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Predicting Tensile Properties of Technical Textiles with Artificial Neural Networks in the Product Development Process

A case study on the requirements for an ANN implementation, the process improvements, and resulting competitive advantages

Master's thesis in the Master's Programme Quality and Operations Management and Data Science and AI

Anna Iversén
Martin Lillö

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
Division of Innovation and R&D Management
CHALMERS UNIVERSITY OF TECHNOLOGY
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Supervisors: Kaj Suneson, Department of Technology Management and Economics, and Marina Axelson-Fisk, Department of Mathematical Sciences
Examiner: Kaj Suneson

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Department of Technology Management and Economics
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone +46 31 772 1000

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Abstract

The end-user environments of technical textiles are often characterized by extreme weather conditions, leading to aging which implies the need for testing in the product development process (PDP). This thesis aims to suggest an Artificial Neural networks (ANN) model predicting the aging of technical textiles and an AI strategy for companies in the technical textile industry. The resulting improvements and competitive advantages of such an implementation will also be studied. A case study of an aging measurement analysis in the testing and validation phase of the PDP in the technical textile industry was conducted. Through semi-structured interviews, focus group and workshop, the PDP, aging measurement analysis, requirements for an ANN implementation, and the resulting improvements and competitive advantages were mapped. This was analyzed using theory on ANNs, the stage-gate process, requirements for AI implementation, improvements from AI, and competitive advantages. It was found that the aging measurement depends on an in-depth understanding of the complex relationships between material components. As a result, several iterations in the PDP to ensure that the prototype meets the aging requirements are often required and lead to a time-consuming and costly process. Another finding was that the industry is characterized by low digital maturity. It was concluded that two single hidden layer backpropagation feedforward ANN models were suitable for predicting the tensile properties. It is recommended to initially use eight categories of input parameters and then employ regularization. Sigmoid and ReLU are suggested as activation functions and Levenberg-Marquardt as optimization functions. A combination of error measures are suggested. This thesis concluded that an AI strategy for the technical textile industry to implement ANN successfully should include plans to fulfill requirements regarding, internal and external data, data anonymization, automated data collection, computing power infrastructure, knowledge, and employee AI trust. Further, it was concluded that the implementation of ANN could improve the knowledge in the PDP, leading to improved speed, quality, and cost. In the technical textile industry, the corresponding competitive advantages are, time to market, superior products, innovation capacity and profitability.

Keywords: Technical textile industry, Tensile properties, Sun-simulation, Product development, Process improvements, competitive advantages, Artificial Neural Networks

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This thesis was written by Anna Iversén and Martin Lillö. Both authors have contributed to all sections of the report. However, Martin focused on areas regarding Data Science, while Anna concentrated on areas related to Quality and Operations Management.

Anna Iversén & Martin Lillö,
Gothenburg, January, 2023

Contents

List of Figures

List of Tables

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ANN	Artificial Neural Networks
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
CSC	Case Study Company
DL	Deep Learning
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MBE	Mean Bias Error
MLA	Machine Learning Algorithm
ML	Machine Learning
MSE	Mean Squared Error
NN	Neural Networks
PDP	Product Development Process
PE	Polyethylene
PET	Polyethylene Terephthalate/polyester
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
R&D	Research and Development
SVM	Support Vector Machines
TTM	Time To Market
UV	Ultraviolet

Terminology

Below is the list of terminology that have been used throughout this thesis listed in alphabetical order:

Batch gradient descent : Computes the gradient using the whole Training sample. The algorithm is both slow and computationally expensive.

Conventional Neural Network : A class of ANNs mostly applied to analyze visual images.

Class label : A class label is a specific category or class that data points are assigned to based on their characteristics.

Fully-connected layer : A layer where every neuron in the layer is connected to every neuron in the preceding and subsequent layers. This means that the output of each neuron in the layer is a weighted sum of the inputs from all the neurons in the previous layer, followed by the application of an activation function.

Genetic algorithms : Methods for solving optimization problems by simulating the process of evolution and natural selection.

Gradient : The change in the weights with regard to the change in error. The higher the gradient the faster an ANN-model can learn. If the gradient is 0 the model stops learning.

Gauss-Newton Method : This is an iterative optimization algorithm for finding the minimum of a nonlinear function. It works by linearizing the function at each iteration and then solving for the minimum of the resulting linear function. This process is repeated until the minimum of the function is found to within a certain tolerance.

Gradient descent : An optimization algorithm that finds the local minimum of a function, by repeatedly taking steps in the opposite direction of the gradient of the function, because that is the direction of the steepest descent.

Gradient descent with momentum : A extension of the gradient descent optimization algorithm that works faster than the standard gradient descent algorithm by computing an exponentially weighted average of your gradients and then using that gradient to update the weights.

Hessian matrix : A matrix that includes all partial second derivatives.

Hyperparameter : Fixed values that are set by the practitioner and determine the performance of a machine learning model.

Learning rate : A hyperparameter in an optimization algorithm that determines how fast the model learns.

Log Hyperbolic cosine / logistic loss : It is defined as the negative logarithm of the hyperbolic cosine of the predicted probability of the correct class. It is a measure of how well the predicted probabilities of a classifier match the actual labels of the data.

Multilayer perception : A type of artificial neural network that is composed of multiple layers of interconnected neurons.

Overfitting : Overfitting occurs when a machine learning model is trained too well on a specific data set and is not able to generalize well to new data. This means that the model performs poorly on new, unseen data.

Reinforcement learning : A machine learning method that rewards the desired behaviors and punishes undesired behaviors.

Sigmoid function : A non-linear activation function for an ANN that guarantees that the output is between 0 and 1.

Steepest descent direction : The steepest descent direction is the direction in which a function decreases the most rapidly.

Support vector machines : Supervised learning models with associated algorithms that analyze data for classification and regression analysis.

Tangent hyperbolic activation function : Is the scaled version of the sigmoid activation function, and maps the input values in the range of -1 to 1.

Work of rupture : The energy needed to break a fiber or fabric.

1
Introduction

The technical textile industry is a fast-growing field driven by technological advancements, innovations, and increasing user requirements (Ahmad, Rasheed & Nawab, 2021). Technical textiles are used in automotive, healthcare, construction, military, and agricultural industries (Bahners, Schmidt & Gutmann, 2012). The application areas of technical textiles often expose the material to extreme weather conditions, mechanical wear, and high levels of chemicals. As a result, the technical textile ages fast, which means a shorter lifetime (Raad, 2020). Typically, the technical textiles age gradually over several years in their end-user environment (Raad, 2020). Thus, ensuring that technical textiles meet the requirements of aging in their application area is of the essence in the product development process (PDP) of such products (Bahners, Schmidt & Gutmann, 2012).

The PDP can be divided into different stages, and before entering the next stage, the product has to pass a gate (Wuest, Liu, Lu & Thoben, 2014). This is known as the stage-gate process. In the testing and validation phase of the stage gate process, tests are conducted to ensure that the prototype meets the requirements. Life cycle tests under similar conditions to the end-user environment are one type of test often conducted in the PDP to obtain information about product quality, reliability, and durability (Raad, 2020). According to Raad (2020), this test can be conducted on the individual units to ensure that all components meet the requirements or on an assembled prototype to study the interaction of the components on the performance. In the technical textile industry, these components can be plastic foils and yarns (Horrocks & Anand, 2015).

As an excellent PDP is characterized by low cost, high quality, and speed, life cycle testing in real-time is not feasible in the development as these tests are time-consuming (Wheelwright & Clark, 1991). Thus, accelerated aging tests can be used to reduce development time. Furthermore, accelerated aging testing allows terminating products with insufficient quality from further progressing in the stage-gate model (Saville, 1999). Using these tests in the PDP, the PDP can be improved in terms of reduced development time, better risk management, and high-quality products (Unger & Eppinger, 2011).

One tool used for accelerated aging tests is a sun simulator, which exposes the product to temperature, humidity, and ultraviolet light (UV) (Bahners, Schmidt & Gutmann, 2012). To measure the impact of the simulated environment, tensile testing can be conducted on the product (Eder, Voronko, Knobl, Dimitriadis, Ujvari, Berger & Neumaier, 2019). Tensile testing is a method for measuring the mechanical performance of a material when a force is applied and is often measured in terms of breaking elongation and breaking strength (Demiryürek & Koç, 2009). The tensile properties depend on the material's components and their interrelationship (Demiryürek & Koç, 2009).

Intensified international competition, new technologies, and fast-growing markets increase the importance of an excellent PDP (Wheelwright & Clark, 1991). Business process improvements can be one way to achieve this in a constantly changing business environment (Holweg, Davies, Meyer, Lawson & Schmener, 2018). New technologies, such as Artificial intelligence (AI), can improve the PDP (Holweg et al., 2018). AI is a collection of analytical techniques that can be used to solve problems in various application areas (Gordon, 2011). Increased computing power, availability of cloud services, and Big Data have enabled several AI-techniques to grow in the past decade (IBM-Cloud-Education, 2020). Examples of subfields within AI are machine learning (ML), deep learning (DL), and expert systems (Gordon, 2011).

In the testing and validation phase of the PDP for technical textiles, the implementation of Artificial Neural Networks (ANN), a type of AI, has grown in popularity (Yildirim, Birant & Alpyildiz, 2017). The ANN can solve problems in new situations and generalize, discover and associate different data sources (Gordon, 2011). ANNs are generally better at predicting tensile properties than conventional statistical methods, which is explained by its ability to deal with high-dimensional data and the non-linear relationships between the components of technical textiles (Fan & Hunter, 2009).

ANNs refer to a category of machine learning algorithms (MLA) inspired by the structure and function of the human brain (Mwasiagi, Huang & Wang 2008). An ANN comprises interconnected computational units called neurons or nodes, which are organized into input, intermediate/hidden, and output layers (Mwasiagi, Huang & Wang 2008). The nodes in the input layer, which are the input variables, send information to nodes in the next layer. The next layer can be a hidden layer or the output layer, which computes values through mathematical operations (Mwasiagi, Huang & Wang 2008). These values are in turn sent to the next layer and so on until the output layer is reached. The output layer provides the prediction of the ANN. (Demiryürek & Koç, 2009).

There are several design choices when building an ANN, and all these choices have implications for the model's performance and interpretability (Vani, Madhusadhana Rao & Kannam Naidu, 2019). The first design choices include the type of ANN, e.g, feedforward ANN, recurrent neural networks (RNNS), and convolutional neural networks (CNN) (Vani et al., 2017). ANNs can approximate a wide range of complex and nonlinear functions and one specific application area is classification tasks (Lindholm, Wahlström, Lindsten & Schön, 2022). Classification tasks predict the output variable and it can be either a numerical value or a classification (Lindholm et al., 2022). After establishing the type of ANN and task, the structure should be determined, including the input layer and the determination of input variables through feature selection (da Silva, Hernane Spatti, Andrade Flauzino, Liboni & dos Reis Alves, 2017). The following design choice is to decide the number of hidden layers, output layers, and the number of nodes in these layers. The activation function determines the output of each layer, given its input, and should be determined for each layer (da Silva et al., 2017). All these choices have implications for the model's performance and interpretability (Vani et al., 2017).

Another consideration is the split of data into training, testing, and validation subsets (Lindholm et al., 2022). To ensure the high performance of the ANN, training the model is required and when training the model, the type of training algorithm, error measure and optimization function to use needs to be decided (Vani et al., 2017). The ANN model should be evaluated which includes using an error measure to compare the predicted output with the actual value. Lastly, as an ANN can generally have low interpretability, a suitable design and methods to increase the interpretability can be considered (Ponomareva & Caenazzo, 2019).

The implementation of AI-models can, according to Enholm, Papagiannidis, Mikalef & Krogstie (2021), lead to several improvements in organizations, such as improved productivity, reduced human error, greater precision, better decision quality, enhanced products, growth, and increased customer satisfaction. Business process improvements can lead to competitive advantages, and examples of these are product quality, differentiation, efficiency, and a short time to market (TTM) (Boutros & Prudie, 2014); (Ma, 2000). A competitive advantage is sustainable if it can persist over time (Aaker, 1989). Companies having a sustained competitive advantage possess an optimal market position by hindering other competitors from entering the market i.e, barriers to enter (Huang, Dyerson & Harindranath, 2015).

To ensure process improvements and in extension, competitive advantages from implementing AI, an AI-strategy consisting of plans and processes to fulfill technological, organizational, and environmental requirements is needed (Enholm et al., 2021). Sufficient quality and quantity of data are crucial factors for successfully implementing AI (Enholm et al., 2021). This often poses a challenge for companies in identifying what data is required, how it should be gathered, and whether it is high quality (Sarangi & Sharma, 2019). Human skills and new roles in the company are essential requirements to implement AI successfully (Enholm et al., 2021). However, as management practices lag behind the digitalization trend, creating a culture and organizational readiness for the implementation of AI can take time and effort (Ross, Beath & Quaadgras, 2013).

A case study company (CSC) was used in this thesis to understand the suitable ANN-model for predicting the breaking elongation of plastic foils and breaking strength of yarns in the aging measurement process in the PDP of technical textile companies. To better understand the improvements, competitive advantages, and requirements in the AI-strategy when implementing an ANN-model for the technical textile industry, the CSC was used as a practical scenario.

2
Scope

In this chapter, the aim, research questions, and demarcations will be presented.

2.1 Aim

Through a CSC, this thesis aims to better understand the implementation of an ANN in the PDP in the technical textile industry. More specifically, to suggest a suitable ANN model predicting the tensile properties of technical textiles in the testing and validation phase of the PDP. In addition, to understand the AI-strategy requirements better, resulting in improvements and competitive advantages from the ANN implementation in the PDP. To achieve this aim, the research questions in section 2.2 will be answered.

2.2 Research Questions

RQ1: How should an ANN-model be designed to predict the breaking elongation of plastic foils and breaking strength of yarns of a technical textile prototype, processed in a sun simulator?

- Which type of task should be done, which subtype of ANN-model is suitable, and how should the ANN be structured in terms of:
  - Input variables in the input layer and feature selection method
  - Hidden layers and hidden nodes, output layer and output nodes
  - Activation functions
- How should the training and evaluation of the ANN-model be conducted?
  - How should the data be split for training, testing, and validation?
  - Which training algorithm, error measure, and optimization function are suitable?
  - How should the ANN model be updated?
- What are suitable methods for making the ANN model more interpretable?

RQ2: Which requirements should an AI-strategy include for the successful implementation of an ANN-model in the aging measurement analysis in the technical textile industry?

RQ3: What potential improvements and competitive advantages can an organization in the technical textile industry gain from implementing an ANN-model in the aging measurement analysis?

2.3 Demarcations

This master thesis is limited to one product development process in an organization producing technical textiles.

3

Frame of Reference

In this chapter, the frame of reference will be presented. Firstly, literature on technical textiles and tensile testing to determine the breaking strength and elongation are presented. Further, the accelerated testing method is presented to understand how the end user's environment affects the technical textile's lifetime. This information is presented first to understand how the technical textiles and testing function and second to understand the input and output of a hypothetical ANN model.

After that, an overview of the ANN, subtypes, types of tasks, architecture, loss functions, optimization algorithms, training, validation, testing, evaluation, and feature selection methods are presented, as these form the design choices of the ANN-model. Subsequently, case studies implementing AI for predicting tensile properties of technical textiles and plastic foils are presented as this serves as guidance when developing the hypothetical ANN-model.

The section after this presents the characteristics of a PDP, the testing and validation phase in the stage-gate model. This information is presented, as this study focuses on the implementation of ANN in the context of a PDP. After that, discrete and compound competitive advantages are described in order to organize the competitive advantages when implementing an ANN in the PDP in the technical textile industry. The penultimate subsection describes business process improvements when implementing AI in terms of first and second-order effects to provide information about the improvements an ANN implementation could lead to in the PDP. The final section describes the requirements for a successful AI implementation in terms of technological, organizational, and environmental factors needed to be fulfilled. This is important as it provides a comprehensive view of the requirements for companies in the technical textile industry.

3.1 Technical Textiles, Tensile Testing, and Accelerated Testing

In this section, an introduction to technical textiles is presented, followed by a description of the testing of textiles.

3.1.1 Technical Textiles

Technical textiles are composed of yarns and plastic foils (Horrocks & Anand, 2015). To obtain desired properties of the technical textiles, chemical substances are often added, e.g., chemical resistance, waterproof, and absorption resistance (Shabbir, Ahmed & Sheikh, 2020). The components of the technical textile are characterized by geometrical complexity and non-linear relationships, which affect the material's properties (Vassiliadis, Rangoussi, Cay & Provatidis, 2010).

Yarns consist of fibers that can be natural, synthetic, or high-performance (Vassiliadis et al., 2010). Synthetic fibers are called filaments, and examples of these are Polyethylene (PE) and Polyethylene Terephthalate (PET) (Shabbir, Ahmed & Sheikh, 2020).

Spinning is conducted to produce yarns from fibers, and weaving or knitting can be used when producing a textile from yarns (Demiryürek & Koç, 2009). The authors describe weaving as arranging two sets of yarn together, whereas knitting is arranging a single yarn. Plastic foils are made of polymers and are produced by melt extrusion (Syranidous, Karkanorachaki, Amorotti, Repouskou, Kroll, Kolvenbach, Corvini, Fava & Kalogerakis, 2017).

3.1.2 Accelerated Testing and Tensile Testing of Technical Textiles

One way of testing textiles is accelerated aging, which is done to predict their long-term performance and lifetime (Bahners, Schmidt & Gutmann, 2012). A sun simulator is used for this purpose (NCPTT, 2022). To simulate the application area of the end product, the technical textile is put in the sun simulator, where it is exposed to temperature, humidity, and UV light (Bahners, Schmidt & Gutmann, 2012). The accelerated aging tests are often compared with measurements conducted on the technical textiles in real-time in its application environment (Eder et al., 2019).

One way of measuring the sun simulator's effect on technical textiles is tensile testing (Saville, 1999). Tensile testing investigates the mechanical performance of technical textiles by measuring how it reacts to applied forces (Demiryürek & Koç, 2009). The tensile properties can be measured in terms of breaking elongation and breaking strength (Demiryürek & Koç, 2009). Saville (1999) defines elongation as the increase in length from the initial state when force is applied and breaking elongation as the point where the sample breaks. The method of measuring the elongation of yarns can be complicated; thus, the breaking strength can be a more helpful measure (Saville, 1999). Breaking strength is defined as the force applied at which the sample breaks. The relationship between these variables can be seen in Figure 3.1 below.

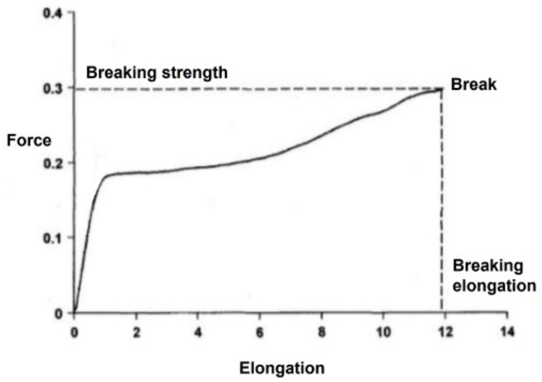

Figure 3.1: Depicts the tensile curve, with force at the y-axis and elongation at the x-axis (Demiryürek & Koç, 2009)

The tensile properties of technical textiles are affected by the properties of their components, such as fiber length, strength, and cross-section, as well as factors like the blend and proportions of different fibers in the yarn and the spinning process used. These properties can significantly impact the yarn's tensile properties (Vassiliadis et al., 2010). Bhat & Bath (2017) note that the degree of order, localization, and the length-to-width ratio of the fibers can also affect the tensile Properties. Alagirusamy, Alagirusamy & Das (2010) describe additional fiber properties that can impact the yarn, such as fiber diameter, specific surface area, and bending and torsional rigidity. Further, the authors describe that density, finesse, diameter, melting point, tenacity, and breaking elongation of the fibers also affect the mechanical properties of the yarn. The superposition and tension of spun yarns can also have an effect on their tensile properties (Demiryürek & Koç, 2009)

The tensile properties of plastic foils are affected by their composition, component sizes, and processing (Alhindawi & Altarazi, 2018). More specifically, the foil ingredients, size, and percentages affect the tensile properties of the foil (Alhindawi & Altarazi, 2018). The production of plastic foils through melt extrusion affects the tensile properties of the material. Both the technology and process conditions affect the tensile properties of the foil (Alhindawi & Altarazi, 2018). The speed of the drawing process in the melt excursion affects the elongation of the plastic foil (Alhindawi & Altarazi, 2018).

3.2 Artificial Neural Networks

There are multiple dimensions to consider when designing an ANN, and in this section, these are presented.

3.2.1 Subtypes of ANN

An ANN consists of many interconnected nodes, which are the computational units of the network (da Silva et al., 2017). Each node receives input from other nodes, processes the input using a mathematical function, and then sends the output to other nodes (da Silva et al., 2017). The strength, i.e., weights and biases of the connections between the nodes, determine how much influence each node has on the other nodes (da Silva et al., 2017). During the training of the network, the weights and biases are adjusted based on the input data and the desired output, so the network learns how to produce the correct output for a given input (da Silva et al., 2017).

There are many types of ANNs, but they all have a similar structure of several layers of interconnected nodes that process and transmit information (Mwasiagi, Huang & Wang 2008). Feedforward ANNs, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) are some of the most common types, and the type of task and data determines which type is the most suitable one (Vani et al., 2019).

RNNs are designed to deal with sequential data, such as time series data or text (Vani et al., 2019). Convolutional neural networks (CNNs) are ANNs designed to process and analyze data of grid-like structure, such as images or video (Vani et al., 2019). In a feedforward ANN, the simplest type of neural network, the interconnections between nodes have no loops, and the information streams through the layers in a forward manner, from the input layer to the output layer, see Figure 3.2 (da Silva et al., 2017).

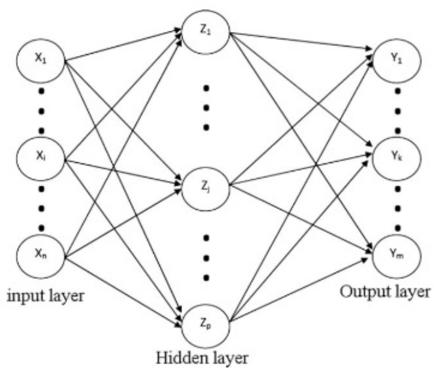

Figure 3.2: A visualization of the feedforward ANN (Moezzi, Ghane & Semmani, 2015)

3.2.2 Type of Task

ANNs are typically used for classification tasks where the output variable is either a class label (see terminology) or regression. In the case of regression, the output value is a continuous value. In supervised learning, the ANN is trained on a dataset that includes several input variables and corresponding output values (Lindholm et al., 2022). The ANN learns the relationship between these variables and can then use this information to make predictions about new data (Lindholm et al., 2022).

3.2.3 Structure of an ANN

The ANN consists of the input layer that receives input data and passes it on to the next layer, which is typically a hidden layer (Mwasiagi, Huang & Wang 2008). In the hidden layer, the input nodes are multiplied with weights, and this product is then summed, and the resulting value enters an activation function (Mwasiagi, Huang & Wang 2008), see Figure 3.3 for the procedure. The activation function determines the layer's output, which is then passed on to each node in the next layer, another hidden layer, or the output layer (Mwasiagi, Huang & Wang 2008). The authors describe that, if it is passed to the output layer, it produces the final result, i.e. the prediction.

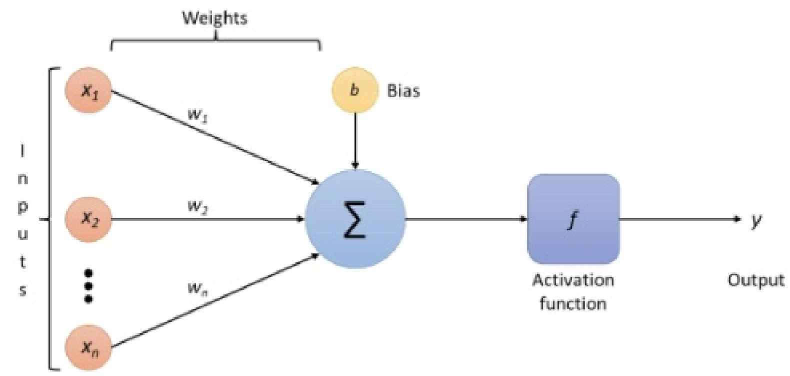

Figure 3.3: Operations executed in a node (Sánchez-Gutiérrez & González-Pérez, 2022)

3.2.4 Activation Functions

The suitable activation function depends on the specific characteristics of the task and experimentation may be necessary to find the optimal one (Lindholm et al., 2022). An ANN can have different activation functions in its layers (Sarang, 2021). Commonly, non-linear activation functions are used in the hidden layers as it enables the learning of more complex relationships between the input and output variables (Fan & Hunter, 2009). The output layer can have linear activation functions, which allow the network to predict a continuous value over the full range of real numbers (Lindholm et al., 2022).

The non-linear activation functions sigmoid and hyperbolic tangent (tanh), see appendix A for mathematical notation, can be appropriate activation functions in the hidden layers of a feedforward ANN that is being used for regression (da Silva et al., 2017). For the output layer, a better choice of activation function is the identity function or rectified linear unit (ReLU) function (Sarang, 2021); see appendix A for mathematical notation. These activation functions have, according to Lindholm et al. (2022), these activation functions have been shown to work well for regression tasks.

3.2.5 Hidden Layers

Another consideration to make when designing the ANN is the number of hidden layers and nodes in each layer (Cheng & Adams, 1995). In a feedforward ANN, these considerations affect the performance and interpretability of the network (da Silva et al., 2017). In general, an ANN with too few hidden layers and nodes may not be able to learn complex pattern data, while too many may overfit (Cheng & Adams, 1995). Overfit means that the model becomes too specialized to the training data and thus has lower performance on new data (Lindholm et al.,2022). It is recommended to experiment with various numbers of hidden layers and nodes when developing an ANN to identify the optimal configuration for the particular dataset and task (da Silva et al., 2017). There are, however, three common approaches.

One approach to determining the suitable number of hidden layers and nodes is to start with a small number of hidden layers and nodes and gradually increase them until the performance of the network reaches a plateau or decreases (Sarang, 2021). Another approach is to use the Universal approximation theorem, which states that a feedforward ANN with a single hidden layer containing a sufficient number of nodes can approximate any continuous function to arbitrary precision (Cybenko, 1989). The last approach is to use regularization techniques (see further explanation in 3.2.12) to prevent overfitting and allow the network to use a larger number of hidden layers and nodes without negatively impacting its performance (Lindholm et al., 2022).

3.2.6 Output Layer

The output layer of a feedforward ANN typically has one node since the goal is to predict one continuous value. However, if it is desired to predict multiple continuous values at once, the output layer may have more than one node (Demiryürek & Koç, 2009).

3.2.7 Training of ANNs

ANNs can be trained using a variety of algorithms (Lindholm et al., 2022). The algorithms are designed to adjust the network's weights and biases in such a way as to minimize the network's error on a given training dataset (da Silva et al., 2017). In supervised learning, the error is obtained by comparing the predicted output to the actual output (Lindholm et al., 2022). These training algorithms use different techniques to search for the weights and biases that will produce the desired outputs of the training data (da Silva et al., 2017). Some of the most commonly used training algorithms for ANNs include backpropagation, reinforcement learning, and genetic algorithms, see terminology (da Silva et al., 2017). Backpropagation is the most popular one, and one reason for this is that the other algorithms may be more complex to implement, not as efficient, or may require more computational resources to run (da Silva et al., 2017).

3.2.7.1 Backpropagation

The backpropagation algorithm works by first making a prediction using the current weights and biases of the network, and then comparing the predicted output to the actual output (Lindholm et al., 2022). The error between the predicted and actual outputs is then back propagated through the network, and the weights and biases are adjusted to the error (Fan & Hunter, 2009). This is an iterative process, which is repeated many times for each training example, and the weights and biases are adjusted after each example to minimize the network's overall error (Fan & Hunter, 2009). To allow the encoding of the different aspects of the data that the hidden units do, the weights and biases are typically initialized into small random numbers (Lindholm et al., 2022).

In the training phase, there are two hyperparameters, (see terminology), and these are batch size and number of epochs (Lindholm et al., 2022). The size of the batch refers to the number of training examples that are used per training iteration (Lindholm et al., 2022). The epochs refer to the number of times the model will go through the entire dataset used for training (Lindholm et al., 2022). The choice of these hyperparameters affects the performance of the model (da Silva et al., 2017). A large batch size can speed up the training process but also result in less accurate weights and biases, while a smaller batch size implies the opposite (Lindholm et al., 2022). A larger number of epochs can result in more accurate weights and biases but may lead to overfitting (Lindholm et al., 2022).

3.2.8 Optimization Algorithms for Backpropagation

In the context of backpropagation, optimization algorithms are used to adjust the weights and biases of the ANN to minimize the loss function, i.e., the error. This process is known as training the network (da Silva et al., 2017).

Common optimization algorithms for backpropagation include gradient descent, steepest gradient descent, stochastic gradient descent (SGD), adaptive moment estimation (adam), and Levenberg-Marquardt (Lindholm et al., 2022). Which optimization function to use depend on factors such as the structure of the network, the characteristics of the training data, and the computational resources available (Lindholm et al., 2022).

Gradient descent updates the weights of the network based on the gradient, see terminology, of the loss function concerning the weights (da Silva et al., 2017). It iteratively moves the weights in the direction that reduces the loss until it reaches a minimum (da Silva et al., 2017). Steepest gradient descent is a variant of gradient descent that uses the steepest descent direction, see terminology, which is the direction of the gradient that maximizes the decrease in the loss function to compute the update step (da Silva et al., 2017). This method can be more efficient than gradient descent, but it can also be more sensitive to the learning rate, i.e., the step size that the algorithm takes towards minimizing the loss function.

Stochastic gradient descent (SGD) updates the weights of the network based on the gradient of the loss function for the weights (Lindholm et al., 2022). Further, this method is computationally efficient but may only sometimes converge to the global minimum of the loss function. It is called stochastic as it uses a randomly selected subset of the training data to compute the gradient of loss function compared to gradient descent which uses the entire training set (Lindholm et al., 2022).

Adaptive moment estimation (Adam) is a more advanced optimization method that uses an adaptive learning rate (see terminology) and momentum (see terminology) to improve the convergence of the algorithm (Sarang, 2021).

Levenberg-Marquardt combines the ideas of gradient descent and the Gauss-Newton method, see terminology (da Silva et al., 2017). It uses a combination of the gradient and an approximate Hessian matrix, see terminology, to compute the update step for the weights (da Silva et al., 2017). For nonlinear problems, this algorithm is often more efficient than gradient descent. It can also be more robust to local minima in the batch size (da Silva et al., 2017). Additionally, it can be used to train networks with a more significant number of parameters, which can be challenging for gradient descent methods (da Silva et al., 2017).

3.2.9 Error Measure

When using an ANN for predicting numerical values, it is important to use a suitable error measure to evaluate the performance of the network, as it depends on the data characteristics and the goals of the analysis (Vandeput, 2021). It may be necessary to experiment with different error measures and combinations of them to determine which one is most suitable for the task (Vandeput, 2021). The measurement of error is often the same in the evaluation of the training, validation, and testing phase of the network (Lindholm et al., 2022).

One of the most used error measures is the mean squared error (MSE) (see Appendix A), which is the average of the squared differences between the predicted output of the network and the actual output (da Silva et al., 2017). MSE penalizes large errors more heavily than small ones, and this can be useful for identifying and correcting large errors in predictions (Vandeput, 2021). Another error measure is the mean absolute error (MAE) (see Appendix A), which is the average of the absolute differences between the predicted and actual outputs (Vandeput, 2021). MAE is less sensitive to outlier values than MSE, which can be useful when working with data that has a high degree of variability (Vandeput, 2021). Mean absolute percentage error (MAPE) (see Appendix A), which is defined as the average of the absolute differences between the predicted values and the actual values, expressed as a percentage of the actual values, is appropriate when it is desired to compare the error with the actual values in a relative sense (Vandeput, 2021).

The correlation coefficient is a measure of the strength and direction of the linear relationship between two variables (Lindholm et al., 2022) (see Appendix A). It is a value between -1 and 1, where a value of 1 indicates a perfect positive linear relationship and a value of 0 indicates no linear relationship (Lindholm et al., 2022). To use the correlation coefficient as an error measure, the predicted output values from the ANN are compared to the actual output values from the training data (Demiryürek & Koç, 2009). The correlation coefficient is then calculated based on the difference between the predicted and actual values (Demiryürek & Koç, 2009).

Mean bias error (MBE) measures the average error in a set of predictions (see Appendix A) (Almetwally, Idrees & Hebeish, 2014). It is defined as the average of the differences between predicted and actual values (Almetwally, Idrees & Hebeish, 2014). A positive MBE indicates that the predictions overestimate the actual values, while a negative indicates underestimation.

Root mean squared error (RMSE), defined as the square root of the mean squared error, is interpretable in the same units as the original data, making it easier to compare the error with the actual values (see Appendix A) (Vandeput, 2021).

It is recommended to have a combination of error measures to get a more comprehensive view of the performance of the network as they highlight different aspects of the prediction error (Jierula, Wang, Oh & Wang, 2021). To achieve this, according to Jierula et al. (2021), the combination should include at least one correlation-based (correlation coefficient), one scale-dependent (MSE/RMSE/MAE), and one percentage-dependent (MAPE) error measure.

3.2.10 Data for Training, Testing, and Validation

It is common to split the data into training, testing, and validation sets because it allows the model to be trained and evaluated on different sets of data, which can help to reduce overfitting and improve the model's performance (da Silva et al., 2017). The training set should be the largest of the three splits, as the model needs a large amount of data to learn from (Lindholm et al., 2022). The validation set should be of moderate size, as it is used to fine-tune the model and improve its performance. In the case of a feedforward ANN for regression, this fine-tuning involves adjusting the number of hidden layers and nodes to improve the model's performance (da Silva et al., 2017). The testing set should be the smallest of the three splits, as it is only used to evaluate the performance of the final model (da Silva et al., 2017).

Depending on the complexity of the ANN and the task, ANNs can require a lot of data (Lindholm et al., 2022). In the case of data scarcity, the technique of k-fold cross-validation can be useful (da Silva et al., 2017). By training and evaluating the model multiple times on different subsets of the data, k-fold cross-validation can provide a more robust estimate of the model's performance than using a single train/test split (da Silva et al., 2017).

3.2.11 Interpretability Methods for ANN

Relevance analysis and sensitivity analysis are two methods that provide insights into the decision-making process of an ANN and the importance of different input variables (Ponomareva & Caenazzo, 2019). Thus, these methods can help to improve the interpretability of the network and better understand its predictions

(Ponomareva & Caenazzo, 2019). Relevance analysis is a method for analyzing the contribution of each input variable to the predictions made by the ANN (Ponomareva & Caenazzo, 2019). It is often used in combination with a technique called saliency mapping, which visualizes the relevance of each input variable by highlighting the parts of the input data that are most important for the ANN´s predictions (Ponomareva & Caenazzo, 2019). Sensitivity analysis is a method for analyzing the sensitivity of the ANN's predictions to changes in the input variables (Ponomareva & Caenazzo, 2019). It is often used in combination with a technique that modifies the input data in various ways and then measures the effect on the network's predictions (Ponomareva & Caenazzo, 2019).

3.2.12 Feature Selection

Feature selection is a method that identifies the most relevant features, i.e input variables (Lindholm et al. 2022). This is necessary as too many features can lead to problems such as longer training time, risk of important information being drowned as well as poor generalization ability i.e overfitting (Muthukrishnan & Rohini, 2016). The goal of feature selection is to minimize the information loss while at the same time only removing redundant features (Muthukrishnan & Rohini, 2016). Reducing the number of features could lead to a more interpretable model with less computational complexity (Jomthanachai, Wong, & Khaw, 2022).

The process of feature selection can be difficult, as one needs to understand the relationship between the features and the output variable as well as the relationship between the features (Dhal & Azad, 2021). Lindholm et al. (2022) describe that feature selection also implies a potentially facilitated data collection process, as some variables due to elimination do not need to be collected. One drawback associated with feature selection is the potential elimination of relevant features, which leads to the risk of overfitting (Rong, Gong & Gao, 2019).

For feedforward ANN, one common feature selection method are the embedded methods, where the feature selection is embedded in the training algorithm (Lindhom et al., 2022). Regularization techniques are common, and they essentially penalize the model when making it too complicated (Liu et al., 2022). These techniques include the L1 regularization that adds a penalty term, equal to the absolute value of the weights multiplied by a constant, to the loss function and causes the model to give less importance to the less relevant features (Lindholm et al., 2022). The other technique is the L2 regularization technique which adds a penalty term to the loss function (Lindholm et al., 2022). The penalty term results in the model reducing the magnitude of the weights with less relevant features (Lindholm et al., 2022).

3.3 Case studies - AI in the Technical Textile Industry

In this section, case studies are presented for the prediction of the tensile properties of plastic foils and yarns consisting of synthetic and natural fibers. As this study focuses on technical textiles made of synthetic yarns, the input variables for natural yarns are irrelevant. However, the model architecture and output of models in these case studies are relevant.

3.3.1 Prediction of Polyester/Viscose Yarn Elongation

Demiryürek & Koç (2009) suggest a feedforward ANN model for regression to predict the breaking elongation of polyester/viscose blended OE-rotor spun yarns. The model's input variables were the blend ratio, polyester length, fineness, yarn count, and rotor speed. The output of the ANN model was the breaking elongation of yarns. More specifically, backpropagation was used to train the model. The learning data was 75% of the data, and the remaining 25% was used for tests. This study used one input layer, one hidden layer with 25 nodes, and one output layer. In the hidden layer, the sigmoid activation function was used, and the gradient descent function was used to optimize. Correlation coefficient-R, MSE, MAE, and MAPE were used to understand the model's performance. It was concluded that the ANN gave reliable results (Demiryürek & Koç, 2009).

3.3.2 Prediction of Polyester/cotton Yarn Tensile Strength

Malik, Haleem, Malik & Tanwari (2012) suggest a feedforward ANN model for regression analysis to predict the tensile strength of polyester cotton blended woven fabrics. The following input variables were used: linear density, yarn strength, float length, and thickness. 135 data points were used and divided into training, testing, and validation data (90%, 5%, 5%). The model used backpropagation, and the number of hidden neurons in a single hidden layer was 9 (Malik et al., 2012). To identify the optimal number of neurons an unspecified trial and error process was conducted. The Levenberg-Marquardt algorithm was used as an optimization function, and the error measurement MSE was to validate performance. Values from the ANN model were sufficiently close to the real values (Malik et al., 2012).

3.3.3 Prediction of Tensile Properties of UV degraded Nylon66/polyester Woven Fabric

Moezzi, Ghane & Semmani (2015) suggest a feedforward ANN to predict the tensile properties of UV degraded Nylon66/polyester woven fabric. The fabric was put in a UV chamber and tensile tested at different points in time. At each time of exposure to UV, the correlation between strain and breaking point was determined. The entire stress-strain curve is input data to the ANN. The analysis conducted was of a time series type. Levenberg-Marquardt was used as an optimization function. The network had one hidden layer and the tangent hyperbolic activation function was used in this layer (Moezzi, Ghane & Semmani, 2015). The linear function was used in the output layer. Sensitivity analysis was conducted by changing weights on the input and output variables. Three groups of data were used, 80% training data, 10% validation data, and 10% testing data. Correlation coefficient and MSE were used to evaluate the model on training and testing data. MAE and MAPE were used to assess the performance of the ANN model. The validation showed that the ANN was a good method for the task (Moezzi, Ghane & Semmani, 2015).

3.3.4 Prediction of Yarn Breaking Elongation of Cotton

Mwasiagi, Huang & Wang (2008) designed a feedforward ANN for regression analysis to predict the breaking elongation of cotton lint. The input of the model has rung frame process variables: spindle, speed, ring, diameter, traveler weight, spinning draft, yarn twist, and yarn count. Also, the cotton fiber characteristics, micronaire, maturity, spinning consistency index, fiber length, length uniformity, short fiber index, strength, elongation, reflectance, yellowness, trash cent, trash area, and trash grade were used as input variables. The most influential factors were yarn twist, yarn count, fiber elongation, fiber length, length uniformity, and spindle speed (Mwasiagi, Huang & Wang, 2008). The data were divided into training, validation, and testing subsets in a 4:1:1 ratio. The output of the ANN model was yarn-breaking elongation. The sigmoid activation function was used in the hidden layer whereas the linear function was used in the output layer. The training algorithm was backpropagation and Levenberg-Marquardt was used as an optimization function. The neurons in the hidden layer were eight. To evaluate the model the MSE and correlation coefficient method was used and it was concluded that the model has a good prediction accuracy (Mwasiagi, Huang & Wang, 2008).

3.3.5 Prediction of Tensile Properties of Yarn of Cotton/spandex

Almetwally, Idrees & Hebeish (2014) predicts the tensile properties of cotton/spandex core-spun yarns with a feedforward ANN for regression analysis. The dataset used in the study was 40 cotton/spandex core-spun yarn examples. The output variables were breaking strength, breaking elongation, and work of rupture (see terminology). The design of the ANN was one input layer with three nodes taking into account linear density, drawing ratio, and twist multiplier, a hidden layer with 12 nodes, and an output layer with one node corresponding to one of the output variables (Almetwally, Idrees & Hebeish, 2014). The activation function in the hidden layer was sigmoid and in the output layer the linear function. The ANN was trained through backpropagation with the optimization function Levenberg-Marquardt. Before learning, the data was split into training, validation, and testing with the ratio 3:1:1. The error measurements used were the RMSE and the MBE. It was concluded that the ANN has a satisfactory performance (Almetwally, Idrees & Hebeish, 2014).

3.3.6 Fiber Strength Prediction of Polypropylene with ANN

Kuo, Hsiao & Wu (2004) conducts a study on the prediction of the properties of polypropylene melt-spun fibers by using a feedforward ANN for regression analysis. The study presents an ANN with a three neuron input layer, consisting of extruder screw speed, gear pump gear speed, and winder winding speed of a melting system. 12 hidden nodes in the hidden layer and two output nodes, tensile strength, and yarn counts, in the output layer, were used. The activation function in the hidden layer was the sigmoid. A reliable prediction model was achieved (Kuo, Hsiao & Wu, 2004). The ANN was trained with a backpropagation algorithm where the steepest gradient descent was the optimization algorithm. It was concluded that the ANN could be applied to other projects as the error of the neural network was +- 2 percent of the tensile strength prediction (Kuo, Hsiao & Wu, 2004).

3.3.7 Prediction of Tensile Properties and Lifetime of Polyethylene Plastic Foils

Lahcene, Amine & Abdelkader (2022) present a hybrid CNN and SVM model (see terminology) to predict the lifetime and mechanical performance degradation of multilayer polyethylene foils. The foils were degraded by thermal aging and UV radiation at different temperatures and times. A tensile test was conducted by applying a lead to the foil. The aging was conducted in five periods: 120h, 550h, 1010h, 2040h, and 4000h. The SVM model was used for classification, while CNN performed feature extraction for regression. Input data consisted of strain in percentage, aging time, the foil's thickness, the melt flow index, and density (Lahcene, Amine & Abdelkader, 2022). A total of 4072 examples of this data were used. The model had two layers, one connected layer, and one output layer. Log Hyperbolic cosine loss function (see terminology) was used to train the model. The activation function ReLU was used for all the layers except for the output layer where the linear function was used. The adam optimizer was used to update the parameters during backpropagation. The model was evaluated with the MSE, RMSE, and MAE and it was concluded that the model has high prediction performance (Lahcene, Amine & Abdelkader, 2022).

3.3.8 Prediction of Tensile Strength of Polyethylene Foils

Alhindawi & Altarazi (2018) suggest a feedforward ANN for regression to predict the tensile strength of polyethylene foil. Input variables for the model were 11, five consisting of material-related properties and six consisting of process-related factors. The input variables were the ingredients of the Polyethene foil in percentages, and the process variables in form of temperature (4 different), mix, and speed (Alhindawi & Altarazi, 2018). The ANN had one hidden layer with 150 nodes. It was trained with the optimization function SGD. The activation function was ReLU. The dataset consisted of 43 records and 80% of the data was used as training data and 20% as testing data. The output of the model was tensile strength. MAE was used to compare the predicted output with actual results. It was concluded that the ANN demonstrates a satisfactory prediction capability (Alhindawi & Altarazi, 2018).

3.3.9 Summary of the AI-models suggested in Case studies

In this subsection, a summary of the case studies in the above section is presented in Table 3.1. The table presents all the design choices conducted in the case studies.

Table 3.1: Overview of the characteristics of the ANN models suggested in the case studies

	Case study authors	Fiber/Foil type	Output	# Input nodes	Input variables	ANN-Model	Analysis	Learning algorithm	Hidden layers & nodes	Activation function/ hidden layer, output layer	Optimization function	Error measurement	Samples, training, testing, validation
Yarn	Demiryürek & Koç	Polyester/viscose	Breaking elongation	4	blend ratio, polyester length, polyesters fineness, yarn count, rotor speed	Feed-forward ANN	Regression	Backpropagation	1, 25	Sigmoid, N/A	Gradient descent	Correlation coefficient, MSE, MAPE	109,, 75%, 25% , -
	Malik, Haleem, Malik & Tanwari	Polyester/cotton	Tensile strength	7	linear density, yarn strength, float length, thickness	Feed-forward ANN	Regression	Backpropagation	1, 9	Sigmoid, N/A	Levenberg-Marquardt	MSE	270, 90%, 5%, 5%
	Moezzi, Ghane & Semmani	Nylon66/polyester	Tensile properties (stress & strain curves)	2	UV-exposure time, correlation between strain, breaking point	Feed forward ANN	Time series analysis	Backpropagation	1, 6	Hyperbolic tangent, identity	Levenberg-Marquardt	Correlation coefficient, MSE, MAPE	80%, 10%, 10%
	Mwasiagi, Huang & Wang	Cotton	Breaking elongation, breaking strength	3	ring frame process variables: spindle, speed, ring, diameter, traveler weight and spinning draft, yarn twist and yarn count. cotton fiber, characteristics, micronaire, maturity, spinning consistency index, fiber length, length uniformity, short fiber index, strength, elongation, reflectance, yellowness, trash cent, trash area, trash grade	Feedforward ANN	Regression	Backpropagation	1, 8	Sigmoid, Linear	Levenberg-Marquardt	MSE, Correlation coefficient	72, 66% 17%, 17%
	Almetwally, Idrees & Hebeish	Cotton/spandex	Breaking strength, breaking elongation, work of rupture	3	spandex filament drawing ratio, linear density, luster, tenacity, elongation, twist-multiplier of the core-spun yarns, cross-head speed, pre-tensional force of tensile machine	Feedforward ANN	Regression	Backpropagation	1, 12	Sigmoid, Linear	Levenberg-Marquardt	RMSE, MBE	40, 60%, 20%, 20%
	Kuo, Hsiao & Wu	Polypropen	Tensile strength, yarn count	3	extruder screw speed, gear pump gear speed, and winder winding speed of a melting system	Feedforward ANN	Regression	Backpropagation	1, 12	Sigmoid, N/A	Steepest gradient descent	MSE	•
Foil	Lahcene, Amine & Abdelkader	Polypropen	Tensile stress-strain curve: Force vs elongation	9	UV radiation, temperature, processing time in aging,weathoromether, %-strain, foil thickness, melt flow index, density	CNN & SVM hybrid	Regression	Backpropagation	1, 30-80	ReLU, Linear	Adam	MSE, RMSE, MAE	4072, 80% 20%, 0%
	Alhindawi & Altarazi	Polyethylene	Tensile strength	11	5 material-related ingredients (% virgin HPDE resin, % reylced HDPE, % CaCO3, % Copolymer, CaCO3 particle size), 4 different temperature in extruder, mixing speed, bubble drawn up speed	Feed-forward ANN	Regression	Backpropagation	N/A, 150	ReLU	Stochastic Gradient Descent	MAPE, MAE, Correlation coefficient	43, 80% 20%, 0%

3.4 Product Development Process

Product development is the activity that transforms customer needs into technical and commercial solutions (Smith & Morrow, 1999). According to Tzokas, Hultink & Hart (2004) the PDP is a complex process as it includes several people, organizational structures, and a heavy flow of information. A well-functioning PDP is essential to reduce development time, manage risk and develop better products (Unger & Eppinger, 2011). New products having technical superiority and link to the voice of the customer, as well as being launched ahead of competitors can, according to the authors, give companies a competitive edge. Thus, the development process is a large factor in determining the success or failure of a company (Smith & Morrow, 1990). Wheelwright & Clark (1991) suggest three categories that enable companies to be successful in the PDP. The first category is quality which includes reliability, functionality, and customer satisfaction. The second category for success is cost or efficiency. Lastly, to be successful in the PDP, time is of the essence as launching the product to the market early is critical.

The PDP of a company is a unique process but can share some common features or steps with other organizations (Smith & Morrow, 1999). The majority of PDPs start with planning and end with product launch and consist of intermediate steps such as idea generation, concept development, building a business case, prototype development, market testing, and market launch (Tzokas, Hultink & Hart, 2004). Additional steps such as concept testing, business analysis, functional product testing, and post-launch evaluation are often included according to the authors.

The PDP can be divided into different stages, and before entering the next stage, the product has to pass a gate (Wuest et al., 2014). This is known as the stage-gate process. The goal of the stage-gate process is, according to the authors, to improve the final product quality by monitoring and controlling the PDP and identifying errors early. Wheelwright & Clark (1991) describe that the gates serve as decision points where milestones, goals, targets, and criteria are assessed to determine if the development should be continued, adapted or terminated, see Figure 3.4 for an example. The input in the gates is a list of deliverables for the product and the output is a decision to either go, kill, hold, or recycle the development project (Wuest et al., 2014). The stage gate process enables an incremental investment approach as early termination of a project helps to lower investment costs and save time (Wuest et al., 2014).

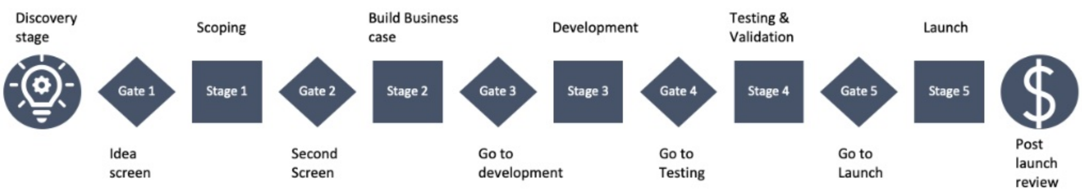

Figure 3.4: The stage-gate model (Wheelwright & Clark, 1991)

The testing and validation in the stage-gate model often involve an evaluation of the prototype (Raad, 2020). The evaluation is on whether the prototype satisfies the requirements and specifications initially set or not (Raad, 2020). This phase of the PDP is of the essence as it decreases the risk of failure before launch as the performance is assured during the testing (Bhuiyan, 2011). Further, Tahera (2014) describes that testing reduces uncertainty during development as it demonstrates the product's reliability.

3.5 Competitive Advantages

Business process improvement is one way to achieve and sustain competitive advantages in terms of effectiveness, efficiency, increase customer satisfaction, reduce unnecessary business costs, produce higher quality products, elimination of wasteful activities, reduction of cycle time, variation and designing robust solutions (Boutos & Prudie, 2014).

Competitive advantages are highly context-specific but can according to Ma (1999) be divided into discrete or compound advantages depending on if it acts as a single factor or in combination with others to create competitiveness (Ma, 1999). The compound competitive advantages are higher order and consist of many individual advantages that together constitute the compound. Examples of these are speed, cost, and flexibility (Ma, 2000). Ma (1999) also states that compound competitive advantages can be brand recognition, differentiation, quality, product or service, low cost, quick response to market, or continuous innovation and efficiency.

Discrete competitive advantages are single advantages that affect competitiveness by impacting the compound advantage (Ma, 2000). Typical discrete competitive advantages are efficiency in the organization and processes (cost); quality and innovation in products; and speed and flexibility of market response (Ma, 2000). The author also describes IT, unique physical assets, patents, IP, exclusive contracts, and product components, knowledge, and capabilities as discrete competitive advantages.

3.6 Business improvements when implementing AI

There are multiple ways AI can result in business improvements and in extension competitive advantages (Enholm et al., 2021). The impacts of AI can be divided into first and second order (Enholm et al., 2021). First-order impacts are related to how AI changes business processes whereas second-order impacts relate to firm-level changes, see Figure 3.5 below.

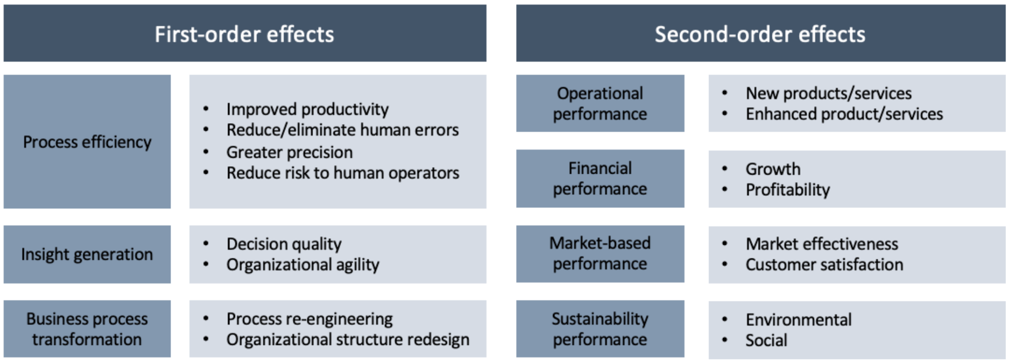

Figure 3.5: First and second order effects of implementing AI (Enholm et al., 2021)

The first order impacts of implementing AI can according to Enholm et al. (2021) be divided into process efficiency, insight generation, and business process transformation. The first improvement when implementing AI is process efficiency (Enholm et al., 2021). As AI enables the automation of tasks, it leads to better process performance and efficiency. This is explained by the fact that human resources can be reallocated to focus on other tasks when the AI conducts more repetitive work (Bauer & Vocke, 2019). Additionally, the machines can increase transparency in the process as well as reduce human errors (Enholm, et al., 2021).

The second improvement of AI is insight generation (Enholm et al., 2021). The authors describe that AI can identify unknown patterns and insights that are hidden in the firm's data. Keding (2020) and Oh, Yang & Lee (2012) explain that this can lead to more insight-driven decisions as AI can provide a more convenient and efficient approach to dealing with more data. It also means that potential uncertainties in decision-making will be limited as the AI model can integrate results from multiple evaluation methods (Oh, Yang & Lee, 2012). Wamba-Taguimdje, Wamba, Kamdjoug & Wanko (2020) explains that organizations as a result can become more agile as AI enables faster and higher quality decision-making.

The third improvement when implementing AI is business process transformation (Enholm et al., 2021). AI is a driving force in making process transformations better e.g an implementation of AI might trigger changes in the design and engineering of the organization (Enholm et al., 2021).

The second-order impacts of AI can according to Enholm et al. (2021) be divided into four types: operations performance, financial or accounting performance, market-based performance, and sustainability performance. The first improvement is, operational performance, as AI can lead to new products being developed and enhancing the quality of current products (Wuest et al., 2014). AI's capacity to process large amounts of data and find patterns can reveal new opportunities for launching products in the market (Asniar & Surendro, 2019). Furthermore, analysis of customer data by AI can provide a better understanding of customer perception and thus lead to better product quality and ultimately customer satisfaction (Enholm et al., 2021).

The second improvement is financial performance as AI can reduce costs and increase revenues (Enholm et al., 2021). Further, AI can improve the growth of the company when adopted and used to develop the organization's capabilities (Enholm et al., 2021).

The third improvement is market-based performance, and customer satisfaction can be improved through AI as companies can understand their customers better, providing customized offerings and thereby work proactively to avoid attrition (Enholm et al., 2021).

The fourth improvement is sustainability performance (Enholm et al., 2021). AI can lead to improved sustainability by reducing energy, waste, and pollution.

3.7 Requirements for a Successful AI Implementation

The resources required for a successful AI implementation can according to Enholm et al. (2021) be divided into technological, organizational, and environmental factors as depicted in Figure 3.6.

Figure 3.6: Requirements for AI implementation (Enholm et al., 2021)

The technological requirements include having a sufficient amount of data as this is required to build a high-quality AI model (Enholm et al., 2021). The organization has to ensure that the data is of sufficient volume, velocity, and variety according to the authors. Skien (2017) explains that data also needs to be structured. Batini & Scannapieco (2006) emphasize the importance of the quality of the data in organizations as it has a significant impact on businesses' efficiency and effectiveness. Apart from data, the process needs a well-established technology infrastructure to enable AI implementation (Enholm et al., 2021). More specifically, the organization needs computing power infrastructure and algorithms to build models based on the data. Organizations can therefore employ a cloud-based solution to achieve sufficient computational hardware to enable the use of AI (Enholm et al., 2021).

The second factor determining the success of an AI implementation is the organization (Enholm et al., 2021). This factor includes the culture in the company that enables the adoption of AI. Organizations must have an innovative culture and willingness for exploring new ideas for AI to be successfully adopted (Enholm et al., 2021). The authors explain that if implementing AI, it demands that employees are willing to use new technology. Furthermore, as implementing AI includes several challenges, top management support in the development is essential (Enholm et al., 2021). The top manager also influences the culture of the organization which in turn enables AI adoption. Through resource allocation and capital, the top manager can facilitate the implementation process (Enholm et al., 2021).

Additionally, organizational readiness in the form of resources such as financials is needed to implement AI successfully (Enholm et al., 2021). One resource demanded is human resources as new skills are required when adopting a new technique such as AI. Both personnel with technical skills and domain experts are required. Furthermore, the implementation of AI leads to changing roles in organizations (Enholm et al.,2021). To create trust in the model, interpretability is important (Lipton, 2018). With higher trust, the greater likelihood is that the model is adopted in the context (Lipton, 2018). The concept of interpretability usually appears as a tradeoff between interpretability and accuracy, meaning the higher interpretability the lower the accuracy, and the other way around (Lipton, 2018).

Organizations should also fulfill the requirement of developing an AI strategy to realize the benefits of the AI implementation and to ensure that the fit between the technology and its application area is adequate, as compatibility leads to better adoption of the technology (Enholm et al., 2021). Moreover, the strategy also includes plans, processes, and deadlines for achieving the set objectives with the implementation. The changes in the structure of the organization, department collaboration, and the process of handling data should also be a part of the AI strategy (Enholm et al., 2021).

The third factor for a successful AI implementation regards the environmental requirements (Enholm et al., 2021). Policies and legal aspects such as GDPR, and intellectual property lead to requirements on the data and the model. Therefore, anonymization of the data sets could be required. The environmental pressure of adopting AI can come from both competitors and customers in the form of increasing expectations of customized products and smarter products (Enholm et al., 2021).

4
Methods

In this chapter, the research strategy, and design will first be described. Thereafter, the data collection methods and data analysis will be presented. Lastly, method discussion, research quality, and ethics are presented.

4.1 Research Strategy

This thesis is of deductive nature as it aims to study existing theories and phenomena and test ideas that emerge from these theories (Bell, Bryman & Harley, 2019). This study will adopt a qualitative research strategy since data in the form of language will be collected and analyzed (Bell et al., 2019).

4.1.1 Research Design

Bell et al.(2019) describe that a research design is a framework for data collection and analysis, the data collection methods used in this study are depicted in Table 4.1.

In this thesis, a case study design was used to study a phenomenon through a specific case context. According to Bell et al. (2019), a case study research design includes a detailed analysis of a single case. The case study in this thesis consists of the process of aging measurement analysis in the testing and validation phase of the PDP in the technical textile industry. The aging measurement analysis at the CSC consists of testing technical textiles with sun simulation and tensile testing. The aging measurement analysis is the most time-consuming and complex process in the PDP. Thus, it influences the development time and by extension the company's time to market, the cost of the project, and the efficiency of the development. The case study of this thesis is intrinsic as it mainly focuses on understanding a situation and then analyzing it in order to find generalizable conclusions.

Table 4.1: Describes the research design of the study

Research question	Required information	Method
Q1: How should an ANN-model be designed to predict the breaking elongation of plastic foils and breaking strength of yarns of a technical textile prototype, processed in a sun simulator?	• Input variables & output for predicting yarn's breaking strength and plastic foils' breaking elongation • Suitable feature selection method • Suitable ANN-model • Type of training and evaluation of ANN-mode	• Frame of reference
	• Existing data and its structure • Input variables & output for predicting yarn's breaking strength and plastic foils' breaking elongation	• Informal contact • First session focus group • 2nd semi-structured interview • Verification during workshop
Q2: Which requirements should an AI-strategy include for the successful implementation of an ANN-model in the aging measurement analysis in the technical textile industry?	• General requirements for successful AI-implementation	• Frame of reference
	• Requirements for implementing the suggested AI-model	• Workshop • Verification of requirements
Q3: What potential improvements and competitive advantages can an organization in the technical textile industry gain from implementing an ANN-model in the aging measurement analysis?	• Improvements from implementing AI • Characteristics of competitive advantages	• Frame of reference
	• CSC's PDP & aging measurement process • Competitive advantages in the technical textile industry • Potential PDP improvements from the ANN implementation • Link between improvements & competitive advantages	• First session & second session focus group • 1st semi-structured interview • Workshop

4.1.2 Phases

The study is divided into three main phases, depicted in Figure 4.1.

Phase 1 - Mapping
The first phase of this study was the mapping phase, where the CSC's PDP and the aging measurement analysis were mapped. This information was collected in the first and second focus group sessions, the first semi-structured interview, and through informal contact. The outcome of this phase was used for developing the hypothetical ANN-model.

Phase 2 - Development
In the second phase of this study, the hypothetical ANN-model was developed. This was based on data from the first phase of this study: the second semi-structured interview, informal contact, and verification during the workshop. The hypothetical AI-model was presented during the workshop to generate insights about requirements, improvements, and competitive advantages from the implementation. After thematic analysis of the data from the workshop, verification of the requirements was conducted with the head of R&D. The competitive advantages for the technical textile industry were collected through the second focus group session. During the workshop, the specific competitive advantages that follow from the improvements were collected.

Phase 3 - Final Analysis
In the last phase of this study, the outcomes of the data collection and thematic analysis conducted during phases 1-2, were synthesized and analyzed in the context of literature to provide a better understanding of the phenomena and draw general conclusions. A final verification with the head of R&D of the CSC was carried out to ensure credibility.

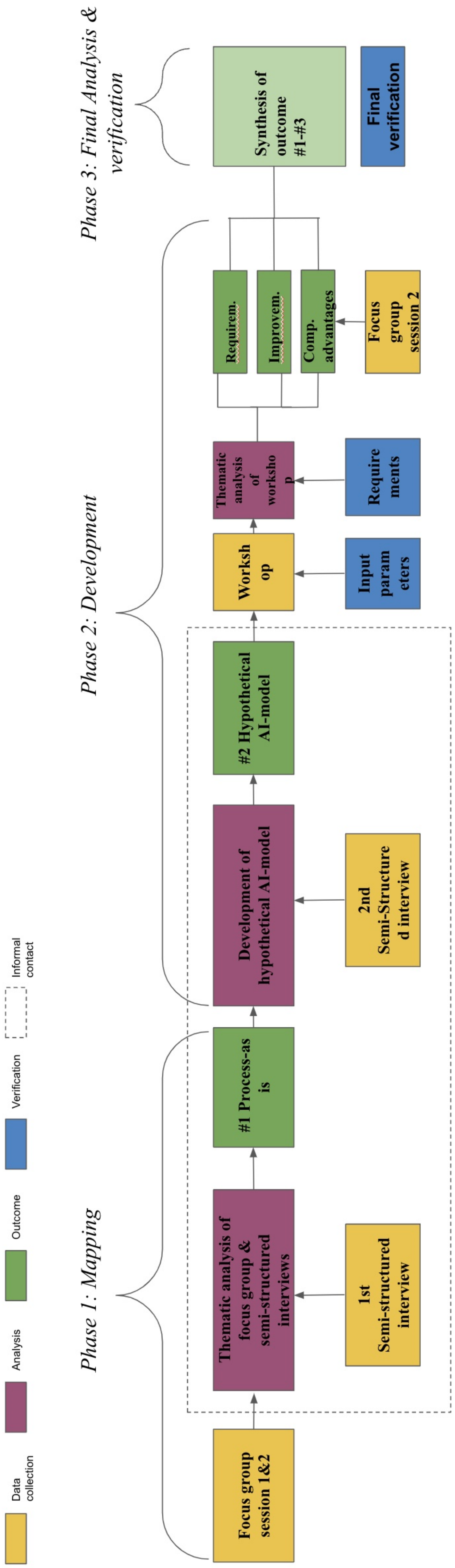

Figure 4.1: Depicts the three phases of the study

4.2 Data Collection Methods

In this study, the data was collected through a focus group, semi-structured interviews, and workshops. For clarification of topics, short informal conversations, referred to as informal contact, were continuously held via telephone with the CSC.

4.2.1 Focus Group

The focus group in this study was divided into two sessions as the first session took longer than expected. The first session focused on understanding the current aging measurement process, PDP, input variables, and existing data. The second session focused on obtaining a deeper understanding of the aging measurement analysis and the competitive advantages in the technical textile industry. In the second session, a schematic depiction of the aging measurement analysis process was drawn by the CSC to provide a clearer overview of the process. A focus group as a data collection method was suitable since it allows for a group with different knowledge to discuss topics in accordance with Bell et al. (2019).

When designing the focus group, the size of the group was considered as it affects the interactional dynamics according to Bell et al. (2019). Three employees from the CSC participated in both focus group sessions, see Table 4.2, which was in accordance with Bell et al. (2019) recommendation of three to nine participants. The participants of the focus group were selected by convenience sampling as they were recommended by the CSC. Bell et al. (2019) describe that this sampling type is appropriate for the case study research design.

In the focus group, the authors of this study acted as moderators with moderate engagement as suggested by Bell et al. (2019). A set of themes to discuss and guide the group was prepared. The focus group sessions were conducted online, via Teams, due to geographical distance and convenience for the CSC. Bell et al. (2019) emphasize the flexibility, cost, and time savings from not traveling and also higher participation due to the convenience of online interviewing.

Table 4.2: Participants in the focus group

Respondent	Title	Location
Respondent 1	Product developer	Teams
Respondent 2	Responsible for lab \& methods	Teams
Respondent 3	Test executor	Teams

4.2.2 Semi-structured Interviews

Two semi-structured interviews with the CSC were conducted in this study with respondent 1 from the focus group. The first interview focused on obtaining a better understanding of the aging measurement analysis. The second interview focused on understanding the input and output variables for the AI-model. The interviews were of semi-structured character as they enabled flexibility and follow-up questions when needed according to Bell et al. (2019). Furthermore, this type of interview was conducted as it allows for the participants' views of the problem being elicited (Creswell & Creswell, 2018).

For both interviews, an interview guide consisting of broad questions was created. When outlining the interview guide, aspects such as suitable language and avoidance of leading questions were considered (Bell et al., 2019). The questions for the first interview were within two themes: the steps in the aging measurement analysis and measurement methods. The questions of the second interview focused on the theme of input in the process. It also focused on questions related to the theme of the output of the process in terms of metrics in the aging measurements, information storage, and the decision process. The interviews were conducted online, via Teams, due to the same reasons as mentioned in section 4.3.1.

4.2.3 Workshop

A workshop about the improvements in the PDP, competitive advantages from a hypothetical ANN-model, and requirements for implementing the ANN-model was conducted with the CSC. This was done in order to understand the implications of implementing an ANN-model in the aging measurement process. The data collection method, workshop, was deemed suitable as it according to Orngreen & Tweddell Levinsen (2017) allows a group of people to develop new knowledge, solve problems and learn in relation to a specific subject. Workshops also allow the participants to both discuss what is and what could be in a situation (Orngreen & Tweddell Levinsen, 2017).

A power-point presentation was shown during the workshop to give an overview of the theoretical background of an ANN and a more detailed description of the developed hypothetical ANN-model in the CSC's context. Thereafter, open-ended questions with themes regarding the requirements of the hypothetical ANN-model, potential improvements, and competitive advantages were presented to initiate the brainstorming. To support the brainstorming, the visual program Miro was used and one example was given to the participants. However, no additional guidance was provided to ensure that participants could brainstorm freely.

Nine employees from the CSC participated in the workshop, which was deemed suitable as Orngreen & Tweddell Levinsen (2017) describe that the participants should be few. The participants were provided by the contact person of the case company, and thus convenience sampling was used. During the workshop, the participants were divided into three separate groups. Discussions were held both in smaller groups and in the whole group. The grouping consisted of a mixture of competencies rather than allocating the same knowledge in a group, see Table 4.3 for grouping.

Table 4.3: Participants in workshop

Respondent	Title	Group
Respondent 1	Head of R\&D	1
Respondent 2	Development Engineer	1
Respondent 3	Test executor	3
Respondent 4	Development Engineer	3
Respondent 5	Senior Product Developer	2
Respondent 6	Project Manager	1
Respondent 7	Support Engineer	2
Respondent 8	Project Manager	2
Respondent 9	Product Development Manager	3

4.3 Qualitative Data Analysis

Qualitative data analysis was done during all phases of this study. Firstly, data from the two sessions of the focus groups were structured into themes and a thematic analysis was conducted, as suggested by Bell et al. (2019). Themes can consist of repeating topics and similarities and differences in the interviews and must be relevant to the research questions (Bell et al., 2019). The themes in this analysis were the stages in the PDP, the stages in the aging measurement analysis, factors affecting the aging of technical textiles, and competitive advantages in the technical textile industry. Based on this thematic analysis, in combination with case studies in the frame of reference, a hypothetical ANN-model was developed. This development process is in detail described in 4.4.1.

The data collected during the workshop were analyzed by conducting a thematic analysis with themes inspired by the frame of reference. The themes when analyzing the requirements for a successful ANN implementation were organizational, technological, and environmental. The first and second effects were used as themes when analyzing the improvements. When analyzing the competitive advantages from improvements by AI-implementation the themes compound and discrete competitive advantages were used.

4.3.1 Development of a Hypothetical ANN-model

The development of the hypothetical ANN-model was done in phase two of this study. The data necessary for the development was however collected through all phases of the study.

By understanding the CSC's PDP, their aging measurement analysis process, input variables, and output variables, the type of ANN-model and other design choices could be determined. Further, the process understanding provided information about what the hypothetical ANN-model should predict, which led to the decision of using two models instead of one.

The specific model architecture was developed by combining the AI-models suggested in case studies with the knowledge about the CSC´s PDP. As there were many similarities between the case studies and CSC, it was clear that the suggested AI-models, input variables, and output variables in the case studies were transferable to the technical textile industry.

4.4 Method Discussion

Using a case study as a research design, allowed this thesis to focus on only one company and provide a more in-depth understanding of the aging measurement in the PDP and the suitable ANN-model. Despite this, case study design can lead to restricted generalizability of the findings. Thus, if studying more than one company's PDP more generalizability could be achieved. However, within the timeframe of this study, it was not feasible.

The data collection method, focus group, allowed this study to obtain a detailed and rich dataset as the participants could speak freely and inspire each other. This was appropriate in this thesis as the PDP is complex and involves several departments and individuals which explains the need for discussion. However, using a focus group as a method for data collection can lead to group effects. This risk was deemed low as all participants were equally engaged in both sessions.

The format of online focus group and semi-structured interviews was appropriate as the monetary expenses of traveling, due to the geographical distance, would otherwise pose a hindrance for conducting all the interviews. Further, the online format allowed the inclusion of personnel from the CSC that had a busy schedule, as it was more convenient for them. The online format could however have negatively affected the possibility for the moderators to establish rapport which in turn affected the engagement of the participants. Lastly, in contrast to a face-to-face setting, the authors could not as easily know if the participants were distracted during the focus group.

In the workshop, the authors of this thesis formed smaller groups based on various roles in the company which led to average groups instead of expert groups. The benefit of forming average groups was that it limited the risk of missing important considerations of an ANN-implementation due to a lack of a holistic understanding of the process. However, the formation of average groups could have led to shallow discussions.

The choice of convenience sampling provided an efficient way of obtaining suitable participants. One risk with this method was evident within the workshop, as no participants were directly involved in the production process of technical textiles. This means that one drawback is that the perspective of how the ANN implementation affects production is lacking.

4.4.1 Research Quality

To assess the quality of business research the four dimensions of trustworthiness: credibility, transferability, dependability, and confirmability, can be used according to Bell et al. (2019).

Credibility evaluates the accuracy and correctness of the findings according to Bell et al. (2019) and this was ensured through end verification with the head of R&D at the CSC in this thesis.

Transferability evaluates if the study can be applied to other contexts (Bell et al., 2019). The transferability of this study is limited due to the CSC's strict requirement of anonymity. In turn, this led to the results only including the most important process features to provide insight into the essence of the CSC.

Dependability assesses the methods used in the study and if they have been conducted appropriately (Bell et al., 2019). To ensure dependability the data collection methods used in this study were described in detail.

Lastly, confirmability evaluates the objectives of the study and its results (Bell et al., 2019). This study has limited confirmability as it is of qualitative nature, and this implies an interpretation of the reality by the authors. To limit this, the CSC reviewed the results of the study to ensure that no bias or misinterpretations occurred.

4.4.2 Research Ethics

Bell et al. (2019) describe four ethical considerations needed to be assessed when performing business research: avoidance of harm, informed consent, privacy, and preventing deception.

Avoidance of harm ensures that participants are not exposed to stressful or harmful situations (Bell et al., 2019) and in this study, it was assured by avoiding harmful interview questions.

Informed consent ensures that the participants are informed about the study so they can decide if they want to participate or not (Bell et al., 2019). To ensure this, the authors of this study wrote a clear statement about the thesis and sent it to participants before the data collection started.

Bell et al. (2019) describe privacy as actions taken to protect the privacy of the participants. All data were anonymized and safely documented to protect the privacy of the participants from the CSC in this thesis. Also, sensitive details of the PDP and aging measurements analysis were not included to ensure the privacy of the organization.

Lastly, the study must present truly to prevent deception (Bell et al., 2019). All information provided to participants in this thesis was reviewed by supervisors at Chalmers University of Technology to ensure that it was clear and not misleading.

5

Case Findings

In this chapter, the data from the two focus group sessions, semi-structured interviews, workshop, verification session in the workshop, and informal conversations are summarized. The information about the CSC's PDP in section 5.1 and the description of the aging measurement process in the testing and validation phase is presented in subsection 5.1.1. Information in section 5.1 was provided during the first and second sessions of the focus group, the first semi-structured interview, and informal contact with the CSC.

Data from the first session focus group, and second semi-structured interview, in combination with the informal contact and verification conversation during the workshop, provided factors affecting the aging of technical textiles, and these are summarized in section 5.2.

Section 5.3 summarizes the requirements for implementing the hypothetical AI-model, mentioned during the workshop. Lastly, section 5.4.1 presents the competitive advantages in the technical textile industry, collected in the second session of the focus group, and the improvements and corresponding competitive advantages obtained from the workshop.

5.1 Product Development Process

In the first session of the focus group, the CSC describes that they develop products through a stage-gate model, see Figure 5.1. The gates in the PDP determine if the project should be further developed or terminated. During the gate meetings, a go/no-go decision for the project is taken based on a scoring model which uses criteria such as economical feasibility, the difficulty of developing the project, and success rate.

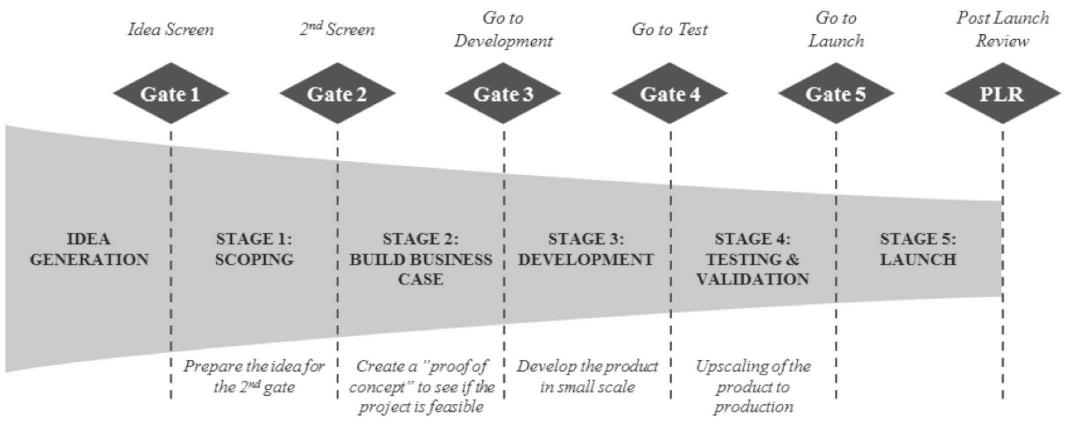

Figure 5.1: Describing the stage-gate model of the CSC during the first focus group session

5.1.1 Stage 0-2: Idea Generation, Scoping and Business Case

In the idea generation stage, ideas are according to the first focus group session generated from sources such as the R&D department, sales force, and customers. A decision on whether to continue or not with the idea is based on certain criteria e.g. available capacity and information about the idea. In the next stage, scoping, the idea is prepared for the second gate (first focus group session). The business case stage includes the evaluation of the idea along two dimensions: technical feasibility and customer value (first session focus group).

5.1.2 Stage 3: Development

In stage three, the idea is realized into a prototype, and the stage includes three steps, which were described during the first and second focus group sessions. These steps are visualized in Figure 5.2 below, which was depicted during the two focus group sessions.

Step 1
The CSC describes during the first semi-structured interview that a prototype consists of three different yarns and one to two different foils. The characteristics of the yarns and foils determine the properties of the prototype and thus the final product performance according to the first focus group session. It is further described that the properties of the end product often are decided by requirements on the technical textile to function in the customer's environment. The CSC explains in the first focus group session, that suitable yarns and foils which meet the requirement of performance are discussed with their suppliers. The outcome of this discussion can either result in similar components as have been used previously or entirely new. The suppliers have all information about the yarns and plastic foils, e.g tensile strength and chemical additives. To ensure that the combination of foils and yarns brings the desired properties of the end product, testing is required and this is done

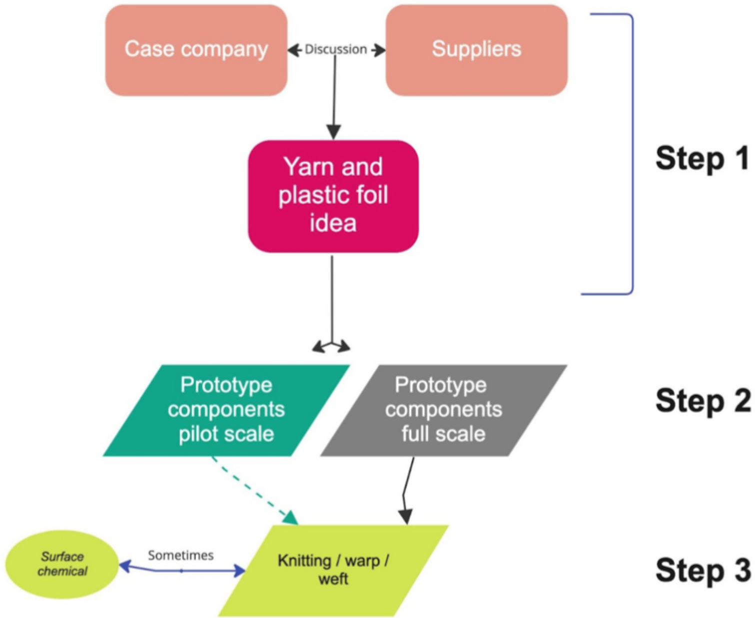

Figure 5.2: Stage three in the CSC's stage gate model described during focus group session 1 & 2.

in stage 4 of the PDP (first focus group session).
In the first semi-structured interview, the CSC mentions that components ordered from the same supplier and that have previously been tested can go directly to launch, stage 5 of the PDP. However, if the component ordered is identical to a previously tested component, but comes from another supplier, it needs to enter stage 4. The reason for this is that the machine settings, chemical additives and processing, etc. can vary between suppliers even though they are producing the same components. If components are not tested before being ordered from suppliers, they need to undergo stage 4 in the PDP and this was mentioned in the first semi-structured interview.

Step 2
The CSC describes during the first semi-structured interview, that depending on the project the prototype components can be ordered in full-scale or pilot scale from the supplier. Prototype components on the pilot scale are not exposed to mechanical effects caused by the production process, as they are made on small scale. The full-scale prototype component is affected by mechanical factors in the production process. However, the CSC describes during informal contact that the latter is mainly used in projects with limited time.

Step 3
The yarns and plastic foils are either knitted or woven into a prototype at the CSC, mentioned in the first session focus group. If the components are knitted, the CSC, describes during informal contact, that the yarns and foils can have three

different placements in the prototype. In the case of weaving, the components can have two different placements in the prototype depending on if it is a warp or weft. The CSC describes in the first session focus group that knitting and weaving affect the components in the prototype. The components can have different exposure to chemicals added, in order to simulate the end-user environment correctly, depending on their position in the prototype (informal contact).

5.1.3 Stage 4-5: Testing and Validation and Launch

The CSC describes in the first focus group session that the prototypes are tested and evaluated in stage four of the stage gate model to determine if they meet requirements. Firstly, various tests are performed to assure the technical and commercial performance of the prototype. If the prototype meets the requirements of the tests it enters the aging measurement analysis. Figure 5.3, was made by adding more details to the figure drawn during the second focus group session. The added details in the figure come from the first focus group session and first semi-structured interview.

As the end-products produced by the CSC are later used in an environment that causes degradation over time, measurements of the aging are critical to ensure quality (first focus group session). The aging measurement test consists of tensile testing on prototypes that have been in the sun simulator. In the sun simulator, the end-user environment is simulated in terms of sun, humidity, and heat. The time in the machine is accelerated, as testing in real-time is too time-consuming. It is explained in the first focus group session that as the aging measurement test is time-consuming and costly for the CSC, it has a significant impact on the PDP. In extension, the aging measurement analysis is critical for TTM, customer satisfaction, and the costs of the development project (first focus group session). In the sun simulator, approximately two months' simulation equals one year in the end-user environment according to the first focus group session. Several samples of the prototypes with the same dimensions are placed in the sun simulator. Normally, a full cycle in the sun simulator is 4800h as described in the first session focus group. It is described that prototypes are withdrawn with an interval of 300h.

In the first session focus group it is explained that when the sample is withdrawn from the sun simulator, at certain points in time, they are tensile tested. The prototype is manually separated into its components and then each component is tensile tested. For each component, five tensile tests are conducted and the average of the breaking strength and breaking elongation is calculated. The CSC describes during informal contact that yarn has a varying thickness and thus its elongation can be difficult to accurately measure. Therefore breaking strength is used for yarns whereas for plastic foils the parameter breaking elongation is used.

The requirements of breaking strength and breaking elongation values are based on previous experience of aging measurement and, if available, tensile tests on prototypes that have been sent to the end-user environment (first focus group session).

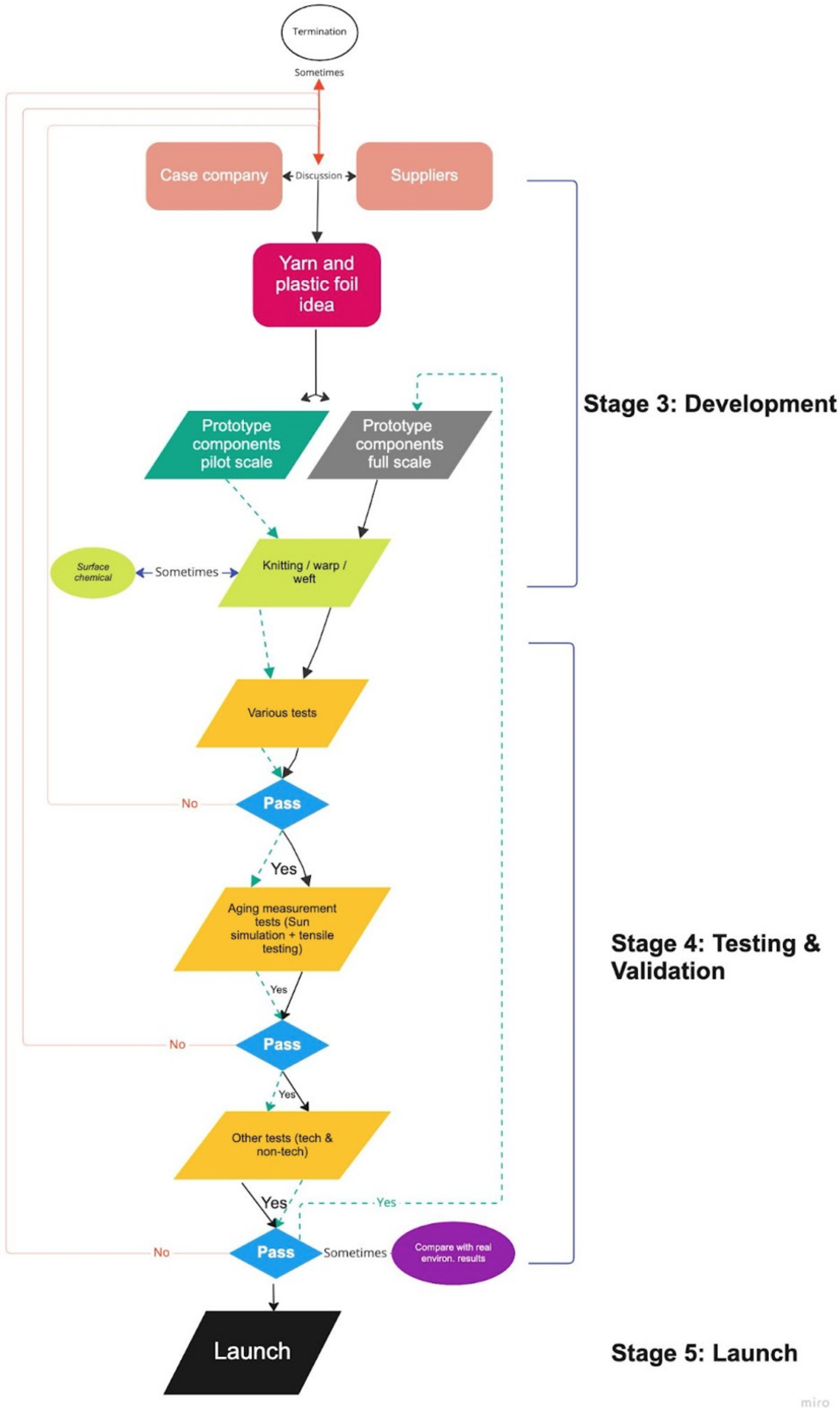

Figure 5.3: The aging measurement process depicted in the second session focus group and described during the first focus group session and semi-structured interviews

If the requirements of the tensile properties are not fulfilled, independent of full scale or pilot, the CSC describes in the first focus group session, that they have discussions with the suppliers and order new prototype components that are more likely to meet the requirements. However, if the prototype's component is deemed to have no potential of meeting requirements the project can be terminated immediately (first focus group session).

The CSC explains in the first focus group session that when the prototype fulfills the requirements in terms of tensile properties, it needs to be assessed in other technical and non-technical requirements before launch. These are referred to as other tests in Figure 5.3. The technical requirements are non-negotiable whereas the possibility of negotiation of the non-technical requirements is situation-dependent (first focus group session).

In the first focus group session it is described that, depending on the scale of the prototype, the step after passing other tests varies. If the full-scale prototype passes the tests it can be launched directly, as all affecting factors are included when testing. If the prototype is of pilot scale and passes these other tests, the case company orders the same components but at full scale from the suppliers. Thereafter, this prototype goes through the whole testing cycle.

The CSC describes in the first focus group session and first semi-structured interview that there is a lack of standardization when it comes to the structuring of test results and all related information to the materials. The information about the materials are written in free text and stored in several different files which require manual involvement. Moreover, not all test results at different steps in stage 4 are stored (first semi-structured interview).

It is described in the first session workshop that if a project meets all the criteria it proceeds to the last stage, which is launching the project.

5.2 Input Variables and Factors Affecting the Aging Process

In this subsection, information from the first session focus group, second semi-structured interview, informal contact, and verification during the workshop is summarized.

5.2.1 Yarn

The fibers in the yarn have a specific length and diameter which in turn determine the properties of the yarn, and according to the CSC in the second semi-structured interview, this is important to include when analyzing the aging of the textiles. An example provided by the CSC is that the diameter of the fiber correlates with the yarn's resistance to sunlight.

During the verification in the workshop, it was described that light absorption should be measured to determine the effects of sunlight on the yarn. Another factor that affects the light absorption, which was explained by the CSC in the verification during the workshop, is the yarn's color determined by the pigmentation added. They explain that the higher percentage of white pigmentation, titanium oxide, in the yarn the less absorption of light it has which in turn implies a longer lifetime. The CSC explains during the second focus group that the degree of reflectance is a factor that affects the degradation of the yarn. The more reflective the material is, the less sunlight it absorbs, which leads to slower aging (verification during the workshop).

The CSC describes during the second-semi structured interview that the melting point of the fibers affects the aging of the yarn. The lower the melting point is, the more sensitive it is to heat. In addition, the chemical additives in the yarn are factors that affect the aging process of the prototype, and examples of these are the percentage of UV-stabilization and antioxidants (First session focus group).

During the first session focus group, it is mentioned that the spinning variables affect the mechanical properties of the yarn and in extension the aging process. The machines and their settings used for spinning at each supplier can differ to some extent and these should therefore be considered (informal contact). During the verification session in the workshop it was mentioned that the spinning variables to include were: speed, temperature, the process of stretching and its proportions, degree of intermingling, count rate, and speed of roller. It is further explained that the spinning speed affects the mechanical properties of the yarn and that in general the higher speed the lower the elongation. Furthermore, the stretch process induces a twist to the yarn which improves its possibility to elongate. The count rate determines how thin or thick the yarn is (verification during the workshop). Lastly, it is described that the intermingling process of yarns is used to give filaments properties such as bulky structure, good coverage and thermal insulation (workshop).

Regarding the tensile machine setting the speed and length of the sample at t=0 are important factors to consider and the grip of the yarn also needs to be considered (verification during the workshop).

Table 5.1: Summary of input variables and factors affecting the yarns tensile properties, described during the first focus group session, second semi-structured interview, informal contact and verification during workshop

Yarn	Factors/input variables
Fiber variables	Filament length, pigmentation (% Titanium Oxide), reflectance, filament diameter, melting point, light absorption, chemical additives (%)
Spinning	Machine type, speed, temperature, stretching process, stretching proportions, count rate, machine type, degree of intermingling, rollers, draw ratio
Tensile machine settings	Speed, L0 (length of sample at t=0), grip type

5.2.2 Plastic Foils

The aging of plastic foils is affected by the type of plastic material used according to the second-semi structured interview. An example is provided by the CSC in the second semi-structured interview, namely that there are certain plastic materials that are more sensitive to humidity whereas other materials are affected by UV-light, and this is dependent on the chemical structures of the materials. During the first focus group session, the CSC mentions that chemicals such as UV-stabilisator are added to the foil which affects the speed of the degradation. Also, a coating containing metal is added to the foil which affects the aging.

During informal contact, it is mentioned that the raw plastic material is melted and then formed into a continuous foil which affects the mechanical properties of the material. In this process, the melting temperature is important to include as it affects the mechanical properties of the textile by impacting the chemical structures in the plastic material (informal contact). In the verification, during the workshop, it was described that the draw ratio affects the minimum thickness of the plastic foils which in turn affects the tensile properties. Further, variables such as stretching also affect the properties. During the verification in the workshop, it was explained that the speed and initial length of the plastic foils should be included as well as the sample type.

5.2.3 Prototype

In the first focus group session, it was described that the yarns and plastic foils are weaved or knitted to a textile. Depending on if the prototype is knitted or woven, it affects the tensile properties differently. In the verification, during the workshop, it was described that the yarns and plastic foils are given different positions in the textile depending on if it is woven or knitted.

The settings of the sun simulator affect the degradation of the textile and thus the light intensity, light filters, degree of humidity, and temperature are important factors to consider (Second semi-structured interview). In the first focus group session, it was described that the time in the sun simulator needs to be considered as

Table 5.2: Summary of input variables and factors affecting the plastic foils tensile properties describes during the first focus group session, second semi-structured interview, informal contact and verification during workshop

Plastic foils	Factors/input variables
Chemical and physical properties	Type of plastic materials, light properties (absorption), coating, chemicals (UV stabilization)
Tensile machine settings	Speed, L0 (length of sample at t=0), Sample type (dumbbell or strip)
Processing	Temperature, stretching, machines, draw ratio prototype scale (pilot/full)

it directly correlates to the degradation of the textile, a longer time in the simulation corresponds to a higher degree of degradation.

When possible, the results from the tensile tests conducted on the components that have been in the end-user environment in real-time, should be considered as input variables in a model (verification during the workshop).

Table 5.3: Summary of input variables and factors affecting the prototype tensile properties described during the first focus group session, second semi-structured interview, informal contact, and verification during workshop

Prototype	Factors/input variables
Weaving or knitting	Weaving (warp/weft), Knitting
Chemical additives	Included/not included
Machine setting of sun simulator	Light intensity, light filters, humidity, temperature
Processing time in sun simulator	0h, 300h, 600h…
Tensile tests on the components in the prototype from the real environment	The time spent in the real environment as well as strength for yarns and elongation for plastic foils

5.3 Requirements

The information in this section was gathered during the workshop with the CSC. Data were described as one requirement for a functioning ANN-model during the workshop. The CSC describes the need for detailed data about the supplier's processes, machines, and chemicals (workshop). However, the CSC raised the concern of this data being challenging to receive as the suppliers often are unwilling to share it due to confidentiality reasons. To overcome this challenge a close collaboration with the suppliers would be necessary (workshop). It is also mentioned during the workshop that data generated internally should be collected. Process variables, end-user environment test data, and physical properties are of relevance to collect. The CSC describes during the workshop that this data is not currently consequently collected, which is a requirement that needs to be fulfilled.

The CSC describes during the workshop that automatization of data collection and storage externally and internally in all steps of the PDP is a requirement for the ANN-model to function. Further, they emphasize the need for storing data in a standardized manner. For example, the data from suppliers needs to be registered automatically to allow all the information required for the ANN to be saved directly with no manual work.

Another type of requirement mentioned by the CSC during the workshop is external knowledge to build the digital infrastructure that is required for the ANN to function. Apart from the digital infrastructure, it is explained that the model itself needs to be developed and this can be done by external competencies such as consultants. In the workshop, the CSC emphasizes a database as a requirement to enable the structuring of existing and new data. Once the digital infrastructure is in place, the CSC describes that either external or internal competencies is a requirement to run the system on a daily basis, as they currently lack that competence. Moreover, internal education, in general, about the ANN and AI-applications is necessary for the implementation of the model.

In the workshop, the requirement of building organizational trust for the model was described. The CSC describes that one way to build this trust is through education by employees with ANN-competence. This would provide the company with knowledge about how to interpret, train and work with the model in their daily operations.

5.4 Improvements and Competitive advantages Resulting from the ANN Implementation

Section 5.4.1 presents the data collected during the second session focus groups about the competitive advantages in the technical textile industry. Section 5.4.2 depicts the data collected in the workshop considering competitive advantages and improvements related to the suggested ANN model.

5.4.1 Competitive Advantages in the Technical Textile Industry

The CSC describes in the second session focus group that a competitive advantage in the technical textile industry is to be first on the market with new innovative products as this gives the possibility to patent these products. In addition, it is explained that being first on the market leads to the possibility to influence the market niche and become the standard as well as being able to price the product higher.

Another competitive advantage described in the second session workshop is the innovation capacity of the company. The CSC explains that a well-functioning innovation process will lead to finding a niche on the market which gives a unique market position.

During the second session focus group, the CSC mentioned that a well-established brand is a competitive advantage in the industry as it gives credibility. A well-established brand is mainly characterized by delivering high and consistent product quality (second session focus group).

A close relationship with customers is another competitive advantage described in the second session focus group. By having a direct sales channel, close customer relationships can be achieved and this enables ideas for new product development projects and direct feedback which can be considered in the PDP.

The last competitive advantage in the industry of technical textiles mentioned by the CSC in the second session focus group is profitability, and this can be achieved through large-scale production as the unit cost is lower.

5.4.2 Improvements and the Resulting Competitive Advantages

Time reduction
The implementation of the ANN in the aging measurement analysis would lead to a significant time reduction in the PDP, which was mentioned in the workshop. The main reason for this is a reduced number of iterations in the PDP as the prototype's characteristics can be predicted by the ANN already at the idea stage, and therefore time-consuming tests would be limited. Further, a faster PDP would lead to lower risk in terms of the market changing during the development process. It is explained, during the workshop, that extensive market changes could lead to a product under development becoming irrelevant and thereby leading to sunk costs related to the terminated project. The CSC mentioned during the workshop that the ANN reduces the amount of work required per iteration, as the ANN model reduces time-consuming processes. Thus, the ANN unlocks capacity and resources which can be allocated to improve other stages of the PDP.

The CSC links the improved development time to the following competitive advantages; shortened TMM, larger market share, increased sales, being first on the market, possibility to patent, faster response to market changes, and higher possibility to seize market opportunities.

Knowledge
Increased knowledge about the aging measurement analysis and the relationships between variables affecting the tensile properties could, according to the CSC in

the workshop, be achieved from the ANN-model. Thus, non-value-adding testing activities could be limited as input variables not affecting the output parameter in the ANN would not have to be gathered or tested. This will lead to a less time-consuming PDP. Further, this knowledge improves the CSC's ability to answer customer questions more insightfully. In the workshop, the CSC explains that the improved knowledge from the ANN could lead to the competitive advantages of higher customer satisfaction, credibility, stronger customer relationships, and shortened TTM.

Cost
In the workshop, it is described that the development costs such as personnel, material, and testing could be decreased as a result of fewer iterations. The implementation would lead to fewer sun simulations and tensile tests as only entirely new components need to be tested conventionally. Another cost improvement mentioned by the CSC during the workshop is the opportunity of using cheaper materials while remaining high in product quality, as the ANN can provide knowledge for selecting components. In the workshop, the CSC linked cost improvement to the competitive advantage of profitability.

Quality
The knowledge obtained about the components generated from the ANN could lead to higher product quality, an improved understanding of the end-user environment, and the sun-simulator data (workshop). Another improvement area of implementing an ANN is the reduction of human judgment. This is problematic as decisions currently are based on "gut feeling" rather than consequent data-driven decisions. In the workshop, the CSC links these improvements with the competitive advantages of product quality and profitability.

Adaptation of products
The CSC describes in the workshop that the ANN can improve its ability to adapt products to specific end-user environments. This was explained by the fact that they could increase the number of samples tested without increasing cost or time, which currently is not possible. During the workshop, this improvement was linked to the competitive advantage of product differentiation.

Sustainability
The CSC describes in the workshop that the lifetime of the technical textiles could be improved as the ANN could provide more precise analysis about the materials, chemicals, or process settings that lead to a longer lifetime and less waste in the PDP. It is further described that a future competitive advantage is having less carbon dioxide emissions as more customers are becoming environmentally cautious.

6
Analytical Discussion and Conclusion

This section provides an analytical discussion and conclusion to provide answers to the research questions and is divided into three main sections. Firstly, in section 6.1, a description of the technical textile industry's characteristics are described based on the empirical data. Next, in section 6.2, corresponding to the first research question, the hypothetical ANN-model for the aging measurement analysis process will be described. To successfully implement the hypothetical ANN-model, an AI-strategy consisting of several key requirements is presented in section 6.3 for the technical textile industry, corresponding to the second research question. In section 6.4, the implications of implementing the hypothetical ANN model in terms of improvements in the aging measurement process and competitive advantages, corresponding to the last research question, will be presented. Lastly, section 6.5 provides an outlook for future research topics.

6.1 Characteristic of the Aging Measurement Analysis in the PDP of Technical Textile Industry

The PDP in the technical textile industry is time-consuming as several iterations of aging measurement analysis are often needed to determine if the material components in the prototype meet the requirement of the end-user environment, as implied during the focus group sessions and semi-structured interviews. In the technical textile industry, the PDP can be costly if the number of iterations is high.

The number of iterations in the PDP directly correlates to when the product can be launched in the technical textile industry, which was suggested in the focus group session one. From focus group session one it is implied that the decision to launch a product, i.e the fulfillment of the aging measurement requirements, is in the technical textile industry dependent on the precision of the numerical values of elongation and strength.

Furthermore, the empirical data suggests that the technical textile industry is dependent on knowledge about the yarns and plastic foils in the prototype, as these determine the performance of the end product in terms of aging. In the technical textile industry, there are many factors affecting the aging of the end product which is suggested in section 5.2. It is also implied that the relationship between the chemical components, processing steps, and the tensile properties of yarns and plastic foils respectively is highly complex and nonlinear. The focus group sessions thus imply that understanding of these relationships on aging is important in the PDP of the technical textile industry. However, the industry is characterized by a lack of knowledge about these relationships which explains the extensive testing conducted in the industry.

The empirical data suggests that the aging measurement analysis in the PDP of the technical textile industry is characterized by manual labor and varying ways of working in terms of data gathering, interpretation of results from testing, and data storage.

The focus group sessions and the workshop implies that the technical textile industry has low maturity for an ANN implementation. The immaturity is interpreted from the focus group sessions which described that there was a lack of understanding and experience within the field of AI. Additionally, immaturity is derived from a lack of sufficient and structured data as well as the fact that essential data, e.g processing of yarns, and plastic foils, is owned by the suppliers and not technical textile companies. This information is sensitive and therefore strictly confidential.

6.2 Development of a Hypothetical ANN-model

In this section, the first research question of the report is answered by assuming a hypothetical ANN-model, where all its data exist and is structured. Firstly, the suitable ANN subtype and type of analysis for predicting the breaking elongation of plastic foils and breaking strength for yarns will be suggested. Secondly, the ANN-model's network structure in terms of the input layer, hidden layers, and output layer will be recommended. This recommendation also includes the suitable activation function both in the hidden layer and the output layer. Thereafter, the recommended procedure for training, validation, and testing will be described. More specifically, the training algorithm, loss function, and optimization function will be recommended. Lastly, how the ANN should be updated is presented along with methods for making the model more interpretable. A brief description of the implementation in python code is provided for each subsection in Appendix B. Unless specified, the implementation holds for both ANN-models recommended.

6.2.1 Suitable ANN-model

Two ANN-models are recommended for the context of predicting the tensile properties of a technical textile prototype consisting of yarns and plastic foils. One ANN-model is suggested for yarns and one ANN-model for plastic foils. One reason for this, described in section 5.2, is that the output variable is different for the two materials, breaking strength for yarns and breaking elongation for plastic foils. The other reason, which is also described in the empirical data, is that the factors affecting aging are different for the yarns and plastic foils. This is also motivated by the case studies in section 3.3 that use one model per material.

The practical context of the aging measurement analysis has similarities with the case studies in section 3.3. The similarities involve the materials that the predictions are made for and their input variables. Thus the recommended type of ANN-model for each component, used in the case studies can be applied in this study. The majority of the case studies use a feedforward ANN and the type of analysis conducted is regression. In the practical context of this study, two feedforward ANNs for regression analysis is suggested as the data is high dimensional, see section 6.1. The feedforward ANN-model is also recommended as the data is not of grid structure which is suitable for using CNN. Similarly, the RNNs are not suggested as the data is not of sequential type. The regression analysis is recommended as the task is to learn the relation between input variables and a numerical target value. As the data in the practical context is not a sequence of values over time, time series analysis is not suitable.

6.2.1.1 Structure

The next step for developing the hypothetical ANN model for the aging measurement analysis is determining the structure of the network i.e the number of nodes and layers in the input, hidden and output layers, see Figure 6.1. In code block A in Appendix B a short description of how the structure of the ANN is implemented.

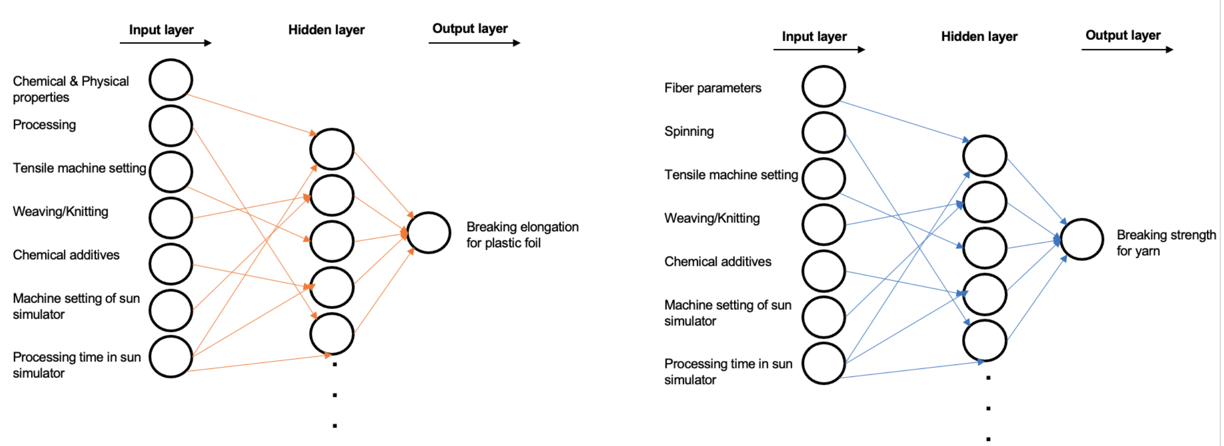

Figure 6.1: The left Figure represents an ANN-model for plastic foils and the right Figure is an example of the ANN-model for yarn. For convenience, only the different input variable categories are presented.

Input Layer

In the case studies in section 3.3, the number of nodes, i.e input variables in the input layer vary i.e as it is dependent on the type of material and processing variables, etc.

The suggested input variables to the models for companies in the industry are based on section 5.2 and case studies. It is initially recommended to consider all of the input variables in Table 6.1 in order to reduce the risk of eliminating important features.

For yarns, it is recommended to consider the input variables presented in Table 6.1, regarding fiber characteristics, the spinning process, and the tensile machine settings. For plastic foils, it is recommended to consider the chemical components in the plastic foil and the plastic foil's physical properties as input variables. In addition, it is recommended to consider the processing of the plastics during production and the tensile machine settings.

The input variables for the sample prototype, presented in Table 6.1, are based on section 5.2 and can broadly be divided into weaving/knitting, chemical additives, the position of yarn/foil in the prototype in sun-simulator, sun-simulator machine setting, and the processing time. The reason for this is that the components are tested in isolation in the case studies and are not a part of a prototype.

Table 6.1: Summary of suggested input variables for companies in the technical textile industry when developing the feedforward ANN-model

Component		Input variables from practical context and literature
Yarn	Fiber variables	Filament/fiber length, pigmentation (% Titanium Oxide), reflectance, filament diameter, melting point, light absorption, chemical additives (%), yarn strength, linear density, float length, yarn thickness, yarn elongation
	Spinning	Machine type, speed, temperature, stretching process, stretching proportions, count rate, machine type, degree of intermingling, rollers, draw ratio, rotor speed, extruder screw speed, gear speed, winding speed, melting system
	Tensile machine setting	Speed, cross-head speed, pre-tensional force, L0 (length of sample at t=0), grip type
Plastic Foils	Chemical and physical properties	Type of plastic materials, (light properties (absorption), coating, chemicals (UV stabilization), particle size, % strain, foil thickness, foil density, chemicals and material ingredients in %)
	Tensile machine settings	Speed, L0 (length of sample at t=0), Sample type (dumbbell or strip)
	Processing	Temperature, stretching, machines, draw, melt flow index, extruder temperature, mixing speed, bubble drawn up speed prototype scale (pilot/full)
Prototype	Weaving or knitting	Weaving (warp/weft), Knitting (Most common
	Chemical additives	Included/not included
	Machine setting of sun simulator	Light intensity, UV-radiation, light filters, humidity, temperature
	Processing time in sun simulator	UV-exposure time, 0h, 300h, 600h…
	Tensile tests on the components in the prototype from the real environment	The time spent in the real environment as well as strength for yarns and elongation for plastic foils

By initially including all recommended variables in the ANN-model, there is a high risk of computational complexity, overfitting and low interpretability. To address these issues, feature selection is recommended to use, as it focuses on the most relevant input variables that contribute to the output. The regularization techniques L1 and L2 are suggested as these are easy to implement and that they do not initially eliminate any features. The implementation of these techniques can be seen in code block H in Appendix B.

Hidden Layer
Based on section 6.1 it is recommended to have one single hidden layer as it increases the interpretability of the model, as visualized in Figure 6.1. This choice is supported by the Universal approximation theorem and by the case studies that use one single hidden layer. The recommendation for companies in order to identify the optimal number of hidden nodes is to gradually increase the number of nodes until the performance of the network decreases, as described in 3.2.5. For reference, the case studies use between 6-150 hidden nodes in the hidden layer. The implementation of how this can be implemented is seen in code block F in Appendix B. Over time when companies understand the relationships between the variables of the material characteristics, more hidden layers can be added to increase the accuracy of the ANN.

Output Layer
The recommendation for companies implementing an ANN in the aging measurement analysis is to have a single node in the output layer, see Figure 6.1. This design choice is supported by the case studies. See code block A in Appendix B for implementation.

Activation function
The suitable activation function to use in the ANN for companies in the technical textile industry is to use a non-linear activation function in the hidden layers of the models. The reason for a non-linear activation function is explained by the non-linear relationships between the variables described in section 6.1. In the majority of the case studies, the sigmoid activation function is used in the hidden layer to predict the tensile properties of yarns, thus it is recommended to use in the practical context. Motivated in a similar manner, ReLU is recommended for the hidden layer for the ANN-model predicting the breaking elongation of the plastic foils. By having these activation functions in the hidden layers, facilitation of the learning of relationships can be achieved. See code block A in appendix B for the implementation of the activation function in the hidden layer.

It is recommended to use a linear activation function in the output layer for both ANN-models and this is motivated by that these functions are capable of outputting a range of values, which is the case of the breaking elongation and breaking strength. The characteristics of the task are similar to the case studies, thus a linear activation function is suitable for the practical case. However, as the application is strictly dealing with positive values, ReLU can be considered. See code block A in Appendix B for the implementation of the activation function in the output layer.

6.2.2 Training, Testing, and Validation

An initial split of the data for the ANN-models is suggested for companies in the technical textile industry. It is recommended to split the data in line with the case studies and in section 3.2.10, thus this means having 60-90% of the data for training, 5-20% for testing and 5-20% for validation. See code block B in Appendix B for implementation.

As an ANN requires a lot of training data to achieve sufficient performance when predicting the desired tensile properties for plastic foils and yarns in the aging measurement data, it is recommended that companies use k-fold cross-validation. This is because it can yield a more robust estimate of the model's performance compared to the above-mentioned split. See code block D in Appendix B for implementation.

Training

It is recommended to train both the ANNs with backpropagation as it is efficient and easy to implement and that the case studies use it for the training of their feedforward ANNs. In order to evaluate the training of the ANN a loss function, i.e an error measure in section 3.2.9, is suggested for the practical context. It is recommended to use a combination of error measures, i.e correlation-based, scale-dependent, and percentage-dependent in order to get a complete picture of the error between the predicted tensile properties and the real output variable. From the case studies, it is recommended that the correlation-based is the correlation coefficient, the scale-dependent is either MSE or MAE or both, and the percentage-dependent, MAPE. See code block C in Appendix B for implementation.

For companies in the industry to minimize the error i.e loss calculated by the loss function, an optimization function should be used. The majority of the case studies for predicting the tensile properties of yarns, use Levenberg-Marquardt. As there are similarities regarding the characteristics of the training data and the structure of the ANN predicting the breaking strength of yarns, it is recommended for companies in the technical textile industry to use the Levenberg-Marquardt for backpropagation. This is further motivated by the fact that in comparison to gradient descent methods, Levenberg-Marquardt is more robust to local minima as well as dealing with a larger number of parameters when training. In the case studies, Adam or Stochastic gradient descent is used as an optimization function for the ANN predicting tensile properties of plastic foils. Thus, it can be suggested for companies in the technical textile industry start with one of these algorithms in the model and then evaluate which yields the highest performance. See code block C in Appendix B for implementation.

Validation and Testing of the Models' Performance

It is recommended for companies in the technical textile industry carry out the evaluation of the model's performance by using the validation dataset, see code block D in Appendix B. This is to fine-tune the hyperparameters which are in the suggested implementation the batch size and the number of epochs. Lastly, it is recommended to evaluate the model's performance on the test data, see code block D in Appendix B. In the evaluation on the validation and the test data set, the recommendation is to use the same combination of error measurements used on the training dataset with the same motivation mentioned. See code block D in Appendix B for implementation.

It is recommended for the practical context to consider what is a tolerated interval (confidence interval) of the error measurement in all three phases of the evaluation. For both ANN-models it is recommended to have a two-sided confidence interval, 95-98%, as section 6.1 describes the requirements of low errors in the prediction. However, specifically for the ANN-model predicting the tensile properties of yarns the tolerance could be suggested to be on a higher level as the yarn inherently have more variance due to the material properties. On the other side of the interval, prototypes having better tensile properties than those required by the customer should not pass the gate. The reason for this is that higher tensile properties imply usage of excessive amounts of expensive additives in the prototype, which if passed the gates becomes costly for actors in the technical textile industry. However, it is described in the empirical data that when the commercial value is deemed high, there is a larger tolerance for errors in the tensile properties. Thus companies can consider having a larger confidence interval for this scenario. In section 5.2, this was explained by the fact that the benefit of launching a high-commercial value in a short time, is higher than the cost of pursuing a product in the PDP that is faulty.

Summary of Design Choices for the ANN model in the Technical Textile Industry

The suggested design features for the aging measurement process for the two ANN models for yarns and foils respectively can be seen in Table 6.2.

Table 6.2: Summarizes the recommended choices of an ANN model in the technical textile industry

Structural choice	Recommendation for the technical textile industry	
	Yarn	Plastic Foil
Subtype of ANN	Feedforward ANN	Feedforward ANN
Type of analysis	Regression	Regression
Input layer & nodes	1,8	1,8
Hidden layer & nodes	1,6-150	1,6-150
Output layer & nodes	1,1	1,1
Feature selection method	Embedded (L1 or L2)	Embedded (L1 or L2)
Activation function: Hidden layer/output layer	Sigmoid, ReLU	ReLU, ReLU
Data split	60-90% training, 5-10% testing, 5-20 validation	60-90% training, 5-10% testing, 5-20 validation
Training algorithm	Backpropagation	Backpropagation
Error measurement	Correlation coefficient, MSE/MAE, MAPE	Correlation coefficient, MSE/MAE, MAPE
Loss function	Levenberg-Marquardt	Levenberg-Marquardt

Updating and Retraining of the Model

As new aging measurements are conducted within the technical textile industry new data can be generated after the ANN-model has been trained and developed. Therefore, it might be relevant to retrain, i.e update the ANNs weights, when this occurs. However, training of the ANNs is likely to be time-consuming and the benefit of it is arguably low if the new data is of low quantity. The recommendation to companies in the industry is thus considered to retrain the network either when the accuracy on new type of test data is too low or at a fixed time interval. The interval can be adapted to when there are new tests. Another approach for companies is to solely update certain weights as some weights might not be affected by new data rather than retraining the entire ANN.

6.2.3 Interpretability Methods

It is recommended to conduct relevance and sensitivity analysis as it can increase the interpretability of the suggested ANN-models for companies in the technical textile industry, and this is of value as described in section 6.1. See code block G in Appendix B for implementation of the relevance analysis and the sensitivity analysis.

Relevance analysis is recommended as knowledge about how much of the output of the ANN-model in terms of breaking elongation or breaking strength, is impacted by the input variables such as % of chemicals, the thickness of the material, and producing process is achieved. This information can lead to the possibility of conducting manual feature selection.

Further, sensitivity analysis would provide implications of how sensitive the breaking elongation and breaking strength are to changes in the input variables. This information provides key insights for the development as described in section 6.1.

6.3 AI-Strategy for Implementing ANN in Aging Measurement Analysis in the PDP

The lack of AI-knowledge, described in 6.1, emphasizes the critical need for an AI-strategy in the technical textile industry as it guides the entire implementation of the ANN in the aging measurement analysis. For a successful ANN-implementation, companies in the technical textile industry are recommended to develop an AI-strategy with specific plans and processes, within the areas seen in Table 6.3.

It is implied in the focus group session that companies PDP in the technical textile industry have a solid foundation for the ANN implementation in terms of culture. This is explained by the fact that the PDP is characterized by an open-minded and innovative culture which are necessary requirements to be fulfilled for a successful ANN implementation. These characteristics are key success factors as it facilitates the organizational changes required when implementing an ANN. Thus, in the technical textile industry, cultural requirements are automatically fulfilled. Hence, no specific plan apart from building upon existing culture is recommended for companies in the technical textile industry.

In the workshop, the requirement of data from internal processes such as weaving/knitting, tensile testing, sun-simulation, and added chemicals was described. Further, it is described during the focus group, that the majority of internal data required already exists but is collected inconsequentially and stored unstructured.

Table 6.3: Describes the AI strategy consisting of several key requirements needed to be fulfilled in order to implement ANN successfully in the PDP of the technical textile industry

AI STRATEGY	
Type of Requirement	Plans/processes to fulfill
Culture	• Activities to build upon existing culture
Internal data	• Process for data collection and storage. • Process, new routines in the organization • Personnel in the PDP
External data	• Data collection plan • Roadmap of frequent supplier contact
Data Anonymization	• Processes to protect confidentiality
Automated data collection process	• New personnel • Suitable database • Close supplier relationships • Process of data transfer • Systems for integration
Data characteristics (quality, volume, variety)	• New personnel, formation of data teams • Establishment of data governance guidelines
Computing power infrastructure	• Required computation power, convenient cloud computing integration
Knowledge, human capacity	• Hiring of personnel with required competencies
Employee AI-trust	• Educational program and interactive activities with the ANN-model

Thus, it is recommended that the AI-strategy, for companies in the technical textile industry, includes a new process for how structuring data collection and storage. To ensure the new process, new routines in the organization and new personnel in the PDP are recommended, see Table 6.3.

Another requirement regarding data, mentioned during the workshop, was the need for external data from suppliers. For the ANN model to be successful, it is essential that all the detailed data is collected from the suppliers as this information is highly correlated with the tensile properties. However, as described in 6.1 this data contains sensitive information and is strictly confidential. Thus, in the AI-strategy it is recommended for companies in the industry to specify how this data collection should be achieved and how the problems of confidentiality should be avoided. Building on the idea of collaboration with the suppliers, mentioned in the workshop, the AI-strategy could include a plan on how to ensure and maintain a close supplier relationship. This could include a roadmap of frequent contact with key account suppliers.

Related to the external data from suppliers is the requirement of anonymization and regulations described by Enholm et al. (2021). The reason for including anonymization in the AI-strategy is to ensure that the strictly confidential nature of the supplier in the technical textile industry is protected. The recommendation for companies in the industry is to include a plan of how to protect the confidential data provided by suppliers in order to ensure no harm and legal penalties, see Table 6.3.

It was described in the empirical data that a database and an automated data collection process from various data sources are required in the technical textile industry. In the AI-strategy, a plan to hire new personnel, to ensure that companies in the technical textile industry have the right competencies to set up a suitable database and automate the data collection process is recommended, see Table 6.3. As the automated data collection process regards both internal and external data, new processes within the PDP that allow automation and close relationships with suppliers to automate the transfer of data from them are required. It is therefore recommended that the AI-strategy include plans on how to reorganize the PDP. Also, plans of how to identify suitable systems that allow the integration of the suppliers' data automatically into the database of the company in the technical textile industry are recommended.

It is recommended for companies in the industry to include a plan in the AI-strategy to ensure data characteristics, i.e quality, volume, velocity and variety, through the hiring of new personnel and formation of teams, and establishment of data governance guidelines. The inclusion of data characteristics is especially important as the technical textile industry as it is described in section 6.1 is immature.

Another requirement suggested by Enholm et al. (2021) is the need of a technological infrastructure, see Table 6.3. This requirement should be included in the AI-strategy in the form of plans regarding computational power, e.g through cloud computing, to allow the ANN to perform its predictions of the tensile properties.

The immaturity of AI in the technical textile industry described in section 6.1, emphasized the need for including the requirement of organizational readiness, and more specifically knowledge and new human capacity in the organization in the AI-strategy, see Table 6.3. The hiring of new personnel provides the knowledge that the technical textile industry currently lacks and it is only with competencies within e.g. automation of the data collection process, technological infrastructure, and data quality, that the requirements can be fulfilled for companies within the technical textile industry.

In the empirical data, it was described that organizations in the technical textile industry could ensure trust for the ANN-model in the aging measurement analysis by educating the employees within the area of AI. It is therefore recommended to include a plan of an educational program and interactive activities with the ANN-model, in the AI-strategy.

6.4 Improvements of Implementing an ANN in the Aging Measurement Process

The suggested improvements in section 5.4.2 when implementing ANN in the technical textile industry is in Figure 6.2 structured in terms of the type of improvement and its contribution to an excellent PDP. The Figure provides an overview of the improvements generated from ANN implementation and its implications on the PDP in the technical textile industry.

The implementation of the suggested hypothetical ANN in section 6.2, leads to increased knowledge about the relationships between input and output variables, which importance is described in section 6.1. The knowledge in turn leads to improvements in terms of a faster PDP, better product quality, and lower costs, see Figure 6.2. Thus, improved knowledge is an underlying improvement and can be considered to have a large impact on the technical textile industry.

		Dimensions of an excellent PDP, described by Wheelwright & Clark (1999)		
		Speed	Quality	Cost
Effects of implementing AI by Enholm et al. (2021)	Process efficiency	• Fewer iterations • Faster PDP		
	Enhanced /new product quality		• Customer-specific products	
	Insight generation		• Standardized & data-driven decision	
	Growth			• New customer segments
	Profitability			• Reduced testing costs
	Customer satisfaction		• Close customer relationship due to understanding of needs	
	Sustainability			• Reduced material usage as conventional testing is limited
	Knowledge	• Decisions earlier in the PDP as information about aging will be present • Willingness to start more products	• Understanding of all parameters affecting aging which enables better products • Knowledge of unique combinations of materials	• Reduction of non-performance adding materials

Figure 6.2: Link between the type of improvements in the PDP and the dimensions of an excellent PDP in the technical textile industry

The dimension of process efficiency can be improved in the technical textile industry as fewer iterations in the stage gate model due to ANN providing knowledge regarding the tensile property of a certain combination of material components. As seen in Figure 6.2, this contributes to a faster PDP which potentially can lead to companies in the industry being more willing to initiate projects in the PDP as the risk in terms of large investments which is followed by a long development with several iterations, is decreased.

In the technical textile industry enhanced product quality and new products, is a potential effects when implementing ANN as the knowledge can lead to more customer-specific products as the testing of unique combinations of material components can be conducted. This effect contributes to a better PDP in terms of quality which can be seen in Figure 6.2. As the ANN allows the technical textile industry to test customer-specific combinations of materials as the new technique is not as costly or time-consuming as conventional manual testing. New products that are customer-specific allow the technical textile industry to reach these previously nontargeted customer segments. Thus, as seen in Figure 6.2, the technical textile industry can experience growth as a result of ANN.

ANN can lead to fewer materials and personnel costs as the aging measurement analysis will be simulated rather than building prototypes, which both lowers the material costs and improves the sustainability performance, see Figure 6.2. The decreased costs can imply higher profitability. Thus, the result of this thesis implies a positive development of a more sustainable technical textile industry.

Insight generation, will in the scenario of the technical textile industry, be improved, as better decision quality will be achieved through an ANN generating more information about the materials, tensile properties, and aging. As the decision will be based on facts rather than “gut feeling” they will become more standardized. Hence, improved insights will lead to better quality in the PDP as can be seen in Figure 6.2. The dimension of market performance in terms of customer satisfaction can also be improved as the knowledge obtained from ANN, allows the companies in the technical textile industry to answer customers’ questions more insightfully.

In the above analysis, it is implied that there is a tradeoff between quality, cost, and speed in conventional testing in the PDP in the technical textile industry. The analysis also implies that the ANN implementation in the aging measurement analysis can potentially lead to the elimination of these tradeoffs. The ANN can allow the technical textile industry to achieve a PDP with a high speed as a result of a more efficient PDP, while at the same time having high quality and lower costs due to increased knowledge compared to conventional testing.

6.4.1 Competitive Advantages from the Improved PDP

In the workshop, it was suggested that there is a link between the improvements described in section 6.4 when implementing ANN in the aging measurement analysis and potential competitive advantages. The mentioned competitive advantages in the workshop can be divided into compound and discrete depending on the effect it has on the organization according to Ma (1999).

In Figure 6.3 the competitive advantages mentioned during the empirical data collection, are depicted as blue boxes. A hierarchy inspired by Ma (1999) was introduced between these competitive advantages (light gray boxes) and the right arrows in Figure 6.3 illustrate how the discrete competitive advantages build up the compound competitive advantages. As seen in Figure 6.3, one compound competitive advantage consists of several discrete advantages. Improvements mentioned during the workshop were divided into three main areas in 6.4, and the arrows to the left from these yellow boxes in Figure 6.3, represent the connection between the improvements and competitive advantages from the ANN implementation.

In the empirical data, it was suggested that improvements related to a faster PDP could lead to competitive advantages in the form of launching products earlier on the market and higher profitability, this relation is visualized in Figure 6.3. Further, Figure 6.3 depicts the relationships between quality improvements in the PDP and innovation capacity, brand recognition, differentiation, and superior products. Lastly, it can be seen in the figure that improvements in the PDP within costs lead

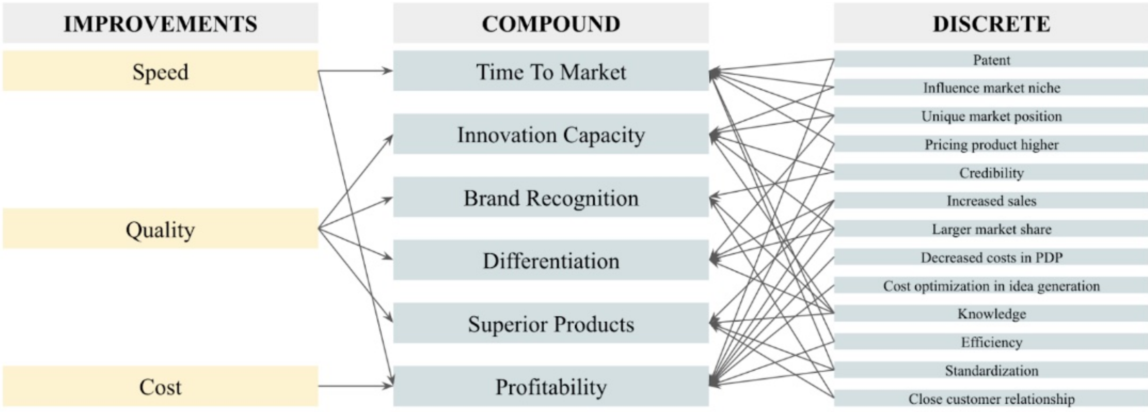

Figure 6.3: Describes the relationships between the competitive advantages suggested in the empirical data to the identified improvements

to competitiveness in terms of profitability.

As described in section 6.1, the technical textile industry is characterized by a low level of knowledge and immaturity. This means that the development and implementation of an ANN model will take a significant amount of time and effort. The reason for this is that knowledge in the industry has to be acquired, and change in internal processes needs to take place as well as building close collaboration with suppliers. This implies that it can take years before a fully functioning ANN model is in place. Thus, the competitive advantages followed by an ANN implementation described in Figure 6.3 can be interpreted as sustainable advantages as competitors will lag behind. For example, the competitive advantage of customer-specific products or differentiation means reaching new market segments if implementing ANN. As these segments will already be saturated by the first mover of ANN implementation, the advantage is sustainable.

6.5 Relevance and Future Research

The relevance of this thesis lies in the fact that it provides key information about the design choices of the ANN-model for the aging measurement analysis and a strategy to fulfill critical requirements for a successful implementation in the technical textile industry. To verify the feasibility of implementing the hypothetical ANN model future research would be interesting. Further, improvements and resulting competitive advantages are provided in this thesis, which in extension can motivate actors in the technical textile industry to consider the implementation of ANN. Future research in more than one CSC would provide interesting nuances about the relevance of the improvements and competitive advantages for the technical textile industry.

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A

Mathematical Notations

In this appendix error measures, optimization algorithms, activation functions, and the methods relevance and sensitivity analysis are presented

A.1 Error Measures

MSE

$$\sum_{i=1}^{D}(x_i - y_i)^2 \tag{A.1}$$

In A.1 the mean squared errors for each data point summed over the dataset D where x is the predicted value and y is the actual value (Demiryürek & Koç, 2009)

RMSE

$$\sqrt{\frac{1}{|D|}\sum_{i\in D}(x_i - y_i)^2} \tag{A.2}$$

In A.2 the root mean squared errors for each data point summed (Vandeput, 2021)

MAE

$$\sum_{i=1}^{D}|x_i - y_i| \tag{A.3}$$

In A.3 The mean absolute error is shown (Vandeput,2021)

MAPE

$$\frac{1}{|D|}\sum_{i\in D}\left|\frac{x_i - y_i}{y_i}\right| \tag{A.4}$$

In A.4 The mean absolute percentage error is shown (Vandeput,2021)

A.2 Optimization Algorithms

In this section, an example of the optimization algorithm steepest gradient descent which minimizes the error measure is briefly presented.

$$w_i = w_i - \alpha \frac{\partial E}{\partial w_i} \tag{A.5}$$

In A.5 the variable alfa is the learning rate, the E is the error, and w is the corresponding weight.

A.3 Activation Functions

In this section, the behavior of the different activation functions with mathematical notation is presented.

ReLU

$$Relu(z) = max(0, z) \tag{A.6}$$

In A.6 the function takes the value zero when the input variable is below zero and otherwise the value of the input value (Lindholm et al., 2022). The function and its derivative are monotonic, which means either entirely non-increasing or non-decreasing (Lindholm et al., 2022).

Linear function

$$f(z) = z \tag{A.7}$$

In A.7 for any input value z, the output of the function will be the same value z. When represented graphically, the identity function is a straight line with a slope of 1, passing through the origin (Lindholm et al., 2022).

Sigmoid

$$f(z) = \frac{1}{1 + e^{-z}} \tag{A.8}$$

In A.8, the output of the sigmoid function is always between 0 and 1, regardless of the input value (Lindholm et al., 2022). The sigmoid function has a characteristic "S" shape. It has a steep slope near the origin, which means that small changes in the input value result in large changes in the output value (Lindholm et al., 2022). As the input value becomes larger in magnitude, the output of the sigmoid function approaches 0 or 1, but the slope of the function becomes very small, which means that large changes in the input value have little effect on the output (Lindholm et al., 2022).

tanh

$$f(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{A.9}$$

The output of the hyperbolic tangent function is always between -1 and 1, regardless of the input value and has a characteristic "S" shape (da Silva et al., 2017).

A.4 Relevance analysis and sensitivity analysis for ANN

For relevance analysis, there is the method of layer-wise relevance propagation and the aim of the method is to assign a specific relevant measure to each input variable of the neural network, such that the output of it, is redistributed along the vector of inputs (Montavon, Binder, Lapuschkin, Samek & Müller, 2017). The authors mention that layer-wise propagation represents the impact each variable used in the input has on the final output. The procedure of layer-wise propagation is done by calculating the propagating relevance scores at a layer on neurons of its lower layer (Montavon et al., 2017). This is done by applying the formula in A.2 where zjk is modeling the amount to which the neuron j contributes to the neuron k, contributing being the relevance score (Montavon et al., 2017). Visualization of the procedure can be seen in Figure A.1.

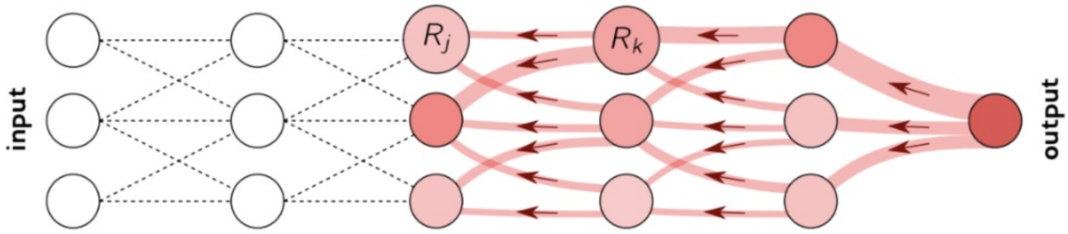

Figure A.1: Illustrating the procedure of layer-wise propagation where every neuron distributes to the corresponding lower layer the amount received from its higher layer (Montavon et al., 2017)

$$R_j = \sum_k \frac{z_{jk}}{\sum_j z_{jk}} R_k$$

Figure A.2: The formula applied in the layer-wise propagation (Montavon et al., 2017)

Regarding sensitivity analysis, the common method is gradient sensitivity (Ponomareva & Caenazzo, 2019). The idea of gradient sensitivity is to examine the partial derivatives of the output with regard to the input variable (Montavon et al., 2017). Specifically, the magnitude of the derivative, and use it as an indication of what input variables are changed to the least but have the greatest impact on the activation function (Ponomareva & Caenazzo, 2019). Noteworthy is that this type of sensitivity analysis can be applied to all layers and neurons in the network (Ponomareva & Caenazzo, 2019).

B

Code blocks

B.1 Code block B for splitting the dataset

Necessary imports
fromsklearn.model_selection import train_test_split

Separating the input variables X and the output variables y from the dataset
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values

Split the dataset into training, test, and validation sets. test_size per specification
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2)

B.2 Code block A for setting up the structure for the ANN

Using the Keras package for implementing ANN
Importing the sequential object on which layers are added from keras.models import Sequential
Fully-connected layer, see terminology from keras.layers import Dense

Define the model architecture
model = Sequential()
Hidden layer with nodes, nr_nodes as preferred as well activation function.
model.add(Dense(nr_nodes, input_dim=X_train.shape[1], activation='sigmoid'))
Output layer with 1 output node and activation function per specification.
model.add(Dense(1, activation='linear'/'relu'))

B.3 Code block C for training

Compile the model
Compile () will cause the model to be trained using backprop. with the specified

optimization
In the loss the error measurement is specified. model.compile(loss='mse', optimizer='adam'/'Levenberg_Marquardt') Levenberg_Marquardt = LM Note, LM is not included in the Keras package, a separate implementation is necessary
Fit the model to the training data
model.fit(X_train, y_train, epochs=10, batch_size=32) Evaluate performance on training data score = model.evaluate(X_test, y_test, batch_size=32)

B.4 Code block D Testing / Validation (follow B-A-C)

Validation data
score = model.evaluate(X_val, y_val, batch_size=32)
Test data
score = model.evaluate(X_test, y_test, batch_size=32)

B.5 Code block E Cross validation implementation

Import necessary modules
import numpy as np
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import cross_val_score
def build_model():
model = Sequential()
model.add(Dense(n_inputs, input_dim=n_inputs, activation='relu'))
model.add(Dense(n_hidden, activation='relu'))
model.add(Dense(n_outputs))
model.compile(loss='mse', optimizer='adam') return model
Use KerasRegressor to create a wrapper for the ANN model
model = KerasRegressor(build_fn=build_model, epochs=100, batch_size=32)
Use cross_val_score to evaluate the model using k-fold cross-validation
scores = cross_val_score(model, X, y, cv=10) Print the mean and standard deviation of the cross-validation scores
print("Mean cross-validation score: :.2f +/- :.2f".format(scores.mean(), scores.std()))

B.6 Code Block F for increasing hidden nodes gradually

Import necessary libraries
from tensorflow import keras
from tensorflow.keras import layers
Set the initial number of nodes and the increment initial_nodes = 8
increment = 8
Define the model
model = keras.Sequential()
Add the first layer with the initial number of nodes
model.add(layers.Dense(units=initial_nodes, activation='relu', input_dim=X.shape[1]))
Loop through the number of hidden layers
for i in range(num_layers):
Add a hidden layer with the specified number of nodes
model.add(layers.Dense(units=initial_nodes + (increment * i), activation='relu'))
Add the output layer
model.add(layers.Dense(units=1))
Compile the model
model.compile(optimizer='adam',
loss='mean_squared_error')
Fit the model to the data
model.fit(X, y, epochs=100, batch_size=32)

This code will create a feedforward ANN with one hidden layer containing initial_nodes number of nodes, and additional hidden layers with initial_nodes + increment * i number of nodes, where i is the index of the hidden layer. The number of hidden layers is specified by the num_layers variable.

B.7 Code Block G for relevance and sensitivity analysis respectively (assuming B-A-C-D-G)

Necessary imports
import numpy as np
from sklearn.neural_network import MLPRegressor
from sklearn.inspection import
permutation_importance
result = permutation_importance(model, X, y,
n_repeats=10, random_state=0)
Print the results
print(result)
Sensitivity analysis

from sklearn.inspection import partial_dependence
model = MLPRegressor(hidden_layer_sizes=(10,),
random_state=0)
Perform the sensitivity analysis (assuming 10 input variables)
result = permutation_importance(model, X, y, n_repeats=10, random_state=0)
pdp, axes = partial_dependence(model, X, [0, 1, 2, 3, 4, 5, 6, 7, 8, 9], grid_resolution=10)
Plot the results
fig, ax = plt.subplots(figsize=(10, 8))
Plot the feature importance
sorted_idx = result.importances_mean.argsort()
ax.boxplot(result.importances[sorted_idx].T,
vert=False, labels=range(X.shape[1]))
ax.set_title("Permutation Importance of each feature") ax.set_ylabel("Features")
Plot the partial dependence
fig, ax = plt.subplots(3, 3, figsize=(12, 8)) v for axi, (idx, title) in zip(ax.flat,
enumerate(range(X.shape[1]))):
pdp_ = pdp[idx]
axi.plot(X[:, idx], pdp_, 'o', alpha=0.6)
axi.set_title(f"Partial Dependence of feature title")
axi.set_xlabel(f"Feature title")
axi.set_ylabel("Partial Dependence")
plt.show()

This code will train a feedforward ANN on the input data X and output labels y, then perform sensitivity analysis using the permutation_importance and partial_dependence functions. The results of the sensitivity analysis will be plotted using matplotlib, with one plot showing the feature's importance and another plot showing the partial dependence of each feature.

B.8 Code block H for implementing embedded feature selection strategy

Import necessary modules
from keras.models import Sequential
from keras.layers import Dense

Set the input and output dimensions
input_dim = 10
output_dim = 1

Set the number of hidden layers and number of neurons in each layer
num_hidden_layers = 2
num_neurons_per_layer = 20

Initialize the model

model = Sequential()

Add the first hidden layer, with L1
regularization
model.add(Dense(num_neurons_per_layer,
input_dim=input_dim,
kernel_initializer='random_uniform',
bias_initializer='zeros', kernel_regularizer='l1',
bias_regularizer='l1'))
Add the remaining hidden layers, with L2
regularization
for i in range(1, num_hidden_layers):
model.add(Dense(num_neurons_per_layer,
kernel_initializer='random_uniform',
bias_initializer='zeros',
kernel_regularizer='l2',
bias_regularizer='l2'))
Add the output layer
model.add(Dense(output_dim,
kernel_initializer='random_uniform', bias_initializer='zeros'))
Compile the model
model.compile(loss='mean_squared_error',
optimizer='sgd')

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF INNOVATION AND R&D MANAGEMENT
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden
www.chalmers.se

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