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TNO report

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D3.1 Design and Solution Development report

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List of abbreviations

ANOVA	ANalysis Of VAriance
API	Application Programming Interface
CoAP	Constrained Application Protocol
DBMS	Database Management System
ETL	Extract, Transform and Load
GPS	Global Positioning System
HIH	Het Internet Huis
HTTP	Hypertext Transfer Protocol
IoT	Internet of Things
MNLR	Multiple Non-Linear Regression
MQTT	Message Queuing Telemetry Transport
NB-IoT	Narrowband Internet of Things
NN	Neural Networks
NOW	Nederlandse Organisatie voor Wetenschappelijk Onderzoek / Dutch Research Council
QCL	Quality Controlled Logistics
SNN	Shallow Neural Networks
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TNO	Nederlandse Organisatie voor toegepast-natuurwetenschappelijk onderzoek / Netherlands Organisation for applied scientific research
UC	Use Case
VOC	Volatile Organic Compounds
VOU	Van Oers United
WFBR	Wageningen Food & Biobased Research
WP	Work Package

Contents

1 Introduction

1.1 Project background ‘Quality Controlled Logistics in IoT-enabled Perishable Supply Chains’

Food supply is one of the main challenges our global society faces, and supply chain innovation is expected to contribute to a secure, efficient and sustainable food supply. The Netherlands plays a significant role in the global food supply system. In supply chains of fresh and perishable food products even minor disruptions in storage/transport conditions can have a considerable effect on product quality and possibly lead to food waste.

Food waste and quality decay is among others caused by suboptimal management of the climate conditions during transport. A lack of insight in (changes of) product quality during storage and transport leads to challenges in managing the quality/shelf life of fresh produce, uncertainties in claims processes, food waste throughout the supply chain, and difficulties to deliver according to agreed product quality standards. The concept of quality-controlled logistics (Vorst et al, 2007), addresses these challenges. Follow up research (Vorst et al., 2012) identifies the possibilities for making chain information directly and real-time available and usable to support decision making of all partners in the horticultural network but concludes that an integrated approach of quality-controlled logistics is still lacking.

By applying innovative IoT applications in combination with knowledge of product quality-loss and logistic decision making we believe that an integrated approach of quality-controlled logistics is possible. Major barriers are the difficulty of precise prediction of remaining product quality/shelf life. By capturing sensor data and using it as input for quality-loss models, we aim to intervene in dynamic supply chains accordingly. As such, we apply quality controlled logistics in an integrated way. Traditional technologies are not able to provide accurate predictions or are extremely expensive. Therefore, investigating the potential use of the next-generation technologies such as IoT become relevant.
This is also recognised both by Dutch Research Council (NWO who granted this project ‘Quality Controlled Logistics in IoT-enabled Perishable Supply Chains’ (IoT4Agri) as part of the research programme ‘*Accelerator - Kennis en innovatie voor een concurrerende logistieke sector*’ and by the consortium partners.

Besides giving the first impetus to an integrated approach of quality-controlled logistics, we contribute to sustainable logistics. Moreover, the project addresses dynamic supply chain planning solutions, enabled by Internet of Things (IoT), and corresponding alternative logistics service offerings (e.g., dynamic en-route changes) based on the remaining perishable product shelf life. This will result in CO_2 savings, transport avoidance (avoiding overripe products that cannot be consumed anymore), and modal shift potential with the aim of a higher product value for the end consumer.

In this IoT4Agri project, the consortium members recognise that IoT technologies are needed to extend the possibilities of monitoring and controlling the quality of perishable products, and to enable implementation of the concept of data-driven quality-controlled logistics.

The project is structured around six work packages, being:

- WP1 IoT enabled Quality Controlled Logistics (QCL), including the QCL conceptual framework[1], the state-of-the-art of supporting technologies, and the SWOT analysis of this QCL-concept[2].
- WP2 Business analysis, including the use cases for demonstration, the business case analysis, and the business model analysis[3].
- WP3 Design and Solution Development, including the development work needed to demonstrate a proof of concept in a real-life setting (= this report)
- WP4 Demonstrations, covering demonstration of the use cases in a maritime and a continental road trade lane.
- WP5 Evaluation and valorisation, ensuring that the project knowledge is being disseminated among the target audience and to support a broader valorisation of the project insights.
- WP6 Project Management, assuring an overall efficient execution of the project and organize and facilitate the cooperation between the consortium parties.

Each Work Package has a corresponding deliverable, that reports on the results. This report reflects the results of Work Package 3 (WP3) and is called *D3.1 Design and Solution Development report*. The next section elaborates the contents and structure of this report.

1.2 Objective and research questions Work Package 3

The key objective of the overall project is to integrate IoT into logistics decision making leading to the research objective '*to explore the potentials and applicability of IoT technologies in enabling dynamic and integrated quality-controlled logistics in the postharvest perishable produce chain*'.

To realize the overall objective, two complementary clusters of research questions from technological and supply chain points of view are formulated[4]. Related to the different Tasks of Work Package 3 the sub-research questions are:

- Technology:
  - Chapter 2: "What are specific connectivity platforms / control tower requirements following sensor data capture and real-time decision support?" (Task 3.1)
  - Chapter 3: "How to convert the collected different type of sensor data into measurable quality indicators?" In other words, "How to incorporate more parameters into the current quality-prediction model to improve the prediction accuracy?" (Task 3.2)

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[1] See: Guo, X., Snels, J.C.M.A., Tromp, S., 2021. Quality-Controlled Logistics with Internet of Things: A conceptual framework (WFBR Report 2131. DOI https:doi.org/10.18174/541694)
[2] See: Finner, S., Zomer, G., 2020. D1.1 State of the Art of IoT technology for quality-controlled logistics in the supply chain of perishable cargo (TNO 2020 P11141)
[3] See: Zomer, G., Bhoraskar, A., 2021. D2.1 Business models, business and use cases of IoT-enabled QCL of perishables. TNO report (TNO 2021 P12076)
[4] As part of *WP3 also sub-research questions related to the level of units that should be applied on container, pallet, crate or individual product level was formulated? However, this sub-research question will be answered in WP 4, more particular in the Use Case 'Optimal sensor positioning in perishable shipment' and will therefore not be part of WP3.*

- Supply Chain:
  - Chapter 4: “How to optimally organize the logistic activities, based on the predicted quality, form a system optimization point of view?” In other words, “What are the underlying supply chain decisions that push the concept of quality-controlled logistics?” (Task 3.3)
  - Chapter 4: “Which supply chain decisions are being supported?” (Task 3.3)

1.3 Contents and structure of the report

To demonstrate the proof-of-concept of comprehensive concept of Quality Controlled Logistics (QCL) it is split in two separate but related work packages. In Work Package 2, the so-called use cases are described. These use cases provide the basis for a proof of concept in a real-life demonstration setting in the project[5]. And in Work Package 3 the solutions for these so-called use cases are being designed and developed.

In this report the ‘design and development’ of the concept of Quality Controlled Logistics in IoT-enabled Perishable Supply Chains will be described on two levels. The first, or more general level focuses on describing the design and solution of ‘what should be in place / is needed to make the concept of Quality Controlled Logistics in IoT-enabled Perishable Supply Chains work in the longer term’.

The second, more specific level will describe the design and development focusing on Use Cases 3 and 4 in showing ‘what is developed to operationalize the concept of Quality Controlled Logistics in IoT-enabled Perishable Supply Chains (= proof-of-concept)’.

These Use Cases (UC) are:

a. UC3: Sensor-enabled quality-loss predictions of a shipment:
   Provide quality-loss predictions based on sensor values of relevant sensors attached to the international shipment(s) of perishables. Relevant sensors include sensors that measure quality-loss indicators such as ethylene, temperature and (relative) humidity.
b. UC4: Decision support for logistics interventions driven by quality-loss predictions:
   Configure possible logistics interventions and provide decision support on executing these interventions based on the quality-loss predictions and remaining transport lead time of corresponding shipments.

The design and development of UC3 include low-cost ethylene sensor development, proof of a functioning connectivity platform, and quality-loss prediction models based on input sensor data. Looking at UC4 sensor data driven logistics decision making will be designed and developed. This will include real-time adjustments to the conditioning parameters (e.g. temperature and (relative) humidity), dynamic acceleration options for the maritime transport (e.g. unload in first port of call and use high speed transport towards destination), acceleration/ deceleration options in port terminal handling (including preparation of the release documents), acceleration/deceleration options in hinterland transport

[5] See Zomer, G. 2021 ‘*D2.1 Business models, business and use cases of IoT-enabled QCL of perishables*’

(e.g. cross-docking, modal shift), avoiding logistics hubs with ripening facilities for particular shipments, and adding additional quality control procedures based on the sensor data.

1.4 Report setup

In chapter 2 we focus on the description of sensor technology and -connectivity in which it addresses the functional design and data flow architecture, data understanding and data standardisation, the design of a central data repository and dashboard, and the connectivity between sensor data, quality-loss model and decision support system. And thus, answering the research questions “What are specific connectivity platforms / control tower requirements following sensor data capture and real-time decision support?” In this chapter also, focused on the demonstrations and use cases, the development of a low-cost sensor, the so-called Sensorbox including ethylene sensors, is described.

In chapter 3 we describe how to connect sensor data to quality-loss models to predict product quality and shelf life. And by this gives answer to the research question “How to convert the collected different type of sensor data into measurable quality indicators?” In other words, “How to incorporate more parameters into the current quality-prediction model to improve the prediction accuracy?”

Then chapter 4 will show the analyses of different decision strategies from a product quality and cost-benefit perspective. Furthermore, in this chapter we formulate decision making models based on product quality by using simulation models to support the decision-making process. The analysis and simulation will include dynamic service differentiation options for logistics operators along the supply chain to accelerate/decelerate the supply chain. The research questions “How to optimally organize the logistics activities, based on the predicted quality, from a system optimization point of view? In other words, “What does it imply for contracts, service level agreement, and operation procedures?”, “What are the underlying supply chain decisions that push the concept of quality-controlled logistics?” and “Which supply chain decisions are being supported?” will be answered.

Finally, in Chapter 5 we discuss scalability and what is needed to get the concept of Quality Controlled Logistics in IoT-enabled Perishable Supply Chains really working, including further development activities.

2 Sensor technology and -connectivity description

2.1 Functional design and data flow architecture

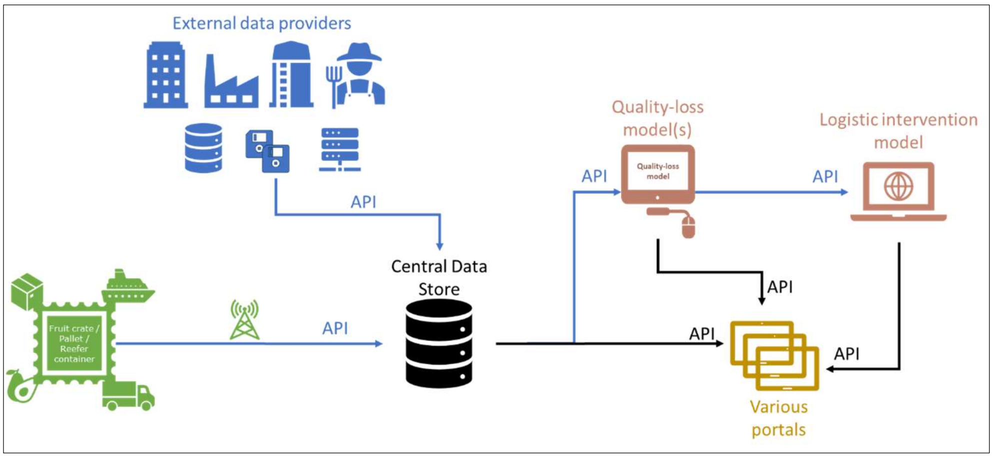

Figure 1: High level architecture (source: WFBR, based on HIH)

Figure 1 is a presentation of the high-level, theoretical project architecture. The main idea is that data is collected in real-time during transport via sensors. This can be at product, box, pallet, crate and vehicle level. This concerns environmental conditions, place, time, et cetera. This data is stored in a Central data store where it is enriched with data from external data suppliers. This concerns, for example, product information, quality reports, harvesting conditions, et cetera. To predict product quality, the central data store retrieves relevant data that is necessary for the quality-loss models. Subsequently, the logistics intervention model is fed with the output of the quality-loss model. The logistics intervention model also retrieves other relevant data, necessary for advising on possible decisions, from the central data store. In order to make the decision, ultimately taken by people, possible, the results are presented via various portals.

2.1.1 *Application for the demonstrations*

For demonstration purposes the ‘ideal’ architectural structure has to be adapted to the companies involved and the available technology. This is shown in Figure 2. In total there are three “data providers”; Sensitech, Van Oers United (VOU) and the Sensorbox (see paragraph 2.5). Only the Sensorbox sends data to the central data store in almost real time. Sensitech provides the data by extracting this data from their platform. VOU is providing the data in a report. Before loading the data into the central data store, the data will be linked together. The link between the various data sources is the date and timestamp.

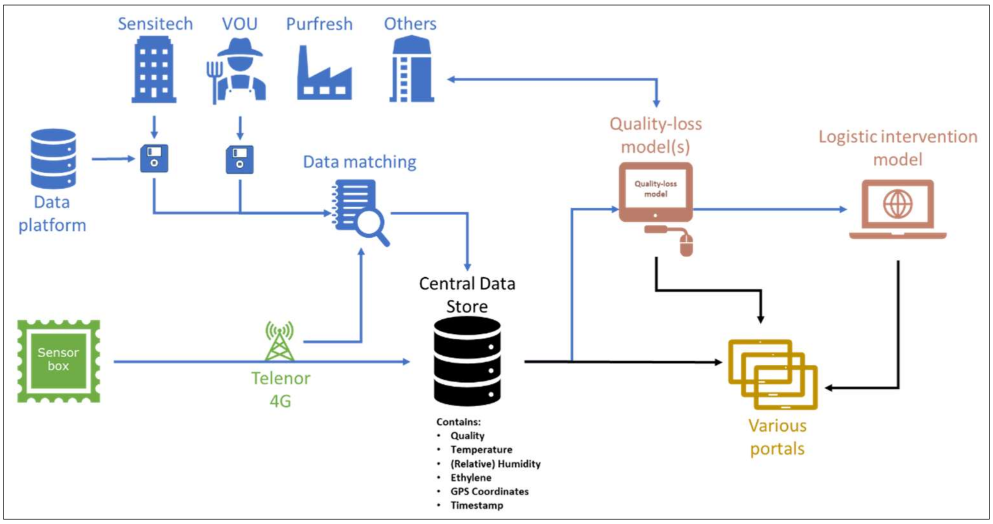

Figure 2: Architecture for demonstration purposes (source: WFBR, based on HIH).

The Sensorbox sends the data via the mobile network of Telenor to the central data store. The Sensorbox is only capable of sending data when the box is directly connected to a "cell tower" of a telecom provider. When the Sensorbox doesn't connect to a cell tower, it stores the data locally. When the Sensorbox is in reach of a cell tower, it will off-load its data.

To be able to use the data in the quality-loss model a three-step process – Extract, Transform and Load (ETL procedure) will be executed by which data is extracted from the data sources that are not optimized for analytics, and moved to a central host to provide the quality-loss model with the necessary data. Details of the quality decay model and the connection to the intervention model are described in Chapter 3.

There is a second way to feed data into the decay model. Other companies having data for determining the quality of fruits and vegetables, can feed their data directly into the decay model. There are several ways to feed data into the model. The easiest way to feed data into the model is by using an ETL approach.

2.2 Data understanding and data standardisation

In the current project there are three data providers; van Oers provides quality data, Sensitech provides temperature and humidity data and Het Internet Huis provides ethylene and GPS data. All these data sources don't meet certain standards. In the project the various data sources are manually matched. This matching process is done before loading data into the central data store. In the central data store a view will be generated to display the data in a portal. This view generates Date, Time, Temperature, (relative) Humidity, Ethylene, and GPS coordinates.

2.3 Design of a Central data repository and Dashboard

Data in the central data store will be presented using Thingsboard. Thingsboard is an open-source IoT platform for data collection, processing, visualization, and device management.

It enables device connectivity via industry standard IoT protocols – MQTT[6], CoAP[7] and HTTP[8] and supports both cloud and on-premises deployments. Thingsboard is thus suitable for this project because it is a system that enables to display data with a variety of dashboards. An example of such a dashboard is shown in Figure 3.

Figure 3: Dashboard example (source: HIH)

Besides the possibility of representing various data in all kinds of graphs. Thingsboard also has features to show data on a topographical map by using the GPS coordinates.

2.4 Connectivity between sensor data, quality-loss model and decision support system

In the current phase of this project, it isn't possible to feed a real-time decision support model. There are two reasons why this isn't possible:

1. The various data sources are not standardized and there is no data governance agreement in place.
2. The determination of the quality of the goods, when the goods are loaded into the truck in the country of origin, is recorded on (written) forms. Also, when the goods arrive in the Netherlands, the quality is written down on forms (see also paragraph **3.1**).

[6] Message Queuing Telemetry Transport (MQTT) is a lightweight, publish-subscribe network protocol that transports messages between devices
[7] Constrained Application Protocol (CoAP) is a specialized Internet Application Protocol for constrained devices which enables those constrained devices called "nodes" to communicate with the wider Internet using similar protocols
[8] Hypertext Transfer Protocol (HTTP) is an application layer protocol for distributed, collaborative, hypermedia information systems and is the foundation of data communication for the World Wide Web.

So, for being able to use this data and information a manual conversion step is required, so that real-time feeding of the decision support model is not possible in current practice.

2.5 Low-cost sensor development: Sensorbox, including ethylene sensors

For demonstration purposes a Sensorbox is developed (see Figure 4).

Figure 4: Sensorbox (Source: HIH).

This Sensorbox is a stand-alone sensor. For the communication with the 4G network we're using a module of Quectel. Currently there are two module providers, Quectel and uBlox. Due to the knowledge and experience within Het Internet Huis, we choose for a module of Quectel. This module makes it possible to communicate over different communication bands of 4G and 5G. The most obvious is to use NB-IoT[9]. Besides communication, this Quectel also has the ability to communicate with GPS satellites. In this way it is possible to register the location of the Sensorbox.

Besides the communication this Sensorbox is equipped with an ethylene sensor (C_2H_4). This is an inexpensive sensor manufactured by a Chinese company called Winsen. We choose for this approach because of a working relationship with Winsen. The detection range of this sensor is 0 ~ 100 ppm.

Figure 5: Winsen Electrochemical Ethylene Gas Sensor ME3-C2H4 (source: https://www.winsen-sensor.com/sensors/c2h4-sensor/me3-c2h4.html)

[9] Narrowband Internet of Things (NB-IoT) is a Low Power Wide Area Network radio technology standard to enable a wide range of cellular devices and services

Another discussion related to the Sensorbox is how to measure climate condition inside a container. More specific, where to place the sensors and how much sensors are needed. These questions that need further investigation are reformulated as Use Case 2 ‘Optimal sensor positioning in perishable shipment’ (this is part of Work Package 4 of this project). In this Use Case research will focus on applying sensors on different locations within a truck or container. Then it will the differences in sensor values will be analysed in order to advise on the number and location of different sensors, and to provide input for the feasibility of the business case of embedded sensors in pallets or crates.

2.6 Scalability and further development

To realize a real time intervention model, based on the quality-loss model which again is based on various data sources from various data providing companies, a lot of work needs to be done.

The work that needs attention is:

- On a business level: roles, responsibilities and fee structures must be clear
- On a legal level: relevant rules and regulations, a governance model and contract must be in place
- On an operational level: service levels, operational governance, incident and change management must be clear
- On a functional level: the interaction model and privacy must be in place
- On a technical level: standards for data and security must be developed and implemented

One direction to develop a data architecture is a federated model. A combined database system is a type of meta Database Management System (DBMS), which transparently combines multiple autonomous database systems into a single combined database. The constituent databases are connected via a computer network and may be geographically decentralised. Since the constituent database systems remain autonomous, a federated database system is a contrasting alternative to the (sometimes daunting) task of merging several disparate databases. A federated database, or virtual database, is a composite of all constituent databases in a federated database system. As a result of Data Federator, there is no actual data integration across the constituent disparate databases.

An example of a federated model is provided in this Figure 6.

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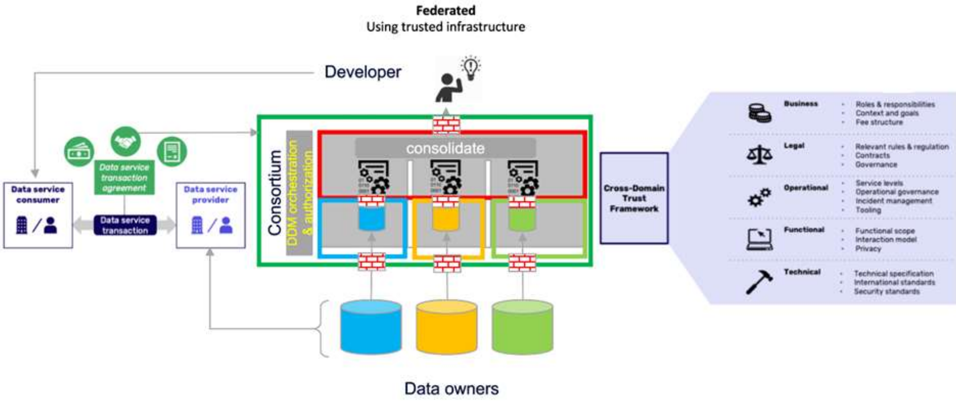

Figure 6: Federated architecture (source: Gommans, L., Prototype Digital Data Marketplace - Enabling Data Sharing for AI Development, Presentation for SURF on DDM prototype in AMdEX context, 23rd June 2020, Utrecht, The Netherlands, https://www.dl4ld.net/presentations/).

2.6.1 Integration for demonstration purposes

In order to facilitate the shipment demonstration data exchange, the post harvest product quality is to be provided by Van Oers United via a form, being developed for the purpose of the demonstration. This form has not yet been standardised but will serve the proof of concept. Moreover, the sensor data captured during the shipment transport is being made available via a central data warehouse dashboard and is approachable by WFBR, who will 'run' the quality-loss model feeded with this sensor data.

The project will not develop an automatic interface (API) between the central data warehouse and WFBR. Similarly, the exchange of the output of the quality-loss model between WFBR and TNO is also not being automated, but pushed by WFBR. Similarly, the intervention model output exchange is being sent to the central data warehouse. Again, not in an automatic manner, but pushed by TNO. Obviously, when the concept is being implemented on a wider scale, these data exchange facilities can easily being automated using API[10] protocols.

[10] Application Programming Interface (API) is an interface that defines interactions between multiple software applications or mixed hardware-software intermediaries

3 Connecting sensor data to predict product quality

3.1 Quality-loss indicators

Quality-loss indicators are normally associated with a physical property of the product like misshapen, dehydration, change in colour or pathogens like fungal or bacterial growth. In a supply chain the choice of which quality-loss indicators are relevant depends on the product, the supply company, and the requirements of the client.

Several researchers have analysed the dependence between quality-loss indicators and environmental conditions such as temperature and relative humidity (see section 3.2). These researchers are mainly interested in the quantitative relationships between the environmental conditions (such as temperature, humidity, air compositions) and the quality-loss indicators along a certain time horizon.
The main quality-loss indicators used by researchers are listed in the graph below (Figure 7).

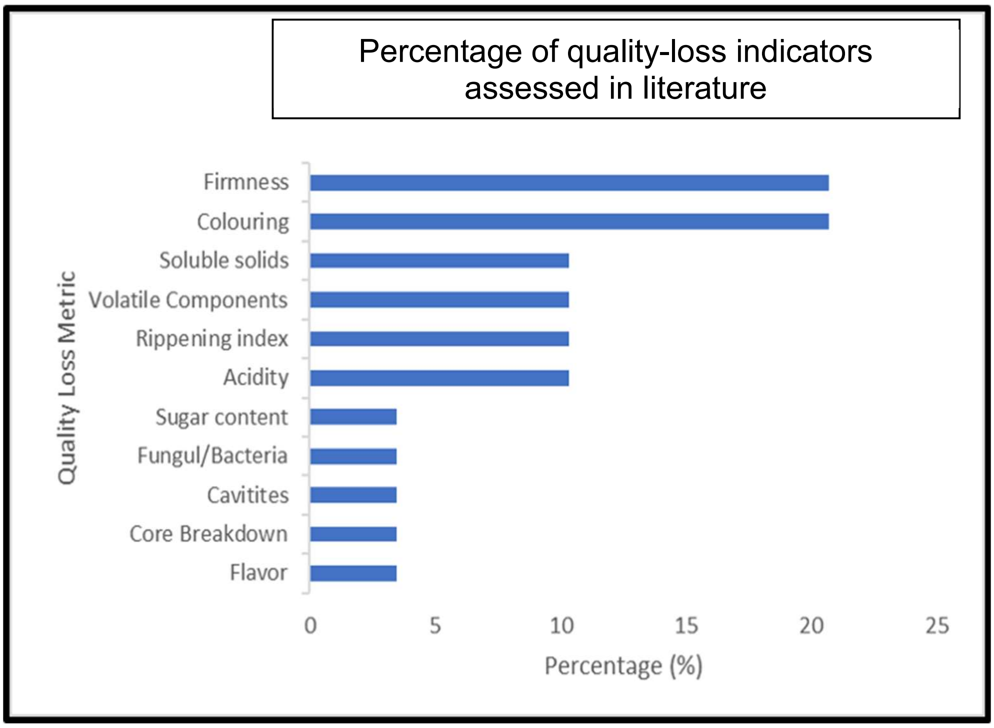

Figure 7: Shows the percentage of different quality-loss indicators used by literature. (Source: WFBR).

We observe that colour and firmness are the quality-loss indicators that have been mostly researched. This is not surprising partly because both firmness and colour are the two most common factors that a consumer pays attention to when purchasing a fresh product. More importantly, firmness and colour give indications of the storability and ripeness of the fresh product, which has significant business relevance.

From the point of view of a supply company, we can extract the quality-loss indicators from quality reports that are used to control product quality along the supply chain. For example, Van Oers United (VOU) performs two quality checks for each shipment from the sourcing countries to the Netherlands. The first report, produced at products' origin, is composed of two sections, the first section completed during harvesting and the second section previous to shipment (if the time between harvest and shipment is less than 24 hours only one section is provided). The second report is produced at destination. An example of both reports can be found in Figure 8 and Figure 9 respectively.

Date	Variety	Farm	Drillingcode	Frui Echant	Frui Defaut	Valeur	Brown coloration	Brown vein	Coloration	Deformation	Dehydration	Insect damage	Prc grain	Rot	Wind damage
1-3-2021	Haricot Vert Coco	Olad Dahou L24	307467	3.000	1.070	0,83	0,50		1,53	10,93		0,83	0,00		0,67
4-3-2021	Haricot Vert Coco	Olad Dahou L24	307467	2.000	658			5,20		9,05	0,50		0,00		2,15

Figure 8: Van Oers' report at origin. Quality check during harvesting and before shipment can be observed in different rows. (Source: VOU)

Keuraspecten:	**Score:**	**3 (very bad) - 9 (very good)**
Free from soil (%)	-	
Strings (%)	0%	
Mould (%)	-	
Thrips (%)	-	
Browning level 3 (%)	1%	
Plant stems Remains (%)	1.5%	
Misshapen (%)	1%	
Wind damage (max 1 cm²) (%)	1.5%	
Flower remains (%)	-	
Dehydration (%)	3.5%	
Virus (%)	-	
Deviation in colour (%)	3%	

Figure 9: Van Oers' report at destination. The figure does not represent the full Van Oers' report, just a part of it. (Source: VOU)

The relevance of the quality-loss indicator scan be evaluated by extracting the metrics that appear in both reports. In this case, the main quality indicators are: colour, deformation, dehydration, and wind damage. For modelling (see section 3.2) it is of crucial importance to have the same type of quality indicators both at origin and at destination. Quality at origin can be used as an initial condition and quality at destination as the variable the model needs to predict. To evaluate the impacts of different environmental conditions during transport on the changes of the quality metrics, the two quality reports need to be linked to the environmental conditions (i.e., matching the original quality of each batch with the environmental conditions during transport as well as the arrival quality of the same batch). This is currently not the case; VOU is currently working on this.

To the best of our knowledge, there is no implementation yet where quality-loss indicators are measured during transport.

3.2 State of the art models and research in the area of fresh food quality-loss

In this project we aim at developing quality-loss models that are non-destructive since in this way the testing methods do not damage the product, the whole product can be tested which can minimise the inaccuracy of test results and any undermined irregularities. In practice we see that several methodologies that are developed to measure quality-loss indicators often cause a quality-loss themselves, because for measuring they need to damage or destruct the product (Llobet, Hines et al., 1999). To avoid the destruction or damage to the product it is important to develop methodologies that can predict the quality-loss without interfering with the normal deterioration process. To this end, it is important to understand the relationships between quality-loss and environmental conditions that influence quality, for example temperature, humidity, etc. As a result, quality-loss models are developed to capture those relationships and predict quality changes under different transportation (or storage) conditions.

We categorize the quality-loss models from the literature into three categories:

- The classical mathematical models: models developed from mathematical approximations of the quality-loss phenomenon. These mathematical models try to describe the kinetics of quality-loss of fresh products.
- Linear data models: models that fit data assuming a linear relationship between quality-loss indicators and variables (sensors). The complexity of the variables' functional relationship is linear for these models. Some of these models are: linear regression, logistic regression, etc.
- Non-Linear data models: These types of models are the most complex ones. They can model non-linear dependencies between variables at the expense of having a large volume of data. The more complex the relationship of the variables, the more data is required for modelling. Some of these models are: random Forest, deep artificial neural networks, etc.

Notice that strictly speaking both linear data models and non-linear data models can be considered as part of a more general modelling technique known as machine learning.

Machine learning models are mathematical algorithms that find a mathematical formula, which, when applied to a collection of inputs (sensors, variables, etc) produces a desired output (quality-loss, shelf-life prediction, etc). In other words, machine learning algorithms, by processing data, are able to find functional relationships between input and outputs, without the need of human intervention.

Besides different types of modelling technologies, another very important distinction is made between models for climacteric and non-climacteric products. A climacteric product presents a ripening associated (related) with the increase in the release of ethylene and rise of cellular respiration. Modelling a climacteric product requires the measurement of ethylene as one of the main indicators of quality-loss. On the contrary, non-climacteric products like strawberries or green beans do not release large amounts of ethylene since they have already done most of their ripening before harvesting.

In the following subsections, we will present a review of the quality-loss models by the types of different modelling techniques.

3.2.1 *The classical mathematical models*

Tijskens and Polderdijk (1996) developed a model that predicts the quality based on temperature, initial quality and the quality acceptance limits. They found that the model correctly predicted quality for 60 different species of fruit and vegetables, amongst which French beans.

Schouten et al. (2018) propose a kinetic model that incorporates the effects of temperature and ethylene on the firmness behavior of “Keitt” and “Kent” mangoes.

Penchaiya et al. (2020) looked at biological indicators for quality of mangoes and found that variation in firmness, total soluble solids and titratable acidity are correlated to variation in maturity. Models could predict the quality better if they take these parameters into account. They also found that mangoes stored at a higher temperature had a higher rate constant for firmness and coloring, which indicates faster fruit ripening. Thus, storage at higher temperatures seems to have a negative effect on the quality of mangoes.

3.2.2 *The general linear and non-linear models*

Besides the classical mathematical models, the linear models including both linear and logistic regressions are another group of models that have been widely used to predict the quality-loss for fruits and vegetables.

For the climacteric products, in the literature, there are quite some studies available on the quality-loss for mango. Most of them applied the analysis of variance (ANOVA) to make the analysis and quality prediction. Ntsoane, Luca, Zude-Sasse, Sivakumar, and Mahajan (2019) investigated the low oxygen (O_2) tolerance limit of the “Shelly’ mango. They measured the quality of the mangoes by looking at pigments and accumulation of O_2 restricted volatile organic compounds (VOC). Low O_2 levels did not have an impact on pigmentation, However, they found that the accumulation of anaerobic VOCs increased with lower O_2 levels. They also found that odour and taste decreased with low O_2 levels. Specifically, 5% is the low O_2 limit for the fruit to accumulate enough anaerobic VOCs to be described as off-flavor. However, 10% O_2 can already result in reduced mass-loss and respiration and maintenance of firmness, soluble solids, and individual sugars. Lalel and Singh (2004) found the same result that higher O_2 levels are more favorable for storage of the green mango. In addition to that, they also found that storage at either 2% O_2 & 3% carbon dioxide (CO_2) or 3% O_2 & 6% CO_2 levels at 13 ˚C is the most effective to prolong shelf life. They measured this by keeping mangoes at different conditions of temperature, and O_2 and CO_2 concentration and measuring biosynthesis and aroma volatile compounds. In similar research Lalel and Singh (2006) found that storage at 3% O_2 and 6% CO_2 levels appears to be the most promising for ‘Delta R2E2’ mangoes. Especially the amount of ethanol and acetaldehyde levels were significantly reduced in fruit stored at those O_2 and CO_2 levels. These results indicate as well that higher CO_2 levels lead to a decrease in quality.

This indication is also supported by Bender, Brecht, Baldwin, and Malundo (2000), who researched the effect of CO_2 levels on aroma volatiles in ‘Tommy Altkins’ mangoes. They found that mangoes stored at 10% CO_2 had little effect on the volatile aroma levels compared with storage in air. However, mangoes stored at 25% CO_2 showed an increase in aroma volatile levels. In addition, they also found that tree ripe fruit contained more volatile levels after storage than mature green fruit. However, Sivakumar, Van Deventer, Terry, Polenta, and Korsten (2012) found that lower O_2 levels and higher CO_2 levels reduced weight and firmness-loss, delayed skin and fresh colour development and prevented the increase of soluble solids/titratable acids ratio. This is in contrast with the previous found result, where it should be noted that the effect of O_2 and CO_2 concentration was measured in combination with the effect of 1-methylcyclopropene (1-MCP). Montalvo, García, Tovar, and Mata (2007) researched the effect of ripening of ‘Ataulfo mangoes’ when exposed to three different amounts of ethylene. They found that when exposed 100 ul ethylene, the ethylene production in the fruits accelerated and the ripening process increased with 4 days. Quality was measured by measuring volatiles. Different from the aforementioned study which used the ANOVA to make the analysis, Rungpichayapichet, Mahayothee, Nagle, Khuwijitjaru, and Müller (2016) investigated how well near-infrared spectroscopy (NIRS) prediction models could predict the post-harvest quality of mangoes using partial least squares (PLS) regression analysis. The models were used to predict firmness, total soluble solids, titratable acidity, and ripening index. They found that NIRS models correctly predicted the quality in 80% of the cases.

In addition to mangos, there are also studies focusing on other climacteric products. Verlinden, de Jager, Lammertyn, Schotsmans, and Nicolai (2002) built a logistic regression model to describe the effect of storage factors on the quality of pears. Quality of the pears was measured by determining the core breakdown. They found that mature fruit stored at lower O_2 and higher CO_2 levels is more susceptible to breakdown.

Lammertyn, Aerts, Verlinden, Schotsmans, and Nicolaı (2000) used a multivariate logistic regression model to predict the quality of Conference pears. They determined the quality of pears by looking at their coloring and number of cavities. They predicted the quality by measuring CO_2 and O_2 concentration and by the size and weight of the pear. The models correctly determined the quality of the pears in 86% of the cases. Melesse, Sobratee, and Workneh (2016) researched the effect of temperature on the postharvest quality of tomatoes. They use a multivariate logistic regression model to study the effect of temperature on the marketability of tomatoes. They used the presence and amount of Fungi, bacteria, coliforms, total soluble solids, glucose, fructose and ascorbic acid as indicators for quality. Their results are supported by Tolesa, Workneh, and Melesse (2018), who also used multivariate logistic regression to determine the effect of temperature on quality in tomatoes. They used firmness, hue angle and total soluble solids as indicators for quality.

Touati, Barba, Louaileche, Frigola, and Esteve (2016) measured the kinetics of physicochemical parameters, bioactive compounds and total antioxidant capacity modifications were measured as an indicator for stability of different fruit nectars. This stability was measured for fruit nectars of pears, orange and grape after storage at 3 different temperatures (4, 25 and 37 °C). They found that stability in fruit nectars stored at 4 °C was better than when stored at 25 and 37 °C. This indicates that lower temperature has a positive effect on the quality of fruits. Véras, de Araújo, Junior, and Finger (2019) investigated the effect of three different temperatures on ‘Galia’ melons. They measured pulp firmness, mass-loss, internal and external appearance, chilling injury, soluble sugars and enzymes to determine the quality. They found that quality significantly decreased when stored at the highest temperature (11 °C). However, they also found chilling injury when the melons were stored at a temperature of 3 °C. This indicates that an optimum temperature for storage of ‘Galia’ melons is 7 °C.

In the case of non-Climacteric products, temperature and time are the most used indicator to predict quality-loss. Vanstreels et al. (2002) investigated red discoloration of chicory using a multiple regression analysis, where red discoloration a negative indicator is for quality. They found that elevated carbon dioxide levels and decreased oxygen levels resulted in lower are favourable for avoiding red discoloration. The optimal condition to prevent red discoloration is where an atmospheric composition of 10% O_2 and 10% CO_2 with a storage temperature of 5°C is maintained.

For the more complex non-linear models, the studies include the following. Llobet, Hines, Gardner, and Franco (1999) trained an electronic nose system on detecting quality by measuring tin oxide, which is an indicator for ethylene (Nabena, Yuliarto, & Iqbal, 2018) and other volatile levels of bananas. Three supervised classifiers were used to predict seven stages of ripeness of bananas. These stages of ripeness were determined by their colour. They found that two classifiers (FuzzyArtmap and LVQ) predicted the states of ripeness correctly with accuracies of resp. 90.2 and 92%. Because FuzzyArtmap does take previously learnt data into account, this makes it the most favourable tool to use when predicting the ripeness of climacteric fruit.

Deshmukh, Kasbe, Mujawar, Mule, and Shaligram (2016) developed a wireless electronic nose system (WEN), which through gas sensors should measure the ripeness of mangos. Three stages of ripeness of the mangoes were determined to see whether the WEN correctly could determine the ripeness. The advantage of WEN is that it is portable, low cost, interactive and can be applied on most species of fruit and vegetables.

Geethapriya and Praveena (2017) developed an electronic nose, which measures the fruit ripeness based on ethylene levels. They determined three stages of ripeness in mangoes and found a positive correlation between the ripeness of the fruit and ethylene levels measured by the electronic nose.

Torres-Sánchez, Martínez-Zafra, Castillejo, Guillamón-Frutos, and Artés-Hernández (2020) used a multiple non-linear regression (MNLR) model to monitor shelf-life reduction based on temperature in lettuce. They used a number of quality parameters to determine the quality of the lettuce, namely the respiration weight, weight, and human sensory analysis. In the human sensory analysis 5 groups of quality were determined based on their compactness, visual appearance, flavour, and colour. They found that all quality parameters were negatively influenced when the temperature increases. A MNLR with interactions was suggested as a model to predict quality-loss during storage.

3.2.2.1 *Usage for demonstration purposes*

For the purpose of this project, especially the demonstration, we want to model the relationship between quality-loss indicators (output variable) and external variables like temperature, humidity, etc. Therefore, we assume that there is a relationship between environmental conditions and quality-loss indicators, in other words, by obtaining sensor data we are able to infer the quality-loss of a product.

For the sake of the demonstration, existing mathematical quality-loss models are adapted to the problem at hand. The lack of data during the initial stages of the project does not allow the fitting of any data model (linear or non-linear). Mathematical models that were developed in a very controlled environment (atmospheric conditions like temperature, humidity and volatile gases were kept constant or strictly regulated) are adapted to the project's needs.

3.2.3 *Future developments: the machine learning model*

Once more data is collected, it will be able to develop data models that would be able to adjust better to fluctuations in the measured variables. For this future scenario it is proposed to use of artificial neural networks to model the relationship between sensors and quality-loss indicators.

Artificial neural networks, or just neural networks (NN) are popular machine learning techniques that simulate the mechanism of learning in biological organisms. The animal nervous system contains cells, called neurons. The neurons are connected on one another with the use of axons and dendrites (see Figure 10 A) and the connecting regions between axons and dendrites are called synapse (see Figure 10 B). The strengths of synaptic connections often change in response to external stimuli. This change is how learning takes place in living organisms.

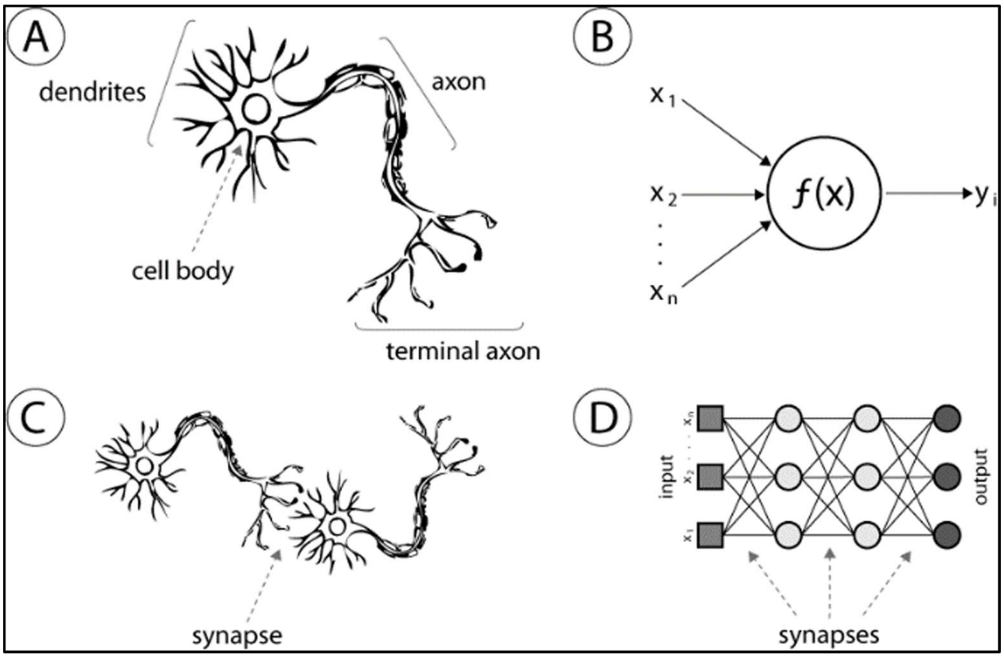

Figure 10: Comparison diagram between biological and artificial neural networks. Figure (A) represents a biological neuron and its constituent parts. Figure (B) shows the corresponding analogy of an artificial neuron. Figure (C) represent the transmission of information between neurons by the synapse process. Figure (D) shows the connection between different neurons constituting an artificial neural network. Diagram extracted from Meng, Hu, and Ancey (2020)

Artificial neural networks try to simulate this biological learning mechanism. A neural network also contains computational units referred as neurons (see Figure 10 C). As with the axons and dendrites, these computational units are connected to one another through mathematical weights (see Figure 10 D). Learning occurs by adjusting the weights connecting the artificial neurons. Just as external stimuli are needed for learning in biological organisms, the external stimuli in an artificial neural network are provided by data containing examples of input (in our case, sensor measurements) and output (in our case quality-loss indicators) pairs of the function to be learned.
Neural networks can model non-linear relationship between the input and output variables, allowing for the modelling of more complex behaviours. Neural networks are very flexible and can be applied to different problems from image recognition to time series analyses.

Regarding its complexity Neural Networks can basically be divided into three main types:

1. Shallow Neural Networks: This type of NN learns the weights of the network directly from the input variables. These are very simple neural networks that can reproduce the linear relationship obtained using linear models, they do not require so much data for modelling. Linear regression and logistic regressions can be modelled as shallow neural networks.
2. Neural Networks: Networks with an increase in complexity (non-linearity) for modelling. More data is required to create an accurate model.

3. Deep Neural Network: the state-of-the-art networks used for image and text recognition. In deep neural networks learning contrary to shallow, most of the weights are learned not directly from the features of the input data, but from outputs of preceding layers. They can model any type of relationships at the expense of requiring a large volume of data.

Neural networks can be applied to many different complexity types of modelling. For example, if it is known that the relationship between inputs and output is linear then a simple shallow neural network (a linear regression) would be enough to capture this functional dependence. On contrary if the relationship between inputs and outputs is more complex (non-linearities present) deeper neural networks would be able to learn the dependence. Therefore, due to its flexibility regarding the amount of available data WFBR believes this type of algorithm can be very beneficial and evolve together with the volume of data collected.

3.2.4 Quality-loss models for demonstration purposes

As already mentioned, for the sake of the demonstration, WFBR will adapt existing mathematical quality-loss models to the problem at hand. WFBR will adapt mathematical models that were developed in a very controlled environment (atmospheric conditions like temperature, humidity and volatile gases were kept constant or strictly regulated), to the project's needs.

Table 1: Products used for demonstrations.

Product	**Cultivar**	**Sourcing country**	**Transport modality**
Green beans	Sonny	Morocco	Road
	Sonny	Senegal	Road
Mangos	Kent	Senegal	Road / Sea

WFBR will adapt the mathematical models for these two products to the project's needs because the existing models were developed in a very controlled environment (atmospheric conditions like temperature, humidity and volatile gases were kept constant or strictly regulated).

3.2.4.1 Green beans

For green beans two quality-loss models exist: a combined senescence and chilling-injury model dependent on time and temperature, and a specific weight-loss model dependent on time, temperature and relative humidity. The impact of ethylene is covered by an additional constraint.

1. <u>Senescence and chilling-injury model</u>

Output: shelf life based on a ‘holistic’ quality perception (most probably covering the quality attributes shriveling (due to weight loss) and color), due to both senescence and chilling injury.

Input: storage time and temperature.

The model and parameters are explained in Table 2.

Model explanation: The French-bean model from (Tijskens & Polderdijk, 1996) has been adapted by adjusting the optimal shelf life to the supply chain of VOU (20 days for Senegal, 14 days for Morocco).

Disclaimer: this model is based on scientific literature, expert opinion and information from VOU. In order to model the supply chain of VOU more accurately, dedicated data collection would be needed.

Table 2: Model and parameters of senescence and chilling-injury model of green beans.

Parameter	**Meaning**	**Unit**	**Value**	**Source**
SL(T)	Shelf life at temperature *T*	d	$SL(T) = \frac{SL_{ref}}{k_{1,ref} * e^{\frac{Ea(1)*1000}{R}*\left(\frac{1}{T_{ref}}-\frac{1}{T}\right)} + k_{2,ref} * e^{\frac{Ea(2)*1000}{R}*\left(\frac{1}{T_{ref}}-\frac{1}{T}\right)}}$	Tijskens & Polderdijk (1996)
SL_{ref}	Shelf life at T_{ref}	d	$SL_{ref} = \frac{SL_{opt}}{6.746} * 5.985$	Tijskens & Polderdijk (1996)
SL_{opt}	Shelf life at T_{opt}	d	20 (Senegal), 14 (Morocco) These values can be adjusted if initial quality is deviating.	VOU
T_{opt}	Optimal temperature	d	280.15	Tijskens & Polderdijk (1996)
$k_{1,ref}$	Reaction rate chilling injury at T_{ref}	1/d	1	Tijskens & Polderdijk (1996)
Ea(1)	Activation energy chilling injury	J/mol	79	Tijskens & Polderdijk (1996)
R	Universal gas constant	J/(K mol)	8.314	
T_{ref}	Reference temperature	K	283.15	Tijskens & Polderdijk (1996)
T	Storage temperature	K	Input	
$K_{2,ref}$	Reaction rate senescence at T_{ref}	1/d	0.0549	Tijskens & Polderdijk (1996)
Ea(2)	Activation energy senescence	J/mol	-271.82	Tijskens & Polderdijk (1996)
Loss(t,T)	Loss of SL_{opt} when stored at temperature *T* for time *t*	d	$Loss(t,T) = t * \frac{SL_{opt}}{SL(T)}$	By calculation
t	Storage time	d	Input	
$SL_{fin,opt}$	Remaining shelf life at T_{opt}	d	$SL_{fin,opt} = SL_{opt} - Loss(t_1,T_1) - \cdots - Loss(t_n,T_n)$ where $T_1,\ldots,T_n$ are the subsequent, stepwise constant temperatures with durations $t_1,\ldots,t_n$	By calculation

2. Weight-loss model

Output: shelf life based on weight loss.
Input: storage time, temperature and relative humidity.

The model and parameters are explained in Table 3.

Model explanation: The weight loss percentage per day equals a product-specific factor β times the vapour pressure deficit. This factor β depends of the product's transpiration coefficient. Values of β have been adapted by adjusting the optimal shelf life to the supply chain of VOU (<5% weight loss at 6-7˚C and 95% RH after 20 days for Senegal, 14 days for Morocco).

Disclaimer: this model is based on scientific literature, expert opinion and information from VOU. In order to model the supply chain of VOU more accurately, dedicated data collection would be needed.

Table 3: Model and parameters of weight-loss model green beans.

Parameter	Meaning	Unit	Value	Source
WL(t, T, RH)	Weight loss if stored at temperature *T* and relative humidity *RH* for time *t*	%	$WL(t,T,RH) = \frac{\beta}{1000} * t * VPD$	Becker (1996), Holcroft (2015)
VPD[11]	Vapour pressure deficit	Pa	$VPD = \left(\frac{100 - RH}{100}\right) * SVP$	Murray (1966)
SVP	Saturated vapour pressure	Pa	$SVP = 610.7 * 10^{\left(\frac{7.5T}{237.3+T}\right)}$	Murray (1966)
t	Storage time	d	Input	
RH	Relative humidity during storage	%	Input	
T	Storage temperature	˚C	Input	
Loss'(t, T, RH)	Loss of shelf life at *T'* and *RH'*, if stored at *T* and *RH* for time *t*	d	$Loss'(t,T,RH) = t * \frac{VPD}{VPD'}$	By calculation
SL_{fin} *(T', RH')*	Remaining shelf life at *T'* and *RH'*	d	$SL_{fin}(T',RH') = \frac{5}{\frac{\beta}{1000} * VPD'} - Loss'(t_1,T_1,RH_1) - \dots - Loss'(t_n,T_n,RH_n)$ where $T_1,\dots,T_n$ and $RH_1,\dots,RH_n$ are the subsequent, stepwise constant temperatures and relative humidities with durations $t_1,\dots,t_n$	By expert knowledge (shelf life ends if weight loss equals 5%) and calculation

[11] Water loss is a common postharvest problem with green beans. About 5% weight loss is needed before shrivel and limpness are observed. After 10-12% weight loss, the beans are no longer marketable. The weight loss of mature green beans can be estimated from the equation: % weight loss per day = 0.754 x vapor pressure deficit. The VPD can be obtained from a psychrometric chart when temperature and relative humidity are measured. The rate of water loss of immature beans is higher than for mature beans (Source: http://postharvest.ucdavis.edu/Commodity_Resources/Fact_Sheets/Datastores/Vegetables_English/?uid=3&ds=799)

β	Weight loss per day per kPa VPD	%/d	6.048 (Morocco) 4.32 (Senegal)	Based on VOU (shelf life equals 20 days for Senegal, 14 days for Morocco)

3. Additional constraint

Based on expert knowledge: if the ethylene concentration exceeds 1 ppm, then the shelf life (according to both models) is reduced by 30-50%.

Assumptions on relative humidity (if non sensored), dependent on packaging

- Loose in crates: RH = 95%
- Loose in boxes: RH = 95%
- Consumer packs of 400g-500g in foil with perforations: RH = 99%

3.2.4.2 Mango

1. Firmness model

Output: firmness; non-destructive stiffness measure using a commercial acoustic firmness tester. This tester combines a resonant frequency and mass into a firmness index.

Input: storage time and temperature

The model and parameters are explained in Table 4.

Model explanation: The model about mango from Brazil (Keitt) from (Schouten et al., 2018) has been applied because this model represents the expected situation of VOU (a moderate decrease of firmness during transport at 9 ˚C, but a rather serious decrease at 12 ˚C), although the real cultivar in the supply chain of Van Oers United is a Kent cultivar.

Disclaimer: this model is based on scientific literature, expert opinion and information from VOU. In order to model the supply chain of VOU more accurately, dedicated data collection would be needed.

Table 4: Model and parameters of firmness model mango.

Parameter	Meaning	Unit	Value	Source
$F(t)$	Firmness at time t		$F(t) = F_{fix} + (F_o - F_{fix}) * e^{k_{fenz}*Eth\left(\frac{-e^{-k_d t}}{k_d^2} - \frac{k_d t - 1}{k_d^2}\right)}$	Schouten et al. (2018)
F_0	Firmness at time 0		60	Expert knowledge
F_{acc}	Acceptability level		25	Expert knowledge
F_{fix}			12.7	Schouten et al. (2018)
Eth			1.52	Schouten et al. (2018)
k_{fenz}	Reaction rate	1/d	$k_{fenz} = k_{fenz,ref} * e^{\frac{E_{fenz}}{R}\left(\frac{1}{T_{ref}} - \frac{1}{T}\right)}$	Schouten et al. (2018)
k_d	Reaction rate	1/d	$k_d = k_{d,ref} * e^{\frac{E_d}{R}\left(\frac{1}{T_{ref}} - \frac{1}{T}\right)}$	Schouten et al. (2018)
$k_{fenz,ref}$	Reaction rate at T_{ref}	1/d	0.099	Schouten et al. (2018)
$k_{d,ref}$	Reaction rate at T_{ref}	1/d	0.219	Schouten et al. (2018)
E_{fenz}	Activation energy	J/mol	169900	Schouten et al. (2018)
E_d	Activation energy	J/mol	10	Schouten et al. (2018)
R	Universal gas constant	J/(K mol)	8.314	
T_{ref}	Reference temperature	K	295.15	Schouten et al. (2018)
T	Storage temperature	K	Input	
t	Storage time	d	Input	

Model use: it is assumed that the initial firmness (before transport) equals 60, and that the product is rejected at unloading if it has become too soft (firmness below 25). As an indication, Table 5 shows the remaining shelf life, based on the firmness model from Table 3, at two different temperatures (9 ˚C and 12 ˚C) for different levels of the current (predicted) firmness.

Table 5: Remaining shelf life at two different temperatures.

Current firmness	Shelf life at 9˚C (d)	Shelf life at 12˚C (d)
26	6	3
27	9	5
28	13	7

3.2.4.3 Operating range and scope of the models

The quality-loss models as described in the former section cover product *physiology*, so senescence of the product due to time and climate conditions:

- For green beans the senescence and chilling-injury model covers the shelf life based on a 'holistic' quality perception due to storage time and temperature (including chilling injury). The weight-loss model covers weight-loss due to storage time, temperature, and relative humidity
- For mango a firmness model is developed based on storage time and temperature.

This means that some other, probably important quality-loss indicators which may occur in practice are not covered by the existing models. Think for example of browning of green beans, and anthracnose and rot of mango.

3.3 Sensors (types, output, types of data)

To predict the loss of quality of a fresh product, quality-loss indicators need to be estimated. Quality-loss indicators (see section 3.1) quantify the quality lost by a product. There are some challenges inherent to a quality-loss indicator:

1. Some quality-loss indicators require expert knowledge for their assessment. Normally product experts asses the quality of a sample of products manually at the beginning and end of the supply chain. Commonly it is hard to measure the quality during transport;
2. Some of the quality-loss indicators are invasive (destructive): In order to be measured, the product needs to be damaged.

For these two reasons, it is important to understand the relationship between the quality-loss indicators and sensors that can be active during transport. Commonly these sensors are not destructive, however they are normally external to the product and thus these sensors measure environmental conditions (temperature, humidity) of the area in which the products are stored or transported that can contribute to the quality-loss of the product.

To predict the relationship between quality-loss and sensors, quality-loss models are developed. Models are mathematical representation of a natural phenomenon; in our case this phenomenon is the quality-loss of a fresh perishable product. When a model is developed there is an implicit assumption: There exists a relationship between inputs (sensor data) and outputs (quality-loss indicators). The model needs to reflect this relationship.

Based on expert knowledge and scientific literature review we can make a list of the most studied sensors (Figure 11):

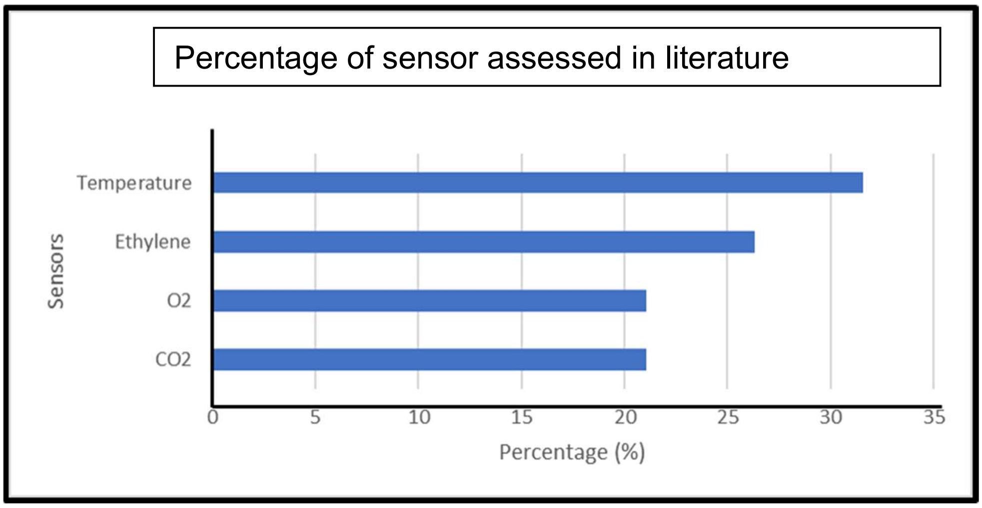

Figure 11: Shows the percentage of the most used type of sensors used by literature. We only focus on time series sensor type. Currently, we are not interested in the research done by analysing quality-loss using images. (Source: WFBR)

From Figure 11, we can observe that temperature sensors and ethylene sensors are the main sensors studied in relation with quality-loss. Especially with respect to climacteric products ethylene can be a relevant sensor, the reason is that climacteric products have a higher respiration rate than non-climacteric ones, speeding up the ripening process. On the contrary, temperature resulted as the main indicator evaluated by literature. And related to the quality-loss model for green beans presented in paragraph 3.2.4.1 also relative humidity is relevant to sense. Following this general research, combined with domain knowledge, three different sensors will be used for demonstration purposes as inputs for a mathematical quality-loss model.

These sensors are:
- Temperature;
- relative humidity;
- ethylene sensor.

Next to the data required to monitor the fresh produce, also the supply chain itself needs to be monitored in order to create a decision-making system. For this (see paragraph 4.3) the geographical position of the shipment is necessary information as well. Depending on the shipment location and quality predictions, a decision-making system can decide which type of intervention is necessary. For this reason, Geo Position System (GPS) data are also part of the data that will be collected.

It is important to highlight a significant difference between mathematical and data modelling. A mathematical model requires expert knowledge and experimentation to infer the relationship between a fix set of inputs (sensors) and output (quality). Data models, on the other hand, are not restricted to a fix set of inputs and do not require to have knowledge expert (however it is always recommended to do modelling together with a product expert) beforehand. Data models, flexible to the number of inputs, try to learn the relationship between inputs and outputs automatically from the data collected.

In the long term, once more data are collected, data models are able to learn more complex relationships than relatively simple mathematical models. Some of the drawbacks of the data modelling approach are the dependency on data collection (more data is required to model more complex relationships) and data quality. Since data models are fully depending on data, the modelling capabilities of a data model is as good as the data provided for their training. As incidents occur incidentally by definition, it may take a long time (a lot of data) before the data model is able to predict these incidents accurately.

Due to the current lack of data, data models are not going to be implemented for demonstration purposes. For this reason, mathematical models will be used during demonstration, please see section paragraph 3.2.4. for a review of the quality-loss models to be used.

3.4 Scalability and further development

The project aims to have a full connected platform where sensor data is collected online during transport. Once more data is collected a so-called machine learning model development cycle will be very promising.

This cycle needs to contain 4 stages, see Figure 12.

1. Data collection: Inserting data into a data central repository for its analysis.
2. Analysis of data: New data needs to be analysed for consistency.
3. Training of the data models: New data will be used to keep training machine learning models, to make them more accurate and general.
4. Service: The use of the machine learning algorithm, as an input for a decision-making model or dashboard.

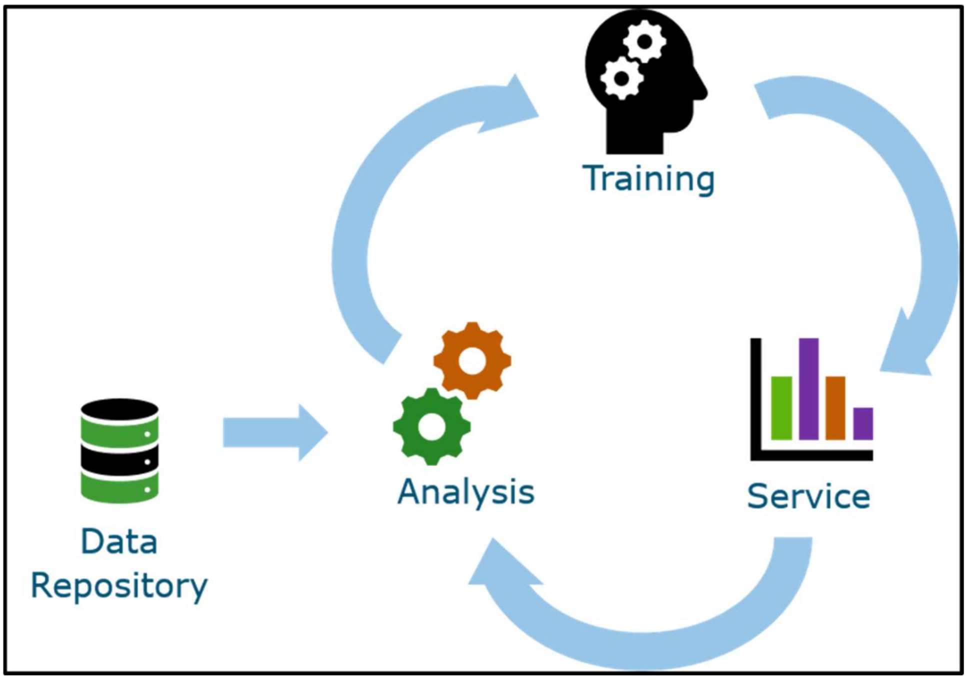

Figure 12: Machine learning model development cycle. (Source: WFBR).

With time more data will be collected. This data could be of different types like images, text, pre-harvesting data, etc. So, in contrast with the traditional mathematical quality-loss models, machine learning models are not limited to specific data from 'traditional' sensors to measure the quality-loss of vegetables and fruits, such as time-temperature indicators, relative humidity sensors and gas sensors.

One promising type of machine learning models are neural networks. Due to the flexibility of neural networks, these differences in type can be analysed without the need to turn to other type of data model algorithms.

One of the current limitations is that quality-loss indicators are only recorded before and after transport. This means that there is no possibility to know the exact quality metric during transport, unfortunately this could limit the performance of any type of modelling.

One limitation of a neural network is the long time that it can take to train them. Training a machine learning algorithm is the process in which the algorithm learns from the input-output data, in the case of neural networks this means the way the algorithm adjusts the different weights in the network (see paragraph 3.3). A data scientist needs to periodically assess the quality of the fitting metrics in case the predictive power of the algorithm decreases, a normal situation at the moment of deploying any type of data model. The data scientist will be responsible to retrain the neural network using a new set of data recorded in the data repository. An added benefit of a neural network is that this type of algorithm belongs to the set of incremental learning algorithms. Incremental learning is a method of machine learning in which new input data is continuously used to extend the existing model's capabilities, without forgetting previous acquired information and without the need to retrain the model from zero using a combination of historical and new data.

4 Recommend logistics interventions based on product quality predictions

4.1 Introduction

The logistics intervention model is derived from the business case as explained in WP2 (see Zomer, G. 2021). It recommends possible logistics interventions based on product quality-loss predictions, the expected impact of the considered interventions and the associated costs of executing those intervention options.

The intervention model is developed in a generic way to:

- Plan an appropriate intervention (given the quality of the produce with the quality-loss model).
- Apply it to different trade lanes and different modalities.

The intervention model heavily relies on the data received from the quality-loss model. Whereas the business case was a more static model which did not take into account the possible changing of quality of the product along the way, the intervention model is dynamic. It considers the changing conditions of the produce in the shipment and with the help of the quality-loss model, helps to understand what the quality of the product would be on arrival. This also allows for planning the interventions in a more dynamic way. The model adapts to the changing conditions of the shipment and takes a decision based on real-time measurement values from the sensors in the shipment and the corresponding quality predicted by the quality-loss model.

The intervention model also takes into account the possible benefits of the location of the shipment to optimize subsequent supply chain processes (such as preparing the unloading personnel at the warehouse dock and avoid waiting times or preparing an extra driver to join the first one to reduce potential lead time to the destination).

4.2 Recap from the business case for assumptions

Before the intervention can be explained, it is also important to have a recap of the inputs/assumptions considered in the business case in WP2 (see Zomer, G. 2021) since they are still valid in the intervention model. The main take-ways have been summarized into the tables that can be found in the annex. For more information about them, refer to the report on the business case report from WP2 (see Zomer, G. 2021).

4.3 The logistic interventions considered

The logistics intervention model considers three possible kinds of interventions based on the inputs from the quality-loss model. Along with the intervention, it also advises on when, in the transport process, the intervention should be applied.

The three kinds of interventions are as follows:

1. Dynamic climate control: The dynamic climate control includes adjusting the temperature and/or humidity inside the container as suggested by the quality-loss model. This could help in reducing the rate of the decay process thereby protecting the produce until the shipment reaches its destination. The idea behind real-time monitoring of these conditions and the corresponding quality-loss prediction is that the sensor data may give ground to dynamically adjust certain settings accordingly. Think of using ventilation, lowering the temperature, reduce the humidity levels, add ozone, or add fresh air / oxygen. It would require monitoring the quality-loss patterns of numerous shipments in order to optimise the settings accordingly. Here, we assume that this is possible when implementing this sensor solution, though this dynamic setting optimisation is out of scope for this project. It would require calibrating the quality-loss model based on large volumes of real monitoring data and feedback loops. We simply assume that it is possible to dynamically adjust the settings, resulting in a slower quality-loss. Obviously, this comes with a cost. An average cost estimate has been included in the model for this intervention which can be found in the report for WP2. For the sake of the demonstrations, the intervention model considers the dynamic climate control to be an optimum climate assurance intervention. The quality decay model considers the shipment to be transported in optimum conditions with respect to temperature and humidity. These conditions can change due to some unforeseen circumstances like the driver leaving the door open/shutting the engine off etc. This particular intervention ensures that those conditions are always met so that the shipment does not deteriorate with respect to quality.
2. Reducing lead time: This includes hiring a 2nd driver for road shipment and opting for a priority treatment at the port for a sea shipment. The idea is that if the sensor values give an indication that products product quality-loss goes faster than anticipated, that the transportation lead time might be reduced by changing the priority of the shipment.

   The reduction of lead time could be explained for both the sea and the road routes separately:

   a. Sea transport: For sea transport, the sea leg is not expected to be shortened by speed adaptations of the vessel because of for example some fast-ripening shipments on board. Moreover, it seems unrealistic to adapt the stowage plan during sea voyage. However, container dwell time in the unloading terminal may be shortened. The idea of this dynamic priority treatment in terminals was discussed with a Rotterdam container terminal and was not infeasible, but mainly depends on the willingness to pay for this service. Nevertheless, it is not common practise today. Priority treatment in unloading sequence may be considered. In a port call with huge call sizes, it matters if a priority container would be unloaded in the first couple of hours or in the last batch. This can make a difference of up to 2 days, though most reefer containers often will be unloaded in the first phases of an unloading plan.

Moreover, the stacking procedures also determine the dwell time of containers on a terminal. The assumption is that a priority treatment could result in a 'cross dock-like' operation, where the container is being unloaded from the sea vessel and directly moved to the place where a truck is ready to load the container. Finally, preparatory activities to ensure a fast release, combined with a fast hinterland slot planning further offer opportunity to shorten the container dwell time. Of course, this kind of priority treatment would come with a price, a fee for a dynamic priority treatment terminal service is included in the cost assumptions for this type of intervention costs. Apart from that, this project does not have the operationalisation of this dynamic priority treatment in scope.

b. Road transport: For road transport the lead time can be reduced by adding a truckdriver and drive and rest simultaneously. Moreover, the trailer could be swapped to another truck-trailer combination halfway, whereas another truckdriver just had his resting hours and is able to continue the journey. This of course requires a tough planning and additional costs. An estimate for these additional costs has been taken into account in the intervention cost assumptions. Since the demonstration of the intervention model would take place on the road shipment, it is important to dive deeper into the implications and applicability of the 2nd driver. The intervention model has 5 pre-decided locations (hubs) where there is a possibility for a 2nd driver to get on board with the 1st driver. These are the border between Senegal and Morocco, the Strait of Gibraltar, the border between Spain and France, Lyon (in France) and the border between France and Luxembourg (via Metz) or Franc and Belgium (via Paris) This helps to arrange the driver at one of these locations in case the quality-loss model predicts a drop in quality and the intervention model predicts the need for a 2nd driver. The intervention model also gives the location where the 2nd driver could be picked up as the location of the truck is known to the model.

3. Re-routing option to sell the produce on the local markets: This option is kept as a last resort for fast ripening shipments. In case all the above-mentioned intervention methods do not work as expected, the last resort in the intervention model is to re-direct the shipment to the local markets of Spain/France to save the shipment from rotting entirely before they reach the destination. The choice of the local market depends on the logistic possibility of selling the shipment in any of the local markets along the way.

4.4 The logistics intervention simulation model

The quality intervention simulation model works according to the rules discussed in the previous sections. This section describes further what the simulation model entails, the inputs needed for the model and the advice given by the model along with the cost benefit of the intervention choice.

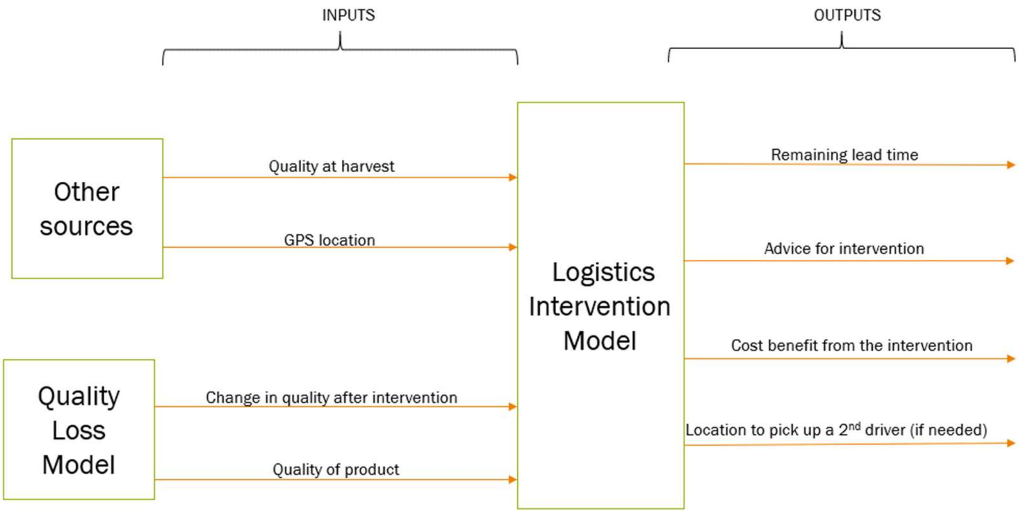

Figure 13: Intervention model schematic (Sources: TNO).

4.4.1 Relation between Quality Loss Model and the Logistics Intervention Model

The logistics intervention model relies on the quality loss model to come up with logical intervention advice. The quality loss model predicts the shelf life of the shipment using the optimum conditions of temperate, humidity and so on. The aim is to safeguard these optimal conditions during transportation. The logistics intervention model thus advices to intervene in case the temperature or humidity is not at the optimum set-point. This makes sure that the prediction of the shelf life of the shipment is true at all points in the transportation process. The market price of the shipment is then determined from the remaining shelf life prediction.
A translation is made from the remaining shelf life to the market price of the shipment. For an example, the translation of the shipment into its market value (based on shipment within specifications, out of specification and waste) can be represented as follows for a shipment which has 14 days of shelf-life after harvest.

Table 6: Intervention model schematic (Sources: TNO).

Shelf life remaining	Within specs	Alternative specs	Waste
14	100.0%	0.0%	0.0%
13	95.0%	5.0%	0.0%
11	90.0%	5.0%	5.0%
10	75.0%	12.5%	12.5%
8	60.0%	20.0%	20.0%
7	45.0%	27.5%	27.5%
6	30.0%	35.0%	35.0%
4	15.0%	42.5%	42.5%
3	0.0%	50.0%	50.0%
1	0.0%	25.0%	75.0%
0	0.0%	0.0%	100%

The intervention also uses the quality prediction from the quality loss model to intervene in case the 2nd driver needs to be on-board or if the shipment is deterioration very fast and needs to be sold in the local market along the way.

4.4.2 *Inputs to the Logistics Intervention Model*

The quality intervention model works on the inputs from the quality-loss model as well as from the Van Oers United data source.

The following is the input needed for the logistics intervention model:

1. Inputs from the quality-loss model:
   a. Quality of the product: This is the quality of the product in terms of what fraction of the product can be sold 'within specifications', what fraction of the shipment can be sold but is 'out of specifications' and what part of the shipment has become valueless. This helps to determine the turnover from selling the goods in the shipment upon arrival. It is also imperative for the quality-loss model to estimate/predict the quality of the product at destination in the three above-mentioned categories if an intervention is applied. This helps to determine the net economic value of applying an intervention.

2. Inputs from other sources:
   a. Quality of harvest: The quality of the harvest is determined by some expert opinion at the source of harvest. This helps to know what part of the shipment is robust, and what part of it is vulnerable. Van Oers United already works on this to try and ship the robust produce via sea and the vulnerable shipment via road. This fraction of robust and vulnerable produce helps the intervention model take an initial decision on the kind of intervention needed at harvest as discussed in the previous section.
   b. GPS location: GPS location of the shipment is imperative for the intervention model since it helps align the need of a 2nd driver along the way. It also guides the intervention model to know the location of the shipment to advice the shipment to pick up the 2nd driver from the nearest pick-up location (or hub, ones which are pre-decided in the model) as discussed in the previous section.

4.4.3 *Outputs from the Logistics Intervention Model*

The logistics intervention model processes the inputs received from the sources and the following outputs can be obtained:

a. Remaining lead time: The quality intervention model aims to provide the lead-time remaining estimate to the destination. The GPS-coordinates and corresponding time stamps allow for mapping what part of the planned route has been expected and what is still remaining. This can be transferred into an estimate of the remaining lead time.
b. Advice for intervention: The quality intervention simulation model takes all the inputs into consideration and based on the logic discussed in the previous section, comes up with an advice weather an intervention is needed or that the shipment is good without any intervention. Some of the interventions are planned already at harvest at the source while some are planned along the way. The latter are also based on a cost analysis.

The intervention model takes into account the cost of the intervention, if any, and compares it with the expected gain in shipment turnover. The intervention is proposed only if the product value gain from the shipment can cover for the cost of the intervention. This helps in not only making the shipment more profitable but also leading to less waste than in the case where the shipment would have continued without any interventions.

c. Location to pick up a 2nd driver (if needed): The model also helps in determining the pick-up location of the 2nd driver if the model suggests this particular intervention. This is done with the help of the GPS location of the shipment. It guides the driver to the nearest hub location where he could be joined by the 2nd driver.
d. Cost benefit analysis of the intervention: The output of the model aims to provide a cost comparison between the different interventions possible along with the advice to opt for an intervention, if needed. The following sections define the ways in which the interventions take place and how the decision to make an intervention is made in the intervention model.

4.5 The mode specific schematics of the interventions

The intervention model follows the following schematic to narrow down on decisions and the reasons for the decision made. The schematic is different for road and sea transported shipments and each of them is explained. In the case of Van Oers United, the modal choice is based on transport costs, available transport capacity and robustness of the shipment.

4.5.1 The schematics for road shipments

The schematic of the road shipment intervention model is as follows:

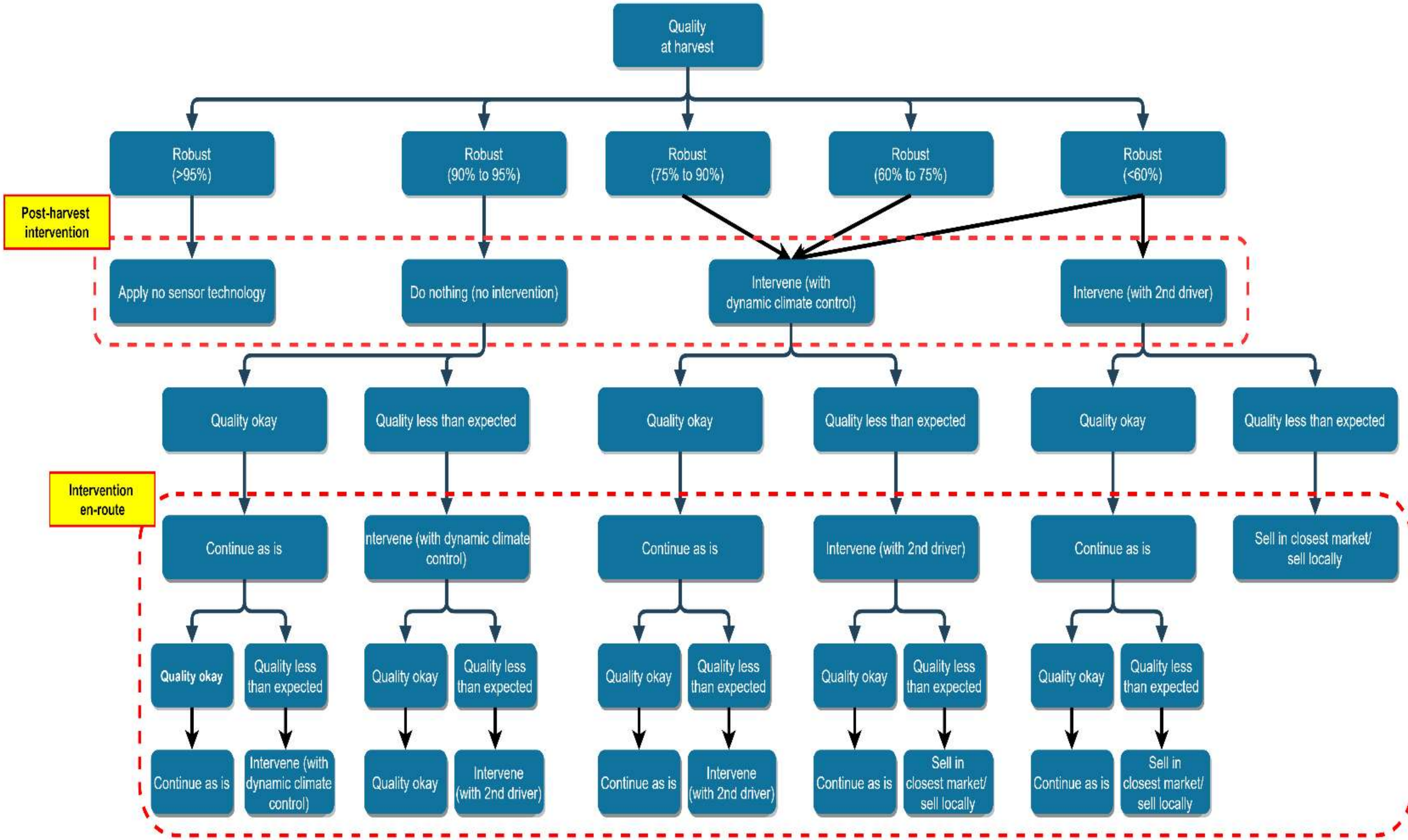

Figure 14: Quality Intervention Model schematic for road shipment (Source: TNO)

The model is dependent on the quality of the produce at harvest. Based on that, the model chooses to intervene right after harvest or en-route. This can be explained in the following way for each of the 5 quality categories of the shipment. As described before, post-harvest product quality can be robust or vulnerable. Depending on the percentual distribution of robust and vulnerable products in a shipment, the model follows a certain intervention logic.

1. When quality of the shipment produce is >95% robust:

This is when the far majority of the shipment contains robust products (>95%). In this case, the shipment is not equipped with sensor technology. This is done as the product is expected to reach the destination with a good quality, with very low possibility that the shipment is going bad during the course of the transport. Applying sensor technology in this case would lead to more costs for monitoring and would in the far majority of the cases not trigger any intervention to be executed..

2. When the quality of the shipment produce is between 90% and 95% robust:

This case also sees quite high robustness in the harvest and hence the choice is made to not deploy any interventions to this case at harvest either. But this case would have the sensor technology in the shipment. This is done so that the shipment can be tracked and acted upon if the quality of the produce deteriorates faster than expected at any time in the transport. As can be seen in Figure 14 this case can have two outcomes along the route:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the advice from the intervention model is to not intervene and continue as is without interference. It could still be possible that the quality of the shipment deteriorates. In this case, the model would advise to intervene with the dynamic climate control. This interventions assures that the conditions inside the shipment are maintained as close to optimal as possible.
ii. When the quality of the produce deteriorates faster than expected and thus does not follow the trajectory of the quality expected at arrival, the advice would be to assure optimal climate conditions. The quality decay model assumes optimal conditions in the shipment for the transport. In spite of this, due to unforeseen circumstances, the conditions in the shipment could vary from optimum. This intervention is to ensure that the optimum conditions still prevail in the shipment. In case the quality of the shipment deteriorates further, the intervention model advices to have a second driver on board to reduce the lead time to destination. The model also gives the location of the closest hub to the truck from where the second driver could be picked up.

3. When the quality of the produce is between 75% and 90% robust:

This case becomes increasingly interesting for the intervention model since this case is where the interventions could make a large difference. When the robustness of the harvest is between 75% and 90%, the intervention already suggests that the shipment should not only be equipped with sensors but also with the dynamic climate control turned on. This would help preserve the quality of the harvest so that they can reach the destination at a better quality than previously expected.

As seen from Figure 14, this case too, can have two outcomes:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the intervention model advices to not intervene anymore and continue with the dynamic climate control which was applied at harvest. In case the quality of the shipment deteriorates further, the intervention model advices to have a second driver on board to reduce the lead time to destination. The model also gives the location of the closest hub to the truck from where the second driver could be picked up.
ii. When the quality of the produce deteriorates faster than expected and the expected quality upon arrival drops below the agreed specifications, the intervention model suggests having the 2nd driver deployed at the nearest station. This is where the model takes into account the coordinates of the shipment and directs the driver to stop at the nearest location (one of the pre-decided locations) to pick up a 2nd driver. In case the shipment is seen to be still deteriorating faster than anticipated and the shipment is predicted to go to waste if it is allowed to continue all the way to the destination even with the 2nd driver on board, the intervention model advices the shipment to be sold in the local market along the way.

4. When the quality of the produce is between 60% and 75% robust:

This case is similar to the previous case since it also becomes more interesting for the intervention model as this case is where the interventions could make an even larger difference. When the robustness of the harvest is between 60% and 75%, the intervention already suggests that the shipment should not only be equipped with sensors but also with the dynamic climate control turned on. This would help preserve the quality of the product so that they can reach the destination at a better quality than previously expected.

As seen from Figure 14, this case too, can have two outcomes:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the intervention model advices to not intervene anymore and continue with the dynamic climate assurance which was applied at harvest. In case the quality of the shipment deteriorates further, the intervention model advices to have a second driver on board to reduce the lead time to destination. The model also gives the location of the closest hub to the truck from where the second driver could be picked up.
ii. When the quality of the produce drops faster than expected, and the expected quality upon arrival drops below the agreed specifications, the intervention model suggests having the 2nd driver deployed at the nearest station. This is where the model takes into account the coordinates of the shipment and directs the driver to stop at the nearest location (one of the pre-decided locations) to pick up a 2nd driver. In case the shipment is seen to be still deteriorating faster than anticipated and the shipment is predicted to go to waste if it is allowed to continue all the way to the destination even with the 2nd driver on board, the intervention model advices the shipment to be sold in the local market along the way.

5. When the quality of the produce is less than 60% robust:

This case is when the quality of the harvest is particularly vulnerable. In this case as well, the interventions could lead to a better outcome of the vulnerable produce and lead to less waste. Since the harvest is so vulnerable, the intervention model advices to deploy both the dynamic climate control as well as put the 2nd driver on board at the origin in order to keep the remaining shelf life upon arrival as high as possible.

Again, en-route, there are two possible outcomes from his shipment:

i. When the expected quality upon arrival remains in accordance with the customer's agreed quality specifications, the intervention model advices to not intervene anymore and continue with the dynamic climate control along with the 2nd driver on-board which was decided and applied at the start of the shipment. In this case, if the shipment is still seen to be deteriorating faster than anticipated and the shipment is predicted to go to waste if it is allowed to continue all the way to the destination even with the 2nd driver on board, the intervention model advices the shipment to be sold in the local market along the way.

ii. When the quality of the produce further drops below the threshold for being able to sell the products at all, the intervention model suggests selling the shipment on the local market along the way. This could be anywhere along the way to the destination wherever it is logistically possible. Other interventions seem to not work anymore and there is nothing that can be done to save the produce from rotting if it is allowed to continue to the destination. Thus, it is recommended to just sell the produce in a local market to prevent the loss of the shipment entirely.

4.5.2 The schematics for sea shipments

The schematic of the sea shipment intervention model is as follows:

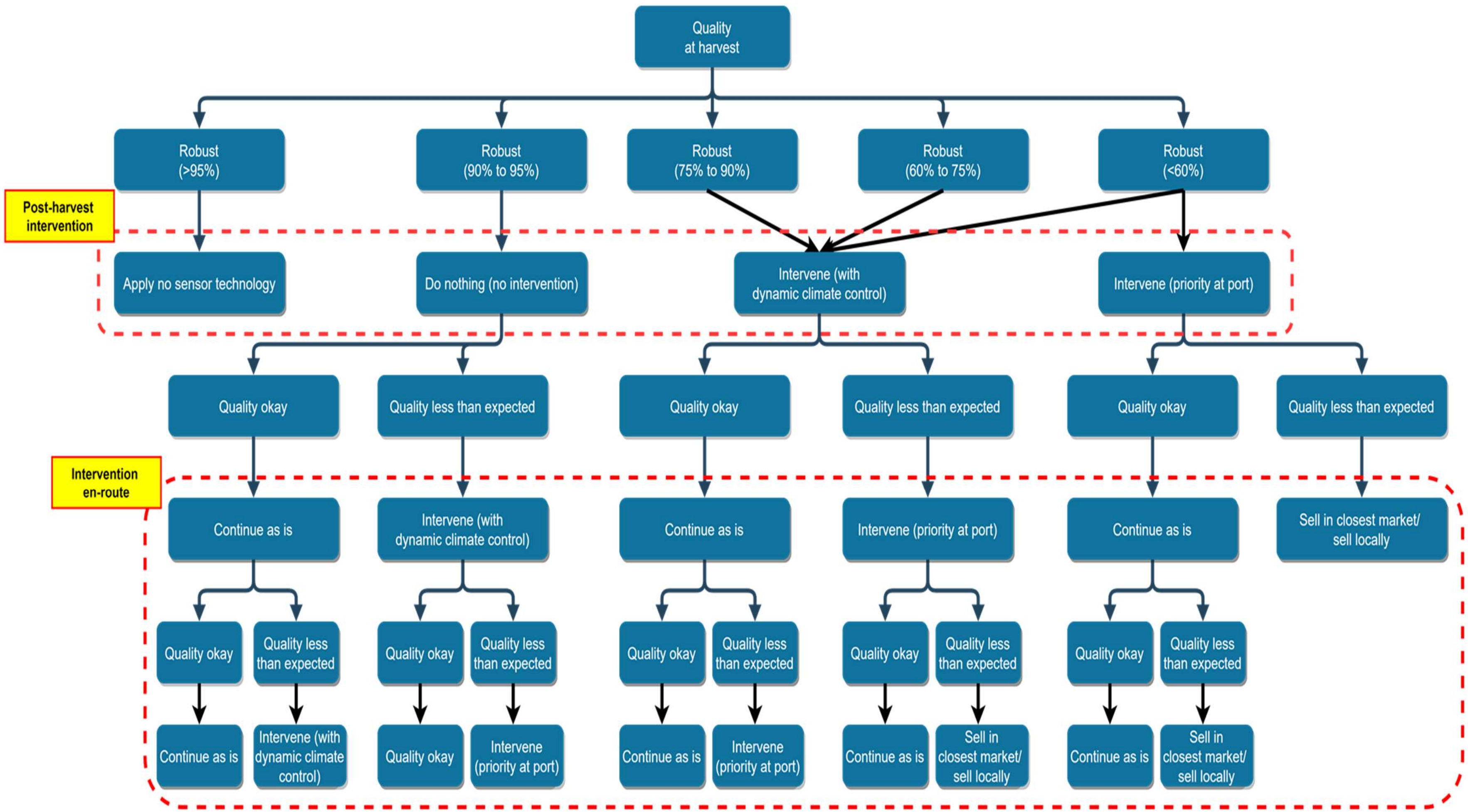

Figure 15: Quality Intervention Model schematic for sea shipment (Source: TNO)

The model is dependent on the quality of the produce at harvest. Based on that, the model chooses to intervene right after harvest or en-route. This can be explained in the following way for each of the 5 quality of the produce at harvest:

1. When quality of harvest is >95% robust:

This is when the produce is relatively very high in robustness (>95%). In this case, the shipment is not equipped with sensor technology. This is done as the product is expected to reach the destination with a good quality and the chances of it going bad during the course of the transport looks bleak. Applying sensor technology in this would only lead to more costs for monitoring and would not lead to very high monetary gains as the need for an intervention along the way would also not be necessary.

2. When the quality of the produce is between 90% and 95% robust:

This case also sees quite high robustness in the harvest and hence the choice is made to not deploy any interventions upon departure. However, the shipment will be equipped with sensors. allowing for monitoring quality decay patterns and intervene accordingly. As can be seen in Figure 15, this case can have two outcomes along the route:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the advice from the intervention model is to not intervene and continue as is without interference. It could still be possible that the quality of the shipment deteriorates. In this case, the model would advise to intervene with the dynamic climate control. This interventions assures that the conditions inside the shipment are maintained as close to optimal as possible.
ii. When the quality of the produce deteriorates faster than expected, and the expected quality upon arrival drops below the agreed specifications, the advice would be to assure optimal climate conditions. The quality decay model assumes optimal conditions in the shipment for the transport. In spite of this, due to unforeseen circumstances, the conditions in the shipment could vary from optimum. This intervention is to ensure that the optimum conditions still prevail in the shipment. In case the quality of the shipment deteriorates further, the intervention model advices to have a second driver on board to reduce the lead time to destination. The model also gives the location of the closest hub to the truck from where the second driver could be picked up..

3. When the quality of the produce is between 75% and 90% robust:

This case becomes increasingly interesting for the intervention model since this case is where the interventions could make a difference. When the robustness of the harvest is between 75% and 90%, the intervention already suggests that the shipment should not only equipped with sensors but also with the dynamic climate control turned on. This would help preserve the quality of the harvest so that they can reach the destination at a better quality than previously expected.
As seen from Figure 15, this case too, can have two outcomes:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the intervention model advices to not intervene anymore and continue with the dynamic climate control which was applied from the start of the shipment journey. In case the quality of the shipment deteriorates further, the intervention model advices to have a second driver on board to reduce the lead time to destination. The model also gives the location of the closest hub to the truck from where the second driver could be picked up.

ii. When the quality of the produce deteriorates faster than expected, and the expected quality upon arrival drops below the agreed specifications, the intervention model suggests having the paperwork for the priority treatment at the destination port ready for the shipment to be released from the port as soon as possible. This means the interventions advices to reduce the lead time at the port by having a priority treatment there. In case the shipment is seen to be still deteriorating faster than anticipated and the shipment is predicted to go to waste if it is allowed to continue all the way to the destination even after the priority treatment at port, the intervention model advices the shipment to be sold in the local market along the way.

4. When the quality of the produce is between 60% and 75% robust:

This case is similar to the previous case since it also becomes more interesting for the intervention model as this case is where the interventions could make a larger difference. When the robustness of the harvest is between 60% and 75%, the intervention already suggests that the shipment should not only be equipped with sensors but also with the dynamic climate control turned on. This would help preserve the quality of the harvest so that they can reach the destination at a better quality than previously expected. As seen from Figure 15, this case too, can have two outcomes:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the intervention model advices to not intervene anymore and continue with the dynamic climate control which was applied from the start of the shipment journey. In case the quality of the shipment deteriorates further, the intervention model advices to have a second driver on board to reduce the lead time to destination. The model also gives the location of the closest hub to the truck from where the second driver could be picked up.

ii. When the quality of the produce drops faster than expected, and the expected quality upon arrival drops below the agreed specifications, the intervention model suggests having the paperwork for the priority treatment at the destination port ready for the shipment to be released from the port as soon as possible. This means the intervention advices to reduce the lead time at the port by having a priority treatment there. In case the shipment is seen to be still deteriorating faster than anticipated and the shipment is predicted to go to waste if it is allowed to continue all the way to the destination even after the priority treatment at port, the intervention model advices the shipment to be sold in the local market along the way.

5. When the quality of the produce is less than 60% robust:

This case is when the quality of the harvest is particularly vulnerable. In this case as well, the interventions could lead to a better outcome of the vulnerable produce and lead to less waste. Since the harvest is so vulnerable, the intervention model advices to deploy both the dynamic climate control as well as prepare for the express treatment at the destination post to reduce the lead time.

This way, the most vulnerable crop sees the most time saved to get it to the destination in the best quality possible in the least time. Again, en-route, there are two possible outcomes from his shipment:

i. When the expected quality upon arrival is in accordance with the customer's agreed quality specifications, the intervention model advices to not intervene anymore and continue with the dynamic climate control along with the express treatment at the destination port to reduce the lead time which was applied at harvest. In this case, if the shipment is still seen to be deteriorating faster than anticipated and the shipment is predicted to go to waste if it is allowed to continue all the way to the destination even after the priority treatment at port, the intervention model advices the shipment to be sold in the local market along the way.
ii. When the quality of the produce drops faster than expected, and the expected quality upon arrival drops below the threshold for being able to sell the products at all, the intervention model suggests selling the shipment in the local market along the way. This could be anywhere along the way to the destination wherever it is logistically possible. The interventions seem to not work anymore and there is nothing that can be done to save the produce from rotting if it is allowed to continue to the destination. In this case, it is smart to just sell the produce in a local market to prevent the loss of the shipment entirely.

4.6 Scalability and further development

This section addresses the important question of scalability and future development of the model. The model described in this chapter was configured to the trade lanes discussed in this study. It requires trade lane specific and product-specific reconfiguration to adjust the model in order to apply it in other situations. Feasibility of interventions are also trade lane specific. Think of kiwi transported from New-Zealand to the Netherlands, this probably involves a maritime transport link to for instance Singapore, and a maritime transport link from Singapore to Rotterdam. Possible interventions could be to speed up the transhipment in Singapore and safeguard that it won't miss the planned scheduled sailing to Rotterdam. But the intervention might also apply to multi-modal transport solutions. A switch to air transport could be considered in Singapore during transhipment but may also be reconsidered in an intermediary port of call, say in Dubai. This example highlights the limitations in terms of scalability of the model.

4.6.1 Interoperability for demonstration purposes

In order to demonstrate a proof of concept of the integrated sensor capturing, quality prediction and intervention advise, some model interoperability issues have to be solved. The quality-loss model does not allow for in-shipment variation of the quality, the complete shipment gets a quality score, based on the actual conditions and remaining lead time. The logistic intervention model was set up to cope with in-shipment variations of the product quality, allowing for specific sorting upon arrival.

Moreover, the intervention model needs to compare the quality upon arrival of not intervening and execute a number of predefined intervention options.

The quality-loss model should provide the expected quality upon arrival in case of executing the possible intervention options. How this is being included in the workflow processes during the demonstration of the proof of concept needs to be elaborated.

5 Conclusion and discussion

The key objective of the overall project is to integrate IoT into logistics decision making leading to the research objective '*to explore the potentials and applicability of IoT technologies in enabling dynamic and integrated quality-controlled logistics in the postharvest perishable produce chain*'. To realize the overall objective, in Work Package 3 four sub-research questions, related to 'technology' and 'Supply Chain' were addressed in the different chapters:

- Technology:
  - Chapter 2: "What are specific connectivity platforms / control tower requirements following sensor data capture and real-time decision support?"
  - Chapter 3: "How to convert the collected different type of sensor data into measurable quality indicators?" In other words, "How to incorporate more parameters into the current quality-prediction model to improve the prediction accuracy?"

- Supply Chain:
  - Chapter 4: "How to optimally organize the logistic activities, based on the predicted quality, form a system optimization point of view?" In other words, "What are the underlying supply chain decisions that push the concept of quality-controlled logistics?"
  - Chapter 4: "Which supply chain decisions are being supported?"

The architecture in Chapter 2 shows what the specific connectivity platform requirements are needed to capture sensor data and 'feed' real-time decision support. The data that is available from the different data providers differs enormously form real-time to written reports. This data will have to be linked together via a date and timestamp before it can be uploaded into the central data store. To be able to use the data in the quality-loss model a three-step process – Extract, Transform and Load (ETL procedure) will be executed by which data is extracted from the data sources that are not optimized for analytics, and moved to a central host to provide the quality-loss model with the necessary data. Data in the central data store will be presented using Thingsboard. In the current phase of this project, it isn't possible to feed a real-time decision support model. This is because the various data sources are not standardized and there is no data governance agreement in place and the determination of the quality of the goods when the goods are loaded into the truck and arrive in the Netherlands is partly recorded on (written) forms.

In Chapter 3 we showed that that colour and firmness are the quality-loss metrics that are the two most common factors that a chain actors pay attention to when purchasing a fresh product because firmness and colour give indications of the storability and ripeness of the fresh product, which has significant business relevance. To be able to capture this via sensor data for green beans we developed a so-called 'senescence and chilling-injury model' (time and temperature), a 'weight-loss model' (time, temperature and relative humidity) and added an additional threshold-constraint regarding ethylene. For mangos we needed a 'firmness model' taking time and temperature into account.

These models are mathematical representation of a natural phenomenon; in our case this phenomenon is the quality-loss of a fresh perishable product. There is an implicit assumption: there exists a relationship between inputs (sensor data) and outputs (quality-loss indicators). The models reflect this relationship.

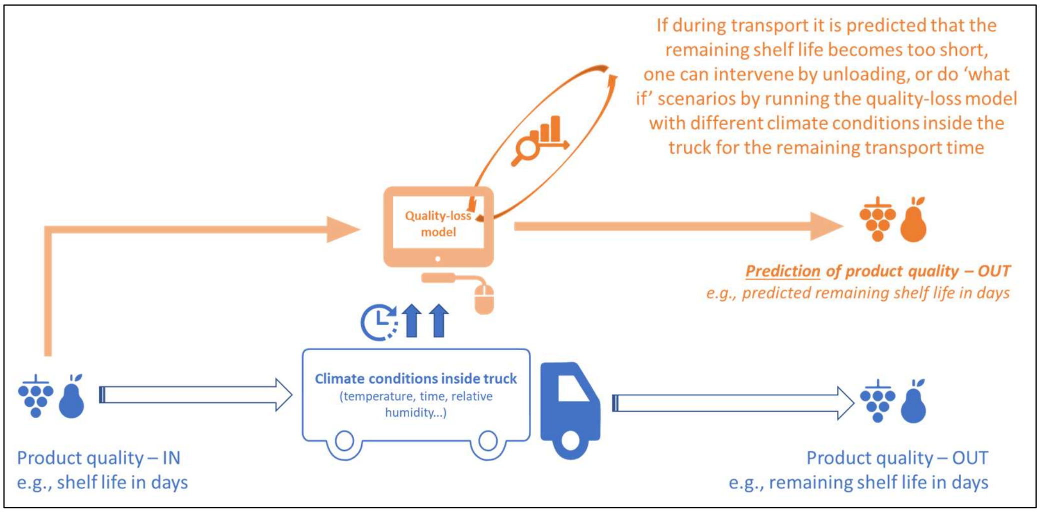

Figure 16: Visualisation of the role of the quality-loss model. (Source: WFBR).

How to optimally organize the logistic activities, based on the predicted quality, from a system optimization point of view? In other words, "What are the underlying supply chain decisions that push the concept of quality-controlled logistics?" And "Which supply chain decisions are being supported?". This is shown in Chapter 4. The logistics intervention model considers three possible kinds of interventions based on the inputs from the quality-loss model. Along with the intervention, it also advises on when, in the transport process, should the intervention to be applied.

The three kinds of interventions are as follows:

- Dynamic climate control
- Reducing lead time
- Re-routing option to sell the produce on the local markets

The model is dependent on the quality of the produce at harvest. Based on that, the model chooses to intervene right after harvest or en-route. A decision right after harvest could be not to intervene at all because the initial (loaded) product quality is very robust, or to set the 'dynamic climate control' in place in anticipating the need to adjust the conditions or to bring a second driver already in advance when the input quality is for a large part 'vulnerable'. Interventions en-route, based on the input from the quality-loss models, could be adapting the climate/conditions, arranging a second driver or re-outing option to sell the produce on the local markets.

The intervention model takes all the inputs into consideration and based on the logic discussed in the previous section, comes up with an advice if an intervention is needed or that the shipment is good without any intervention.

Some of the interventions are planned already at harvest at the source while some are planned along the way. The latter are also based on a cost analysis. The intervention model takes into account the cost of the intervention, if any, and compares it with the shipment value gain.

5.1 From theory to practice: the demonstrations

In this report it is researched what the theoretical ideal design, layout and configuration should look like. But also how we can arrive at feasible pilots, within the context of this project, that are designed in such a way that they can show whether the concept works. For this, all components, i.e. the architecture, the data links, the platform design, the sensors and connectivity, the quality-loss models and the intervention model are made ‘fit for use’. In short, not a fully automated design is developed, but a practical and functional design that is sufficiently suitable for examining the possibilities and challenges of this concept in the demonstrations. And it is precisely this experimental environment that must show what is feasible, what works and what does not, and what is needed for upscaling.

5.2 Scalability and future development

To realize a real time intervention model, based on the quality-loss model which again is based on various data sources from various data providing companies, a lot of work needs to be done.

The work that needs attention is:

- On a business level: roles and responsibilities and fee structures must be clear
- On a legal level: relevant rules and regulations, a governance model and contract must be in place
- On an operational level: service levels, operational governance, incident and change management must be clear
- On a functional level: the interaction model and privacy must be in place
- On a technical level: standards for data and security must be developed and implemented

One direction to develop a data architecture is a federated model, or virtual database, is a composite of all constituent databases in a federated database system. As a result of Data Federator, there is no actual data integration across the constituent disparate databases. And once more data, of all kind of different types like images, text, pre-harvesting data, etc., is collected machine learning could be the technique to build product quality-loss models. For this, a so-called machine learning model development cycle will be very promising. This cycle needs to contain 4 stages:

1. Data collection: Inserting data into a data central repository for its analysis.
2. Analysis of data: New data needs to be analysed for consistency.
3. Training of the data models: New data will be used to keep training machine learning models, to make them more accurate and general.
4. Service: The use of the machine learning algorithm, as an input for a decision-making model or dashboard.

One promising type of machine learning models are neural networks. Due to the flexibility of neural networks, these differences in type can be analysed without the need to turn to other type of data model algorithms. One of the current limitations is that quality-loss models are only recorded before and after transport. This means that there is no possibility to know the exact quality metric during transport, unfortunately this could limit the performance of any type of modelling. One limitation of Neural Network is the long time that it can take to train them.

When using sensors, sensor-data, and quality-loss models to feed the logistical intervention and/or decision support models, future development of the intervention model presented is necessary. The intervention model described in this report is limited to the trade lanes discussed and therefore it requires tradelane specific and product-specific reconfiguration to adjust the model in order to apply it in other situations. And thus this also makes the feasibility of the discussed interventions trade-lane specific.

6 Literature

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A Cost assumptions and other assumptions about the intervention model

The cost assumptions and other assumptions about the intervention model are summarized below:

Table 7: Trade lanes for IoT4AGRI.

Product	**Trade lanes**	**Lead times**
Green Beans Senegal	Sea: Dakar – R'dam/Antwerp – Dinteloord Road: Senegal – Gibraltar Strait - Dinteloord	Sea: 10 days Road: 8 days
Green Beans Morocco	Sea: Agadier – R'dam/Antwerp – Dinteloord Road: Agadier – Gibraltar Strait – Dinteloord (note: from Tangiers is 1 day shorter)	Sea: 7 days Road: 4,5 days
Mango Senegal	Sea: Dakar – R'dam/Antwerp – Dinteloord Road: Senegal – Gibraltar Strait – Dinteloord	Sea: 10 days Road: 8 days
Galia Melons Senegal	Sea: Dakar – R'dam/Antwerp – Dinteloord Road: Senegal – Gibraltar Strait – Dinteloord	Sea: 10 days Road: 8 days

Table 8: Characteristics of the IoT4AGRI perishable products (price per ton).

Prices in € per ton	**Delivery within specs**	**Alternative sales channel**	**Waste**	**Spot market price**
Green beans Senegal	€ 2.000	€ 1.000	€ 0	€ 2.400
Green Beans Morocco	€ 2.000	€ 1.000	€ 0	€ 2.400
Mango Senegal	€ 2.500	€ 1.250	€ 0	€ 3.000
Galia Melons Senegal	€ 1.600	€ 960	€ 0	€ 1.920

Table 9: Cost ranges for the sensors.

Equipment	**Ideal specs**	**Cost (low)**	**Cost (mid.)**	**Cost (high)**
Ethylene sensor	0-10ppm	€100	€800	€1500
Temperature sensor	-10° to 50°C, accuracy 0.3°C		14,97	€27
Temperature sensor		€2,95		€210
Oxygen sensor	1-22%, accuracy 0.5%	€5,17	€90	€175
CO_2 sensor	0-10%, accuracy 0.3%	€23,12	€41,50	€59,95
Humidity sensor	30-100%, accuracy 1.0%	€4,45	€45,00	€86,07

Table 10: Sensor handling cost estimates per shipment.

Category	**Description**	**Cost estimate**
Sensor shipment	Air freight parcel (up to 5 kg)	€ 25
Placement and activation	Per shipment (15 minutes a €40/hr)	€ 10
Removal and collection	Per shipment (10 minutes a €60/hr)	€ 10
Administrative system	Per shipment	€ 10
Total handling cost	**Per shipment**	**€ 55**

Table 11: Lead-time reduction costs for sea transport (priority at port) per shipment.

Sea transport	**48-hour reduction**	**36-hour estimation**	**24 hours estimation**	**12-hour estimation**
Morocco	€1.000	€800	€200	€100
Senegal	€1.000	€800	€200	€100

Table 12: Lead-time reduction costs for road transport (hiring a 2nd driver) per shipment.

Road transport	**48-hour reduction**	**36-hour estimation**	**24 hours estimation**	**12-hour estimation**
Morocco	€1.255,50	€558	€418,50	€279
Senegal	€1.395	€1.046	€697,50	€418,50

Table 13: Other costs for logistic interventions (per shipment).

Category	**Description**	**Cost**
Dynamic Climate control	Costs incurred for controlling the shipment remotely/on-board by the driver	€75
Re-routing	Arranging the possibility of selling the shipment in a local market	€75
Use of logistics intervention model	Service fees for the logistics intervention model	€3,85
Use of quality loss model	Service fees for the quality loss model	€5,50