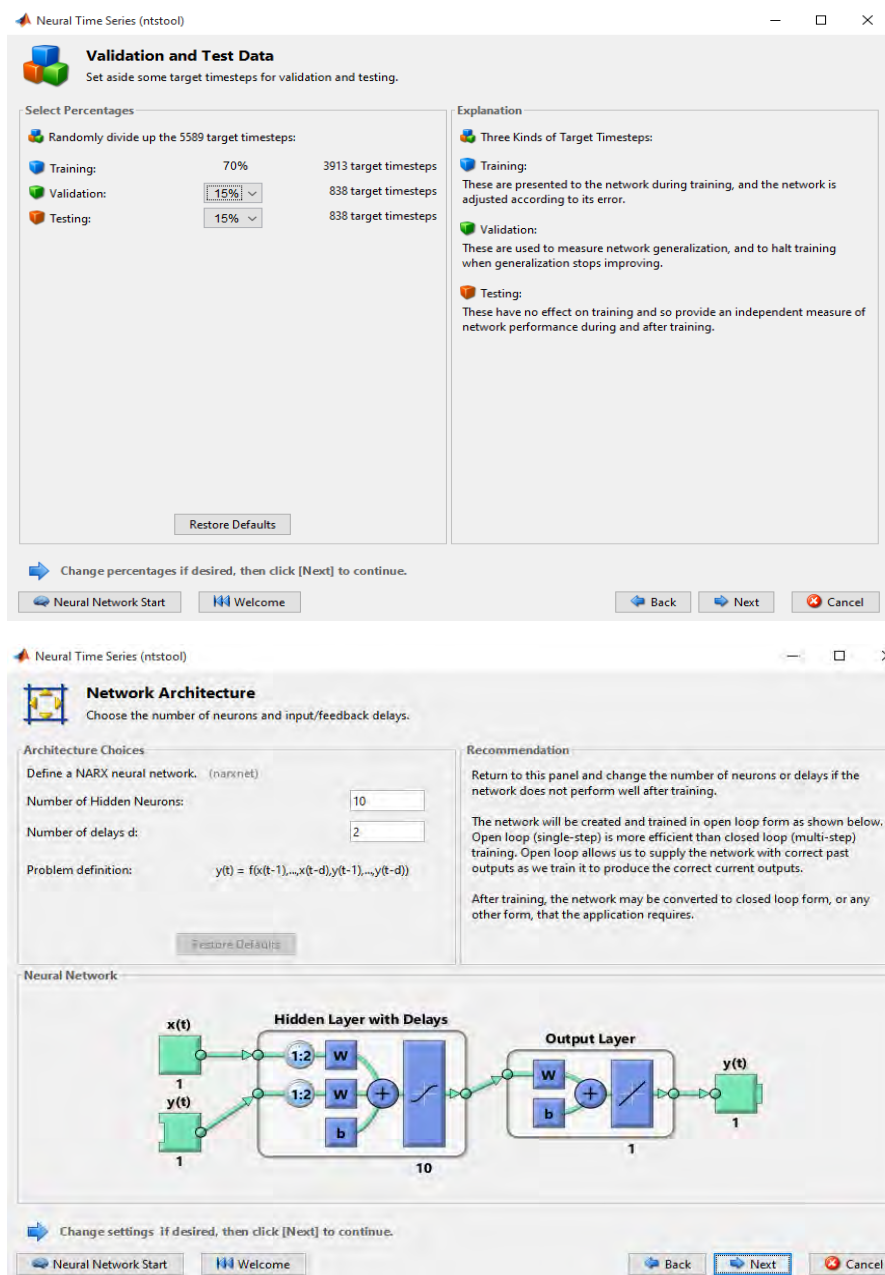


Figure 5-12: Screenshots showing the breakdown into training, testing and validation sets and the Network architecture

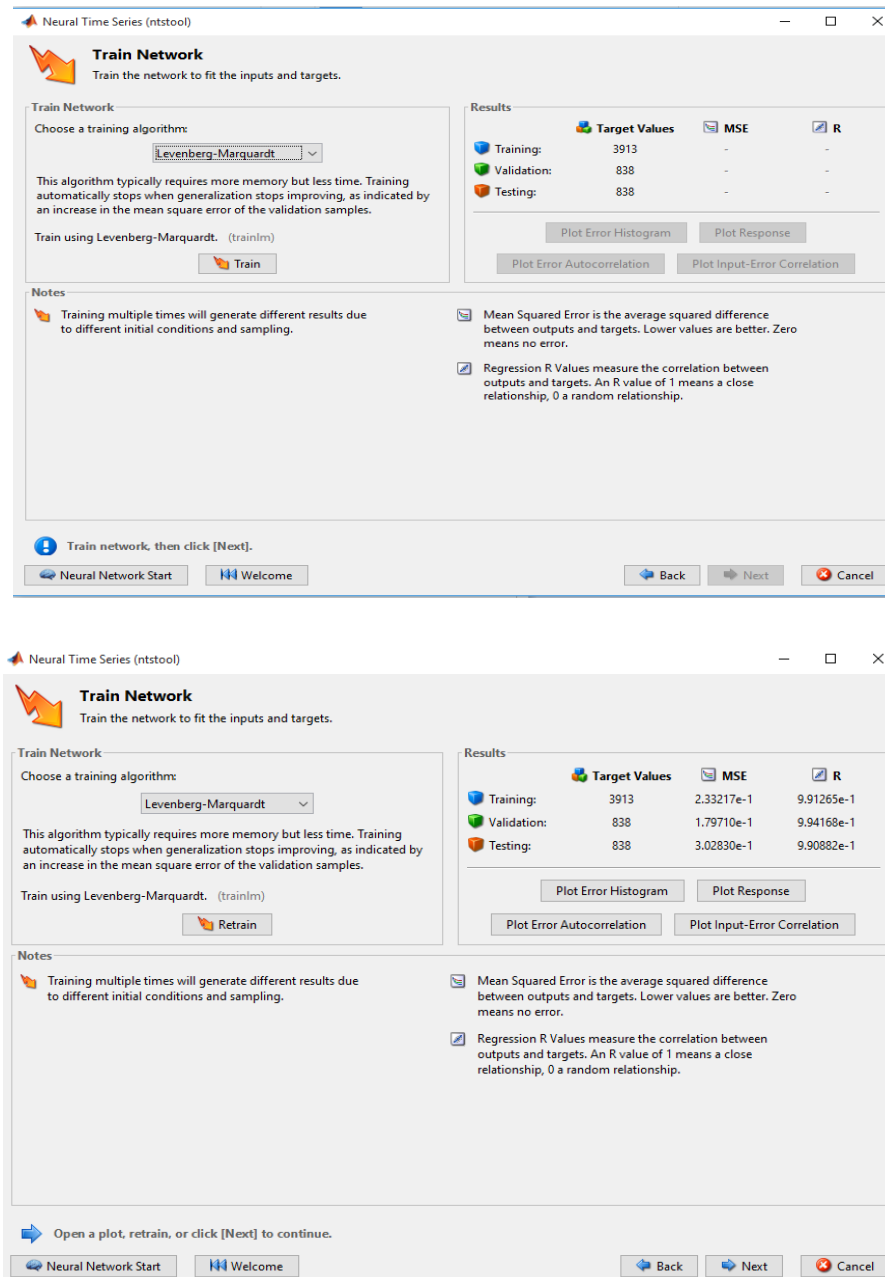


Figure 5-13: Screenshots showing the selection of training algorithm, the network training and the training, validation and testing results

Also presented is the performance, the magnitude of the gradient of performance and the number of validation checks. As the training reaches a minimum performance value the gradient will become very small. The number of successive training iterations that don't yield lower performance values is represented by the number of validation checks. If the default or nominated values for either the gradient magnitude or validation checks are reached the training is stopped.

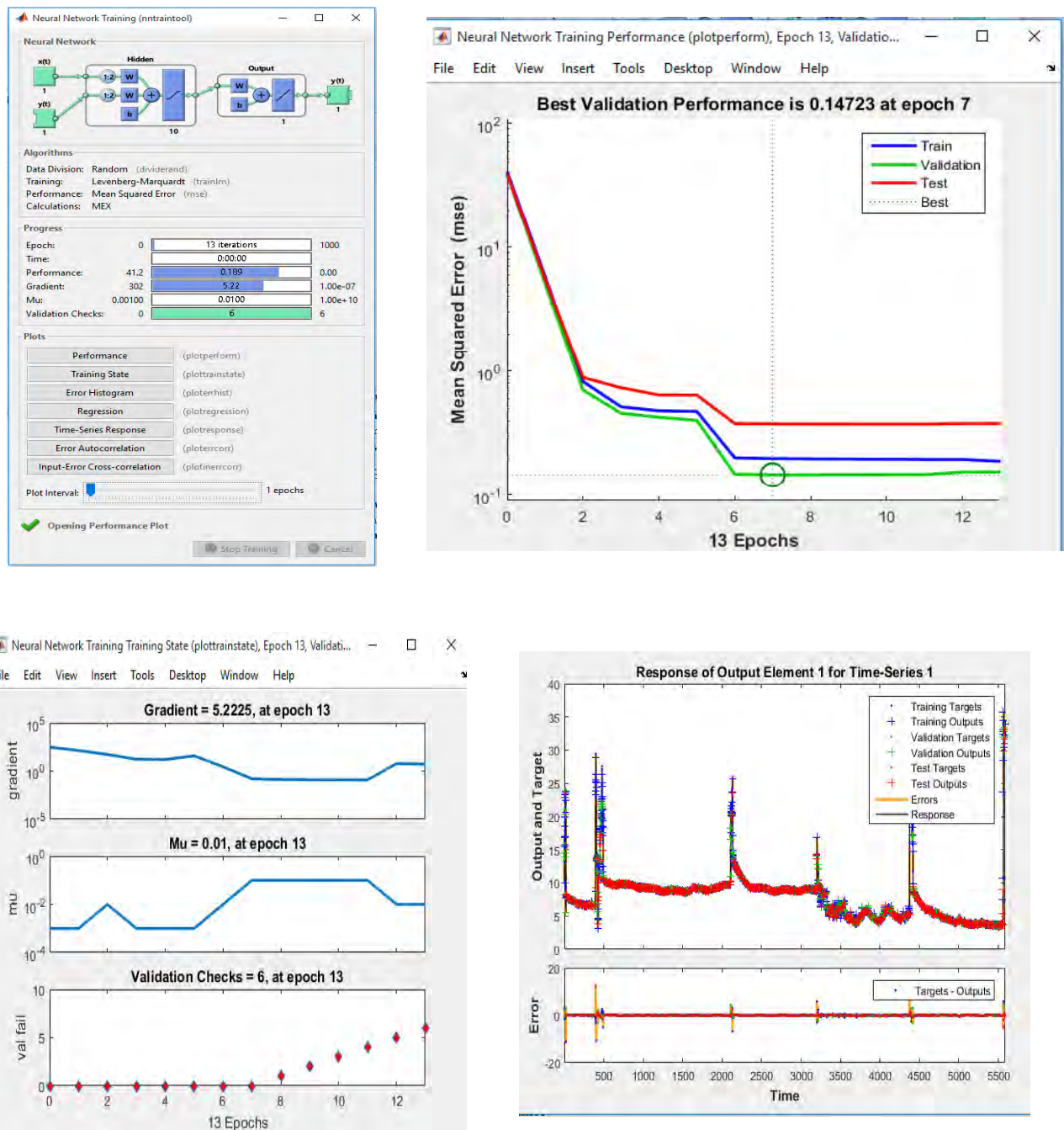


Figure 5-14: Screenshots showing the neural network, the training mean square error and validation performance, the training state and the error graphs.

The performance, training state, error histogram and regression plots can be accessed from the training window. The value of the performance function for the training, validation and test subsets are plotted against the iteration number in the performance plot. The progress of the other training variables like the gradient magnitude and number of validation checks is plotted in the training state plot. The plot of error histogram depicts the network error distribution. The regression plots may be used to validate the performance of the network as it shows a regression between network outputs and network targets for each of the data subsets

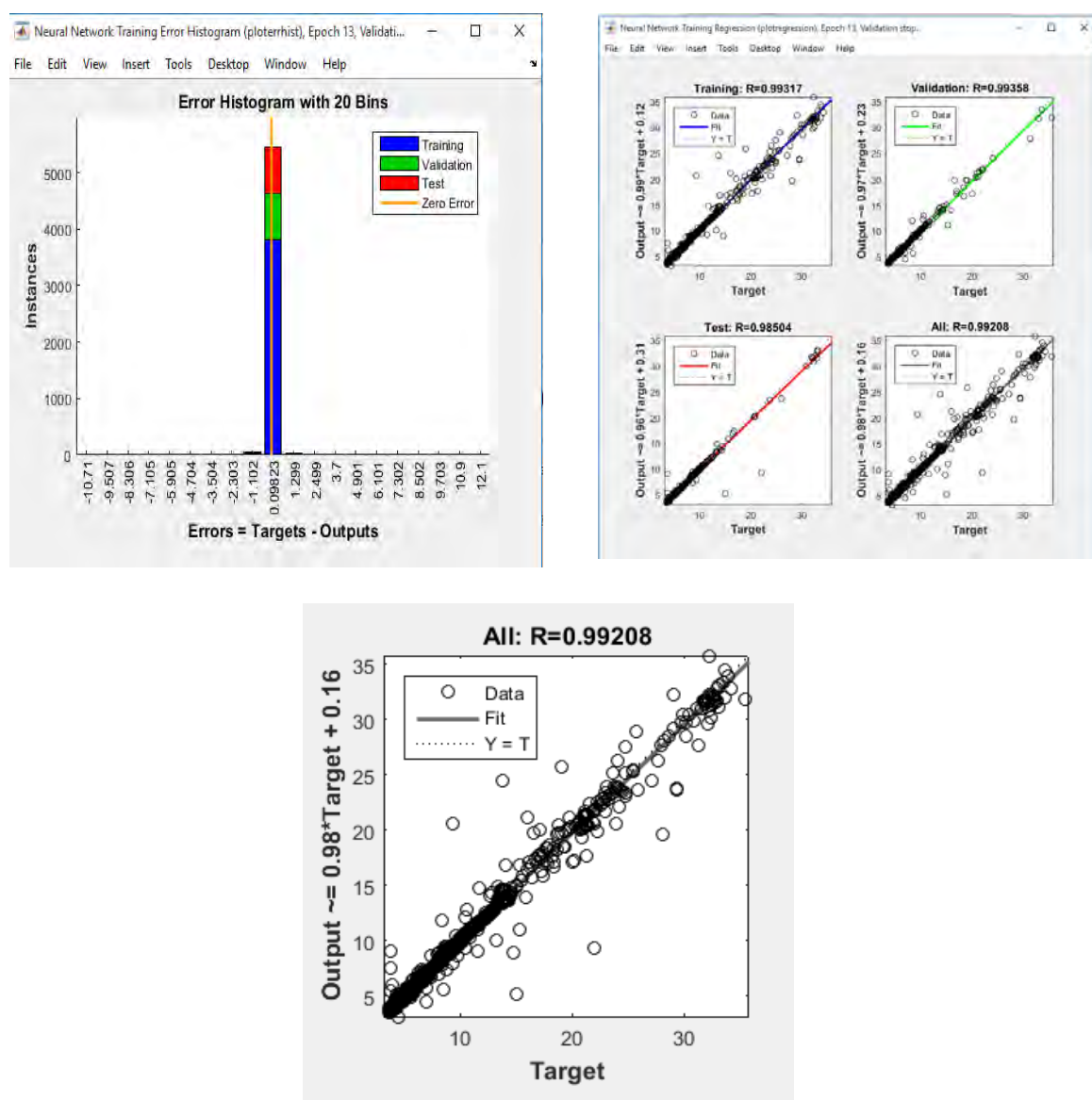


Figure 5-15: Screenshots showing the error histogram, the training, validation and test regressions plot and the overall regression plot.

5.6 Spatial and Temporal Modelling work carried out explained

In this section, a detailed explanation is given in respect to the modelling work carried out.

As the relationships between the different variables are nonlinear and dynamic as function of time, ANN as a flexible modelling tool had to be used, given that these networks can in principle capture complex input-output relationships with an arbitrary level of accuracy (Bishop). The Neural Network Toolbox of Matlab®, was employed and implemented the models as so-called NARX (nonlinear autoregressive with exogenous variables) models. This model assumes that variables appear as time series, and allows historical values of the modelled variable, as well as current and historical values of other variables, to be used as inputs

The development of NARX networks follows an approach where it is assumed that the target variables are available to the model within a training set, while only the input variables are available to the model within the test set. During the training process the model is therefore fed with both exogenous variables as well as with past values of the targets. This allows the network to learn as much as possible from both spatial and temporal relationships. The network is thus trained in the so-called open loop mode, as displayed in Figure 5-16 below.

During the testing phase it is assumed that the measured targets are not available any more but must be derived from the inputs only. Within the model architecture the historical target values are then replaced by historical network outputs that are fed back into the network. The model is thus tested in so-called closed loop mode as displayed in Figure 5-17 below.

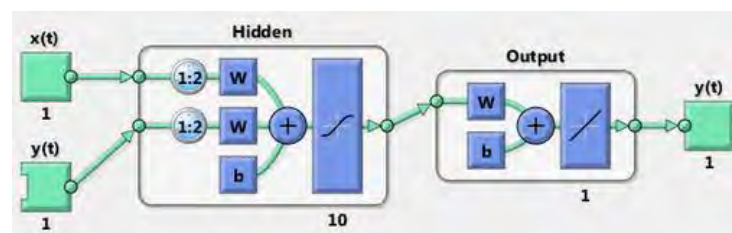


Figure 5-16: Open loop neural network architecture

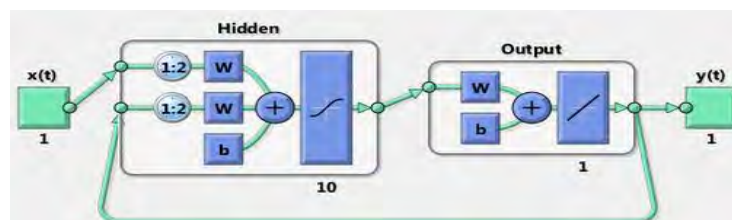


Figure 5-17: Closed loop neural network architecture

The training of a reliable model that will perform consistently under most circumstances requires a training set that is representative of all foreseeable conditions. In this case it was important to ensure that the training set contains temperature variations that span all realistically possible values of practical importance. Training set data collected for trips during the summer months when extreme temperatures occurred on a daily basis were used. Figure 4-8 to Figure 4-13 above or Figure 5-1 and Figure 5-2 above displays the temperatures measured along the sides of the trailer during such a trip. For test set data collected during other trips were used, with sensors placed in more or less the same locations.

The training set was further subdivided into training, validation and testing samples. Only the error over the training samples are used to determine how the model weights should be modified from one training epoch to the next. The error made over the validation samples is used to decide when to stop the training process; this helps to prevent overtraining. The error over the training samples provides an indication of how well the model generalizes with the training set. A typical example of the behavior of the training, validation and test errors across the training epochs is displayed in Figure 5-18 below.

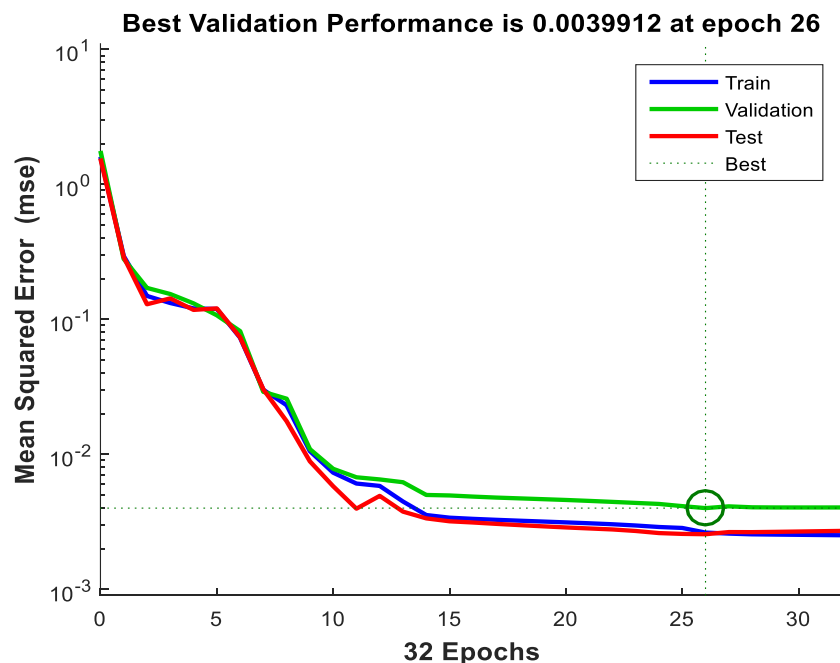


Figure 5-18: Behaviour of Training, validation and test errors

As part of the modelling experiment the impact of different model parameters were evaluated, including the number of historical time samples to use, the size of the training set, the sampling

frequency, the time duration over which the samples were spread, the number of hidden network nodes, the training algorithm used, and the regularization technique employed (to keep the model relationships as 'smooth' as possible). As the time behavior of temperatures tend to be cyclic with a period of one day, a time delay corresponding to exactly one day was included, as this is known to improve the accuracy of cyclic models. The other inputs were spread at a period of 2 hours from the last measured variable up to 8 hours from the present time.

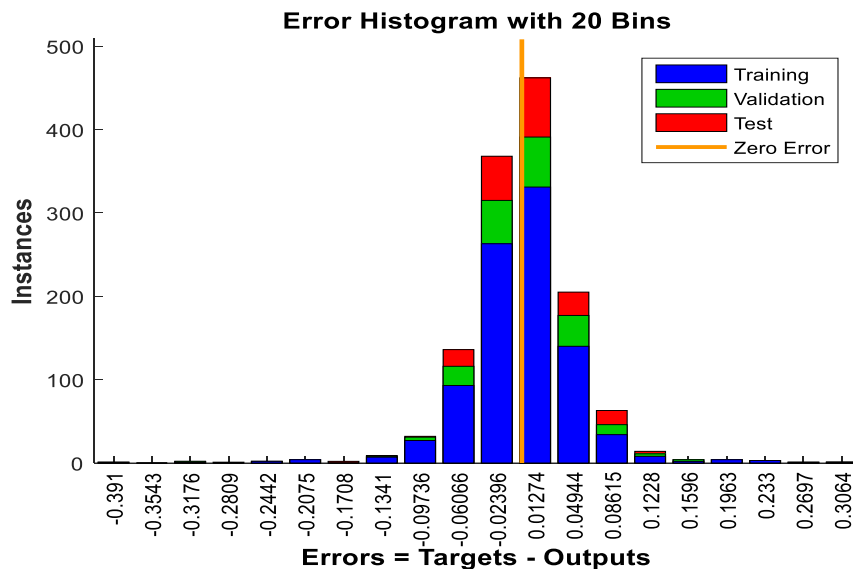


Figure 5-19: Error histogram

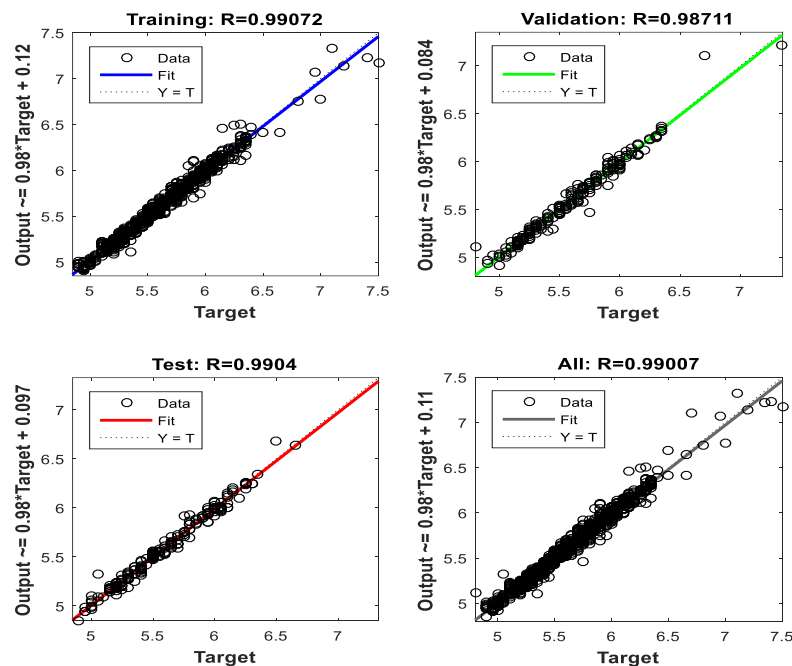


Figure 5-20: Regression plots

During the training process it is important to monitor a number of results: the reduction in modelled error, the regression accuracy between target and model output values (a typical example is given in Figure 5-20). The mean square normalized error (MSE) of output versus target measured over the training set and the MSE measured over the test set. In addition, we also check the MSE obtained when the most suitable input variable is directly used as estimate for the output instead of using a model as shown in Figure 5-19.

The following types of neural network models were trained:

- Spatial models to determine temperature values in locations where no sensors would normally be present as function of concurrent temperature values on the periphery where sensors will be located.
- Temporal models to determine future worst case cargo temperatures based on historical temperature data for sensors at specific locations on the periphery.

5.7 Spatial Predicting of temperatures

One of the primary objectives of this research was to determine how accurately temperature at various points within the cargo could be derived from temperatures that are physically measured at other locations. Assumption that in most operations it will be impractical to deploy sensors within the cargo during normal operations, and that physical sensing would be restricted to a few sensors stuck to the inside of the trailer was made. This implies a need for a computerized mathematical model that will accept temperature measured at some fixed locations as inputs and that will produce temperatures at other locations as output.

In order to determine which temperatures will represent worst case unknown temperatures, the data that was collected during the set of trips were investigated. Figure 5-21 below provides a typical time graph of temperatures measured at the periphery of the trailer within different tiers, while Figure 5-22 displays temperatures measured deep inside the cargo within the same tiers. It can be seen that, due to the thermal inertia of the cargo, the temperature deep inside the cargo is in general much more stable than temperatures at the periphery of the trailer where much higher fluctuations occur. Most cases where allowed thresholds are exceeded also occur along the sides or roof of a trailer – this is to be expected due to the impact of the sun.

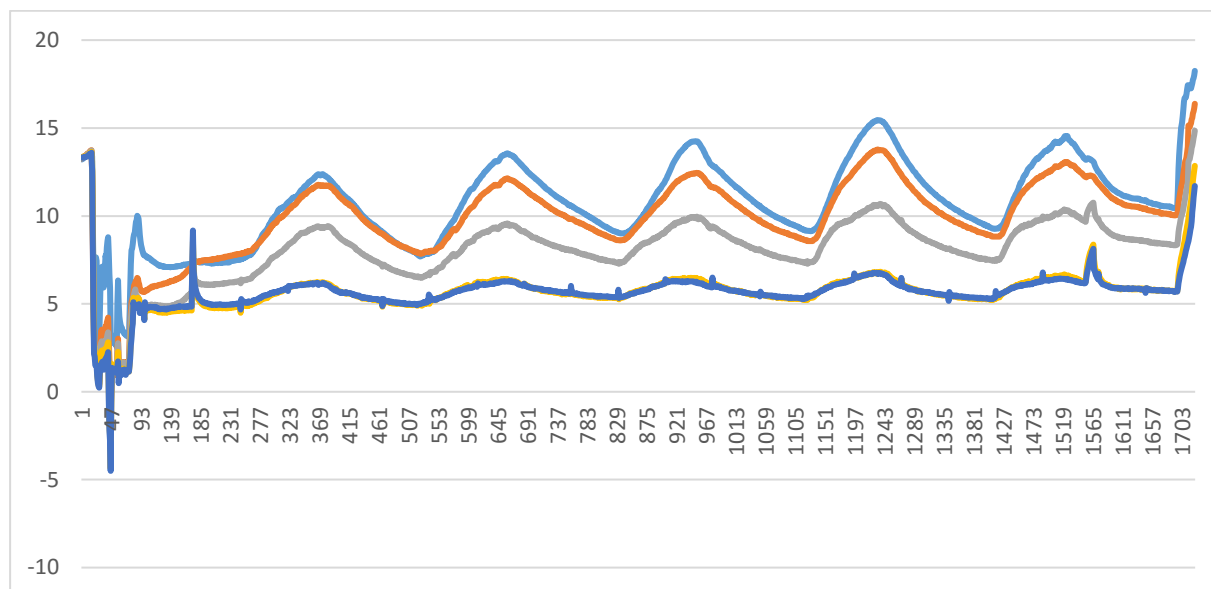


Figure 5-21: Example of Periphery temperatures over trip duration

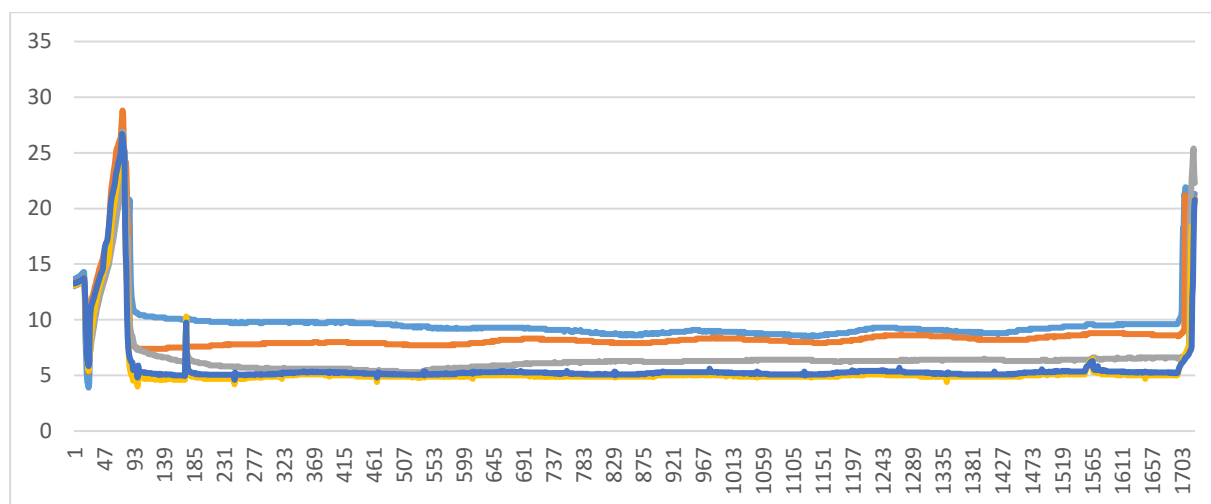


Figure 5-22: Example of In-cargo temperatures over trip duration

As packaging conventions cause cargo to be packed tightly against the sides of the trailers, we can accept that worst case cargo temperatures occur not deep inside the cargo but along the sides where there is physical contact with the trailer. The spatial temperature model development was therefore focused on temperatures collected from sensors on the sides of the trailers. It was assumed that in practical operations temperature would be measured only at a few locations (in this case we regarded tiers 1, 3 and 5 as the locations for installed sensors) and that temperatures

in other locations (tiers 2 and 4 were used for this purpose) would be derived from the measured temperatures. The neural network configuration used for the spatial model is summarized in Table 5-2 below.

Table 5-2: Spatial Neural Network Configuration

Network architecture	NARX Closed Loop
Feedback Delays (hours)	0.08; 2; 4; 6; 8; 24
Input Delays	0.08; 2; 4; 6; 8; 24
Training Function	Levenberg-Marquardt backpropagation
Hidden Layer Size	5
Sampling Period	5 minutes
Size of training set	1601
Size of test set	1093
Input temperatures	Tier 1; Tier 3; Tier 5
Target temperatures	Tier 2; Tier 4
Fraction of training samples	70%
Fraction of validation samples	15%
Fraction of testing samples	15%
Regularization technique	Bayesian

Figure 5-23 and Figure 5-24 show a typical result where the tier 4 temperature was modelled in terms of the tier 1, 3 and 5 temperatures. Results for the training set are displayed in Figure 5-23 and for the test set in Figure 5-24 below.

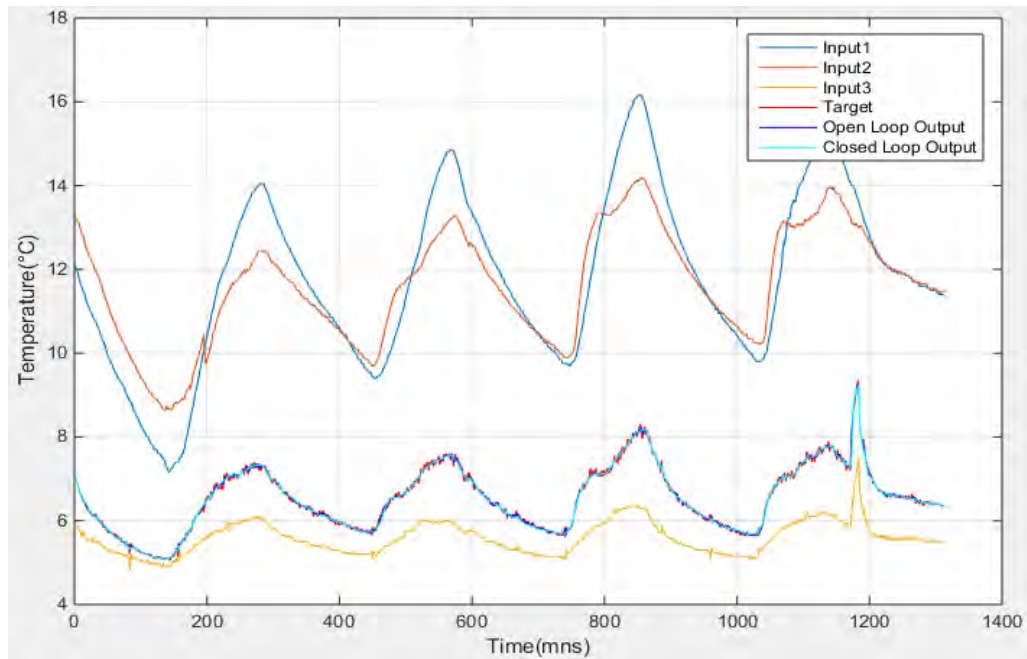


Figure 5-23: Spatial model Training set: Tier 4 temperature modelled results in terms of Tiers 1,3 and 5

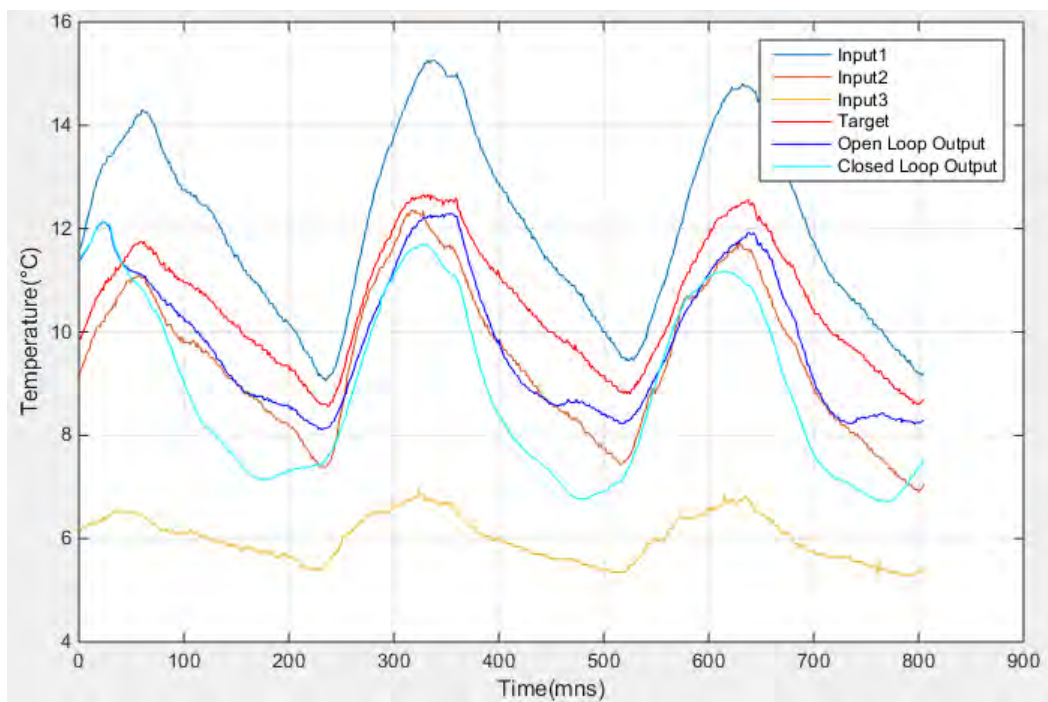


Figure 5-24: Spatial model Test set: Tier 4 temperature modelled results in terms of Tiers 1,3 and 5

Table 5-3 below summarizes the MSE performance of the different models on the different data sets and for open vs closed loop mode. It can be seen that over the training set an almost perfect fit is achieved (the target, open loop output and closed loop outputs overlap almost completely) as we also used the historical values of the target as inputs (with the model in open loop mode as explained above).

Table 5-3: MSE Performance of Spatial Neural Network

Tier	1	2	3	4	5
open_trn	0.001	0.001	0.001	0.004	0.001
closed_trn	0.001	0.001	0.001	0.004	0.002
closed_tst	0.140	2.841	1.242	0.683	0.481
Default_tst	15.048	8.385	6.692	14.889	17.230

For the test set the data from tier 4 was totally unseen during the training process and no historical target values were used for predictions (as the model is now in closed loop mode). It can also be seen that in the test set the tier 4 temperature behaved somewhat differently compared to the other tier temperatures that what was the case for the training set. In spite of this the test set performance is still superior compared to the default situation where no information would be available for this tier and where the temperature in another tier would be used as best available estimate.

5.8 Forecasting future cargo temperatures

The previous section demonstrated that a reliable model can be extracted to accurately predict concurrent temperature fluctuations over time at any location along the length of the cold container by using a small number of measured temperatures at fixed locations spread along the container body. The additional requirement however exists to not only model concurrent temperature at any location but to derive future worst case cargo temperatures (which may adversely impact cargo quality) from current and historical periphery temperatures. More importantly, once an event has occurred that is known to negatively impact upon cargo temperature (e.g. a prolonged stop at a border post), it will be of significant value to be able to estimate what the future cargo temperature can be expected to be should the cargo be exposed to non-ideal circumstances.

5.8.1 Future temperature prediction for position with sensors

In order to determine how accurately future worst case cargo temperatures can be derived from temperatures on the periphery the artificial neural network used in the previous section was adapted to provide for the forecasting of future temperatures from historical temperatures. In this case, only delayed input values were used with respect to the target values, and determined the maximum prediction horizon over which an acceptable forecasting accuracy could still be achieved.

Both single variable NAR models (nonlinear autoregressive models where only the historical values of a target temperature were used to predict its future values), as well as multiple input NARX models (where the historical values of several different temperatures were used to predict the future values of all these variables) were employed in this process.

The single variable models (i.e. using multiple models to predict different temperatures) proved to produce more accurate results compared to using a single model with multiple input and target variables. This can partly be attributed to the fact that, due to limited size of the training and test sets, the relationships between the average temperatures for the same variables were not the same across the training and test sets. This caused the predicted values for the test set to be biased in favour of the relationships between the average values appearing in the training sets. This factor was largely eliminated by using only one variable per model. Should more representative training and test sets be available this should prove to be less of a problem.

The future predictions are displayed in Figure 5-25 below for tier 1. It can be seen that the 2 hours ahead forecast of temperature is much more accurate compared to using the current (input) value as default estimate for the future (target) value.

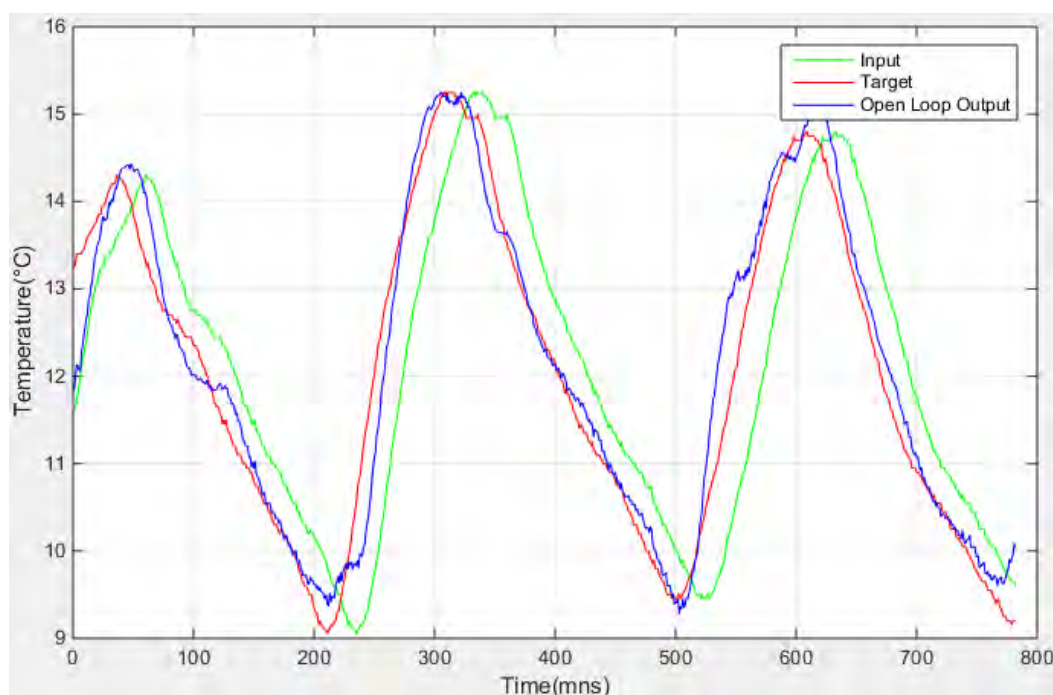


Figure 5-25: Temporal model: inputs vs target and output (Tier 1)

Table 5-4 below summarizes the neural network configuration for the temporal single variable models (in those respects where it differs from the spatial network), while Table 5-5 displays the performance results; default values refer to using current values as estimates for future predicted values.

Table 5-4: Temporal Neural Network Configuration

Network architecture	NAR Open Loop
Input Delays	2; 4; 6; 8; 24
Input temperatures	Any one of Tier 1; Tier 3; Tier 5
Target temperatures	Any one of Tier 1; Tier 3; Tier 5

Table 5-5: MSE Performance of Temporal Neural Network

Tier	1	2	3	4	5
open_trn	0.025	0.029	0.037	0.044	0.016
Default_trn	1.016	0.520	0.526	0.219	0.068
open_tst	0.188	0.520	1.320	0.126	0.097

Default_tst	0.991	0.460	0.664	0.151	0.066
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5.8.2 Future temperature prediction for position without sensors

Future temperature forecasting were also implemented for temperatures in locations where no sensor is present. This was achieved by combining the spatial and temporal neural network architectures, as displayed in Table 5-6 below. The inputs were historical values for tiers 1, 3 and 5 while targets were future values for tiers 2 and 4. This proved to be a more challenging problem; as can be seen in Figure 5-26 and Table 5-7 below the results were significantly worse compared to the spatial only or temporal only models.

In general, the modelled outputs were however superior compared to the default values in terms of MSE.

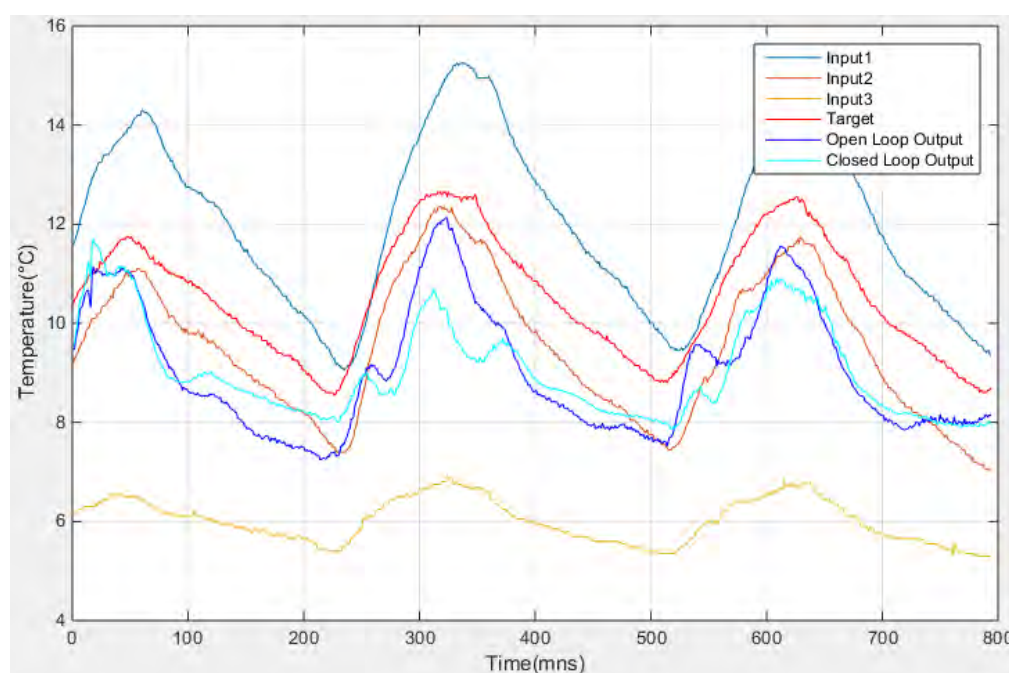


Figure 5-26: Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 2)

Table 5-6: Combined Spatial Temporal Neural Network Configuration

Network architecture	NARX Closed Loop
Input Delays	2; 4; 6; 8; 24
Input temperatures	Tier 1; Tier 3; Tier 5
Target temperatures	Tier 2; Tier 4

Table 5-7: MSE Performance of Combined Spatial Temporal Neural Network

open_trn	0.004	0.002	0.007	0.008	0.002
closed_trn	1.016	0.520	0.526	0.219	0.068
open_tst	0.452	2.336	10.051	15.411	0.731
closed_tst	0.743	1.758	6.948	14.345	1.627
Default_tst	15.151	8.618	7.499	15.794	17.989

5.9 Predicting temperature as function of position

As the observed spatial temperature deviations displayed relatively simple and predictable behavior, the spatial model was based on nonlinear polynomial regression. The inputs to the model were obtained by taking the average of all periphery temperatures within a tier to represent the temperature at the corresponding distance from the chilling unit. The output of the model was the temperatures in between the centre points of the various tiers. It was found that a 4th order polynomial was sufficiently accurate to provide an acceptable approximation of actual temperature as function of location, as displayed in Figure 5-27 and Figure 5-28 below.

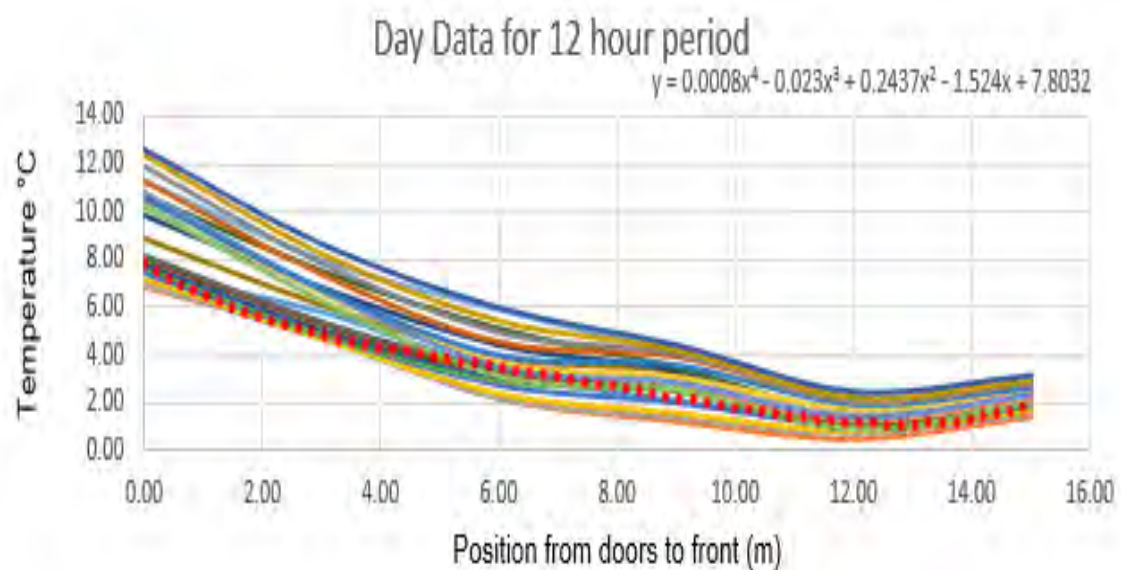


Figure 5-27: 12-hour day period temperature graph as function of location in trailer

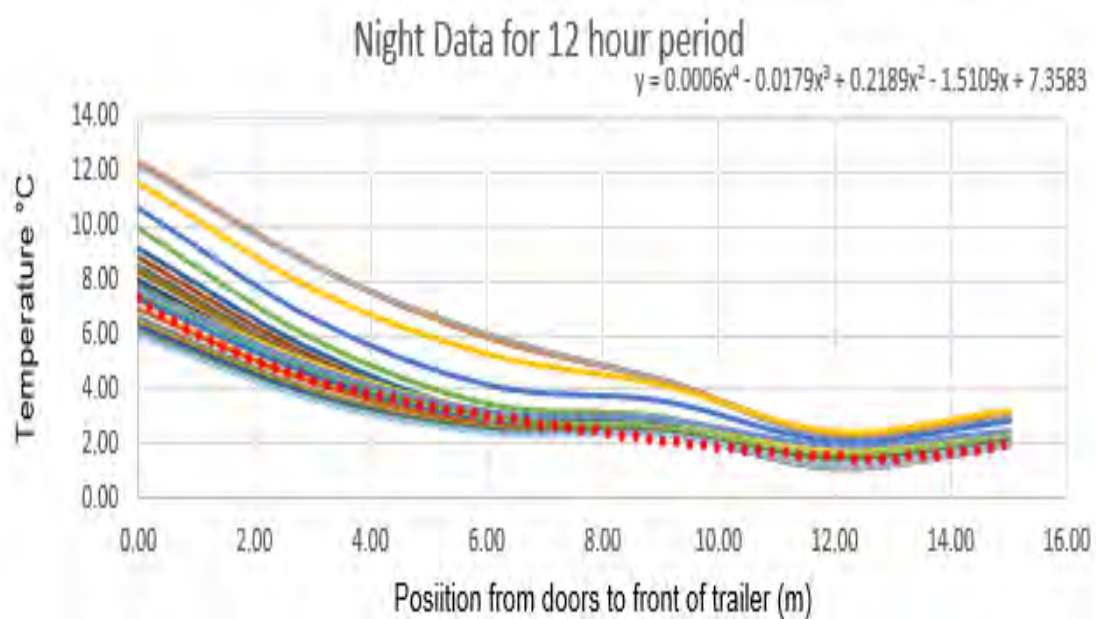


Figure 5-28: 12-hour night period temperature graph as function of location in trailer

What is however also apparent from this graph is that the worst case temperature at the doors significantly varies between different trips, ranging from about 6 °C (which will result in very little or no cargo losses) up to more than 12 °C (which may imply that all cargo in the last tier was lost during the trip). This difference in cold chain performance can be mostly attributed to different events occurring during different trips. It therefore emphasizes the need for a temporal model that can predict future temperature as function of historical temperature once an event has occurred that may be detrimental to cargo. This is the topic of the next section.

5.9.1 Conclusions and Future Work

The need for improved techniques for effective in-transit cold chain management was motivated. Different scenarios were described where the absence of accurate in-transit monitoring of perishable cargo can both lead to significant cargo losses and to unresolved disputes between consignor, transporter and consignee. Practical investigations revealed that the need exist to derive worst case in-cargo temperatures from temperatures measured along the periphery of the vessel, as well as to predict future cargo temperatures from current temperatures to enable pro-active prevention of situations that may lead to cargo losses.

5.10 Implementation of selected models in practical scenarios

The implementation of the models will be used at various stages of the real world process. The most general scenario would be the implementation to evaluate the internal temperatures from a set of real time/ passive data values received. The software will process the data and transmit the data queues to the model. The models will then receive the data and process the values returning only the information on pallet level for the goods placed at the different positions in the trailer.

The second would be a predictive recall function for real time data only, the model will calculate and evaluate the average calculated values for a specified period of time into the future, comparing this with the set points defined for the trip; such an effective warning system can provide information to managers in real time.

5.11 Cost benefit analysis

A cost benefit analysis was developed as shown in 171 (Appendix F).

The model evaluates different scenarios for different levels of actual losses, and consider two systems:

- one using tags of which the data is only collected once the truck arrives at the depot
- one using tags with real time monitoring inside the truck.

Different loss saving levels for these scenarios (2%, 5%, 15%, 35%, 40% and 50% respectively) are presented.

5.12 In summary

The operation of Neural Network was described. Experimental data set were subsequently used to train neural network models that predict current in-cargo temperatures from temperatures on the periphery, as well as future temperatures from current temperatures. It was shown that the models are sufficiently accurate to allow worst case in-cargo temperatures to be estimated with high confidence levels from temperatures that can be measured using a small number of permanently installed sensors. A cost benefit model analysis was also developed as detailed in 171 (Appendix F).

"There is no love without giving."

- TB Joshua

CHAPTER 6

6 Conclusion

6.1 Introduction

This chapter summarises and bring together the main areas covered in this dissertation. It also provides an evaluation of the research and its outcomes, and direction for future study.

6.2 Summary of work

This dissertation has investigated the following:

1. A comprehensive literature study on containers
2. A literature survey on RFID
3. A literature survey on cold chain operations in the world and southern Africa
4. The determination of the needs of the fresh produce industry in southern Africa.
5. The establishment of the state-of-art technology in the cold chain industry and their communication protocols.
6. The intelligence level and communication capabilities for an improved cold chain monitoring system.
7. Various experimental field tests conducted to and fro from Johannesburg to Lusaka.
8. Data analysis of data collated from the field tests.
9. Development of artificial neural network models for different cold chain events susceptible to losses and DLL deployment for VBA integration
10. Development of cost-benefit analysis model

6.3 Research outcomes

The following research outcomes were achieved:

1. The cold chain logistics (CCL) problem for typical cold chain operations in Southern Africa was quantified and ascertained.

2. A monitoring methodology was designed to characterize cold chain operations with sufficient accuracy to pinpoint problem areas.
3. Cold chain logistics monitoring during the transportation leg of the value chain was achieved and data captured which included thresholds exceeding required transit temperatures.
4. Accurate spatial temperature profiles and cargo conditions within reefer containers loaded with different kinds of perishable cargo were generated and it was determined that single point monitoring in a tier is sufficient for effective monitoring. This gives us five temperature monitoring points based on the five tiers.
5. Temperature data of the cargo on the five tiers were collated and used in a temporal temperature prediction model based on neural networks.
6. It was demonstrated in the visual representation in chapter 5 how all the models can be used to prevent cargo losses by predicting how long it will take for cargo temperatures to exceed allowed thresholds once an unforeseen event occurs.
7. A detailed databank was produced containing a representative set of data for different kinds of cold chain operations events. Such a databank can still be used in future cold chain researches to design more effective cold chain logistics processes in order to protect the quality of the goods, and to create cold chain performance benchmarks.
8. An optimal approach was designed to conduct cold chain monitoring on an on-going basis as part of standard operations. This involved the incorporation of the models in this work and the work carried out in the cold chain RFID implementation.
9. A list of alternatives for the deployment of optimal cold chain monitoring solutions customized to the end-user's problems, needs and budget was created.

6.4 Recommendations for future work

Future work will focus on the integration of the temperature prediction model with a practical in-transit temperature monitoring system that uses RFID based wireless sensors that will simplify the deployment of the system and support the automated collection of data in real time. This will allow the predictive model to be used for the pro-active prevention of cargo losses as well as for resolving disputes based on accurate records of the actual situation in the field.

6.5 In summary

The research objectives initially set out, were achieved regardless of the physical limitations and challenges. Results of this work will be used in real time predictive cold chain monitoring logistics.

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APPENDICES

Appendix A: Containers Detailed Description

1. Dry Storage Container: The most commonly used shipping container. Used for shipping of dry materials



Figure 6-1: Dry Storage container

2. Flat rack container: Used for shipping wide variety of goods



Figure 6-2: Flat Rack Container

3. Open Top Container: Has a convertible top that can be completely removed to make an open top so that material of various heights can be shipped with ease.



Figure 6-3: Open top container

4. Tunnel container: Has doors on both ends and are used in quick loading and unloading of goods



Figure 6-4: A Tunnel Container

5. Open Side Storage Container: It is completely changed into open sides; hence provide space for loading of products.



Figure 6-5: Open Side Storage Container

6. Double Doors Container: Has wider room for loading and unloading of materials. Construction materials like steel, iron etc. are transported with Double doors containers.



Figure 6-6: Double Doors Container

7. Refrigerated ISO containers: They are also called Reefers Container. These are temperature regulated shipping containers that always have a carefully controlled low temperature. Used for shipping of perishable goods like fruits and vegetables over long distances



Figure 6-7: Refrigerated ISO Container

8. Insulated or Thermal Containers: They are Reefer containers. These are the shipping storage containers that come with a regulated temperature control allowing them to maintain a higher temperature. The choice of material is so done to allow them long life without being damaged by constant exposure to high temperature. They are most suitable for long distance transportation of products



Figure 6-8: Insulated or thermal containers

9. Tank containers: Used mainly for the transportation of liquid materials.



Figure 6-9: Tanks

10. Cargo Storage Roll Container: A foldable container, this is one of the specialized container units made for purpose of transporting sets or stacks of materials.



Figure 6-10: Cargo storage roll container

11. Half Height Containers: Usually half the height of full sized containers. Used especially for goods like coal, stones etc. which need easy loading and unloading



Figure 6-11: Half height Carriers

12. Car Carriers: Container storage units made especially for shipment of cars over long distances. They come with collapsible sides that help a car fit snugly inside the containers without the risk of being damaged or moving from the spot.



Figure 6-12: Car carriers

13. Intermediate Bulk Shift Containers: These are specialized storage shipping containers made solely for the purpose of intermediate shipping of goods. They are designed to handle large amounts of materials and made for purpose of shipping materials to a destination where they can be further packed and sent off to final spot.



Figure 6-13: Intermediate bulk shift containers

14. Drums: As the name suggests, circular shipping containers, made from a choice of materials like steel, light weight metals, fiber, hard plastic etc. they are most suitable for bulk transport of liquid materials.



Figure 6-14: Drums

15. Special Purpose Containers: These are the container units, custom made for shipment of weapons and arson.

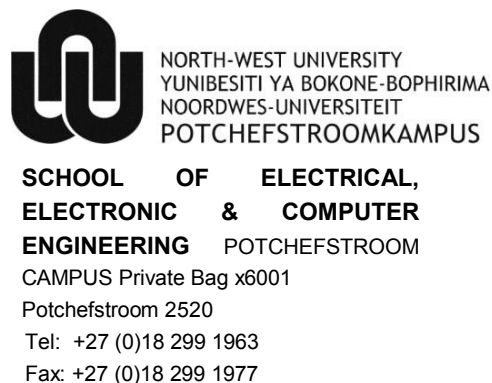


Figure 6-15: Special purpose containers

16. Swap Bodies: They are mostly used in Europe. Not made according to the ISO standards, they are not standardized shipping container units but extremely useful all the same. They are provided with a strong bottom and a convertible top making them suitable for shipping of many types of products.



Figure 6-16: Swap bodies

Appendix B: Letters of Invitation, Questionnaires & Approvals**Letter of Invitation to Participate in NWU Intelligent Freight Monitoring Project**

Dear Transporter,

My name is Chris Emenike, a researcher in the field of Intelligent Freight Monitoring at the School of Electrical, Electronic and Computer Engineering at the North West University Potchefstroom, North West.

The research intends solving problems experienced by transporters in the areas of temperature monitoring, fuel monitoring during cross border operations.

I am currently involved in the Field data gathering by the installation of telemetry systems. The end results will allow transporters best monitor goods of their clients and cut cost during temperature monitoring and select best technologies needed for their business.

I would like to set up a meeting with you to discuss how we can be of assistance to your organisation in providing solutions in these areas.

These will be at no cost to your organisation, other than to make available some data and also providing access to your trailers for equipment installation.

An MOU will be signed in order to protect your identity and data.

I thank you for your attention in this matter and I hope to hear from you soon!

Kind Regards,

Chris Emenike
Researcher in Intelligent Freight Monitoring
North West University
23718528@nwu.ac.za
Cell: 078246985



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1977

**QUESTIONNAIRE:
COLD CHAIN MANAGEMENT OF PERISHABLE GOODS**

All answer provided in this questionnaire is confidential and no mention will be made to a company or individual by name. The answers will only be used as research data to evaluate the process of perishable goods handling and the structures in place to ensure product quality.

1. What procedures are followed when a consignment arrives from the growers/producers?
2. What is the process of quality verification followed at this time?
3. What are the criteria used during this quality verification?
4. Do you verify that the cold chain has been maintained during the entire duration of transportation, or is the temperature of the reefer and consignment only verified at arrival?
5. What are the temperature parameters for consignment arriving at the DC, goods in storage, goods being exported and the allowed deviations in these temperatures?
6. For what duration is goods stored at your facility before it is forwarded to its destination?

-
7. What systems/technology do you use to verify that the temperature is maintained in your storage area? Please name the system provider.
 8. What functionality do these systems offer for cold chain management? Are they locally operated or via a webserver?
 9. During the exportation (sea/air/land) of goods what systems and structures do you use to verify the cold chain is maintained and how do you use the data from this verification to maintain quality of goods?
 10. What are the main causes for losses of perishable goods in your supply chain?
 11. What is the annual loss of goods due to temperature and humidity fluctuations?
 12.
 - Fruits: _____%
 - Vegetables: _____%
 - Other: _____%
 13. Do you have any area where you feel research can be done to improve your overall process and provide improved management tools for your company?
 14. Would you be interested in participating in pilots and experiments we will be performing in the future on cold chain management?
-

COLD CHAIN ISSUES QUESTIONNAIRE RESPONSE

Please fill out the questionnaire and forward it to any of the email:

Alwyn.Hoffman@nwu.ac.za

23718528@nwu.ac.za

1. Which technologies do you use for temperature, humidity and air flow monitoring in your cold chain transportation.

Response: It has a built in data recorder, hence each machine is different which is specified by the manufacturer. Carrier Thermo king

2. What do you think are the greatest weaknesses of the current technology been used in your organisation for temperature, humidity and air flow monitoring in Southern Africa?

Response: Data travels with the machine, so if you need the data one needs to have access to the machine in an environment that can supply power.

3. What are the biggest issues and challenges affecting temperature, humidity and air flow monitoring in your company? How can these be improved in the future?

Response: Temp: Fruit placed into the container that is not on temperature.
Air Flow: Container Airflow design is based on a Vertical airflow.
Air Flow: Cold room airflow design is based on horizontal airflow.
Carton design must be able to accommodate both airflow designs .

4. What do you think are the greatest strengths of temperature monitoring in cold chain in Southern Africa?

Response: Having an hourly reading on the fruit while the container is on its sea voyage. If any spikes do occur, the temperature can be affectively changed to supply the correct air flow.

5. What do you see as major opportunities for improving temperature, humidity and air flow monitoring in the cold chain in the Southern African region?

Response: Refcon: This is a program that will allow the carrier to obtain temperature readings in the port and while the vessel sails. More spikes can be rectified. This system will allow the spikes to be correctly faster and more efficiently.

6. Are there any specific issues that you hope will be included/captured in the Southern African freight mobility monitoring plan, and why?

Government white paper for intermodal transport is driving more towards rail transportation. The concern is if rail transport is not privatised, it could negatively impact on the export industry.

7. Do you have any suggestions for enhancing the interaction between public and private sector stakeholders involved in freight transportation in the region?

Response: The interaction between the public sectors and private sectors works, it is done through industry bodies e.g. Fresh Produce Exporter forum- thus sufficient interaction. The problem is the speed that public sector acts on issues e.g. DAFF.

8. Are there any comments or recommendations that you would like to provide to the university in order to improve the research of freight visibility in Southern Africa?

Response: Besides the questionnaire. Interviews should be held with the Carrier and Exporter as their views may differ.

COLD CHAIN ISSUES QUESTIONNAIRE RESPONSE

Please fill out the questionnaire and forward it to any of the email:

Alwyn.Hoffman@nwu.ac.za

23718528@nwu.ac.za

1. Which technologies do you use for temperature, humidity and air flow monitoring in your cold chain transportation.

We only take responsibility for the product from the point where fruit is loaded in the container to till when it is discharged at destination. We use a disposable temperature device in each container. There are many product and distributors. We use the USB TempMate device

2. What do you think are the greatest weaknesses of the current technology been used in your organisation for temperature, humidity and air flow monitoring in Southern Africa?

For temp measurement the available products are adequate for us. We have now tools to measure humidity and air flow.

3. What are the biggest issues and challenges affecting temperature, humidity and air flow monitoring in your company? How can these be improved in the future?

We only require the data in event of quality problems at discharge. For this we believe the current products are adequate.

4. What do you think are the greatest strengths of temperature monitoring in cold chain in Southern Africa?

Since deregulation, the fruit industry has "matured" greatly with regards to handling the products and maintaining the cold chain. This is a direct result of mistakes made in the past and losses made as a result. These days the agreements between service providers and clients are legally tight and each party ensure they deliver a professional service to eliminate risk.

5. What do you see as major opportunities for improving temperature, humidity and air flow monitoring in the cold chain in the Southern African region?

Loading as close as possible to the source.

6. Are there any specific issues that you hope will be included/captured in the Southern African freight mobility monitoring plan, and why?

No

7. Do you have any suggestions for enhancing the interaction between public and private sector stakeholders involved in freight transportation in the region?

No

8. Are there any comments or recommendations that you would like to provide to the university in order to improve the research of freight visibility in Southern Africa?

No



Date: 20-05-2014

The High Commission of the Republic of Zambia,
570 Ziervogel Street, Arcadia,
Pretoria
0083

Sir,

LETTER OF INTRODUCTION

The School of Electrical, Electronic and Computer Engineering at the North West University Potchefstroom, South Africa is conducting a research project in Intelligent Freight Monitoring. Mr. Christian Chuks Emenike (personnel No: 23718528 and passport no: A02045509) is one of our researchers and students in the cold chain monitoring aspect of the research. As part of this project he needs to complete field research within the Southern African Development Community (SADC), and will be required to visit several SADC countries, including Zimbabwe, Zambia, Botswana and Mozambique during the course of 2014 **by road accompanying one of our transporters trucks**, after which he will return to South Africa to complete his studies. Mr Emenike therefore requires a visa from your country in order to allow him to transit to and from your country during this project. We will appreciate your assistance in this respect.

Kind regards



Prof. Alwyn Hoffman
Project Leader
Cell: 082 851 6537
E-mail: Alwyn.Hoffman@nwu.ac.za



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Accommodation during Travel to Zambia

NAME: Mr. Emenike Christian Chuks

DEPARTING: Lonrho Logistics Johannesburg, South Africa

DATE: 24th July 2014 *

RETURNING: Roseblooms Zambia, Tata Farms, Ngwerere Road, Lusaka, Zambia

PURPOSE: Research Experiment to monitor installed sensing equipment in Trailers

DATE: 29th July 2014 *

Vehicle Documentation:

Class or Model: Horse: BF14WVGP, Trailer: PVM744GP **or**
Horse: BG40JFGP, Trailer: VZY045GP

The above named personnel from our institution is carrying out his field experimental work to monitor sensing devices mounted within a 14tonne trailers.

The truck is fitted with on-board accommodation hence Mr. Emenike will be with the truck at all times during the course of his journey

* NOTE: *All dates are subject to change due to visa issuance and delays at border post*



NORTH-WEST UNIVERSITY
YUNIBESITI YA BOKONE-BOPHIRIMA
NOORDWES-UNIVERSITEIT
POTCHEFSTROOMKAMPUS

INTELLIGENT FREIGHT MONITORING
RESEARCH GROUP
SCHOOL OF ELECTRICAL, ELECTRONIC &
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POTCHEFSTROOM CAMPUS Private Bag x6001
Potchefstroom 2520
Tel: +27 (0)18 299 1963
Fax: +27 (0)18 299 1977

Travel Itinerary

NAME: Mr. Emenike Christian Chuks

DEPARTING: Lonrho Logistics Johannesburg, South Africa

DATE: 22nd July 2014 *

RETURNING: Roseblossoms Zambia, Tata Farms, Ngwerere Road, Lusaka, Zambia

PURPOSE: Research Experiment to monitor installed sensing equipment in Trailers

DATE: 29th July 2014 *

Leg 1

Departure: Lonrho Logistics Johannesburg, South Africa.

Arrival: Roseblossoms Zambia, Tata Farms, Ngwerere Road, Lusaka, Zambia

Via: Botswana Border Post / Kazangula or
Beit bridge / Victoria Fall or
Beit bridge / Chirundu or

Vehicle Registration Number: Horse: BF74WVGP, Trailer: PVM744GP or
Horse: BG40JFGP, Trailer: VZY045GP

Mode of Transport: Truck by Road

Depart Date and Time: * 22nd July 2014 *

Arrival Date and Time: * 24th July 2014 *

Leg 2

Departure: Roseblossoms Zambia, Tata Farms, Ngwerere Road, Lusaka, Zambia

To: Lonrho Logistics Johannesburg, South Africa

Via: Kazangula / Botswana Border Post or
Victoria Fall / Beit bridge / or
Chirundu / Beit bridge / or

Vehicle Registration Number: Horse: BF14WVGP, Trailer: PVM744GP or

Horse: BG40JFGP, Trailer: VZY045GP

Class or Model: Horse: BF14WVGP, Trailer: PVM744GP or

Horse: BG40JFGP, Trailer: VZY045GP

Hotel / Accommodations:

The 14 Tone Trailer is fitted with beds and bunks hence Mr. Emenike will make stay with the truck at all times during the course of the trip

The High Commission of the Republic of Zambia,
570 Ziervogel Street,
Arcadia,
Pretoria
0083
Sir,

TO WHOM IT MAY CONCERN

The School of Electrical, Electronic and Computer Engineering at the North West University Potchefstroom, South Africa in conjunction with our company Lonrho Logistics is conducting a research project in Intelligent Freight Monitoring.

Mr. Christian Chuks Emenike (personnel No: 23718528 and passport no: A02045509) is one of our researchers and students in the cold chain monitoring aspect of the research.

As part of this project he needs to complete field research within the Southern African Development Community (SADC), and will be required to visit several SADC countries, including Zimbabwe, Zambia, Botswana and Mozambique where we offer our services, after which he will return to South Africa to complete his studies.

Mr Emenike therefore requires a visa from your country in order to allow him to transit to and from your country during this project. We will appreciate your assistance in this respect.

Kind regards

Liandri Erasmus
Operations Manager
Lonrho Logistics
Tel: +27(0) 11 571 9786
Mobile: +27 (0) 82 497 6455

Appendix C: Field Tests Events Capturing

Border Posts Delays

For a trip from South Africa (SA) to Zambia (ZB) delays are experienced at the Botswana border post at Martins' drift then at Zambia border post at the Kazangula ferry.

- Instance for each trip: Botswana border at martins' drift, Zambia border at Kazangula and Zimbabwe at Victoria falls
- Time period when the event took place: when the truck stopped at the border and when it left the border post
- The data are stored and saved as border posts (day and night, winter and summer, different trips,
- Visualization of the events through temperature behaviour graphs for these time windows (day and night, winter and summer, different trips during border posts)
- Selection of more important event from the visualization

Field Test 1

Table 6-1: Experiment 1 breakdown of events

Date	Time of Waiting, Reason and Place	Event / Time waiting
15.07.2014	14:52 pm, finished loading	Reefer loaded with cargo
15.07.2014 to 16.07.2014	6:39 pm – 05:29am Clearance to travel, Depot (Lonrho)	10hrs 50min or 650min
16.07.2014 to 16.07.2014	3:50 pm to 5:08pm @ Grobler's Bridge Clearing paper from Agent	1hr 18min or 78min
17.07.2014 to 17.07.2014	5:09pm to 5:56pm @ Botswana Martin's drift clearing agents	47min
18.07.2014 to 18.07.2014	12:48pm to 5:56pm @ Botswana Kazangula, queue for the ferry	5hr 08min or 308min
18/07/2014 to 19/07/2014	10:10pm to 10:52am. Breakdown	12hrs 42min or 762min
Offloading		
19/07/2014 to 19/07/2014	12:20pm to 1:50pm	1hr 30min or 90min
Fridge off	13:30pm	
Departure from loading point	16.07.2014 05:29am	
Arrival at destination centre	19/07/2014 12:12pm	

Time taken for the trip	3 days 6hrs 43min or 78 hours or 4723min
Total Time due to delay	1day 8hrs 25min or 32hours 25min or 1935min

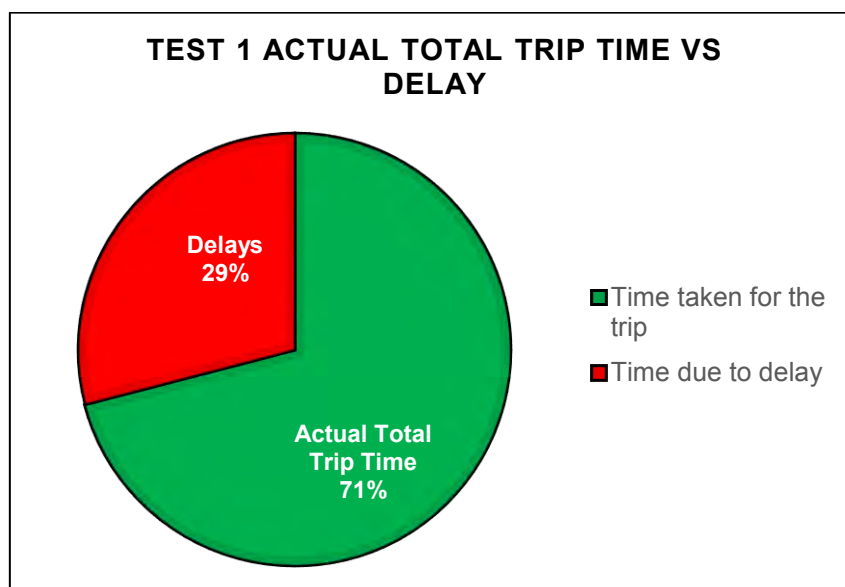


Figure 6-17: Experiment 1 time taken vs delay during trip chart

Field Test 2

Table 6-2: Experiment 2 breakdown of events

Date	Time of Waiting, Reason and Place	Event / Time waiting
01/08/2014 to 01/08/2014	5:22pm, finished loading Fridge ON 5:30pm	Reefer loaded with cargo
01/08/2014 to 02/08/2014 Night	7:00pm to 7:10am Returned to Lonrho, Awaiting Clearance to travel, trip incentive, Leaving Lonrho Depot (Lonrho)	12hrs 10min 730min
02/08/2014 to 02/08/2014 Day	11:42am to 1:34pm, Parked to shop since couldn't make the shopping because he didn't get incentives on time	1hr 52min or 112min
02/08/2014 to 02/08/2014 Day	4:59pm to 6:15pm, Waiting @ Grobler's border post for clearing and on the queue	1 hr 16min or 76min
02/08/2014 to 02/08/2014	6:51 pm to 7:29 Arriving Botswana border post and leaving it	38min

02/08/2014 to 03/08/2014 Night	8:20pm to 5:00am, Parked for the night to sleep, Departed in the morning	8hrs 40min or 520min
03/08/2014 to 04/08/2014 Night Time 7pm to 5am is 10 hrs or 600min	5:15pm to 12:19pm, Waiting time @ Kazangula Ferry before finally crossing	19 hrs 4min or 1144min
04/08/2014 to 04/08/2014 Day	1:35pm to 6:45pm, waiting in Kazangula town for papers to be approved by clearing authorities	5hrs 10min or 310min
04/08/2014 to 05/08/2014 Night Time	8:17pm to 6am, Arrived Livingstone and passed the night while waiting for clearance papers (9hrs 43min or 583min)	(1day 14hrs 8min or 2288min)
05/08/2014 to 05/08/2014 Day	6:00am to 6pm, Reefer stationary in the blazing sun while fridge running (12hrs or 720min)	
05/08/2014 to 06/08/2014 Night	6:00pm to 6:00am, Reefer stationary in the Cold of the Night while fridge running (12hrs or 720min)	
06/08/2014 to 06/08/2014 Day	6:am to 10:25am, Reefer stationary in the blazing sun while fridge running (4hrs 25min or 265min)	
Total Waiting Time @Livingstone	Waiting for papers clearance	
06/08/2014 – 07/08/2014 Night	8:00pm – 6:30am Arrival at destination and slept at the farms	10hrs 30min or 630min
07/08/2014 to 07/08/2014 Day	6:30 to 7:20am Waiting for offloading	50min
Offloading		
07/08/2014 to 07/08/2014	7:20a.m to 9:30am	2hrs 10min or 130min

Departure from loading point	02/08/2014 at 7:10am
Arrival at destination centre	07/08/2014 at 7:20am
Time taken for the trip	5 days 10min or 7210min

Total Time due to delay	4 days 2 hrs 18min or 5898 minutes
-------------------------	------------------------------------

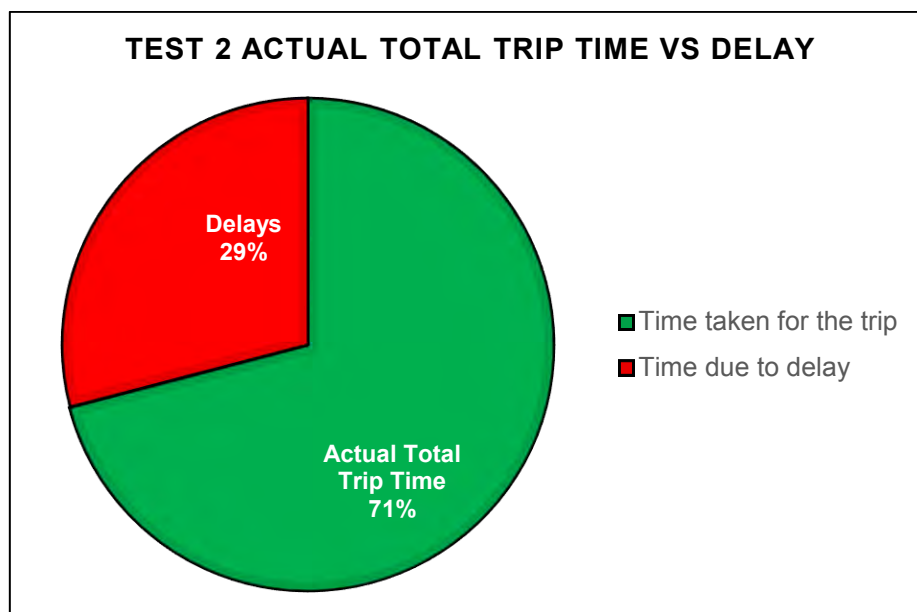


Figure 6-18: Experiment 2 time taken vs delay during trip chart

Field Test 3

Table 6-3: Experiment 3 breakdown of events

Date	Time of Waiting, Reason and Place	Event / Time waiting
20/08/2014 to 20/08/2014	2:42pm, finished loading at Loading Point	Reefer loaded with cargo
20/08/2014 to 21/08/2014 Night	4:11pm to 10:00am Returned to Lonrho, Awaiting Clearance to travel, collect trip incentive, Leaving Lonrho	17 hours 1069 minutes
21/08/2014 to 21/08/2014	6:32pm to 7:15pm Waiting @ Martin's drift border post	43 minutes
22/08/2014 to 22/08/2014	5:37am – 07:46am Arrival at Kazangula Ferry (Waiting)and leaving to take Victoria falls border due delay.	2 hours, 9 minutes 129 minutes
22/08/2014 to 22/08/2014	8hours delay time at Victoria falls	8hours delay time at Victoria falls or 480
23/08/2014 to 23/08/2014	9pm arrive destination	
23/08/2014 to 24/08/2014 Night	9pm to 7:38am Fridge stayed overnight standing at destination	10 hours, 38 minutes 638 minutes
24/08/2014 to 24/08/2014	Offloading 7:38am to 9:00 am	2hr 38min
Departure from loading point	21/08/2014 at 10:00am	

Arrival at destination centre	24/08/2014 at 7:38 am
Time taken for the trip	2 days, 21 hours, 38 minutes or 4178 minutes
Total Time due to delay	1day 15hrs 19min or 2359 minutes

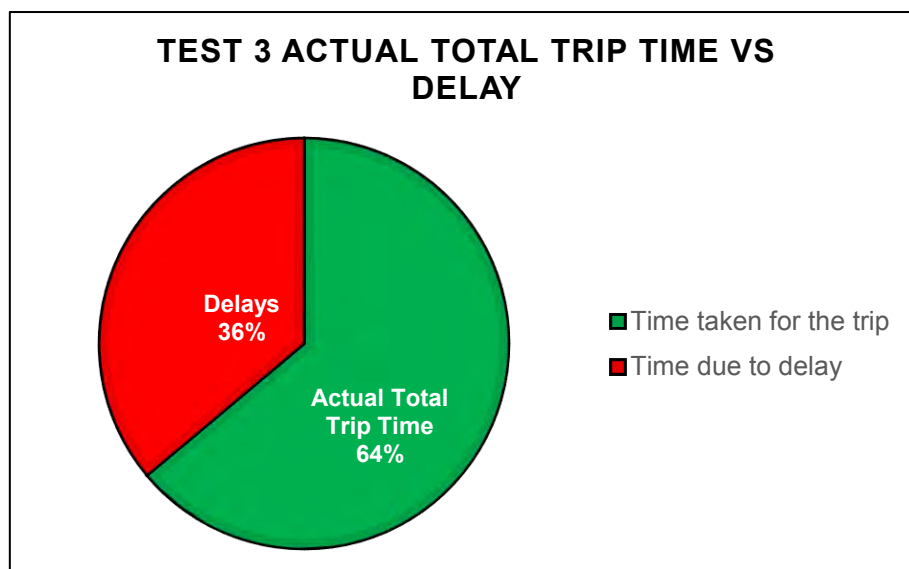


Figure 6-19: Experiment 3 actual trip vs delay during trip chart

Field Test 4

Table 6-4: Experiment 4 breakdown of events

Date	Time of Waiting, Reason and Place	Event / Time waiting
17/10/2014 to 17/10/2014	11am finished loading at Loading Point and departed by Lonrho 17:00pm	Reefer loaded with cargo 6 hours, 38 minutes 398 minutes
Night 18/10/2014 to 18/10/2014	12am to 8h50 am Arrived @ Grobler's Bridge 12 am and waited to cross to the border at 8h50	8hr or 50min or 530 minutes
18/10/2014 to 18/10/2014	8:50 am to 12:45pm Waiting @ Grobler's Bridge	3 hours, 55 minutes 235 minutes
Night 19/10/2014 to 19/10/2014	Standing at Garage at Kazangula 3am to 6am	3hrs or 180min
19/10/2014 to 20/10/2014	8:11am – 17:00pm Arrival at Kazangula Ferry and crossing the next day	1 day, 8 hours, 49 minutes 1969 minutes
Night 20/10/2014 to 21/10/2014	Waiting for to pass the night @ Livingstone 20:00 pm to 6:00 am	10 hours or 600 minutes
21/10/2014	Offloading 16:20pm to 17:00 pm	40 minutes

Time taken for the trip	4 days, 5 hours, 20 minutes or 6080 minutes
Total Time due to delay	2days 17hours, 12 minutes or 3912 minutes

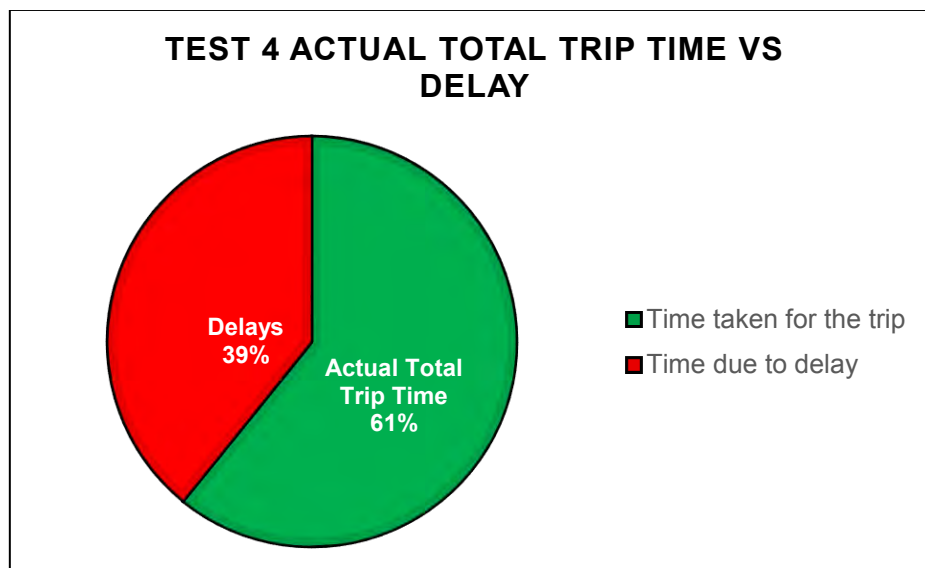


Figure 6-20: Experiment 4 time taken vs delay during trip chart

Field Test 5

Table 6-5: Experiment 5 breakdown of events

Date	Time of Waiting, Reason and Place	Event / Time waiting
31/10/2014		
01/11/2014 to 02/11/2014	17:57 pm to 07:45 am Waiting @ Grobler's Bridge	13 hours, 48 minutes 828minutes
Night		
03/11/2014 to 03/11/2014	09:17am – 19:03pm Arrival at Kazangula Ferry and crossing the next day	9 hours, 46 minutes 586 minutes
Night		
04/11/2014	Offloading 13:30pm to 15:30 pm	2hrs or 120 minutes
Time taken for the trip	2 days, 19 hours, 33 minutes or 4053 minutes	
Total Time due to delay	1 day 1hour 34minutes or 1534minutes	

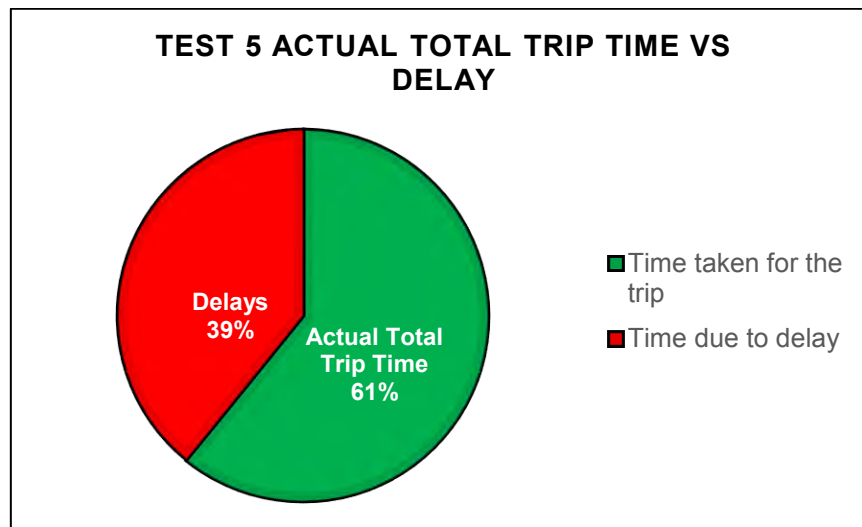


Figure 6-21: Experiment 5 time taken vs delay during trip chart

Appendix D: Field Tests Results Analysis Visualization

Experiment 2 Average temperature graphs behaviour within the trailer at tier levels

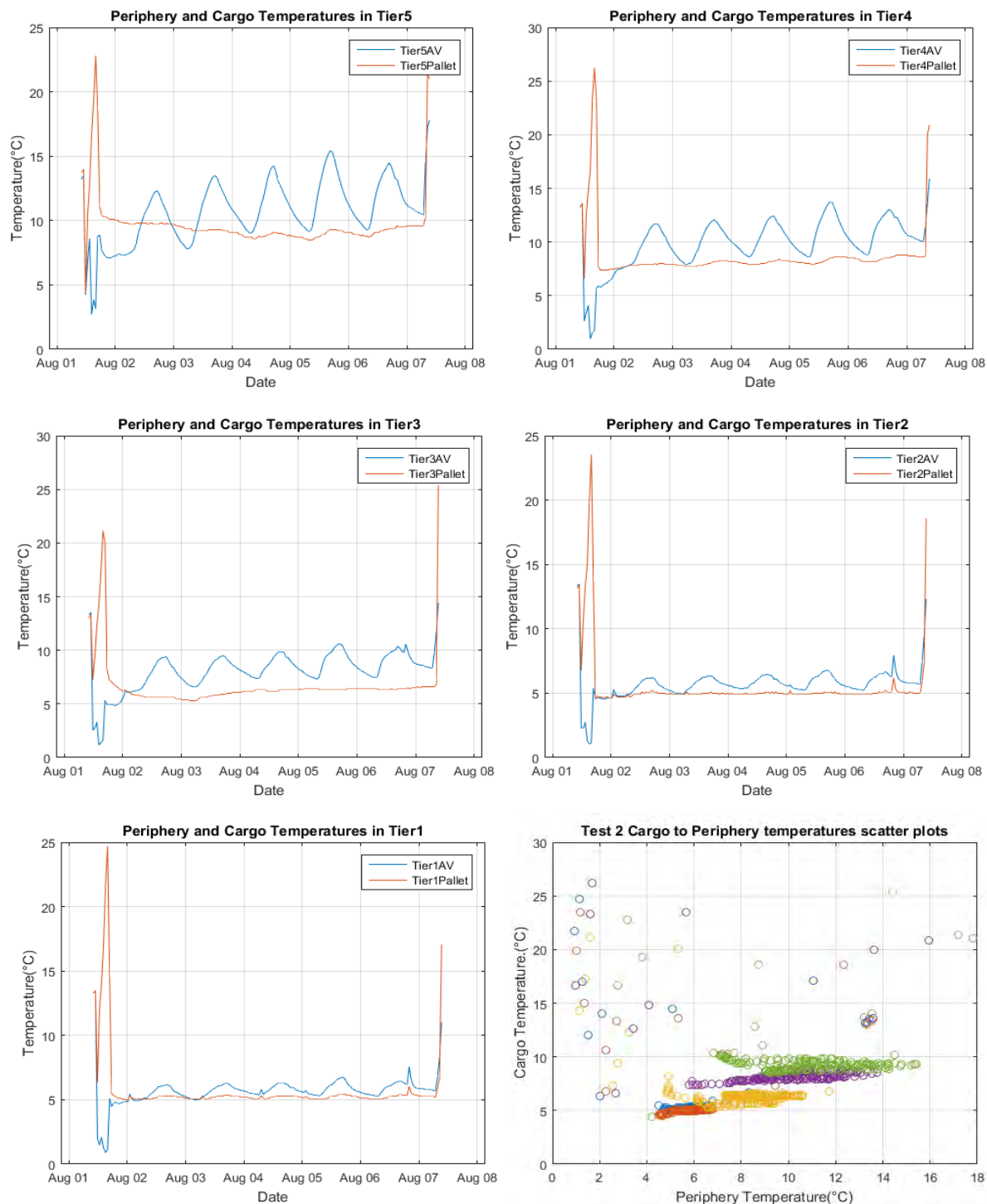


Figure 6-22: Average Temperature behaviour within the trailer at tier level in test2

The set point temperature was 5°C. The total time delay was 45% of the total time during the experiment.

From the experiment 2 above, the temperature profiles depict different behavioural tendencies of the cargo and periphery sensors. The beginning of the pallet profiles in the graphs shows pre-configured data sensors waiting to be embedded within cargo at the right time. The beginning of the Tiers profiles temperatures shows decrease in temperature because the reefer container was switched on and the temperature cooled down. In some tiers the temperatures were high due to the reefer been opened and closed during the voyage. The driver purchased some additional cargo that needed to be cooled hence he had to opened the reefer.

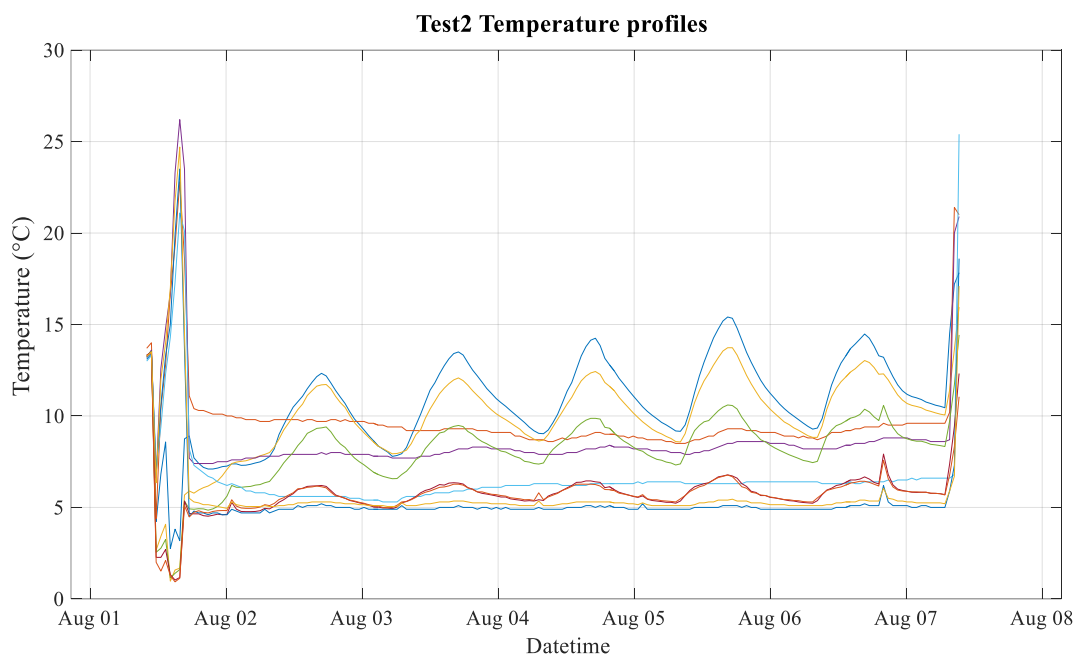


Figure 6-23: Experiment 2 complete trip time based plots

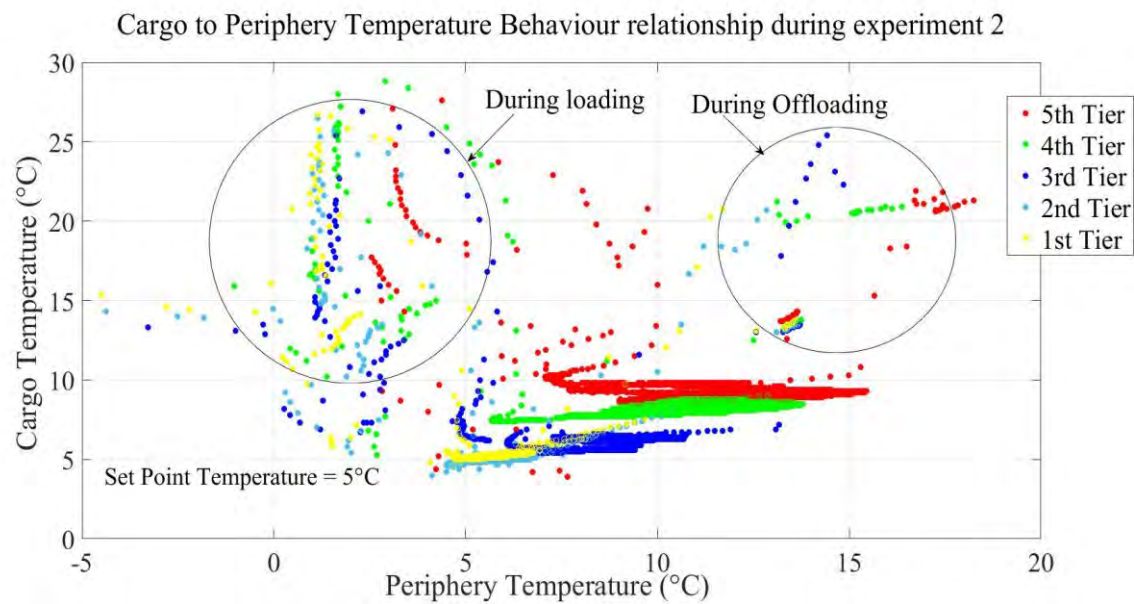


Figure 6-24: Experiment 2 complete trip scatter plot

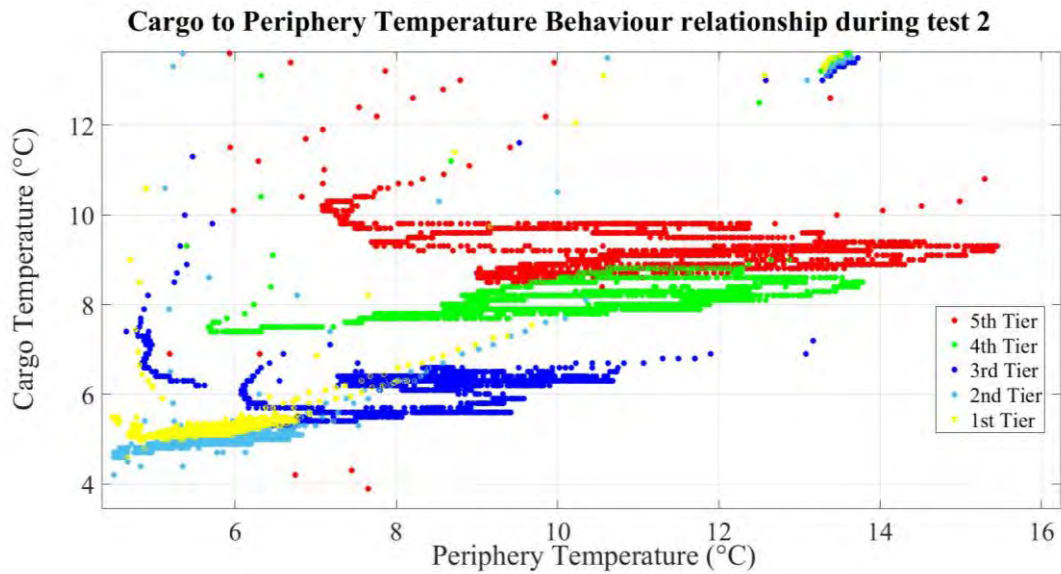


Figure 6-25: Experiment 2 complete trip scatter plot zoomed-in

Experiment 2 border crossing delay event scatter plot

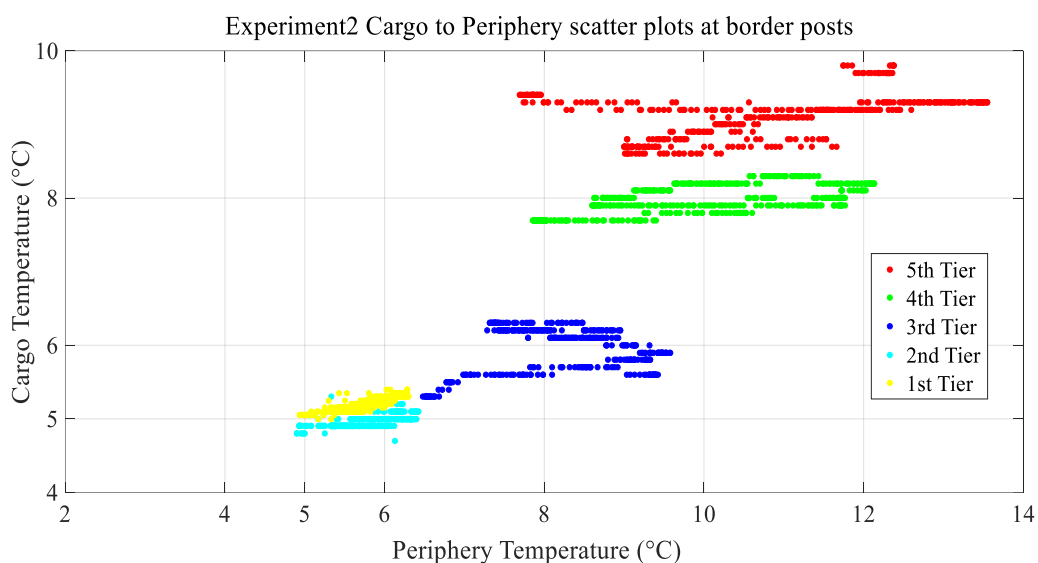


Figure 6-26: Test 2 border crossing delay event scatter plot

Experiment 2 border post delays time based temperatures plots

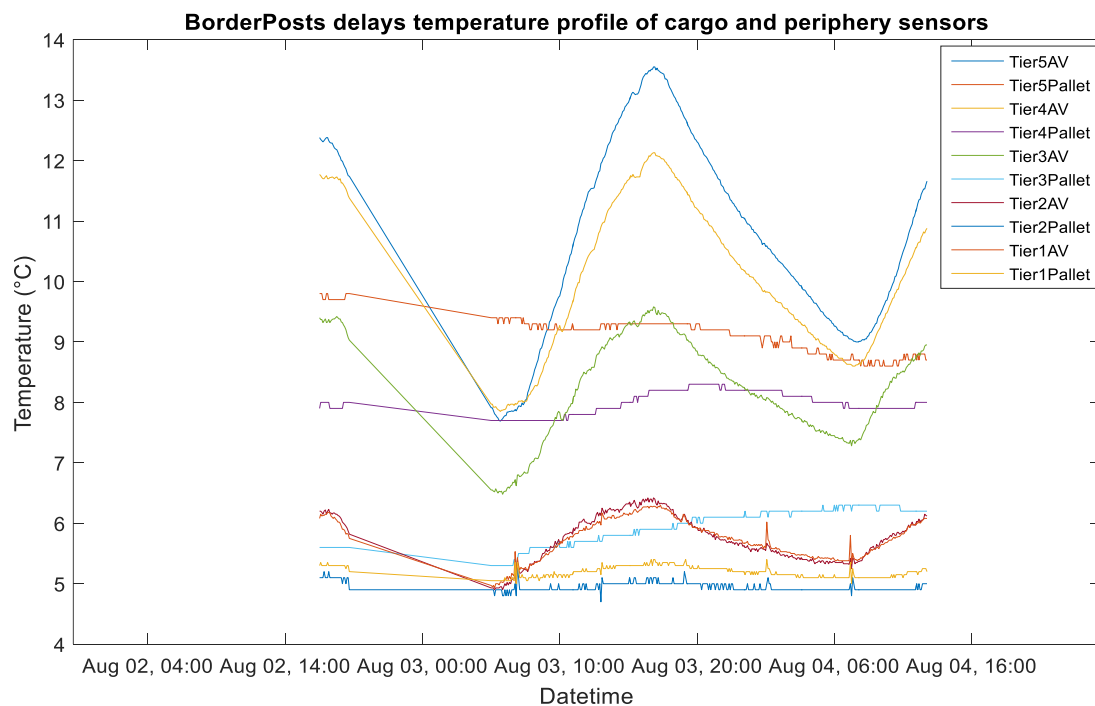


Figure 6-27: Test 2 border post delays time based temperatures plots

Experiment 3 Average temperature graphs behaviour within the trailer at tier levels

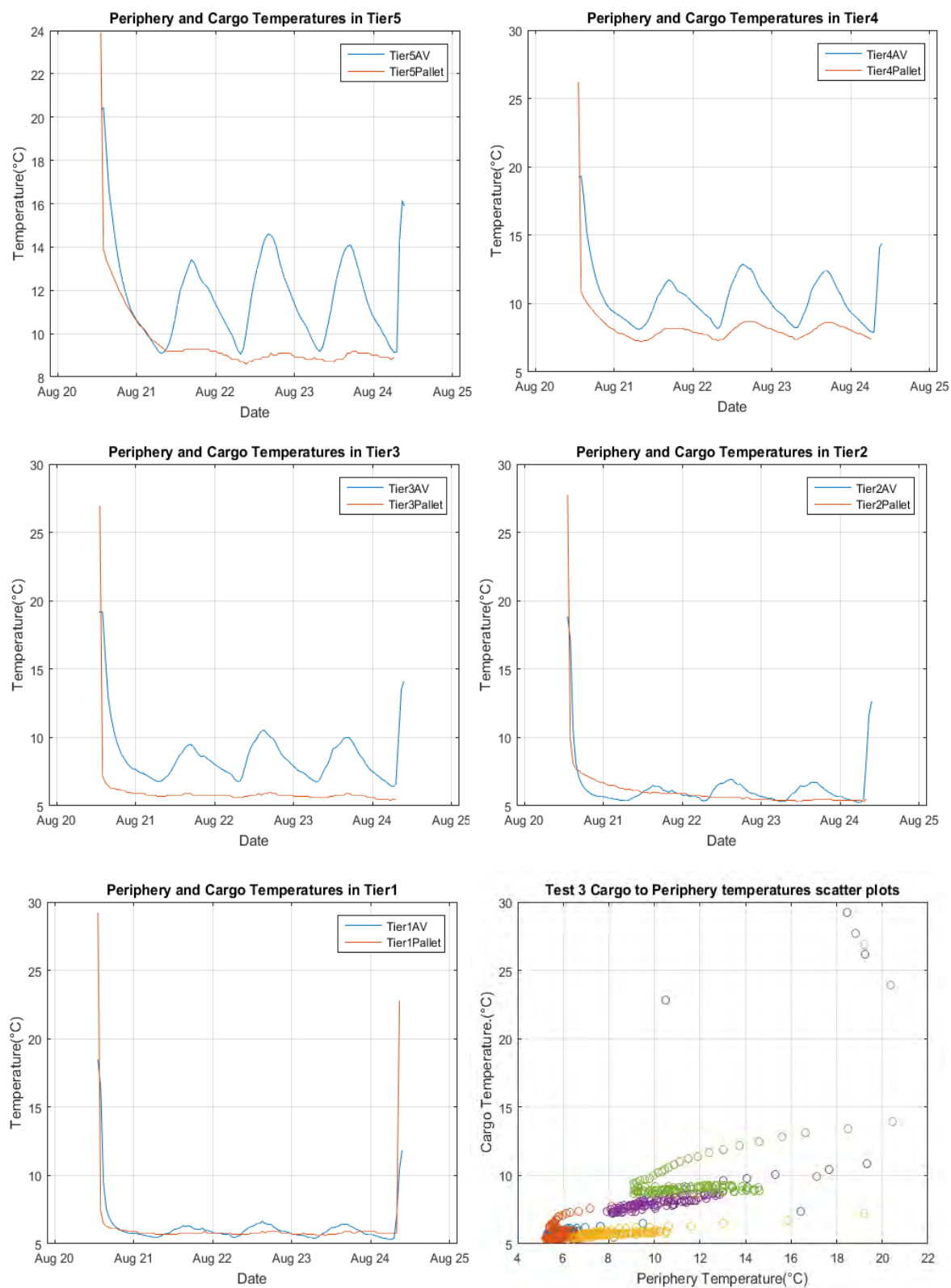


Figure 6-28: Temperature behaviour within the trailer at tier level in test3

The set point temperature was 5°C. The total delay was 36% of the total experiment time.

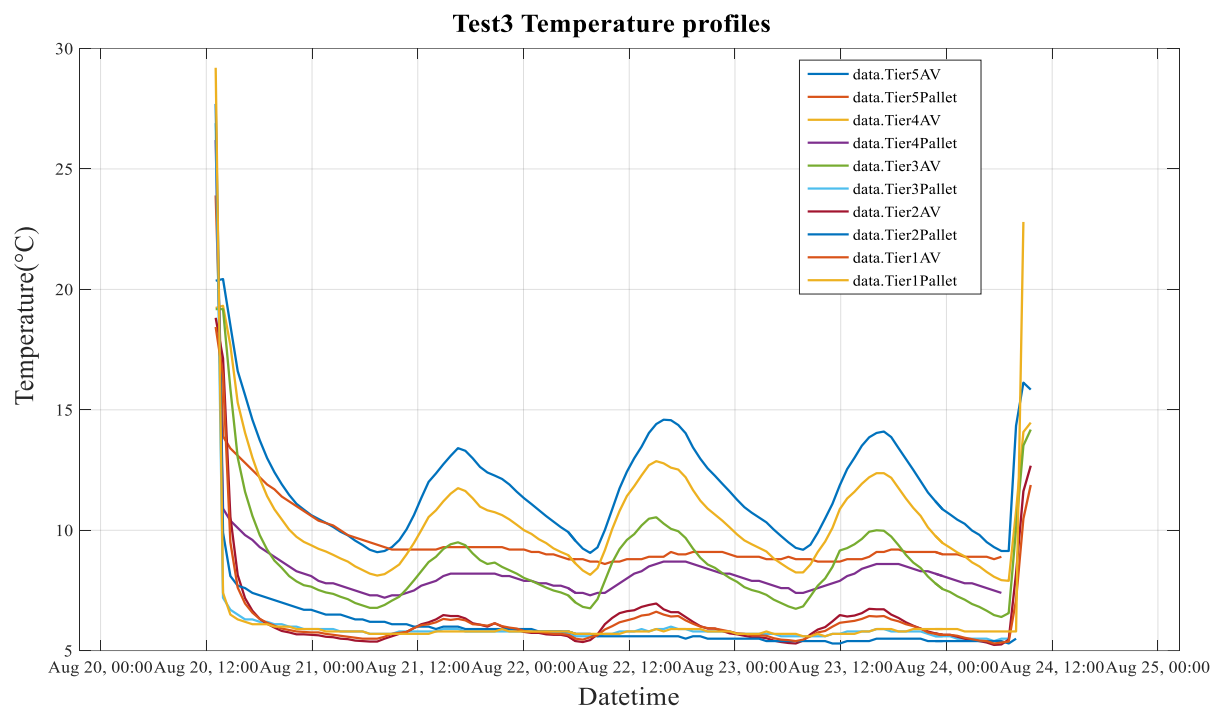


Figure 6-29: Experiment 3 complete trip time based plots

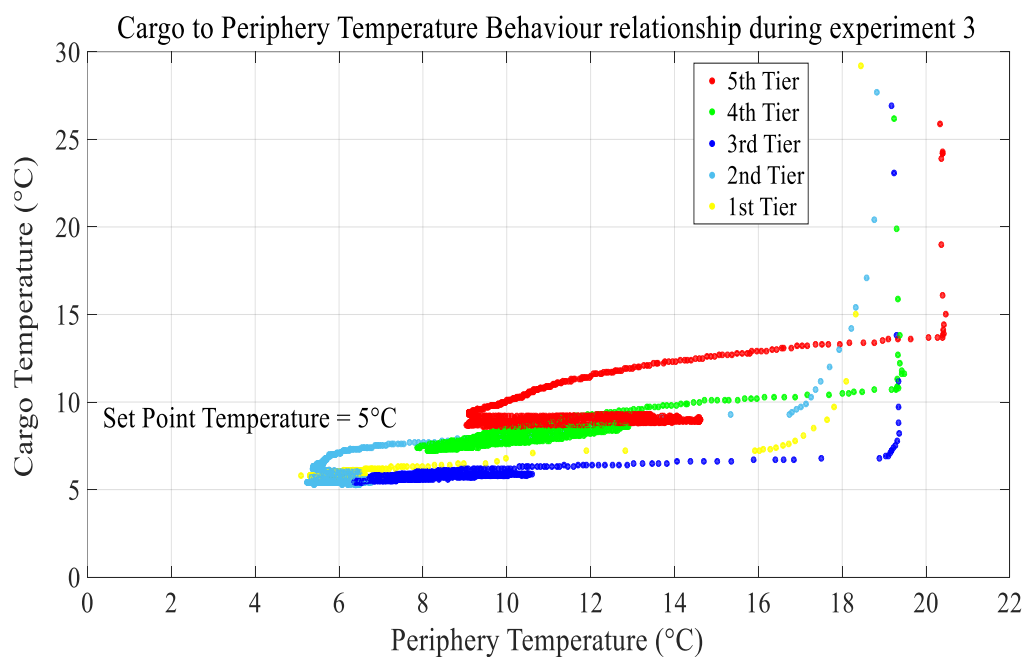
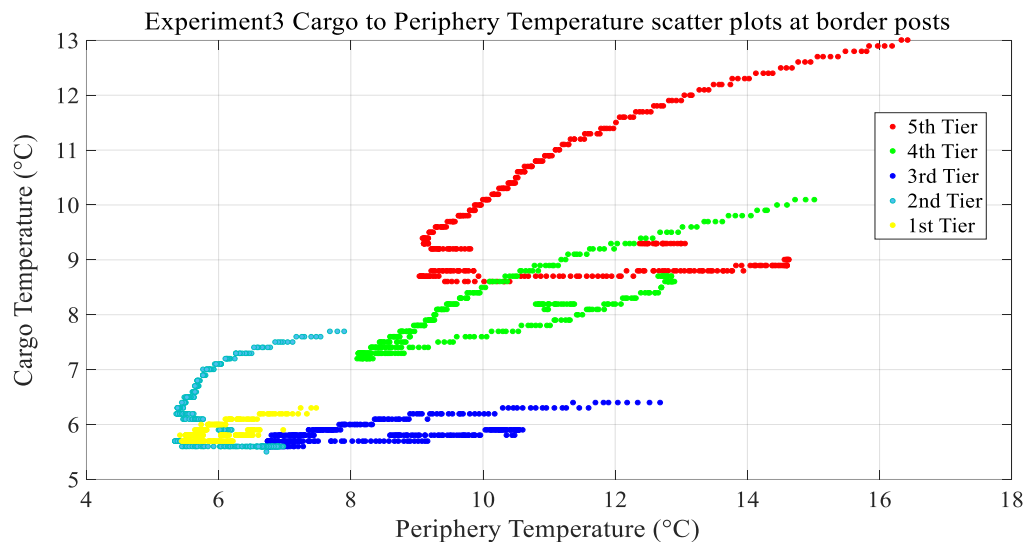
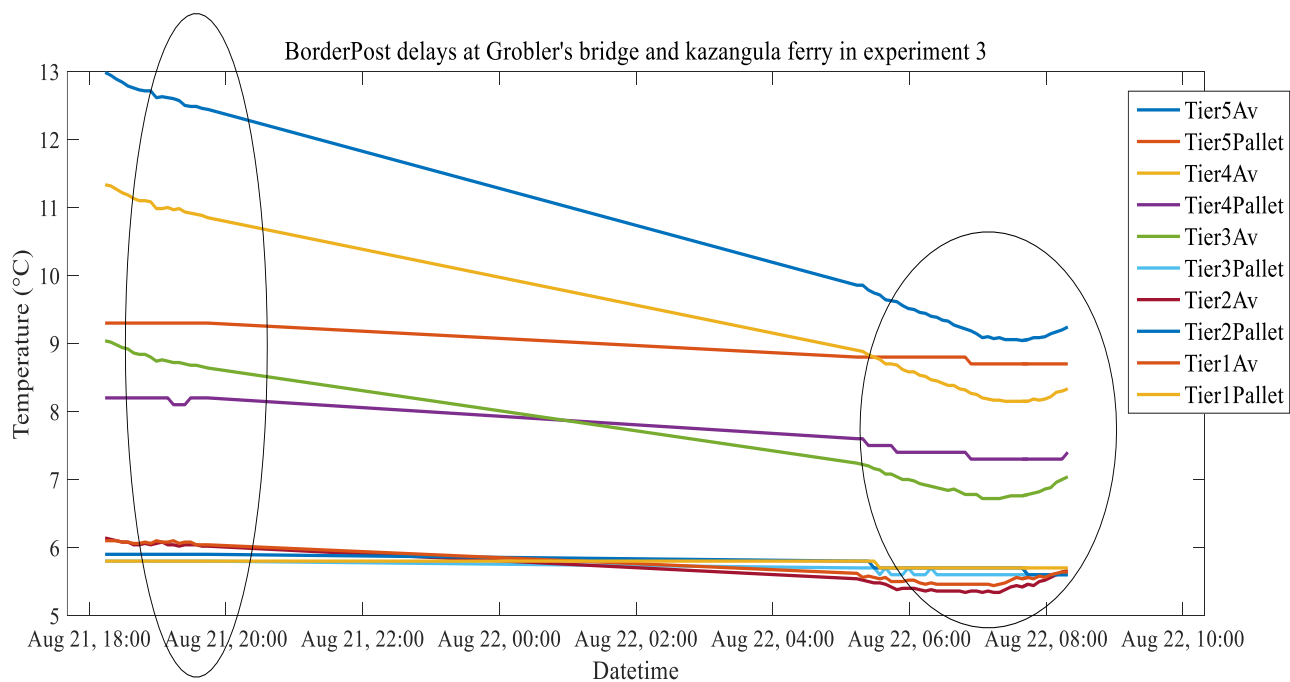
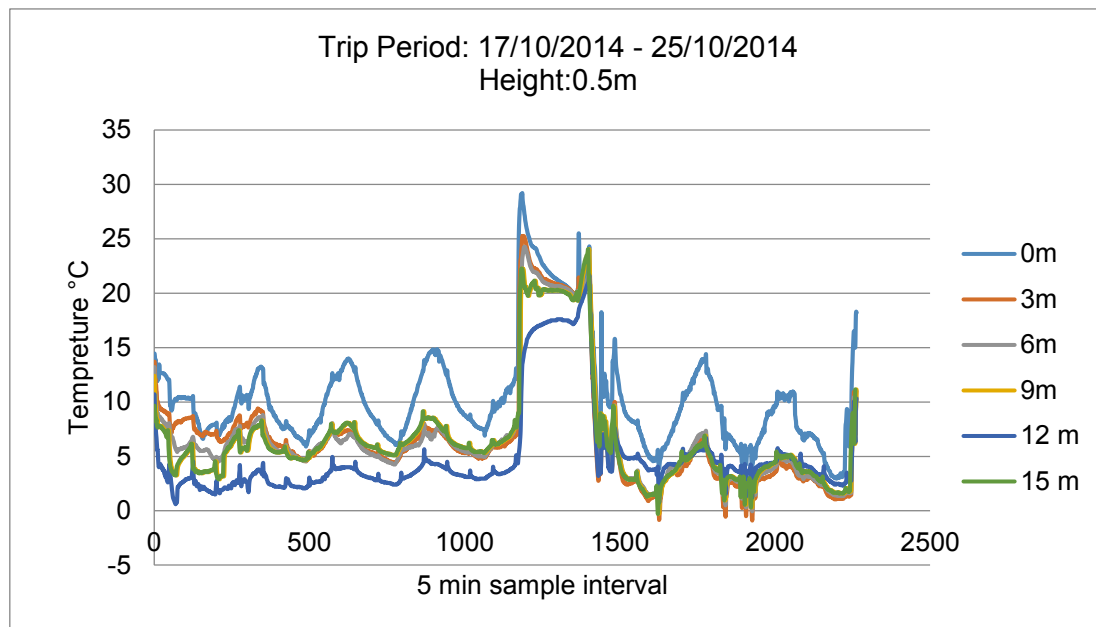
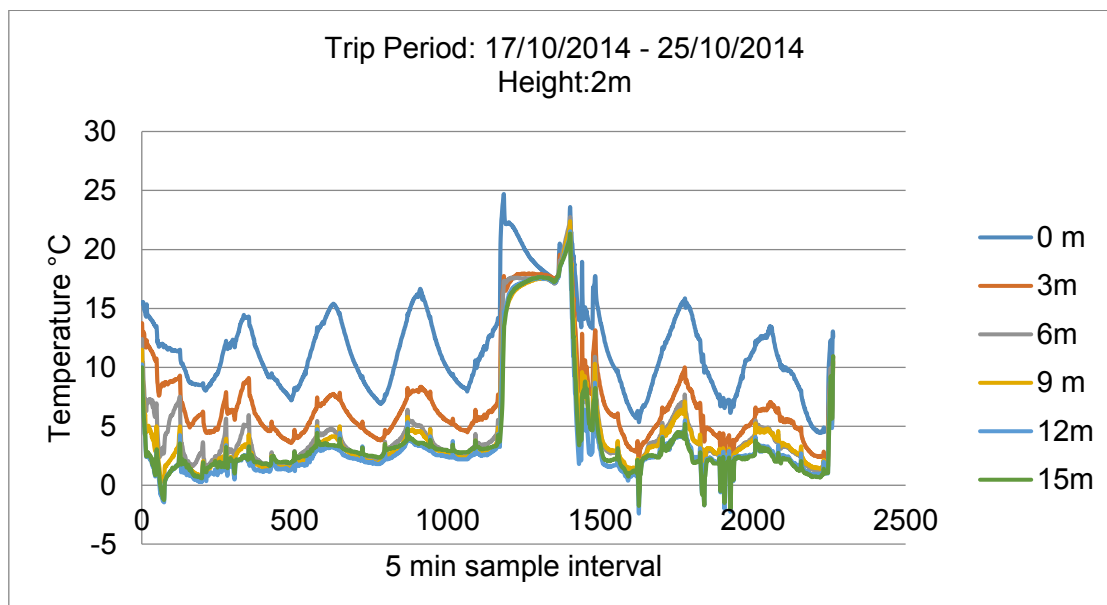


Figure 6-30: Experiment 3 complete trip scatter plots

Experiment 3 border crossing delay event scatter plot**Figure 6-31: Test 3 border crossing delay event scatter plot****Experiment 3 border post delays time based temperatures plots****Figure 6-32: Test 3 border post delays time based temperatures plots**

Complete experiment 4 Johannesburg to Lusaka 17th to 25th.10. 2014**Periphery Average temperature vs. time graphs****Figure 6-33: Average temperature time graphs at height 0.5m in the trailer****Figure 6-34: Average temperature time graphs at height 2m in the trailer**

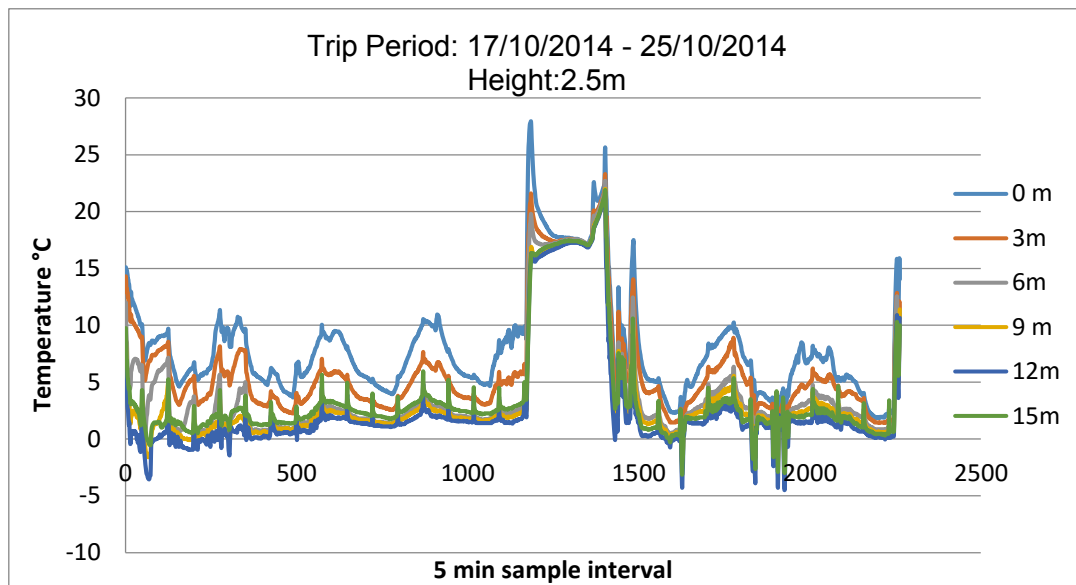


Figure 6-35: Average temperature time graphs at height 2.5m in the trailer

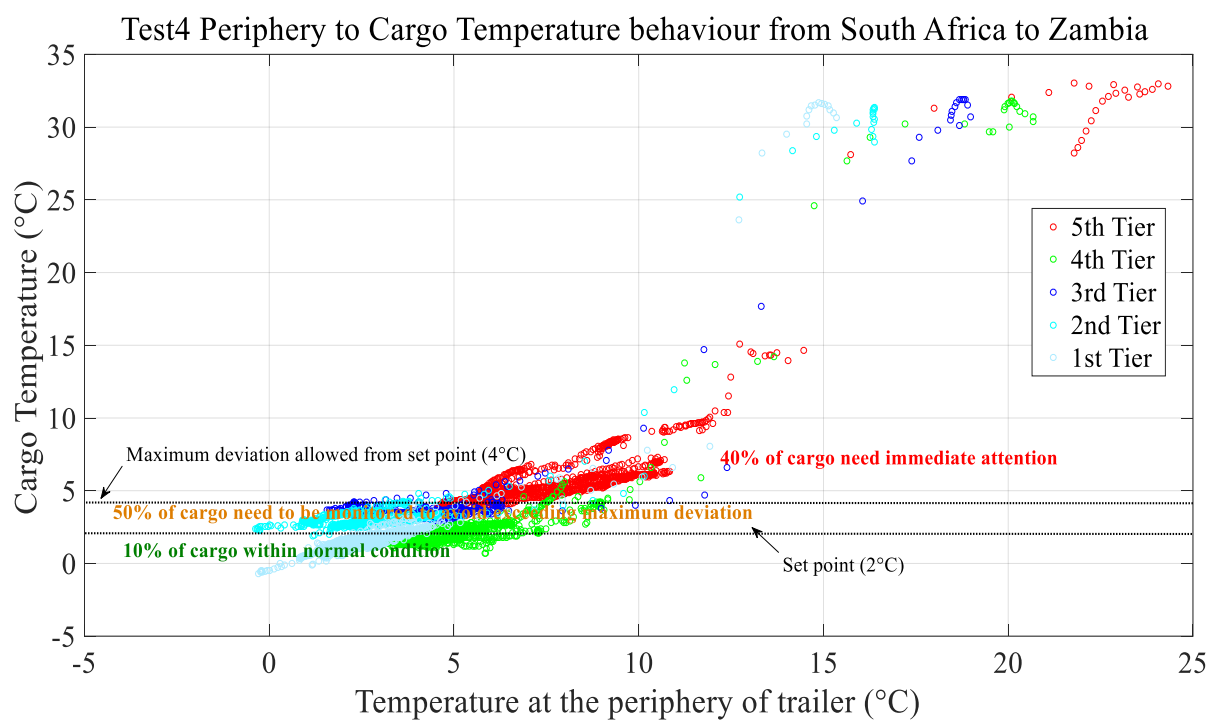


Figure 6-36: Scatter plot temperature behaviour at all 5 tiers in the trailer

Percentage deviation during transportation relative to allowed temperature range

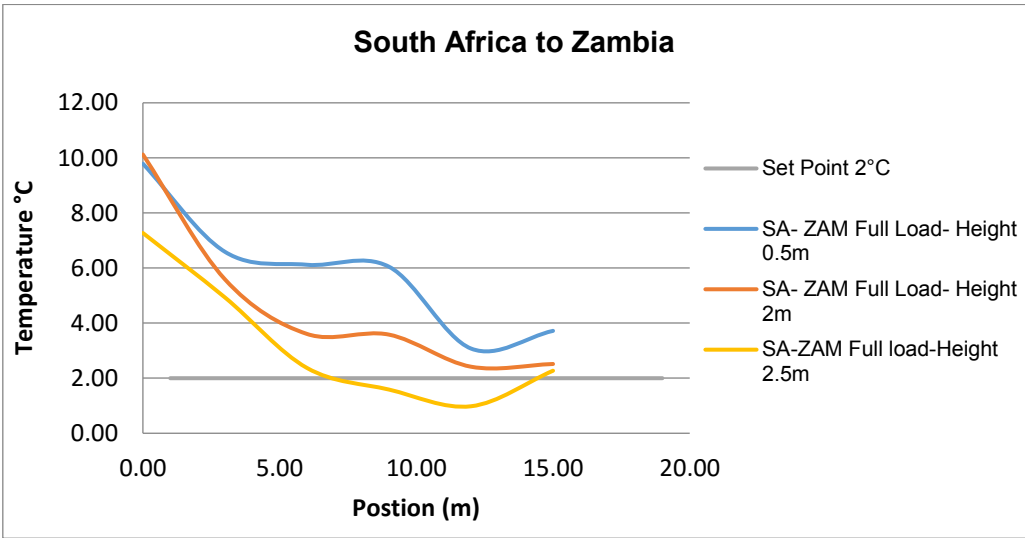


Figure 6-37: South Africa to Zambia Percentage deviation from set point temperature

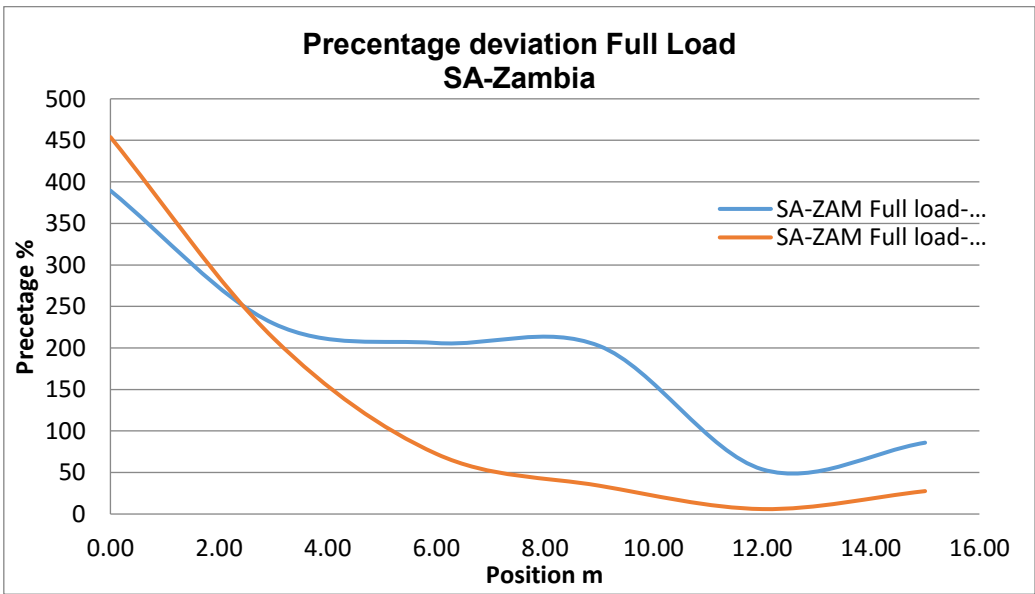


Figure 6-38: Zambia to South Africa Percentage deviation from set point temperature

The graph above shows lower percentage at the vent (15.00m) and higher percentage increase close to the door (0.00 m).

Experiment 4 temperature graphs behaviour within the trailer at tier levels

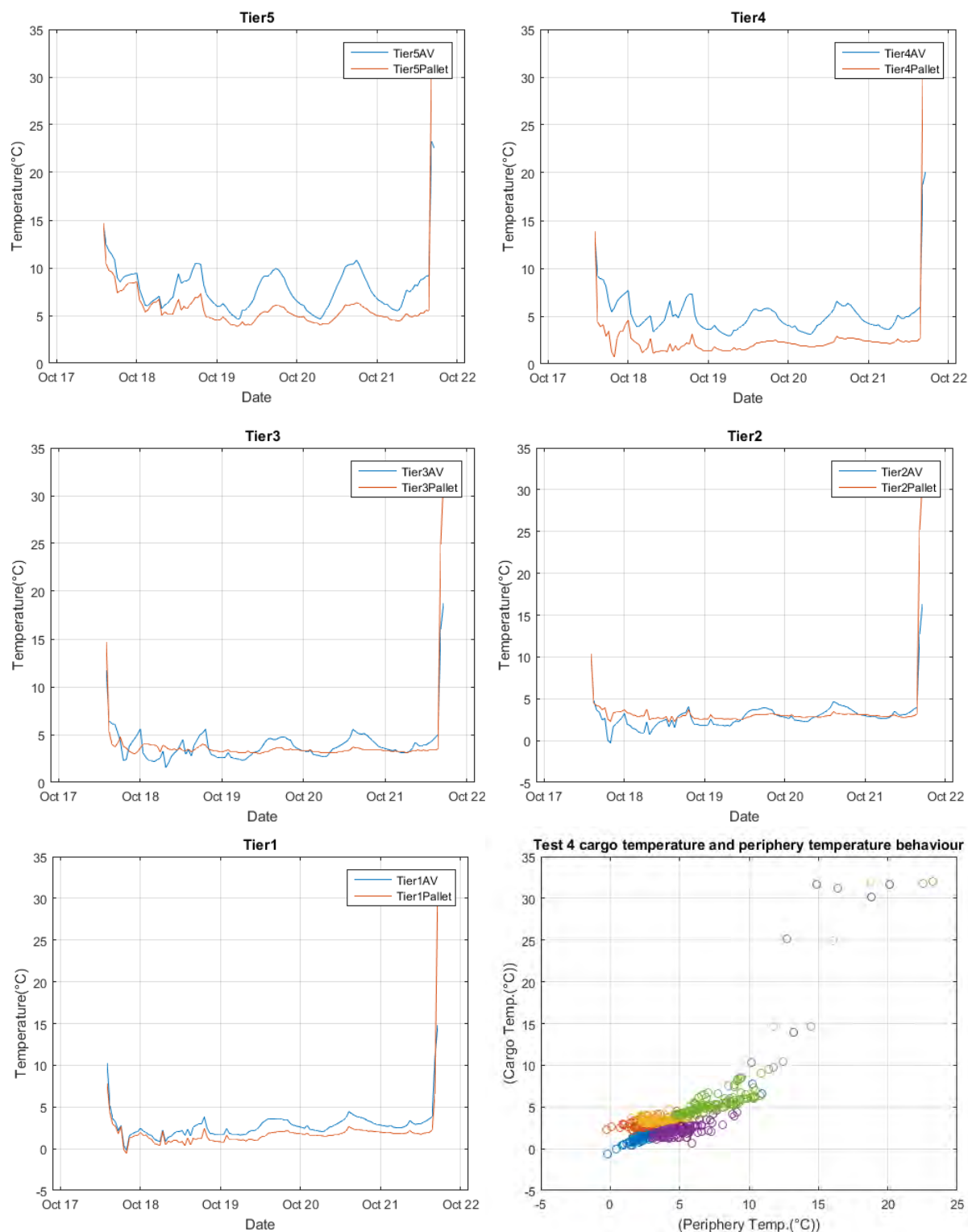


Figure 6-39: Temperature behaviour within the trailer at tier level in test4

The set point temperature was 2°C. The total time delay was 39% of the total time during the experiment

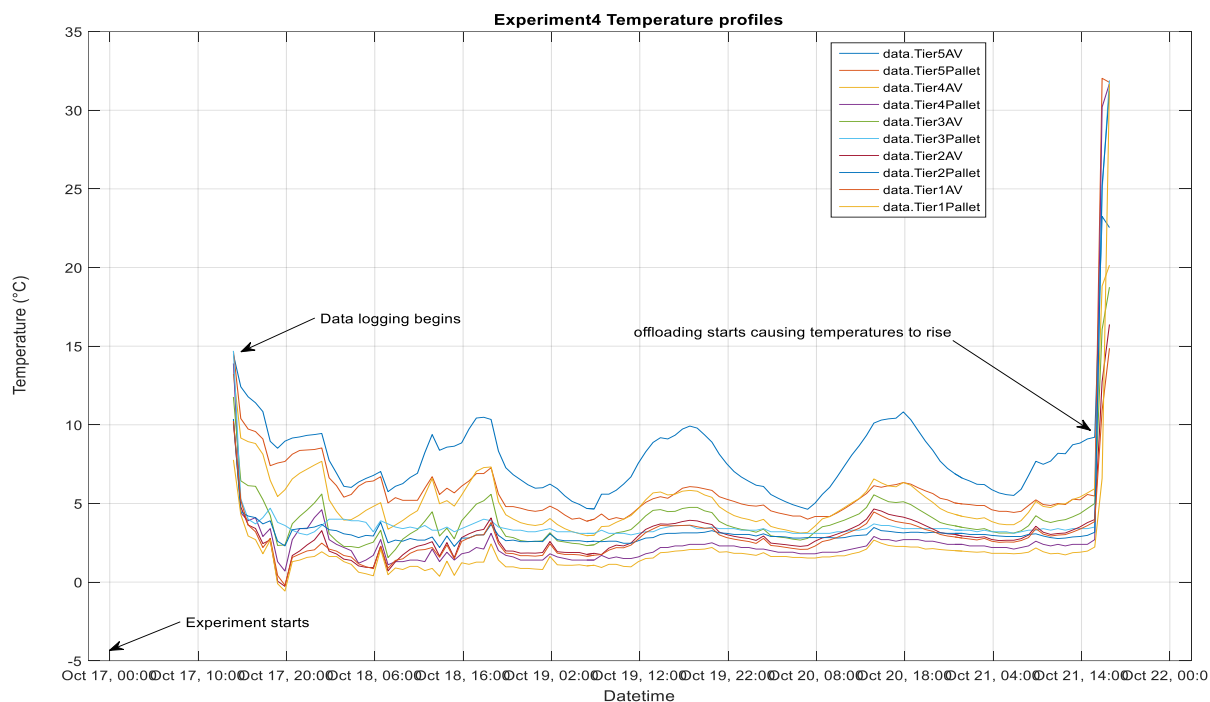


Figure 6-40: Experiment 4 complete trip time based plots

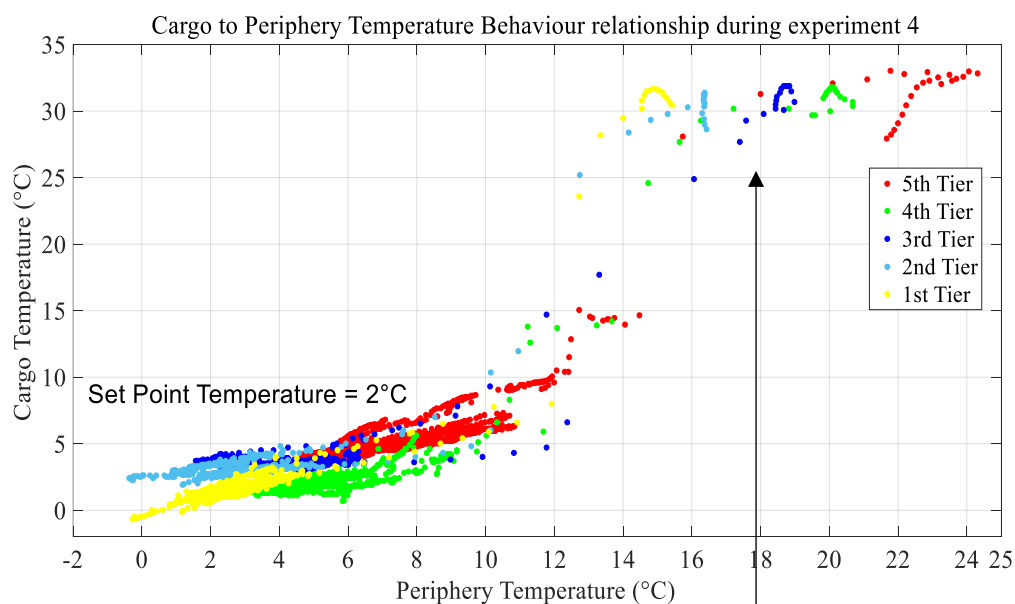


Figure 6-41: Experiment 4 complete trip scatter plots

This section depicts the temperature increase during offloading. As the doors were opened for offloading. Hence the reason why cargoes are immediately transferred in the cold room during offloading.

Test 4 border crossing delay event scatter plot

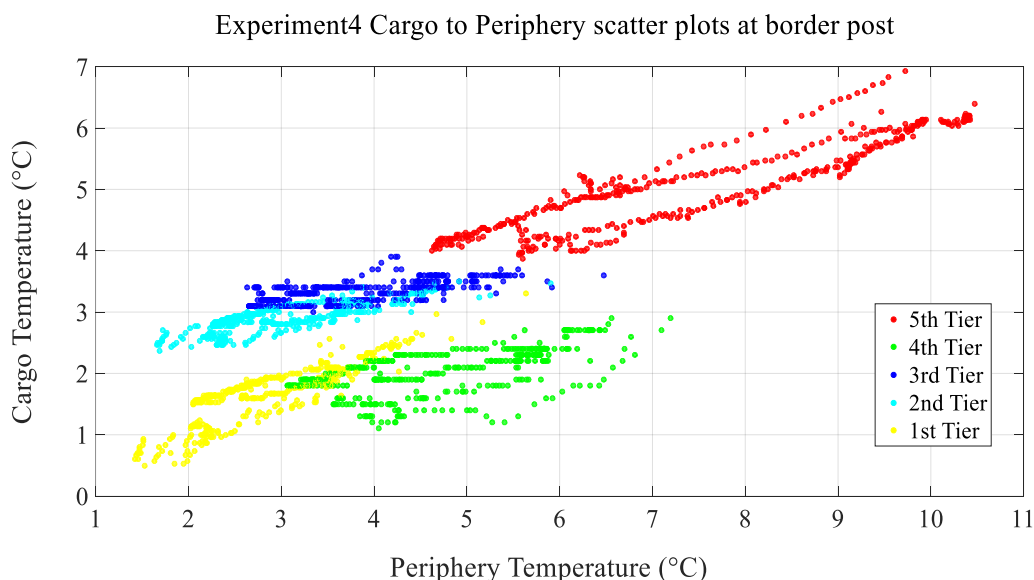


Figure 6-42: Test 4 border crossing delay event scatter plot

Test 4 border post delays time based temperatures plots

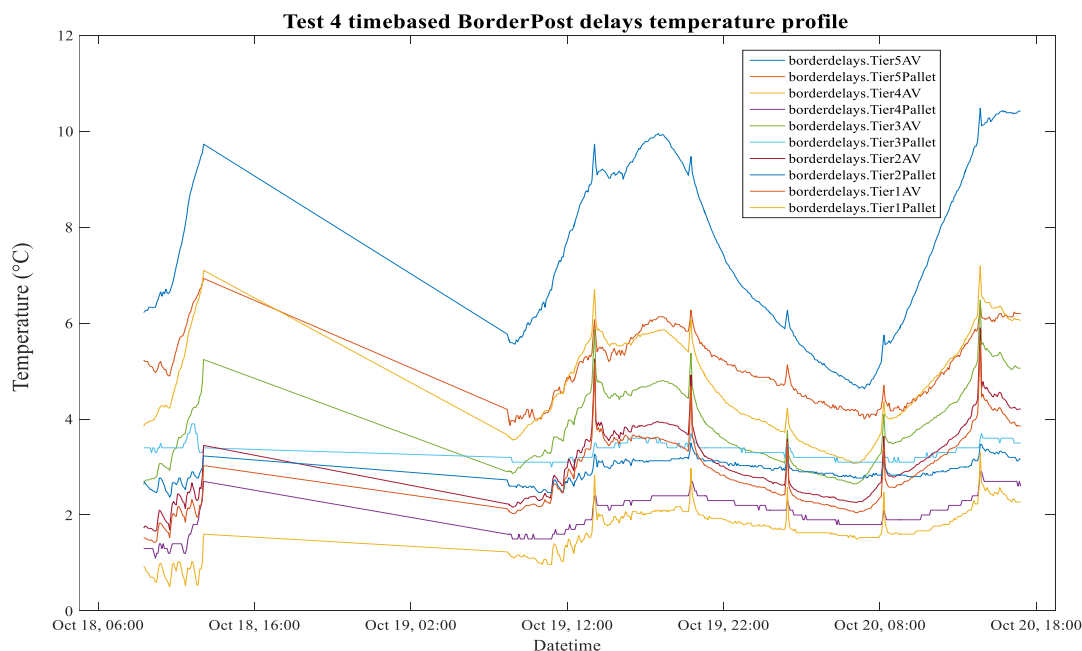


Figure 6-43: Test 4 border post delays time based temperatures plots

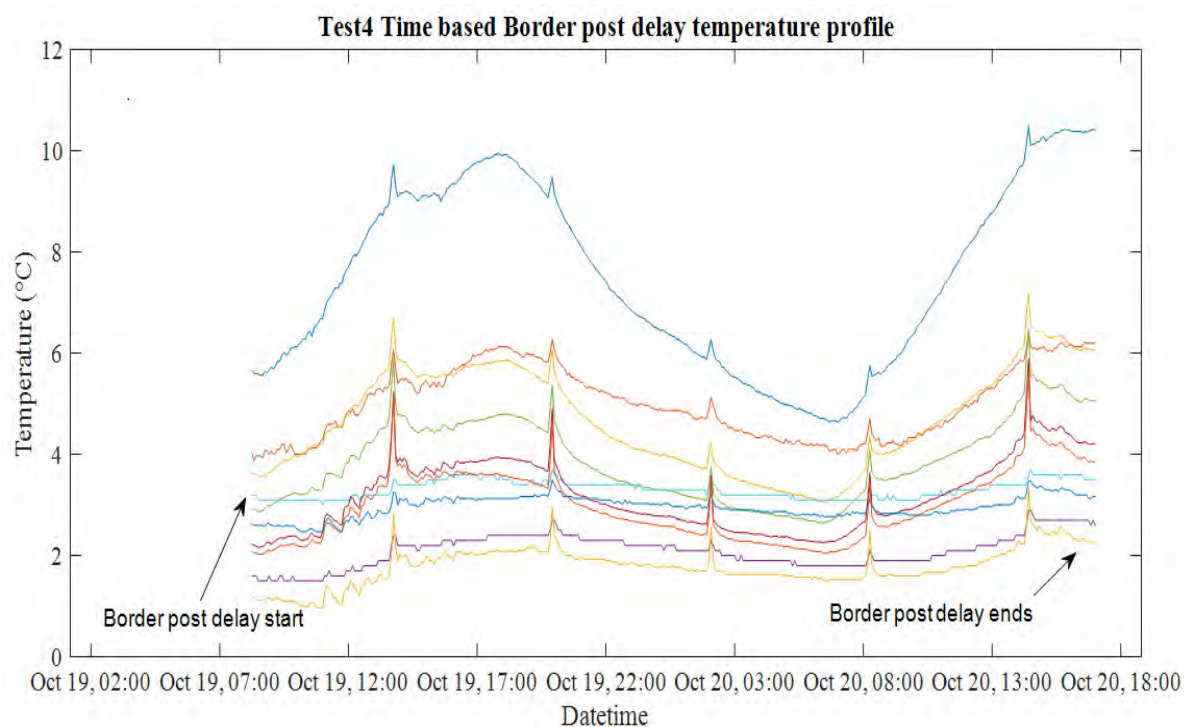


Figure 6-44: Test4 Border post indicating beginning and end of delay

Experiment 5 Johannesburg to Lusaka 31/10/2014 to 07/11/2014

Average temperature vs time graph

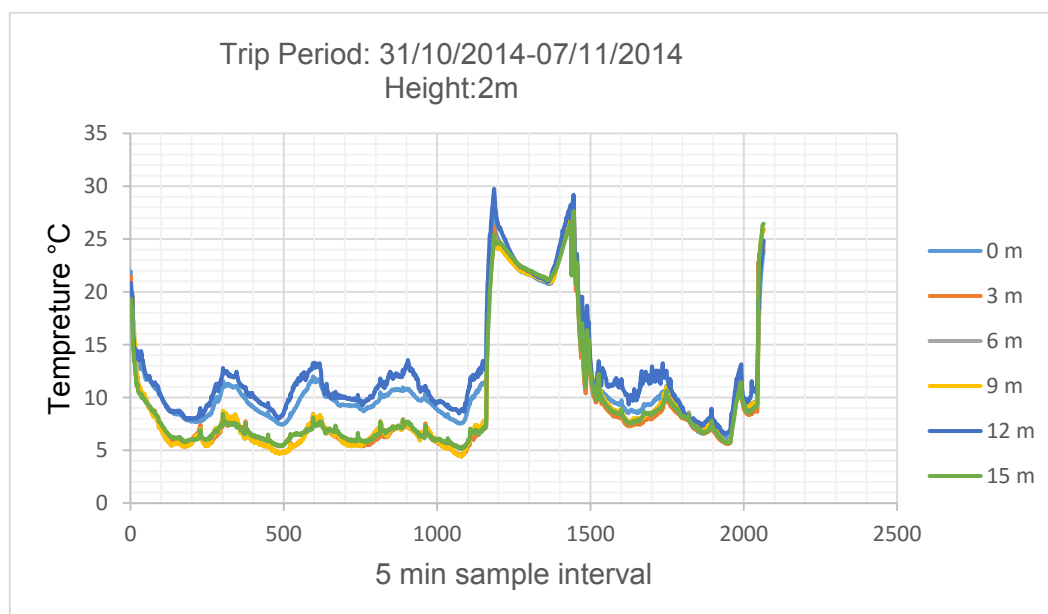


Figure 6-45: Average temperature time graphs at height 2m in the trailer

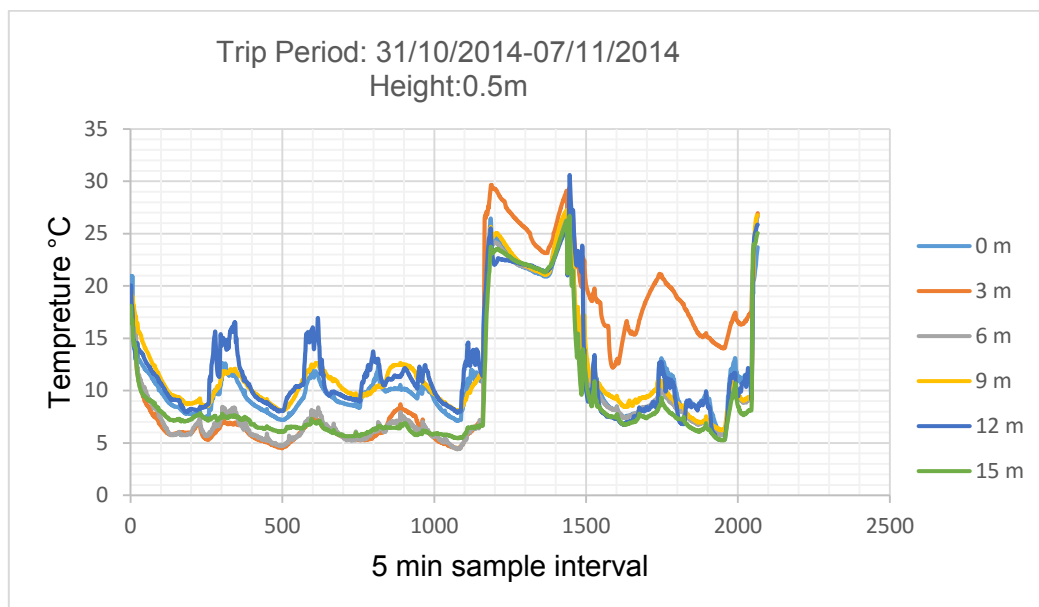


Figure 6-46: Average temperature time graphs at height 0.5m in the trailer

Percentage deviation during transportation relative to position / length of trailer

The graph below shows lower percentage at the vent (0.00m) and higher percentage increase close to the door (13 – 15 m).

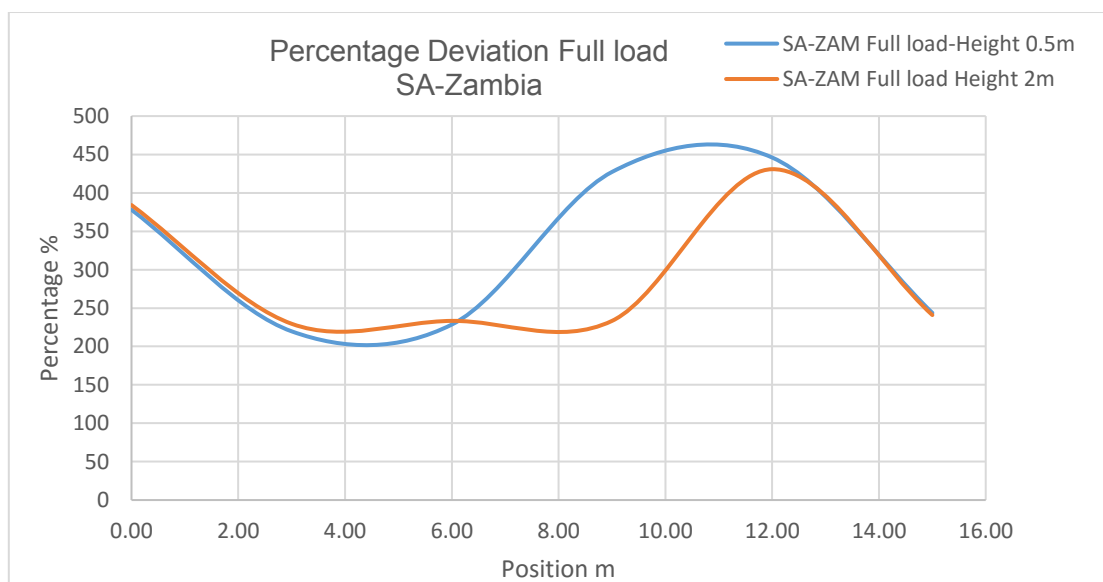


Figure 6-47: South Africa to Zambia Percentage deviation from set point temperature

Experiment 5 temperatures graphs behaviour within the trailer at tier levels

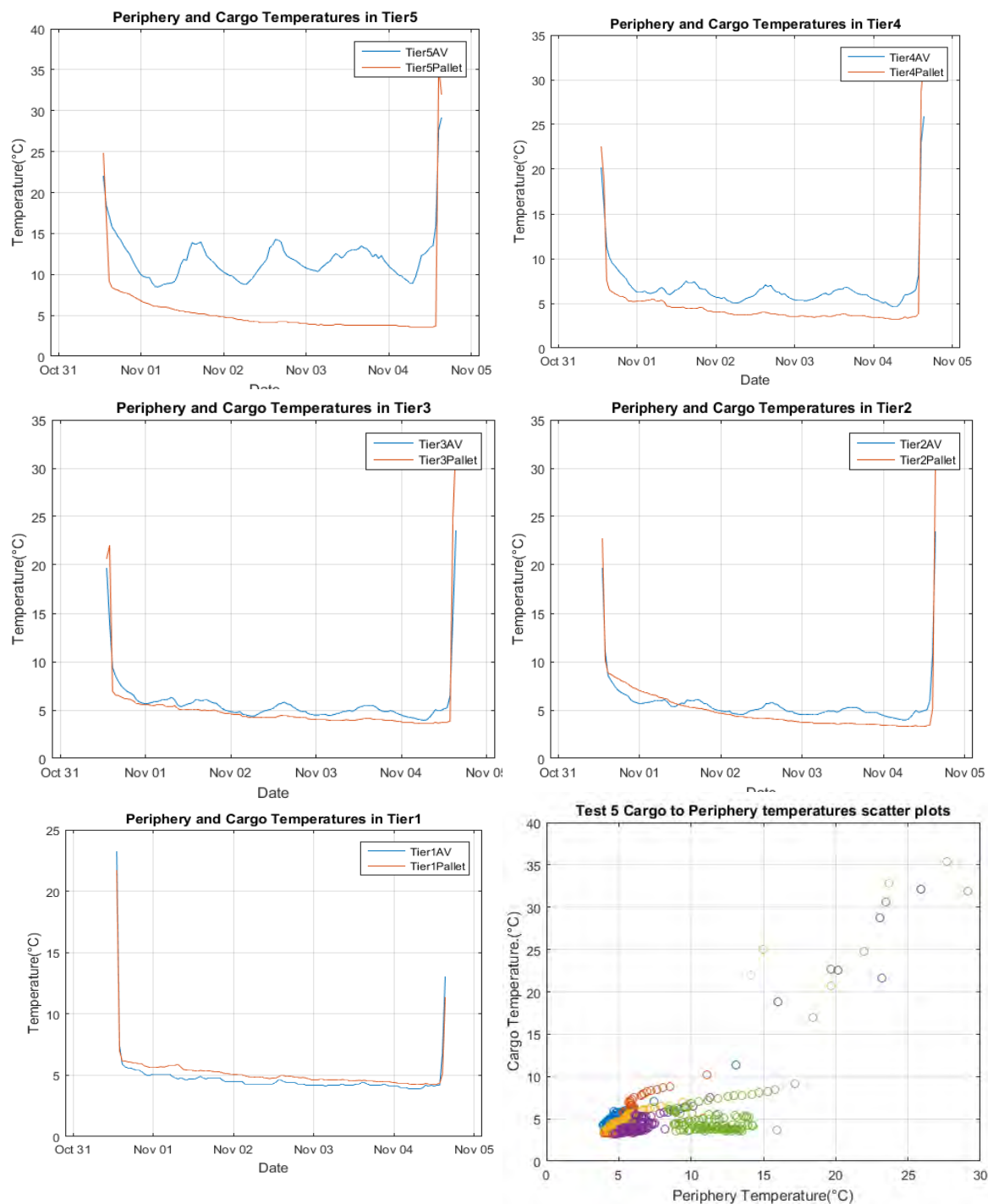


Figure 6-48: Temperature behaviour within the trailer at tier levels in test5

The set point temperature was 2°C. The total time delay was 27% of the total time during the experiment

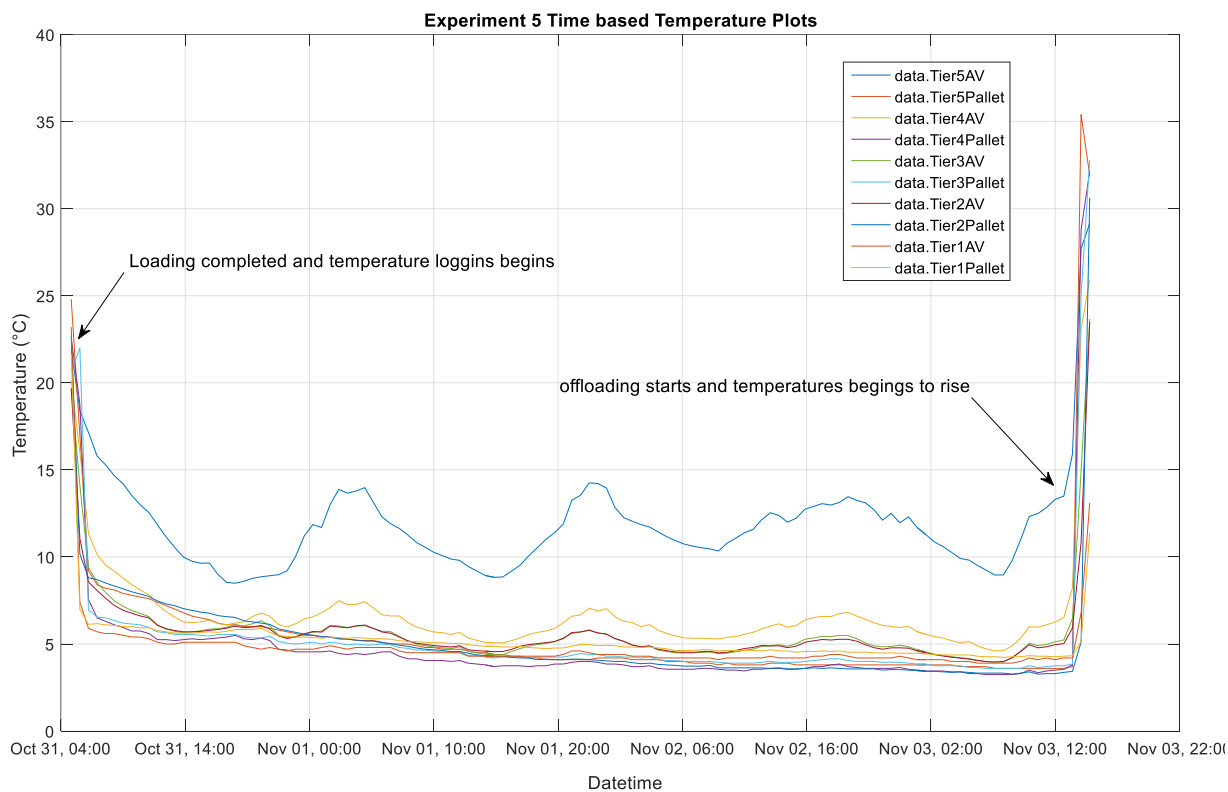


Figure 6-49: Experiment 5 complete trip time based plots

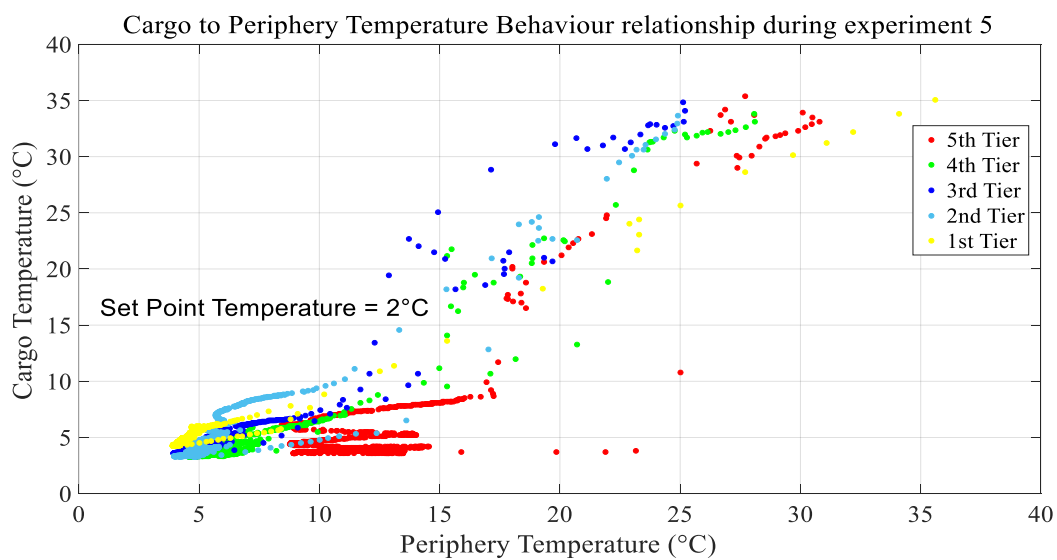


Figure 6-50: Test 5 complete trip scatter plots

From the temperature profiles above, the complete trip show similarities in the tier temperature distribution with the 5th Tier always having high temperatures while the 1st Tier having low temperature. Tests 1 to 5 are similar but with tests 1,2,3 and tests 4,5 having similar pattern. This can be attributed to the fact that test 1,2, 3 had a set point of 5°C while test 4,5 had a set point of 2°C.

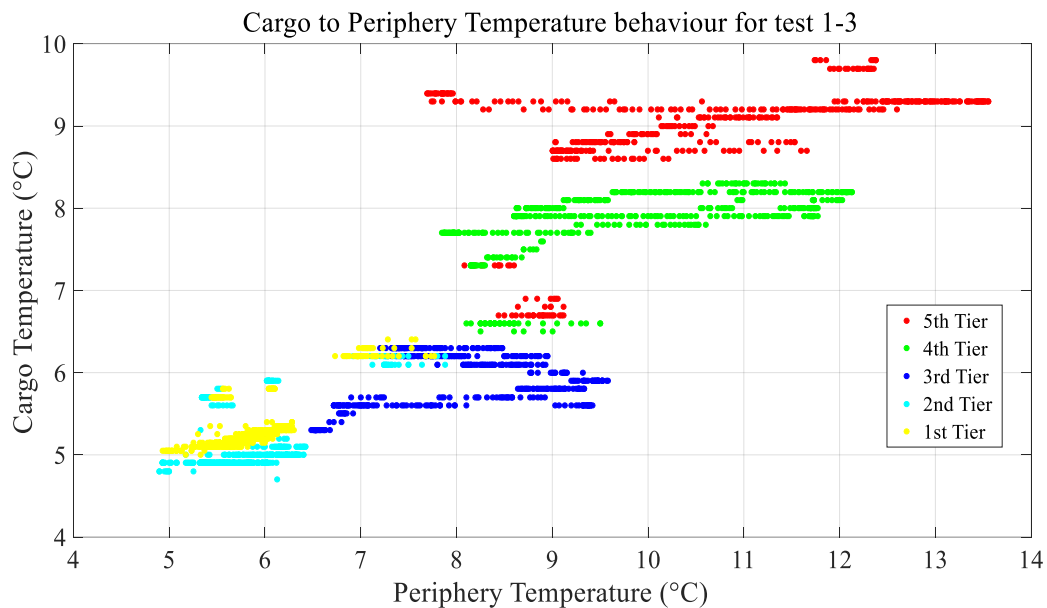


Figure 6-51: Test 1-3 complete trip scatter plots

Test 5 border crossing delay event scatter plot

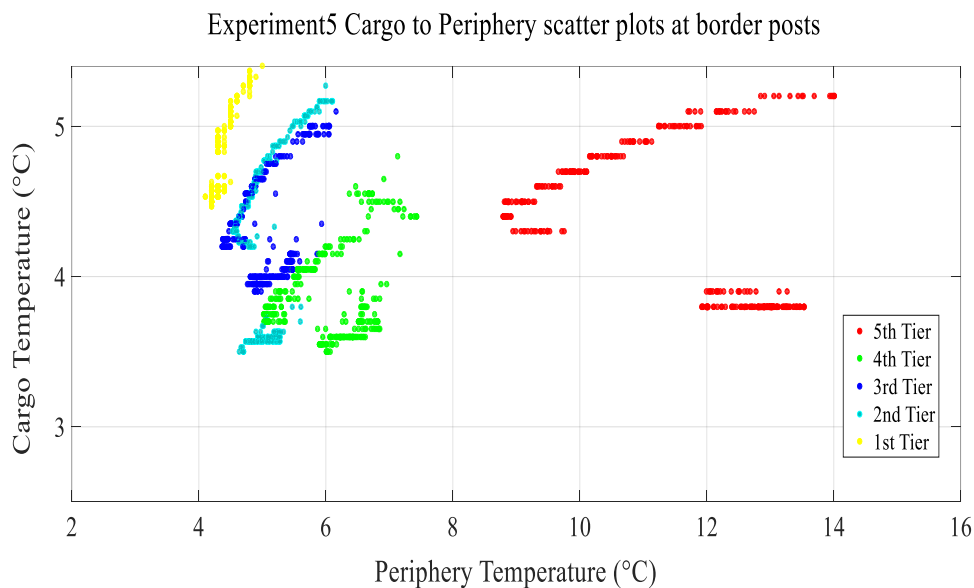


Figure 6-52: Test 5 border crossing delay event scatter plot

Test 5 border post delays time based temperatures plots

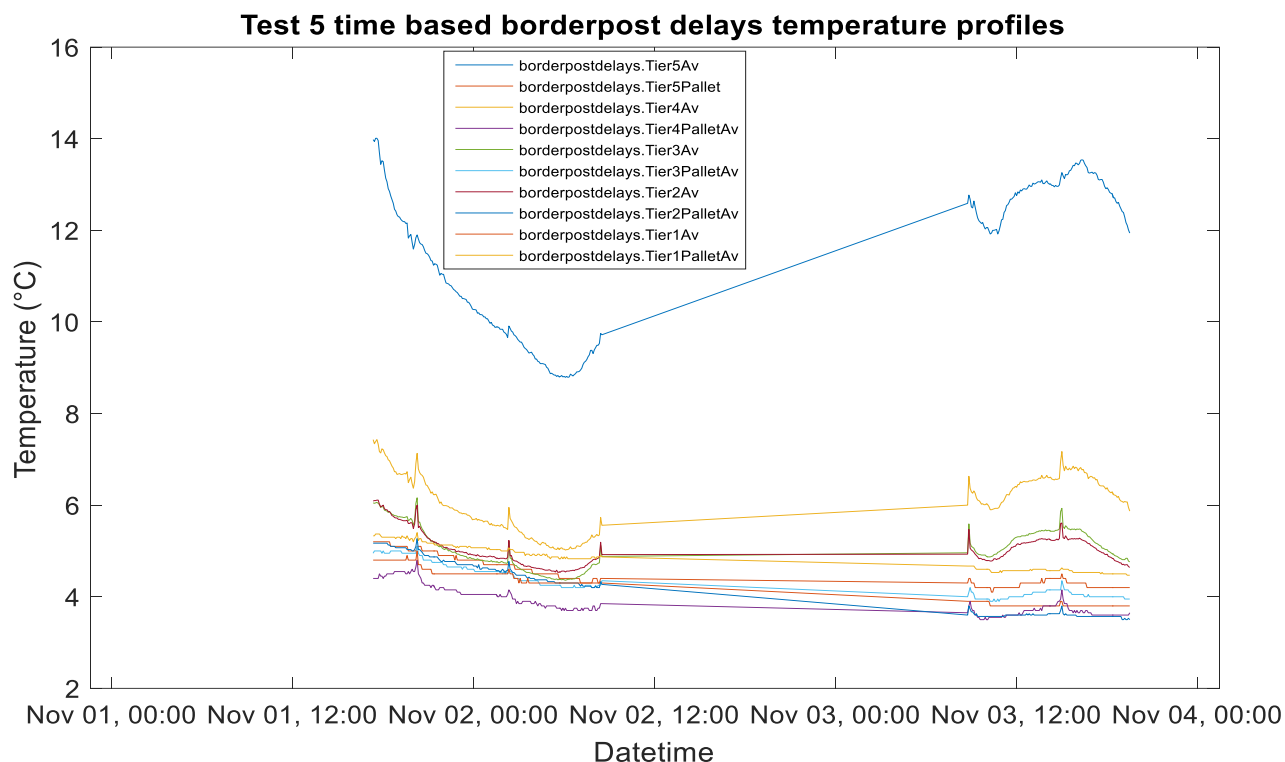


Figure 6-53: Test 5 border post delays time based temperatures plots

Tests 1,2,3 border crossing delay event scatter plots

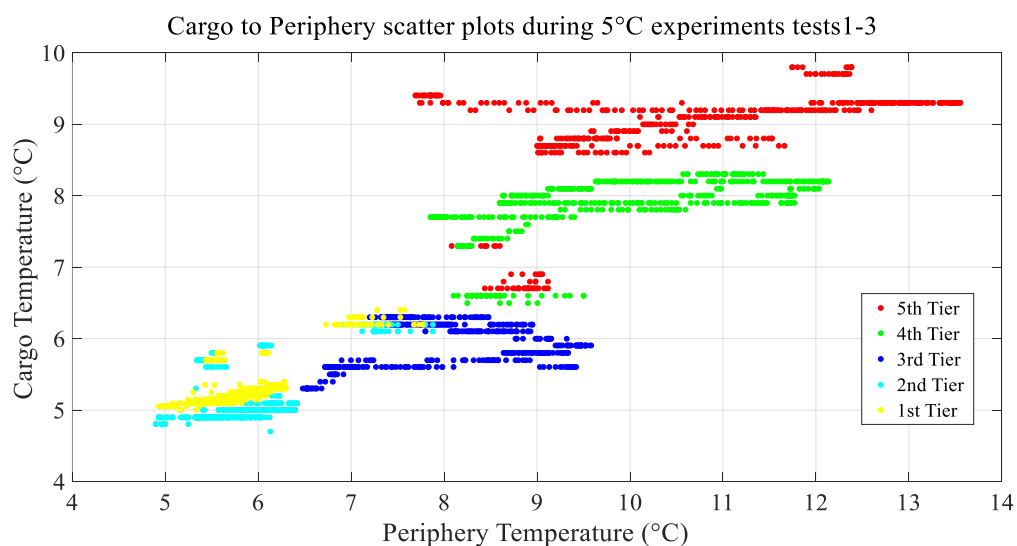
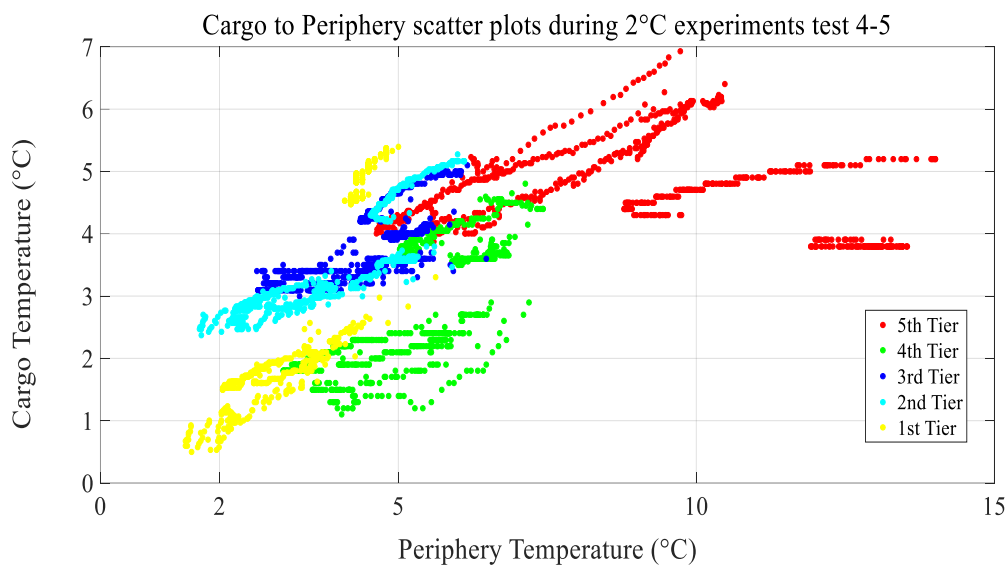
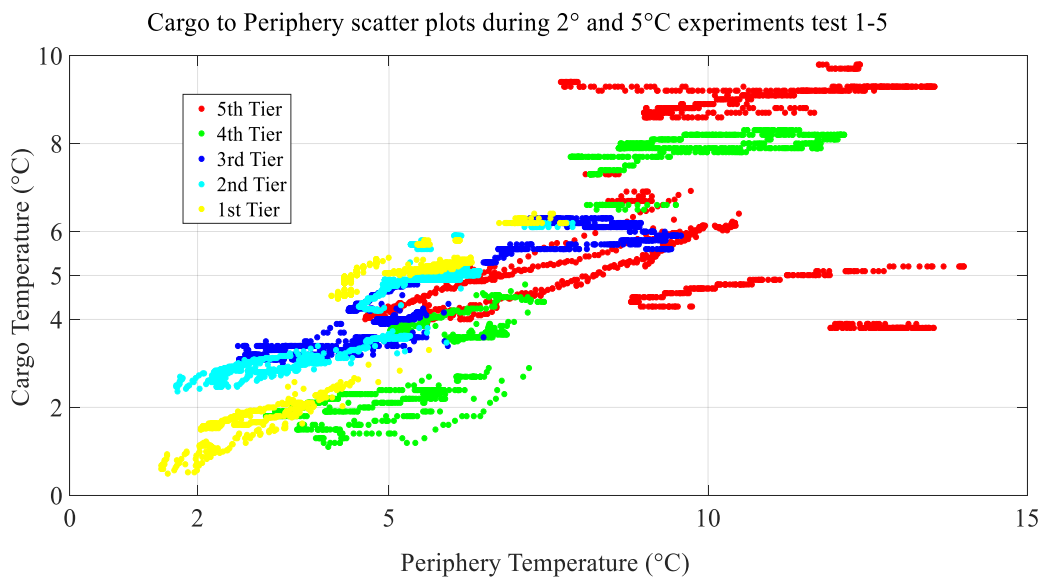


Figure 6-54: Tests 1,2,3 border crossing delay event scatter plots

Tests 4,5 border crossing delay event scatter plots**Figure 6-55: Tests 4,5 border crossing delay event scatter plots****Test 1,2,3,4,5 border crossing delay events scatter plot****Figure 6-56: Test 1,2,3,4,5 border crossing delay events scatter plot**

As the border post delays show similarities in their pattern distribution for all trips a single dataset for all border post delays was compiled. From a risk management perspective, the border post delays are more important considering the significant percentage of total trip time that is spent during trip delays (mostly at border posts) as enumerated in appendix C.

Appendix E: Modelling Visualization

Model development results

Training the model and Testing it

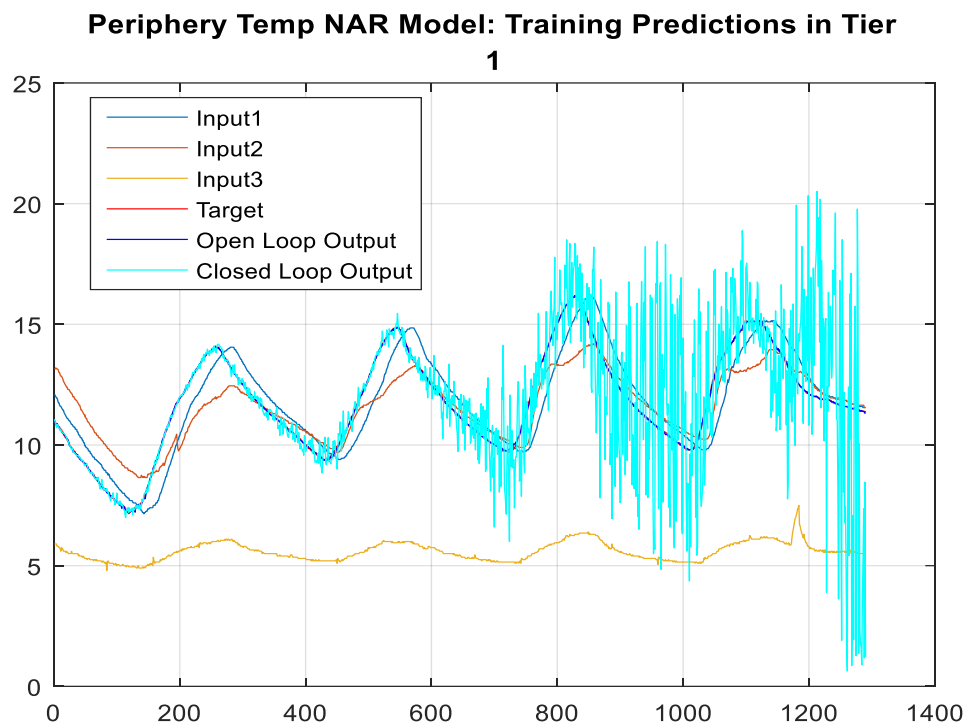


Figure 6-57: Spatial model Training set: Tier 1 temperature modelled results in terms of Tiers 1,3 and 5

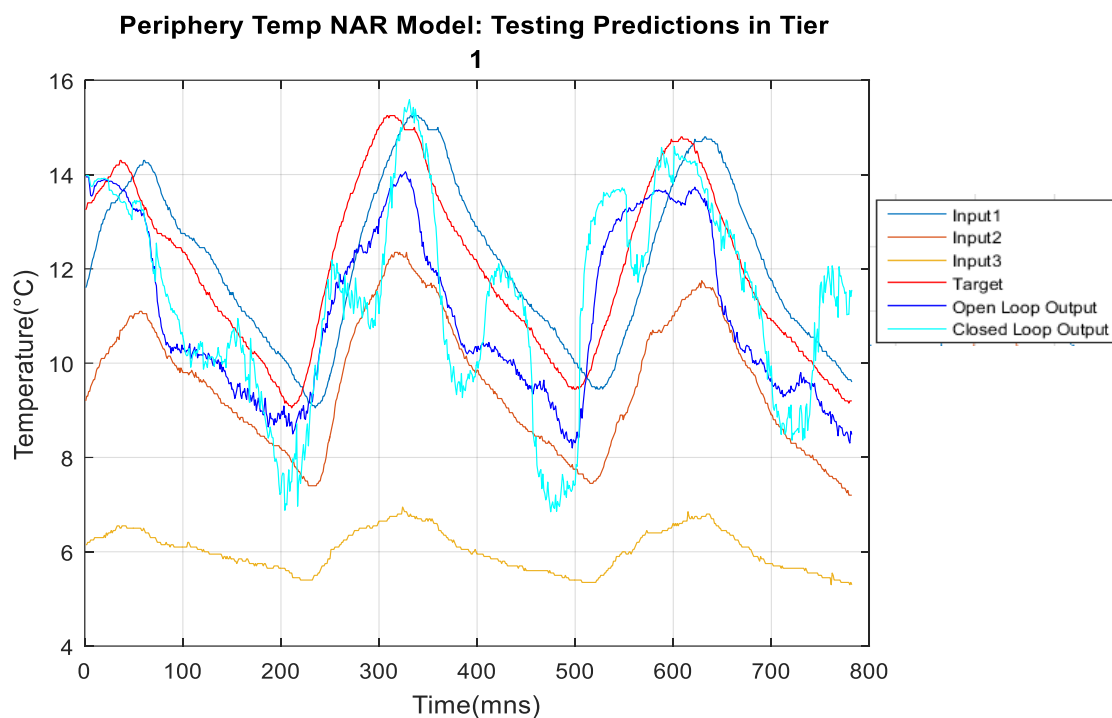


Figure 6-58: Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 1)

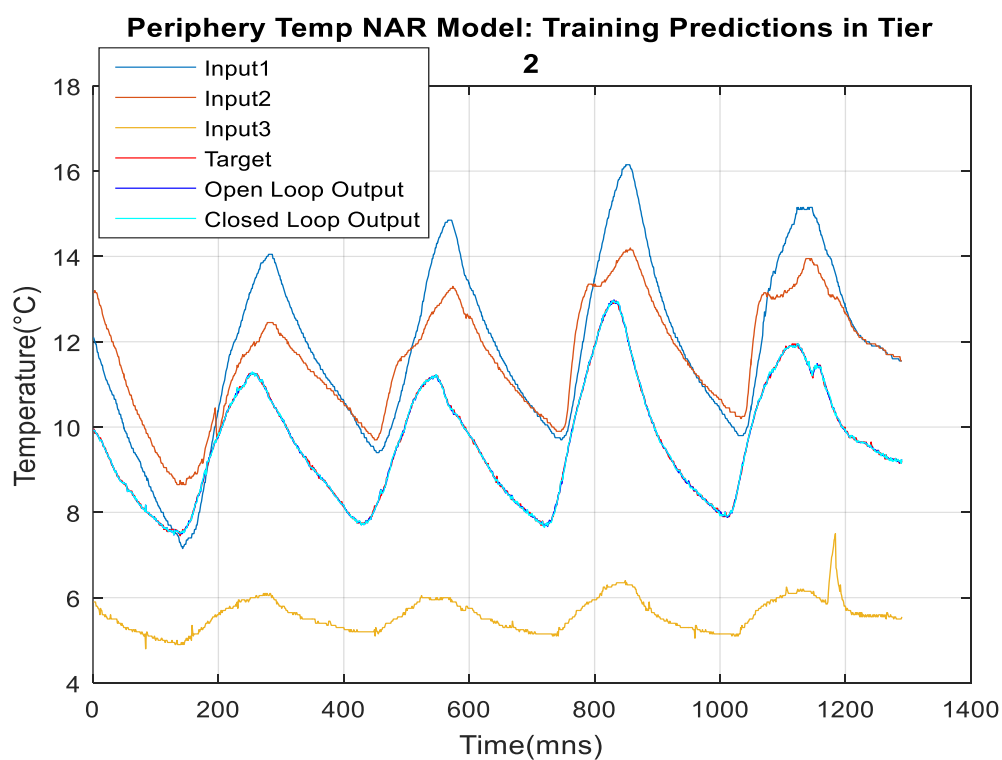


Figure 6-59: Spatial model Training set: Tier 2 temperature modelled results in terms of Tiers 1,3 and 5

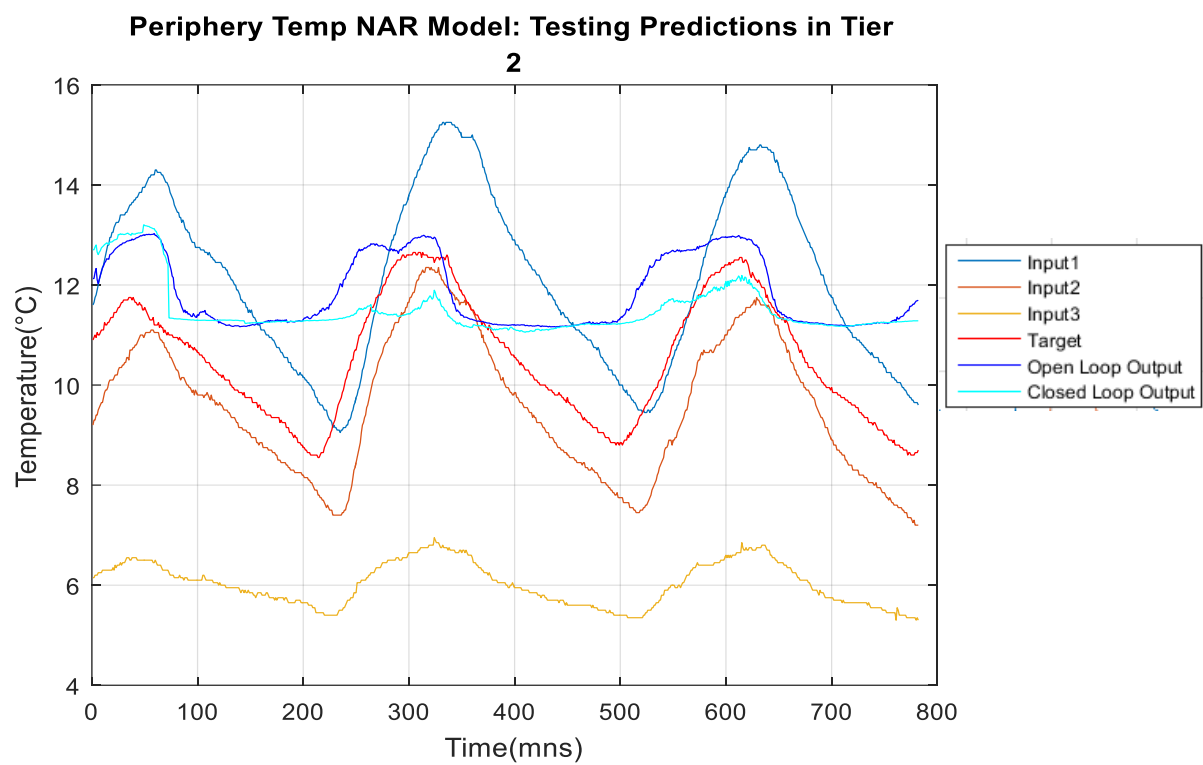


Figure 6-60: Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 2)

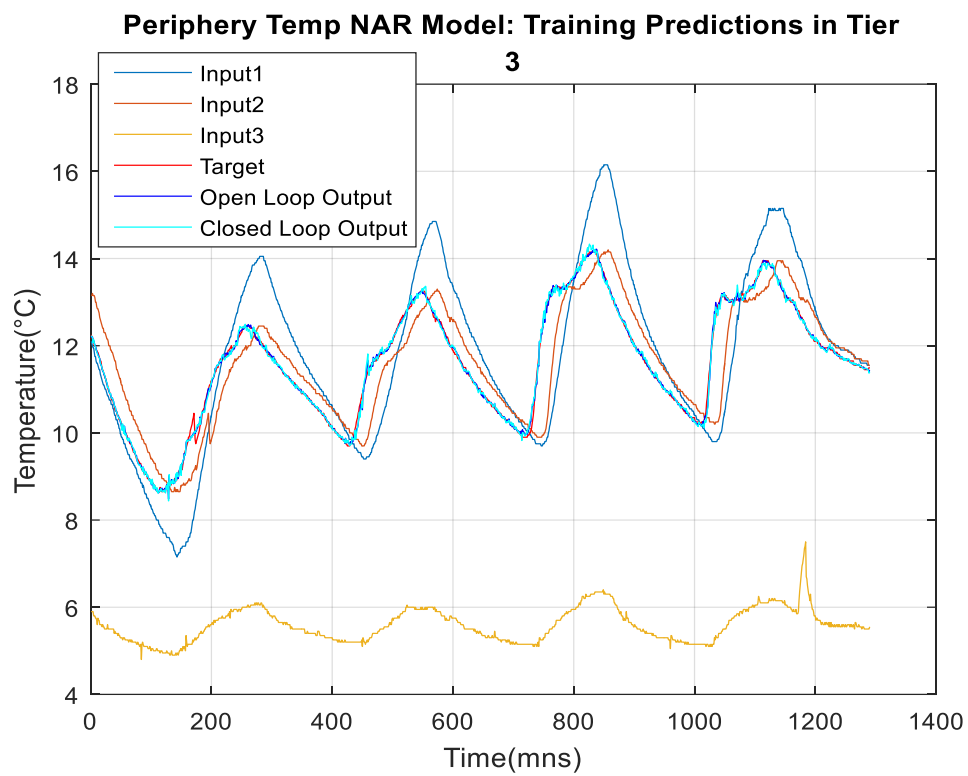


Figure 6-61: Spatial model Training set: Tier 3 temperature modelled results in terms of Tiers 1,3 and 5

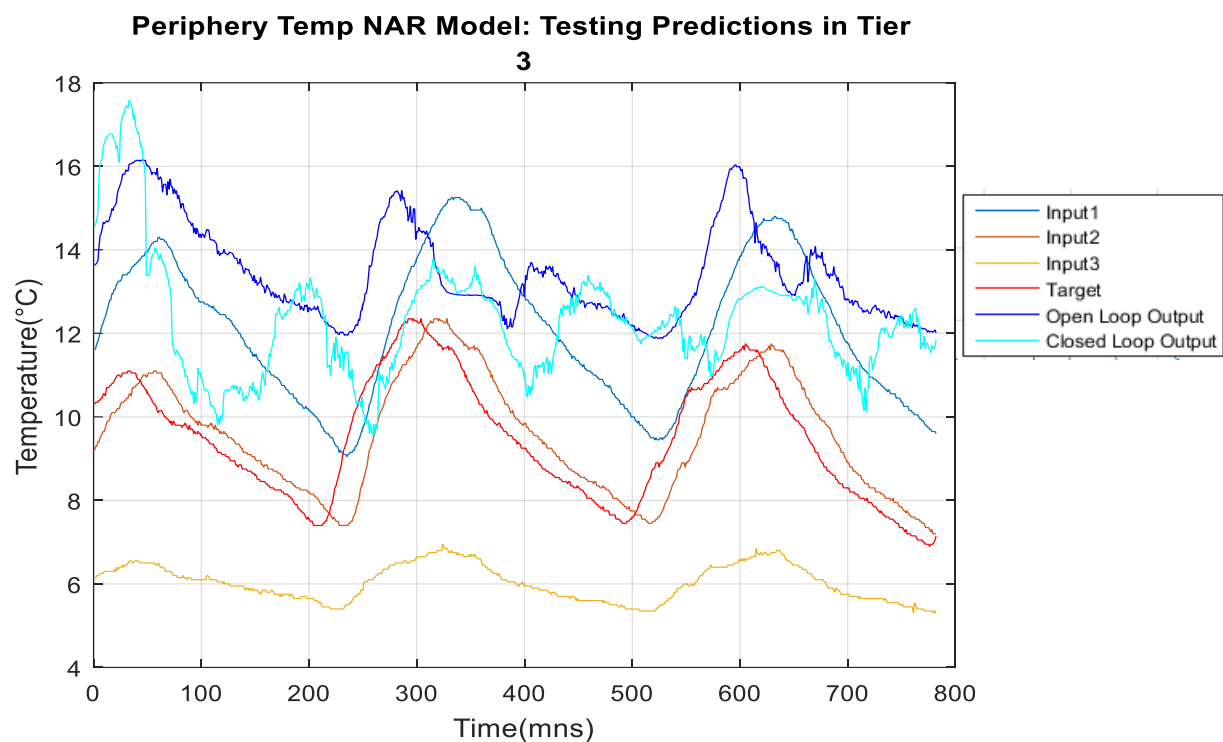


Figure 6-62: Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 3)

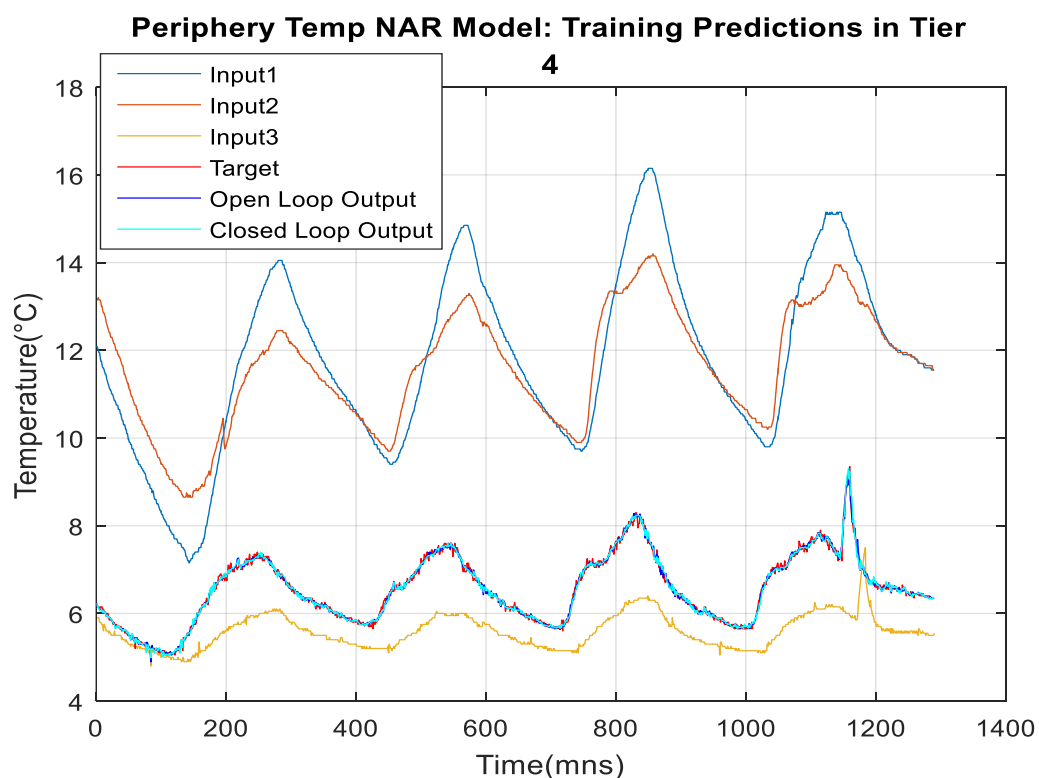


Figure 6-63: Spatial model Training set: Tier 4 temperature modelled results in terms of Tiers 1,3 and 5

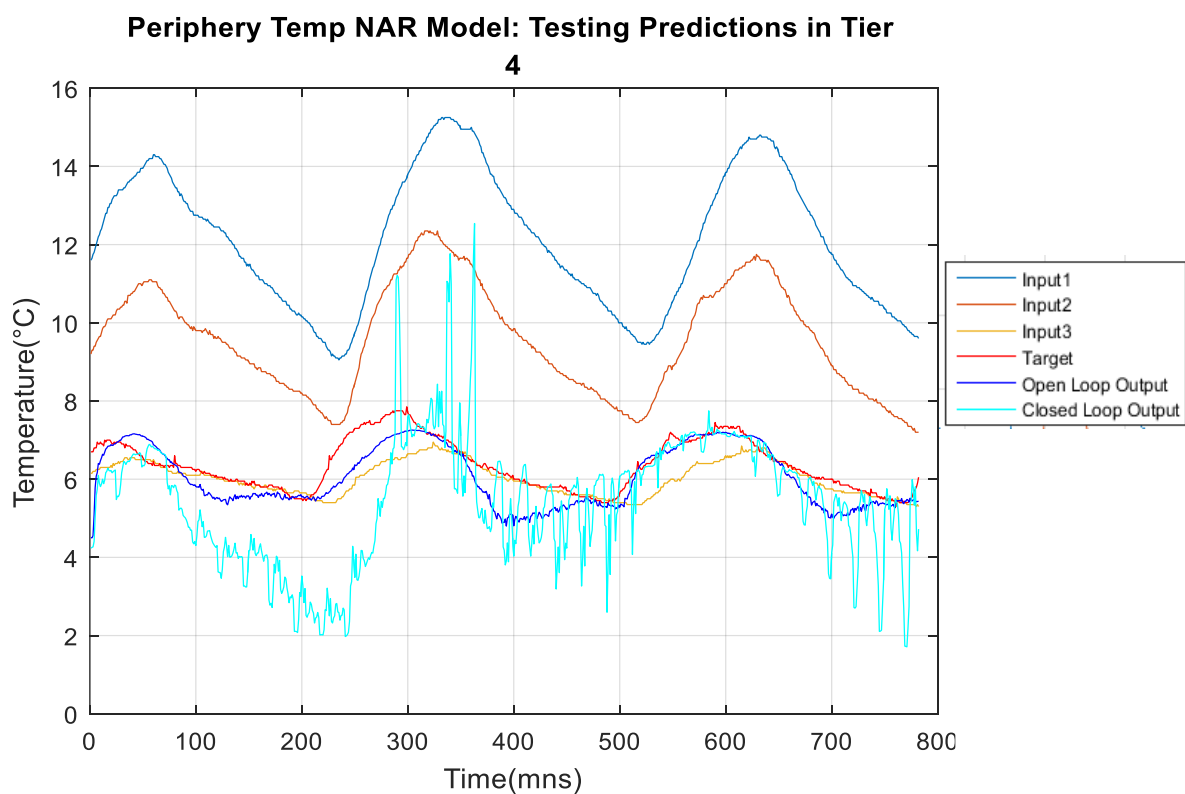


Figure 6-64: Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 4)

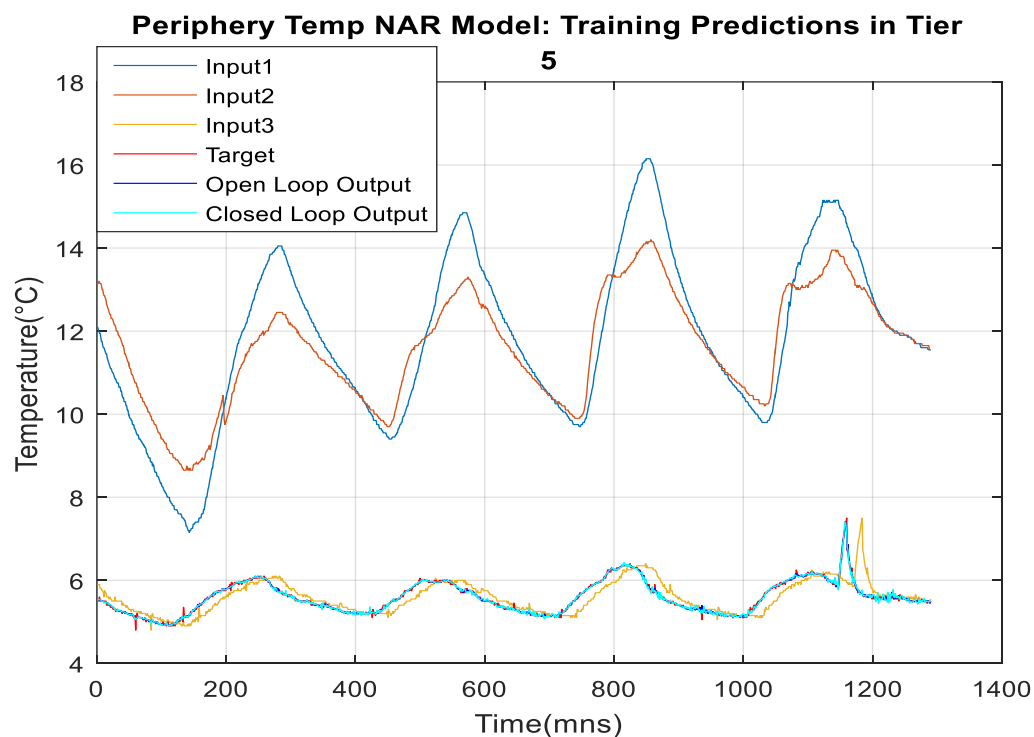


Figure 6-65: Spatial model Training set: Tier 5 temperature modelled results in terms of Tiers 1,3 and 5

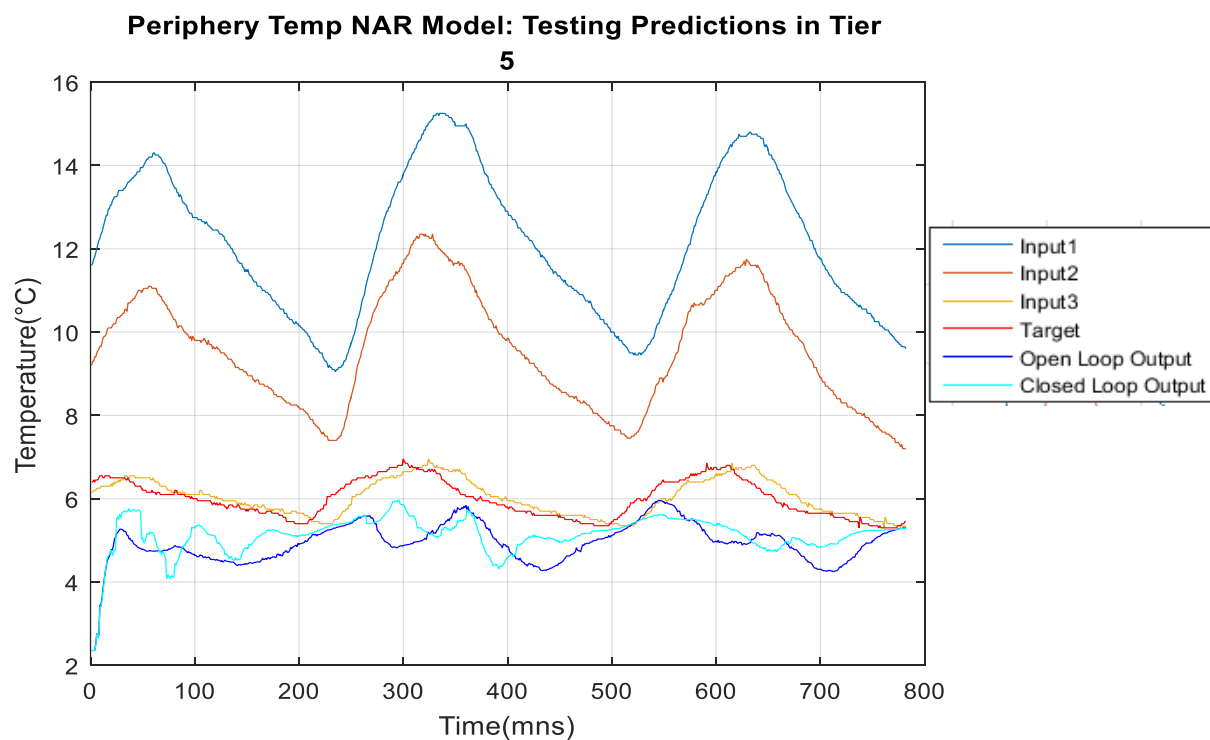
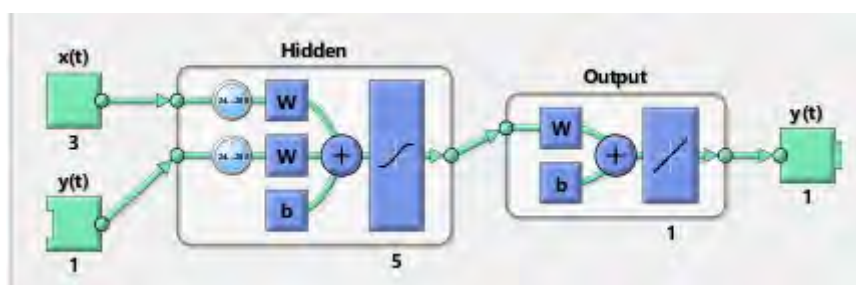


Figure 6-66: Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 5)

Neural Network, training Performance and Regressions plots



Appendix F: Cost benefit analysis**Table 6-6: Cost benefit analysis**

Cargo Type	F & Veg	F& Veg	F& Veg	F& Veg	F& Veg	F& Veg
Fraction of cargo impacted by cold chain losses	2.0%	5.0%	15.0%	35.0%	40.0%	50.0%
Life expectancy of equipment (Months)	6	6	6	6	6	6
Number of trucks in average fleet	18	18	18	18	18	18
Number of equipped depots	2	2	2	2	2	2
Cost to install tracking equipment in truck	\$1,500	\$1,500	\$1,500	\$1,500	\$1,500	\$1,500
Cost per tag	\$60	\$60	\$60	\$60	\$60	\$60
Average duration of trip (days)	7	7	7	7	7	7
Fraction of year truck active	0.8	0.8	0.8	0.8	0.8	0.8
Number of trips per annum	41.7	41.7	41.7	41.7	41.7	41.7
Value of typical cold consignment	\$50,000	\$50,000	\$50,000	\$50,000	\$50,000	\$50,000
Average value of cargo lost per trip	\$1,000	\$2,500	\$7,500	\$17,500	\$20,000	\$25,000
Total value of cargo lost per annum	\$750,857	\$1,877,143	\$5,631,429	\$13,140,000	\$15,017,143	\$18,771,429
Income per trip	\$3,000	\$3,000	\$3,000	\$3,000	\$3,000	\$3,000
Annual turnover per truck	\$125,143	\$125,143	\$125,143	\$125,143	\$125,143	\$125,143
Total annual turnover	\$2,252,571	\$2,252,571	\$2,252,571	\$2,252,571	\$2,252,571	\$2,252,571

Option 1: Permanent and cargo tags read continuously in truck						
Monthly subscription to service per truck	\$100	\$100	\$60	\$60	\$60	\$60
Annual subscription to service per truck	\$1,200	\$1,200	\$1,200	\$1,200	\$1,200	\$1,200
Total annual service subscription	\$21,600	\$21,600	\$21,600	\$21,600	\$21,600	\$21,600
Cost of installed comms & comp infrastructure in depot	\$5,000	\$5,000	\$5,000	\$5,000	\$5,000	\$5,000
No of permanent tags per trailer	5	5	5	5	5	5
No of tags in cargo per trip	5	5	5	5	5	5
Fraction of cargo tags lost per trip	30%	30%	30%	30%	30%	30%
Cost of all tracking units	\$27,000	\$27,000	\$27,000	\$27,000	\$27,000	\$27,000
Cost of all tags	\$10,800	\$10,800	\$10,800	\$10,800	\$10,800	\$10,800
Cost of capital outlay at depots	\$10,000	\$10,000	\$10,000	\$10,000	\$10,000	\$10,000
Total capital outlay at depots and in trucks	\$47,800	\$47,800	\$47,800	\$47,800	\$47,800	\$47,800
Annual maintenance cost	\$9,560	\$9,560	\$9,560	\$9,560	\$9,560	\$9,560
Annual cost to replace cargo tags	\$67,577	\$67,577	\$67,577	\$67,577	\$67,577	\$67,577
Transmit period GSM (min)	10	10	10	10	10	10
Transmit period Satellite (min)	10	10	10	10	10	10
Number of GSM transmissions per annum	756864	756864	756864	756864	756864	756864
Number of satellite transmissions per annum	756864	756864	756864	756864	756864	756864
Cost per transmission Vodacom	\$0.05	\$0.05	\$0.05	\$0.05	\$0.05	\$0.05

Cost per transmission Iridium	\$0.08	\$0.08	\$0.08	\$0.08	\$0.08	\$0.08
Total cost of comms per annum	\$94,608	\$94,608	\$94,608	\$94,608	\$94,608	\$94,608
Total annual costs	\$193,345	\$193,345	\$193,345	\$193,345	\$193,345	\$193,345
% decrease in losses due to temp monitoring with ideal comms	50.0%	50.0%	50.0%	50.0%	50.0%	50.0%
Probability of comms with combined GSM and satellite	90%	90%	90%	90%	90%	90%
% decrease in losses due to temp monitoring	45.00%	45.00%	45.00%	45.00%	45.00%	45.00%
Reduction in cargo losses	0.90%	2.25%	6.75%	15.75%	18.00%	22.50%
Value of goods saved on average per trip	\$450	\$1,125	\$3,375	\$7,875	\$9,000	\$11,250
Value of goods saved per annum for all trucks	\$337,886	\$844,714	\$2,534,143	\$5,913,000	\$6,757,714	\$8,447,143
Increase in annual profits due to temp monitoring	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
Option 2: Tags read at depot						
Monthly subscription to service per truck	\$50	\$50	\$50	\$50	\$50	\$50
Annual subscription to service per truck	\$600	\$600	\$600	\$600	\$600	\$600
Total annual service subscription	\$10,800	\$10,800	\$10,800	\$10,800	\$10,800	\$10,800
Cost of installed comms & comp infrastructure in depot	\$10,000	\$10,000	\$10,000	\$10,000	\$10,000	\$10,000
No of tags in cargo per trip	5	5	5	5	5	5
Fraction of cargo tags lost per trip	30%	30%	30%	30%	30%	30%

Cost of all tags	\$5,400	\$5,400	\$5,400	\$5,400	\$5,400	\$5,400
Cost of capital outlay at depots	\$20,000	\$20,000	\$20,000	\$20,000	\$20,000	\$20,000
Total capital outlay at depots and in trucks	\$25,400	\$25,400	\$25,400	\$25,400	\$25,400	\$25,400
Annual maintenance cost	\$5,080	\$5,080	\$5,080	\$5,080	\$5,080	\$5,080
Annual cost to replace cargo tags	\$67,577	\$67,577	\$67,577	\$67,577	\$67,577	\$67,577
Total annual costs	\$83,457	\$83,457	\$83,457	\$83,457	\$83,457	\$83,457
% decrease in losses due to temp monitoring	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%
Reduction in cargo losses	0.400%	1.000%	3.000%	7.000%	8.000%	10.000%
Value of goods saved on average per trip	\$200	\$500	\$1,500	\$3,500	\$4,000	\$5,000
Value of goods saved per annum for all trucks	\$150,171	\$375,429	\$1,126,286	\$2,628,000	\$3,003,429	\$3,754,286
Increase in annual profits due to temp monitoring	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
Option 1: Permanent and cargo tags read continuously in truck						
IRR:	302%	1363%	4897%	11966%	13733%	17267%
Capital outlay	-\$47,800	-\$47,800	-\$47,800	-\$47,800	-\$47,800	-\$47,800
Annual profit increase	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
	\$144,541	\$651,369	\$2,340,798	\$5,719,655	\$6,564,369	\$8,253,798
Option 2: Tags read at depot						

IRR:	263%	1149%	4106%	10018%	11496%	14452%
Capital outlay	-\$25,400	-\$25,400	-\$25,400	-\$25,400	-\$25,400	-\$25,400
Annual profit increase	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829
	\$66,714	\$291,971	\$1,042,829	\$2,544,543	\$2,919,971	\$3,670,829

Appendix G: Software Code and Databank

The various matlab codes and the databank are found in the enclosed CD

Appendix H: IEEE ITSC Article

Improving Cold Chain Logistics through RFID temperature sensing and Predictive Modelling*

Christian C. Emenike, Nardus P. Van Eyk, and Alwyn J. Hoffman

Abstract— The global Cold Chain Logistics (CCL) industry has grown in size with significant positive impact on the GDP of many economies. It however stills suffers from poorly managed service level agreements, inadequate cold chain visibility and cargo losses. Such losses are mainly caused by lack of real time information about the current status of cargo as well as lacking insight into the possible impact of supply chain incidents on cargo quality. This paper presents an improved approach to cold chain management (CCM) that is based on the real time monitoring of perishable cargo using RFID based sensing techniques, combined with the modelling of current and future in-cargo temperatures using the available sensed data. An empirical method is described for the characterization of cold chain processes and the development of predictive neural network models based on information that is collected using RFID temperature sensors. It is demonstrated that the use of advanced modelling techniques enables accurate monitoring using a small number of sensors, and that the models can estimate actual cargo temperatures more accurately compared to using temperatures measured on the periphery of the cold container.

I. BACKGROUND

There is an increasing international trend towards the containerization of freight [1], [3], [4]. This results from the increasing globalization of economies and the need to effectively move freight between different modes of transport from area of production to distribution centers. Intense international competition in the agricultural, manufacturing, logistics and retail industries requires high levels of efficiency across the entire value chain. Much focus has been placed on the transportation element of global value chains, as this area has suffered from significant inefficiencies in the past [5]–[7]. There are several reasons why the transport leg of global value chains offers several difficult challenges. Firstly, this activity normally involves the service of a third party that does not have a direct interest in the cargo, as would be the case for the seller and the

buyer of the goods. Transporters may tend to be more concerned about the utilization levels of their assets than about the goods they are transporting. Secondly the international transport process normally involves a number of independent players, most of whom are managing infrastructure and services that are essential for the completion of the transport cycle but who are not directly affected if something goes wrong along the way. This includes: roads operators, customs authorities, ports operators, rail operators and others.

It can therefore easily happen that cargo is either mistreated, get delayed or subjected to inappropriate services during the transport process. Such deviations from the planned process can result not only in costly delays in the overall value chain, but more importantly in damage to the cargo itself. This is of specific importance to fresh produce.

In the case of fresh produce the transport activity forms a very big portion of the overall landed cost of the goods [8]. This results from the fact that the goods have limited shelf life, that there is usually a large distance between areas of production and consumption, and that specific conditions must be maintained during the entire transport process to ensure that the quality of the goods is retained until delivery to the customer. A reduction in quality leading to the downgrading of the product has a huge impact on the value of the delivered product or can even cause it to be scrapped [9].

Technology based solutions have found increasing levels of application in the transport industry in recent years [10]–[12]. The most widely known is the use of GPS technology, in combination with wireless networks (typically GSM networks) to provide real-time traceability of freight vehicles. Initial applications of GPS focused on vehicle recovery, fleet management and driver management. In specialized transport applications, e.g. cash-in-transit applications, technology is also used extensively to provide visibility of the status of cargo in transit. The transport of goods

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required to be cooled while in transit resulted in the deployment of a special kind of container, called a reefer container, that is equipped to provide temperature and humidity controlled conditions using on-board equipment.

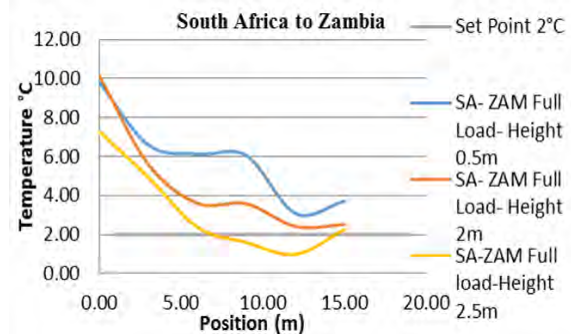
II. INTRODUCTION

Cold Chain Logistics (CCL) involves the transportation of temperature sensitive products by means of refrigerated trucks, also known as reefers, along a supply chain through thermally controlled and refrigerated packaging methods. The CCL industry is a significant and steadily growing business in Southern Africa and the world [13]. The South African fruit industry as substantial employment generator; employs more or less 460 000 people who have two million dependents[14]. The industry accounts for 50% of all agricultural exports in South Africa [15], with an annual export value of approximately \$1,02 billion [14]. Unfortunately, a huge chunk of this profit and commodities are lost due to poor quality of these products before they reach their target destinations. The internal biological and chemical process of fresh produce, such as respiration, continues after harvesting. This implies that the product absorbs oxygen and releases carbon dioxide and ethylene. This results in the liberation of heat energy. Lowering the temperature reduces the respiration and consequently the heat considerably, hence avoiding deterioration due to high concentrations that may be caused by these latent activities. The delivery of these cargo types in good conditions from point of production to point of distribution or consumption has been an issue for all players (the growers or producers, the logistic service provider and other transport companies, and the final consumer) involved the supply chain. Efficient monitoring of the temperature of these cargoes at a reasonable cost is the cry-for-help of these stake holders. Approximately 35% of fruits and vegetables are lost in the cold chain [16], partly due to the lack of cost-effective alternatives.

Refrigeration is basically removing heat by evaporation. Farm produce in the cold chain are refrigerated for the sole purpose of prolonging their shelf life [17], state and quality thereby avoiding cold chain ruptures. Maintaining the required transportation temperature and humidity is of key importance in actualizing this goal. The required temperature in cold chain mainly depends on the cargo type. Fresh fruits and vegetables are usually transported between 0°C to 8°C, Meat and cold chilled products at a temperature below -18°C, dairy products like margarine, butter usually between -8°C to 7°C, frozen foods and ice cream are usually transported at -24°C to -18°C while chocolate at -8°C to -18°C and pharmaceutical products usually between 2°C to 8°C.

III. NEEDS OF THE COLD CHAIN INDUSTRY

While reefer containers are designed to maintain automated temperature control inside the cargo hold, there are still many reasons why perishable cargo may suffer damage in transit. The mechanism to cool down the cargo typically consist of a single cooling unit, located close to the front of the container (i.e. furthest away from the doors) that injects cold air into the cargo hold. If the circulation of cold air is not sufficient due to the way that the cargo is packed a significant



temperature gradient can exist across the hold. In climates that are typically experienced on the African continent the impact of the sun on cargo close to the top of the container can also be significant, specifically when the consignment is delayed for several hours (or in extreme cases even for days) at a border crossing, as typically happens at African border posts.

Another cause of cargo exceeding allowed temperature ranges is if offloading does not commence immediately after arrival at the final destination. If the container doors are left open while the goods receive area is very congested it can easily happen that cargo is left for several hours without sufficient cooling; cases have been recorded where the driver left the loaded container in the care of goods receive personnel and where the cooling unit subsequently ran out of fuel, resulting in the loss of a complete consignment. If such a container was equipped with automated temperature recording sensors that could communicate with the outside world it would have been possible to generate an alarm at a central control room from where corrective action could have been organized.

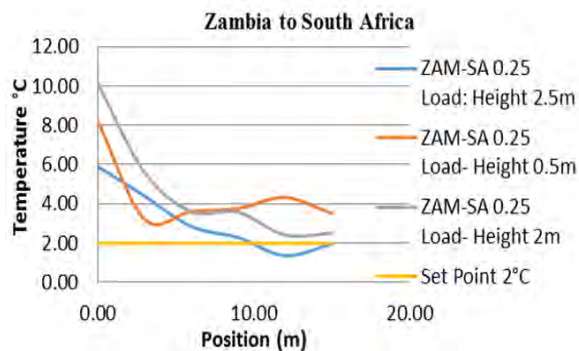
(a) South Africa – Zambia

(b) Zambia – South Africa

Figure1: Typical temperature profiles

Even in the presence of a well-controlled environment there is the need for accurate temperature monitoring. Service level agreements (SLAs) between consignor and consignee usually require perishable cargo to be delivered within the agreed temperature range; should these thresholds be exceeded the consignee has the right to reject a consignment. In the absence of automated real time temperature measurements, it is possible that either a consignment that is outside of specification is accepted, resulting in a loss to the consignor, or that consignments that are within specification are rejected (where an alleged temperature transgression is used as a convenient excuse not to receive a consignment in case the goods are no longer required at the store). In such cases the availability of real time temperature measurements could help to resolve SLA related disputes.

Against this background it is surprising that only a small fraction of the cold chain industry currently uses real time temperature monitoring including the remote reporting of temperature alarms. Our practical investigation into this matter has revealed that this



mainly results from a perception of high cost, high complexity and low reliability of existing in-transit temperature monitoring systems.

A further problem that must be solved to implement effective in-transit cold chain management is that it is difficult to monitor the actual temperatures inside the cargo without running the risk of losing the costly sensors that have to be embedded in the cargo for this purpose. Personnel responsible for the loading and offloading of cargo usually have low levels of training and tend not to be concerned about the correct placement of sensors and the recovery of such devices while offloading cargo. Practical tests performed in Southern Africa with a cold chain operator has shown that the majority of sensing devices planted in the cargo are lost even during the first trip, in spite of training that was provided to personnel before the experiment was performed. It is therefore clear that an in-transit monitoring system will have to rely mostly on sensing

devices that are permanently installed in the cold container or trailer.

The need therefore exists for an in-transit cold chain monitoring system that is easy to deploy and operate, but furthermore that can derive cargo temperatures from temperatures measured around the periphery of the container. The focus of this paper is to develop a model that can reliably model in-cargo temperatures from temperatures measured along the roof and the sides of the container. It is furthermore investigated where extreme cargo temperatures tend to occur, which conditions or incidents tend to precede temperature transgressions and what number of permanently installed sensors are required to allow the accurate modelling of in-cargo temperatures.

IV. RESEARCH OBJECTIVES

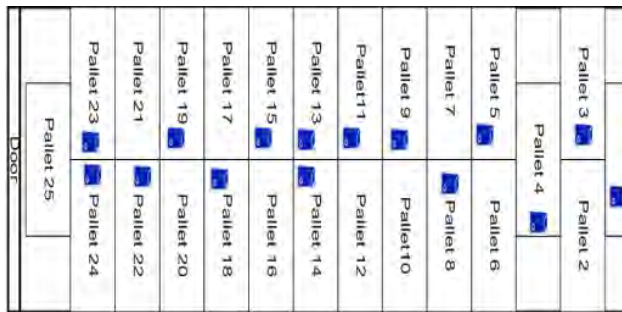
In order to make a contribution towards developing an improved solution for in-transit cold chain management the following research objectives were defined:

- Design an experimental monitoring methodology to characterize in detail actual cold chain operations for a representative set of actual trips, including different types of cargo and trips to different destinations in Southern Africa.
- Design predictive models using this experimental data that will derive in-cargo temperatures during trips from temperatures at points where permanent sensors can be installed, and comparing these modelled values against measured in-cargo temperatures.
- Design and recommend an improved approach for cold chain logistics in the region for operational implementation where cargo monitoring relies only on periphery temperature measurements; the proposed method has the objective to pro-actively detect problematic situations at an early stage before damage has occurred, in order to prevent losses to cargo.

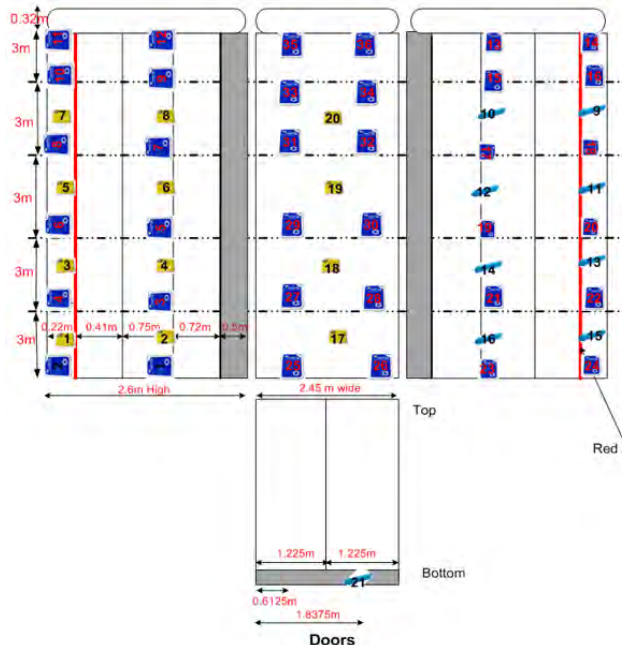
The importance of such models that can predict future expected cargo temperatures is based on the fact that it will allow conditions to be anticipated where cargo may be exposed to unacceptable temperatures before it has actually occurred; this will enable corrective action to be implemented before any damage has been suffered. A typical case would be where a consignment is stationary at a border post with rising temperatures due to climatic conditions and the lack of cooling due to lack of movement of the vessel. If it is known at the same time that customs have not yet cleared the consignment to move across the border, an estimate can be made regarding the duration of time before cargo will experience damage to quality. The expected worst-case cargo temperatures by the time that the consignment is expected to be cleared can also be predicted and it can be determined whether the cargo is at risk and if other measures are justified to accelerate its progress through the customs process.

V. MATERIAL, METHODS AND RESULTS

Five sets of experiments were conducted based on normal cold chain operations of refrigerated 15.32m trailers, each taking a full load of 25 pallets as schematically displayed in figure 8 below. The reefer containers were loaded with fruits and vegetables and operated at a set point of 2°C. The trailers could be filled up to the so-called ‘red line’ which is 1.8m above the floor level; this restriction allows cooled air to flow over the cargo from the chilling unit in the front to the doors at the back. Trailers were fully loaded from South Africa (SA) to Zambia (ZMB) and back to South Africa the trailers were one quarter full. The duration of each experiment ranged from 6 to 10 days. These experiments were conducted from February 2014 to November 2014, thus covering all seasons (typically hot weather during summer months and moderate weather during winter months).



(a) Pallet placement inside trailer



(b) Deployment of sensors inside trailer

Figure2: Trailer and sensor layouts

For each experimental trip 53 Logtag Data loggers and 20 CAEN RFID sensors were used. For the purpose of the modelling exercise each trailer is divided into 5 sections or ‘tiers’, each with a length of approximately 3m, as schematically displayed in figure 7. 57 sensors were installed on the periphery of the trailer within each tier and at various heights above and below the ‘red line’, while the rest (typically 13 to 15 per trailer) were embedded within the cargo, with at least 2 sensors within each tier. A research assistant accompanied each experimental vessel in order to ensure that sensors were correctly placed and recovered, and furthermore to record events that occurred during each trip. This included the times of loading, sealing, departure, arrival at border posts, duration of interruptions of the journey, time of arrival at destination, time that doors were opened and time when offloading was completed.

The collected data was first captured and stored in a databank. Subsequently the data was synchronized with the recorded times of events and incidents that occurred during each trip. This allowed specific sections of the data to be used for the training of specific models and allowed the models to be exposed to various kinds of behavior that could reasonably be foreseen during such trips.

Spatial and temporal temperature profiles at the periphery of the trailer and inside the cargo during transportation were captured, collated and extracted from experimental data sets in specific formats as required by the model extraction process described in the following sections. These were evaluated and further analyzed. The figures below reveal the results that were observed. In order to sensibly interpret temperature deviations from set point the deviations outside of the allowed range of temperatures (typically set point $\pm 2^\circ\text{C}$) are expressed as percentage of the range of allowed temperatures (4°C). Temperatures as high 10°C were experienced at the doors (corresponding to position 0.00m) while the lowest temperatures ($1.7^\circ\text{C} - 3.5^\circ\text{C}$) were observed at the region close to the vent (corresponding to position 15.3m). In general, it was deduced that cargo within 5m from the vent were normally within set point temperature, while cargo approximately 7m away from vent experienced ~100% set point deviation, cargo 10m away experienced 200% temperature deviation while those 10-15m away experienced up to 400% set point temperature deviation.

An initial interpretation of the results therefore confirmed that the need exists for more accurate in-transit temperature monitoring to allow the consignor and consignee to enforce SLAs while allowing the transporter to improve the management of its operation. It is also important to note that it is not only necessary to know that a threshold was exceeded, but also by how much, when it occurred and for what reason. This will

allow the parties involved to calculate the possible extent of damage, who the responsible party was at that point in time and what could be improved in terms of the management of the operation to prevent similar incidents in future.

At the same time, it must be recognized that ongoing monitoring of cargo temperatures for each cold chain trip would potentially be costly and time consuming, specifically if sensors must be installed and recovered per trip. It is hence essential to reconcile the need for improved monitoring with the need for a cost-effective approach for operational circumstances. To achieve this objective two types of modelling was undertaken:

- Firstly, the cargo temperature was modelled as function of position along the length of the trailer from chiller to doors. The accuracy of this spatial model will determine how many points of monitoring are required across the different tiers to estimate the expected worst case conditions while physically measuring temperature only at a limited number of positions. This scenario assumes that the cargo is in a stable state and that time fluctuations do not play a significant role.
- Secondly the temporal behavior of cargo temperature was modelled in order to determine how long it will take for cargo temperature, which may currently be within the allowed range, to drift out of this range. This is specifically applicable once an external event has occurred (e.g. a border post stop or the opening of the doors) that could be expected to impact cargo temperature. This temporal model will provide early warning if such an event has occurred, even before cargo temperatures are outside of the limits.

VI. PREDICTING TEMPERATURE AS FUNCTION OF POSITION

As the observed spatial temperature deviations displayed relatively simple and predictable behavior, the spatial model was based on nonlinear polynomial regression. The inputs to the model were obtained by taking the average of all periphery temperatures within a tier to represent the temperature at the corresponding distance from the chilling unit. The output of the model was the temperatures in between the center points of the various tiers. It was found that a 4th order polynomial was sufficiently accurate to provide an acceptable approximation of actual temperature as function of location, as displayed in figure X below.

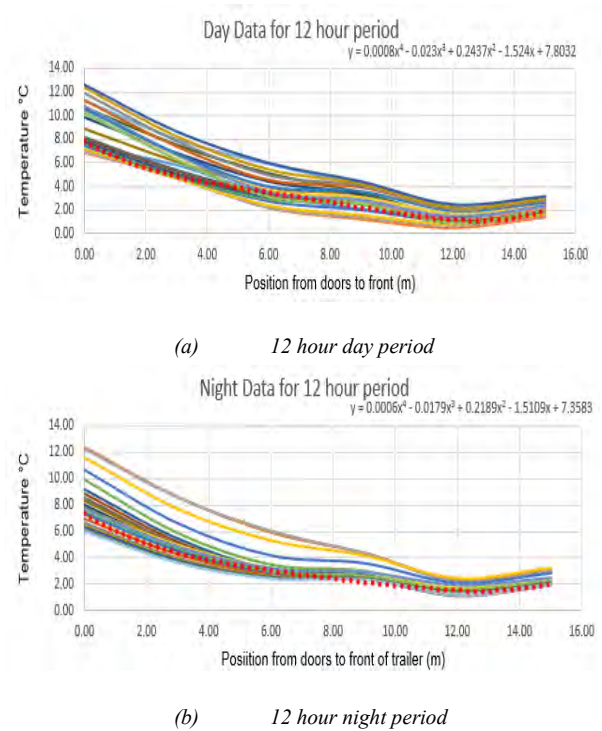


Figure3: Temperature graphs as function of location in trailer

What is however also apparent from this graph is that the worst case temperature at the doors significantly varies between different trips, ranging from about 6 °C (which will result in very little or no cargo losses) up to more than 12 °C (which may imply that all cargo in the last tier was lost during the trip). This difference in cold chain performance can be mostly attributed to different events occurring during different trips. It therefore emphasizes the need for a temporal model that can predict future temperature as function of historical temperature once an event has occurred that may be detrimental to cargo. This is the topic of the next section.

VII. USING ARTIFICIAL NEURAL NETWORKS FOR SPATIAL AND TEMPORAL PREDICTIONS

As the relationships between the different variables could be expected to be nonlinear and dynamic as function of time, we used artificial neural networks as a flexible modelling tool, given that these networks can in principle capture complex input-output relationships with an arbitrary level of accuracy (Bishop). We specifically employed the Neural Network Toolbox of Matlab®, and implemented the models as so-called NARX (nonlinear autoregressive with exogenous variables) models. This model assumes that variables appear as time series, and allows historical values of the modelled variable, as well as current and historical values of other variables, to be used as inputs.

The development of NARX networks follows an approach where it is assumed that the target variables

are available to the model within a training set, while only the input variables are available to the model within the test set. During the training process the model is therefore fed with both exogenous variables as well as with past values of the targets. This allows the network to learn as much as possible from both spatial and temporal relationships. The network is thus trained in the so-called open loop mode, as displayed in figure y(a) below.

During the testing phase it is assumed that the measured targets are not available any more but must be derived from the inputs only. Within the model architecture the historical target values are then replaced by historical network outputs that are fed back into the network. The model is thus tested in so-called closed loop mode as displayed in figure y(b) below.

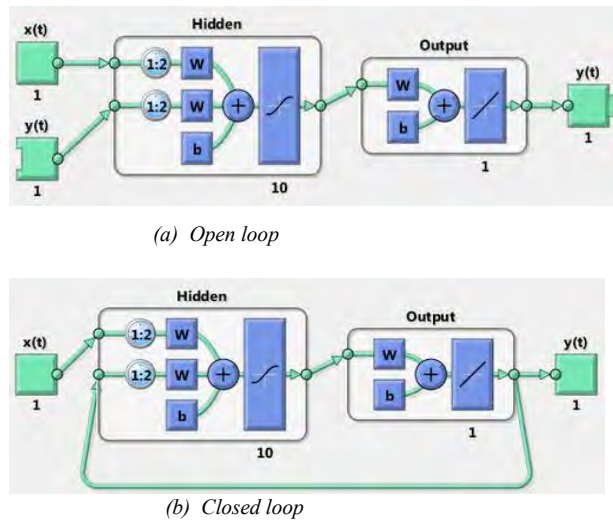


Figure4: Open and closed loop neural network architectures

The training of a reliable model that will perform consistently under most circumstances requires a training set that is representative of all foreseeable conditions. In this case it was important to ensure that the training set contains temperature variations that span all realistically possible values of practical importance. We therefore used as training set data collected for trips during the summer months when extreme temperatures occurred on a daily basis. Figure z below displays the temperatures measured along the sides of the trailer during such a trip. For test set we used data collected during other trips, with sensors placed in more or less the same locations.

The training set was further subdivided into training, validation and testing samples. Only the error over the training samples are used to determine how the model weights should be modified from one training epoch to the next. The error made over the validation samples is used to decide when to stop the training process; this helps to prevent overtraining. The error over the training samples provides an indication of how well the

model generalizes with the training set. A typical example of the behavior of the training, validation and test errors across the training epochs is displayed in figure X(a) below.

As part of the modelling experiment we evaluated the impact of different model parameters, including the number of historical time samples to use, the size of the training set, the sampling frequency, the time duration over which the samples were spread, the number of hidden network nodes, the training algorithm used, and the regularization technique employed (to keep the model relationships as ‘smooth’ as possible). As the time behavior of temperatures tend to be cyclic with a period of one day, we included a time delay corresponding to exactly one day, as this is known to improve the accuracy of cyclic models. The other inputs were spread at a period of 2 hours from the last measured variable up to 8 hours from the present time.

During the training process it is important to monitor a number of results: the reduction in modelled error, the regression accuracy between target and model output values (a typical example is given in figure X(b)), the mean square normalized error (MSE) of output versus target measured over the training set and the MSE measured over the test set. In addition, we also check the MSE obtained when the most suitable input variable is directly used as estimate for the output instead of using a model.

The following types of neural network models were trained:

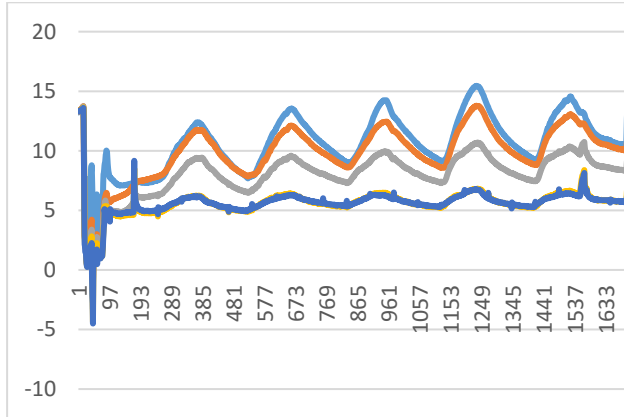
- Spatial models to determine temperature values in locations where no sensors would normally be present as function of concurrent temperature values on the periphery where sensors will be located.
- Temporal models to determine future worst case cargo temperatures based on historical temperature data for sensors at specific locations on the periphery.

VIII. SPATIAL PREDICTING OF TEMPERATURES

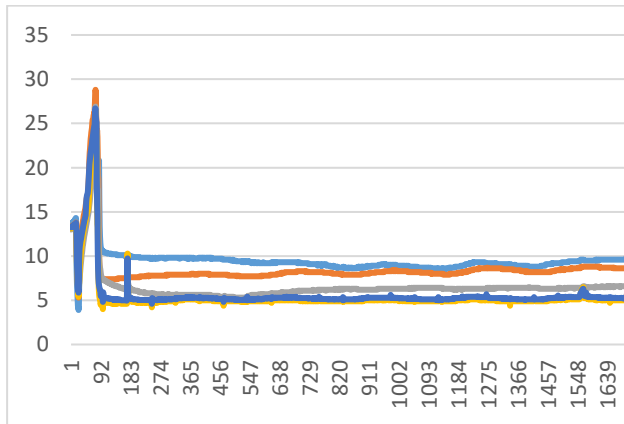
One of the primary objectives of this research was to determine how accurately temperature at various points within the cargo could be derived from temperatures that are physically measured at other locations. We worked from the assumption that in most operations it will be impractical to deploy sensors within the cargo during normal operations, and that physical sensing would be restricted to a few sensors stuck to the inside of the trailer. This implies a need for a computerized mathematical model that will accept temperature measured at some fixed locations as inputs and that will produce temperatures at other locations as output.

In order to determine which temperatures will represent worst case unknown temperatures we investigated the data that was collected during the set of

trips. Figure x(a) below provides a typical time graph of temperatures measured at the periphery of the trailer within different tiers, while figure x(b) displays temperatures measured deep inside the cargo within the same tiers. It can be seen that, due to the thermal inertia of the cargo, the temperature deep inside the cargo is in general much more stable than temperatures at the periphery of the trailer where much higher fluctuations occur. Most cases where allowed thresholds are exceeded also occur along the sides or roof of a trailer – this is to be expected due to the impact of the sun.



(a) Periphery temperatures



(b) In-cargo temperatures

Figure5: Example of temperatures measured in tiers over trip duration

As packaging conventions cause cargo to be packed tightly against the sides of the trailers, we can accept that worst case cargo temperatures occur not deep inside the cargo but along the sides where there is physical contact with the trailer. The spatial temperature model development was therefore focused on temperatures collected from sensors on the sides of the trailers. It was assumed that in practical operations temperature would be measured only at a few locations (in this case we regarded tiers 1, 3 and 5 as the locations for installed

sensors) and that temperatures in other locations (we used tiers 2 and 4 for this purpose) would be derived from the measured temperatures. The neural network configuration used for the spatial model is summarized in Table I below.

TABLE I. SPATIAL NEURAL NETWORK CONFIGURATION

Network architecture	NARX Closed Loop
Feedback Delays (hours)	0.08; 2; 4; 6; 8; 24
Input Delays	0.08; 2; 4; 6; 8; 24
Training Function	Levenberg-Marquardt backpropagation
Hidden Layer Size	5
Sampling Period	5 minutes
Size of training set	1601
Size of test set	1093
Input temperatures	Tier 1; Tier 3; Tier 5
Target temperatures	Tier 2; Tier 4
Fraction of training	70%
Fraction of validation	15%
Fraction of testing	15%
Regularization technique	Bayesian

Figure Z show a typical result where the tier 4 temperature was modelled in terms of the tier 1, 3 and 5 temperatures; results for the training set are displayed in figure Z(a) and for the test set in figure Z(b). Table II below summarizes the MSE performance of the different models on the different data sets and for open vs closed loop mode. It can be seen that over the training set an almost perfect fit is achieved (the target, open loop output and closed loop outputs overlap almost completely) as we also used the historical values of the target as inputs (with the model in open loop mode as explained above). For the test set the data from tier 4 was totally unseen during the training process and no historical target values were used for predictions (as the model is now in closed loop mode). It can also be seen that in the test set the tier 4 temperature behaved somewhat differently compared to the other tier temperatures that what was the case for the training set. In spite of this the test set performance is still superior compared to the default situation where no information would be available for this tier and where the temperature in another tier would be used as best available estimate.

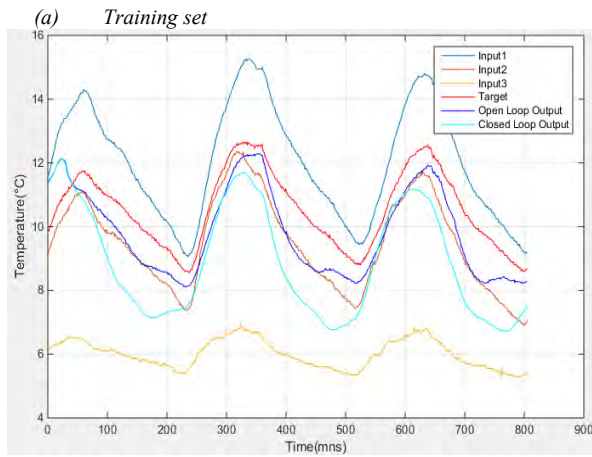
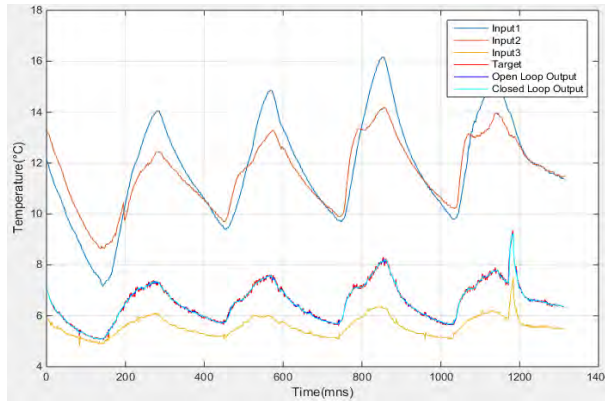


Figure6. Spatial model: inputs (tiers 1, 3, 5) vs target and output (tier 4)

MSE PERFORMANCE OF SPATIAL NEURAL NETWORK

Tier	1	2	3	4	5
open_trn	0.001	0.001	0.001	0.004	0.001
closed_trn	0.001	0.001	0.001	0.004	0.002
closed_tst	0.140	2.841	1.242	0.683	0.481
Default_tst	15.048	8.385	6.692	14.889	17.230

IX. FORECASTING FUTURE CARGO TEMPERATURES

The previous section demonstrated that a reliable model can be extracted to accurately predict concurrent temperature fluctuations over time at any location along the length of the cold container by using a small number of measured temperatures at fixed locations spread along the container body. The additional requirement however exists to not only model concurrent temperature at any location but to derive future worst case cargo temperatures (which may adversely impact cargo quality) from current and historical periphery temperatures. More importantly, once an event has occurred that is known to negatively impact upon cargo temperature (e.g. a prolonged stop at a border post), it will be of significant value to be able to estimate what

the future cargo temperature can be expected to be should the cargo be exposed to non-ideal circumstances.

In order to determine how accurately future worst case cargo temperatures can be derived from temperatures on the periphery the artificial neural network used in the previous section was adapted to provide for the forecasting of future temperatures from historical temperatures. In this case we used only delayed input values with respect to the target values, and determined the maximum prediction horizon over which an acceptable forecasting accuracy could still be achieved.

We experimented both with single variable NAR models (nonlinear autoregressive models where only the historical values of a target temperature were used to predict its future values), as well as multiple input NARX models (where the historical values of several different temperatures were used to predict the future values of all these variables). The single variable models (i.e. using multiple models to predict different temperatures) proved to produce more accurate results compared to using a single model with multiple input and target variables. This can partly be attributed to the fact that, due to limited size of the training and test sets, the relationships between the average temperatures for the same variables were not the same across the training and test sets. This caused the predicted values for the test set to be biased in favor of the relationships between the average values appearing in the training sets. This factor was largely eliminated by using only one variable per model. Should more representative training and test sets be available this should prove to be less of a problem. The future predictions are displayed in figure X below for tier 1. It can be seen that the 2 hours ahead forecast of temperature is much more accurate compared to using the current (input) value as estimate for the future (target) value. Table III below summarizes the neural network configuration for the temporal single variable models (in those respects where it differs from the spatial network), while Table IV displays the performance results.

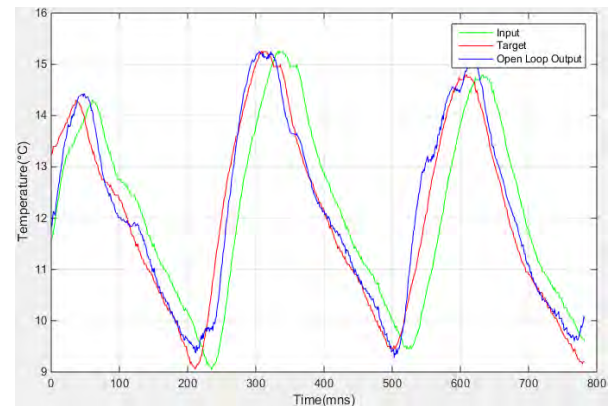


Figure7. Temporal model: inputs vs target and output (tier 1)

TABLE III. TEMPORAL NEURAL NETWORK CONFIGURATION

Network architecture	NAR Open Loop
Input Delays	2; 4; 6; 8; 24
Input temperatures	Any one of Tier 1; Tier 3; Tier 5
Target temperatures	Any one of Tier 1; Tier 3; Tier 5

TABLE IV. MSE PERFORMANCE OF TEMPORAL NEURAL NETWORK

Tier	1	2	3	4	5
open_trn	0.025	0.029	0.037	0.044	0.016
Default_trn	1.016	0.520	0.526	0.219	0.068
open_tst	0.188	0.520	1.320	0.126	0.097
Default_tst	0.991	0.460	0.664	0.151	0.066

Lastly we also implemented future temperature forecasting for temperatures in locations where no sensor is present. This was achieved by combining the spatial and temporal neural network architectures, as displayed in Table V below. The inputs were historical values for tiers 1, 3 and 5 while target were future values for tiers 2 and 4. This proved to be a more challenging problem; as can be seen in figure x and Table VI below the results were significantly worse compared to the spatial only or temporal only models. In general, the modelled outputs were however superior compared to the default values in terms of MSE.

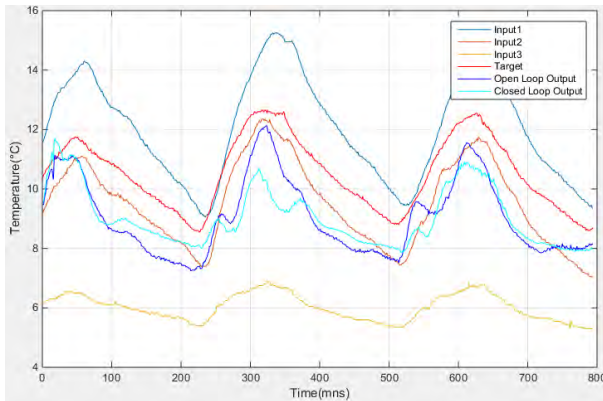


Figure 8. Combined Spatial temporal model: inputs (tiers 1, 3, 5) vs target and output (tier 2)

TABLE V. COMBINED SPATIAL TEMPORAL NEURAL NETWORK CONFIGURATION

Network architecture	NARX Closed Loop
Input Delays	2; 4; 6; 8; 24
Input temperatures	Tier 1; Tier 3; Tier 5
Target temperatures	Tier 2; Tier 4

TABLE VI. MSE PERFORMANCE OF COMBINED SPATIAL TEMPORAL NEURAL NETWORK

open_trn	0.004	0.002	0.007	0.008	0.002
closed_trn	1.016	0.520	0.526	0.219	0.068
open_tst	0.452	2.336	10.051	15.411	0.731

closed_tst	0.743	1.758	6.948	14.345	1.627
Default_ts	15.151	8.618	7.499	15.794	17.989

X. CONCLUSIONS AND FUTURE WORK

The need for improved techniques for effective in-transit cold chain management was motivated. Different scenarios were described where the absence of accurate in-transit monitoring of perishable cargo can both lead to significant cargo losses and to unresolved disputes between consignor, transporter and consignee. Practical investigations revealed that the need exist to derive worst case in-cargo temperatures from temperatures measured along the periphery of the vessel, as well as to predict future cargo temperatures from current temperatures to enable pro-active prevention of situations that may lead to cargo losses.

A series of experiments were conducted to compile a data set representative of cold chain operations in Southern Africa. This data set was subsequently used to train neural network models that predict current in-cargo temperatures from temperatures on the periphery, as well as future temperatures from current temperatures. It was shown that the models are sufficiently accurate to allow worst case in-cargo temperatures to be estimated with high confidence levels from temperatures that can be measured using a small number of permanently installed sensors.

Future work will focus on the integration of the temperature prediction model with a practical in-transit temperature monitoring system that uses RFID based wireless sensors that will simplify not only the deployment of the system but will also support the automated collection of data in real time. This will allow the predictive model to be used for the pro-active prevention of cargo losses as well as for resolving disputes based on accurate records of the actual situation in the field.

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