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AI based modeling method for predicting failure related parameters in conveyor belts at mines

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Declaration of Authorship

I, Parthkumar Anilbhai Parmar, declare that this thesis titled, "AI based modeling method for predicting failure related parameters in conveyor belts at mines" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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"I owe much of the progress made in this work to the guidance of my mentors and the support of my colleagues, whose wisdom has far exceeded my own."

Parthkumar Parmar

Abstract

Conveyor belts operating in harsh mining environments are susceptible to damage during material transport, and the failure of a belt section in a loop can disrupt conveyor operation, potentially leading to significant financial losses. The extent of these losses is directly dependent on the scale of mining operations and their production capacity. The scientific objective of this dissertation is to develop an artificial intelligence (AI)-based method for predicting parameters associated with conveyor belt failures, including damage size and occurrence metrics, by utilizing operational characteristics and historical maintenance records obtained from mining environments. The utilitarian goal of the thesis is to improve the operational efficiency of mines by developing an AI-based predictive maintenance system for conveyor belts. Preventive repairs based on predicted condition can prevent advanced damage and emergency downtime in conveyor belts, while also enabling more efficient resource allocation, extending belt service life, and improving safety to ensure smooth operations in mining environments.

Previous studies [1], [2], [3], [4], [5], [6] have identified combinations of dependent (output) and independent (input) parameters affecting the severity of conveyor belt failures, such as the type of material being conveyed, the conveyor length, and the belt speed. However, the less frequently studied parameters and additional elements considered in this thesis—identified through an Ishikawa diagram within a root cause analysis—include the conveyor slope and the route configuration (fixed or sliding), as well as the type of conveyed material (overburden, lignite and its mixtures, and limestone).

This dissertation develops and validates a predictive method based on long short-term memory (LSTM) neural networks for forecasting the size and characteristics of conveyor-belt damage in surface mining. Two independent empirical datasets were used: (i) a visual-inspection database from the lignite mine (927 records, 11 input variables describing belt geometry, transported material, age and repair history; 5 damage-related outputs) and (ii) a DiagBelt+ magnetic scan database from the limestone mine (929 records, 6 inputs, 5 outputs). The method was developed and verified using subjective historical data from visual inspections (lignite mine located in Poland which uses straight conveyors) and objective data from the assessment of the belt core condition generated by the DiagBelt+ magnetic diagnostic system during subsequent scans (at the limestone mine located in Poland, which uses a very long curved conveyor).

Dependent parameters considered in this dissertation include the number of cut cords in the core, the cumulative number of repairs, the total number of damages for sections, the damage density (number of damages per meter of belt in the section), the damage area and dimensions (length and width of the recorded damage signals), and the timing of these events. The models specifically predicted belt condition indicators including number of repairs, number of cut steel cords, and damage geometry (length, width, area).

The method was implemented in Python/TensorFlow and tested with alternative hyperparameters (e.g., 3 hidden layers with 36 neurons, batch size

16, optimizers Adam/Nadam/RMSprop, ReLU or Swish activation). The rationale for selecting the LSTM neural network algorithm over other prominent modeling approaches is discussed, along with hyperparameter choices for network training. Evaluation used three relative error indicators and multiple training/testing splits. For DiagBelt+ data, median relative errors were ≈55% for damage length and ≈60% for width; for visual-inspection data, the best models achieved median errors of ≈33% for age- and repair-related targets. Furthermore, the models were extended to future forecasting through a recursive modeling framework, demonstrating their capability to provide reliable insights that can inform proactive repair and maintenance planning.

The study demonstrates that the proposed LSTM approach can support predictive maintenance of conveyor belts, while highlighting the influence of data quality and belt segment length on accuracy. All issues discussed in this dissertation—including the importance of belt conveyors in mining operations, their structural characteristics, the occurrence of damage during material transport, and the selection of appropriate machine learning algorithms—are situated in the context of international literature, taking into account both the historical perspective and the latest achievements in scientific research.

Abstract

Przenośniki taśmowe pracujące w trudnych warunkach górniczych są podatne na uszkodzenia podczas transportu materiałów, a awaria odcinka taśmy w pętli może zakłócić pracę przenośnika, potencjalnie prowadząc do znacznych strat finansowych. Zakres tych strat jest bezpośrednio uzależniony od skali działalności górniczej i jej zdolności produkcyjnej. Celem naukowym niniejszej rozprawy jest opracowanie metody opartej na sztucznej inteligencji (AI) do przewidywania parametrów związanych z awariami taśm przenośnikowych, w tym wielkości uszkodzeń i wskaźników ich występowania, z wykorzystaniem charakterystyk eksploatacyjnych i historycznych danych konserwacyjnych uzyskanych z kopalni. Celem utylitarnym rozprawy jest poprawa efektywności operacyjnej kopalń poprzez opracowanie systemu predykcyjnego utrzymania ruchu taśm przenośnikowych opartego na AI. Naprawy zapobiegawcze oparte na przewidywanym stanie technicznym mogą zapobiegać zaawansowanym uszkodzeniom i awaryjnym przestojom taśm przenośnikowych, a jednocześnie umożliwiają bardziej efektywną alokację zasobów, wydłużenie żywotności taśm i poprawę bezpieczeństwa, zapewniając płynną pracę w kopalniach.

Wcześniejsze badania [1], [2], [3], [4], [5], [6] zidentyfikowały kombinacje parametrów zależnych (wyjściowych) i niezależnych (wejściowych) wpływających na skalę uszkodzeń taśm przenośnikowych, takich jak rodzaj transportowanego materiału, długość przenośnika i prędkość taśmy. Jednakże rzadziej badane parametry i dodatkowe elementy uwzględnione w niniejszej rozprawie – zidentyfikowane za pomocą diagramu Ishikawy w ramach analizy przyczyn źródłowych – obejmują nachylenie przenośnika i konfigurację trasy (stała lub przesuwna), a także rodzaj transportowanego materiału (nadkład, węgiel brunatny i jego mieszanki oraz wapień).

Niniejsza rozprawa doktorska opracowuje i weryfikuje metodę predykcyjną opartą na sieciach neuronowych o długiej i krótkiej pamięci (LSTM) do prognozowania wielkości i charakterystyki uszkodzeń taśm przenośnikowych w górnictwie odkrywkowym. Wykorzystano dwa niezależne zbiory danych empirycznych: (i) bazę danych z inspekcji wizualnej z kopalni węgla brunatnego (927 rekordów, 11 zmiennych wejściowych opisujących geometrię taśmy, transportowany materiał, wiek i historię napraw; 5 danych wyjściowych dotyczących uszkodzeń) oraz (ii) bazę danych skanowania magnetycznego DiagBelt+ z kopalni wapienia (929 rekordów, 6 danych wejściowych, 5 danych wyjściowych). Metodę opracowano i zweryfikowano, wykorzystując subiektywne dane historyczne z inspekcji wizualnych (kopalnia węgla brunatnego w Polsce, wykorzystująca przenośniki proste) oraz obiektywne dane z oceny stanu rdzenia taśmy, generowane przez system diagnostyki magnetycznej DiagBelt+ podczas kolejnych skanowań (w kopalni wapienia w Polsce, wykorzystującej bardzo długi przenośnik zakrzywiony).

Parametry zależne rozważane w niniejszej rozprawie obejmują liczbę przeciętych linek stalowych w rdzeniu, skumulowaną liczbę napraw, całkowitą liczbę uszkodzeń na odcinkach, gęstość uszkodzeń (liczba uszkodzeń na metr taśmy w odcinku), obszar i wymiary uszkodzeń (długość i szerokość

zarejestrowanych sygnałów uszkodzeń) oraz czas wystąpienia tych zdarzeń. Modele szczegółowo przewidywały wskaźniki stanu taśmy, w tym liczbę napraw, liczbę przeciętych linek stalowych oraz geometrię uszkodzeń (długość, szerokość, powierzchnia).

Metodę zaimplementowano w Pythonie/TensorFlow i przetestowano z alternatywnymi hiperparametrami (np. 3 ukryte warstwy z 36 neuronami, rozmiar partii 16, optymalizatory Adam/Nadam/RMSprop, aktywacja ReLU lub Swish). Omówiono uzasadnienie wyboru algorytmu sieci neuronowej LSTM spośród innych popularnych metod modelowania, a także wybór hiperparametrów do trenowania sieci. W ewaluacji wykorzystano trzy wskaźniki błędu względnego i wielokrotne podziały treningowo-testowe. W przypadku danych z DiagBelt+ mediana błędów względnych wyniosła około 55% dla długości uszkodzenia i około 60% dla szerokości; w przypadku danych z inspekcji wizualnej najlepsze modele osiągnęły medianę błędów na poziomie około 33% dla celów związanych z wiekiem i naprawą. Ponadto modele zostały rozszerzone o prognozowanie przyszłości za pomocą rekurencyjnych ram modelowania, co dowodzi ich zdolności do dostarczania wiarygodnych informacji, które mogą być wykorzystane do proaktywnego planowania napraw i konserwacji.

Badanie dowodzi, że proponowane podejście LSTM może wspierać predykcyjne utrzymanie taśm przenośnikowych, podkreślając jednocześnie wpływ jakości danych i długości segmentu taśmy na dokładność. Wszystkie zagadnienia omawiane w niniejszej rozprawie – w tym znaczenie przenośników taśmowych w działalności górniczej, ich charakterystyka konstrukcyjna, występowanie uszkodzeń podczas transportu materiałów oraz dobór odpowiednich algorytmów uczenia maszynowego – zostały osadzone w kontekście literatury międzynarodowej, uwzględniając zarówno perspektywę historyczną, jak i najnowsze osiągnięcia w badaniach naukowych.

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Introduction

Conveyor belt systems (CBSs) are crucial for operational efficiency across various industries, especially in coal mining, where they play a key role in transporting large volumes of coal and overburden. Serving as the primary means of material transport, conveyor belts (CBs) ensure continuous production by efficiently moving coal from extraction points to processing plants and storage facilities. However, these systems operate under extremely challenging conditions, including exposure to abrasive materials, variable loads, and harsh environmental parameters, which lead to frequent wear and tear [7], [8]. Wear and damage to conveyor belts have a major impact on their service life and operational efficiency. Continuous or occasional severe damage can result in unplanned machinery shutdowns, causing significant financial losses for operating companies [6], [9], [10], [11]. The operational costs of mines can be reduced by maintaining optimal conditions and implementing effective strategies [12], [13], [14]. One of the effective strategies could be predictive modeling of failures to CBs using artificial intelligence (AI) for timely maintenance and repairs.

Artificial neural networks (ANNs) [15] are particularly well-suited for modeling damage in conveyor belts due to their ability to handle the complex and non-linear nature of the underlying parameters, such as operational speed, material properties, environmental influences, and belt construction. Unlike traditional regression models, ANNs can learn intricate relationships and interactions among a large number of input-output features without requiring manual specification or dimensionality reduction. Their capacity to generalize from large volumes of operational and failure data makes them effective also in high-dimensional [16] and noisy datasets, which are common in mining environments. Furthermore, ANNs demonstrate robustness against errors [17] and inconsistencies in recorded data, offering more reliable and scalable predictions of damage progression over time. The use of ANNs in research has been evolving rapidly, with several key trends emerging in 2024 [18]. These trends reflect the increasing complexity and application of ANNs across various fields. These trends highlight the dynamic nature of ANN research, focusing on enhancing technical capabilities while addressing ethical and practical challenges. Moreover, the applicability of ANNs in predictive maintenance has been further validated through a keyword-based search within academic database. The results confirm that the use of ANN is widely recognized within the research community and in the field of mining as well.

The graph in Fig. 1 was generated using the Scopus [19] platform for the period from 2014 to 2024, utilizing the following keywords: "modelling using artificial neural network." It illustrates the increasing trend in scientific studies employing ANNs for modeling purposes. This upward trend reflects the growing recognition of ANNs as a powerful tool for handling complex, nonlinear systems across a range of scientific and engineering disciplines. The consistent rise in publications over the decade suggests that researchers

are increasingly turning to ANN based approaches due to their adaptability, high accuracy, and capability to learn from large and high-dimensional datasets. The data also reinforces the relevance and timeliness of the presented research, situating it within a broader global movement toward AI-driven modeling methodologies.

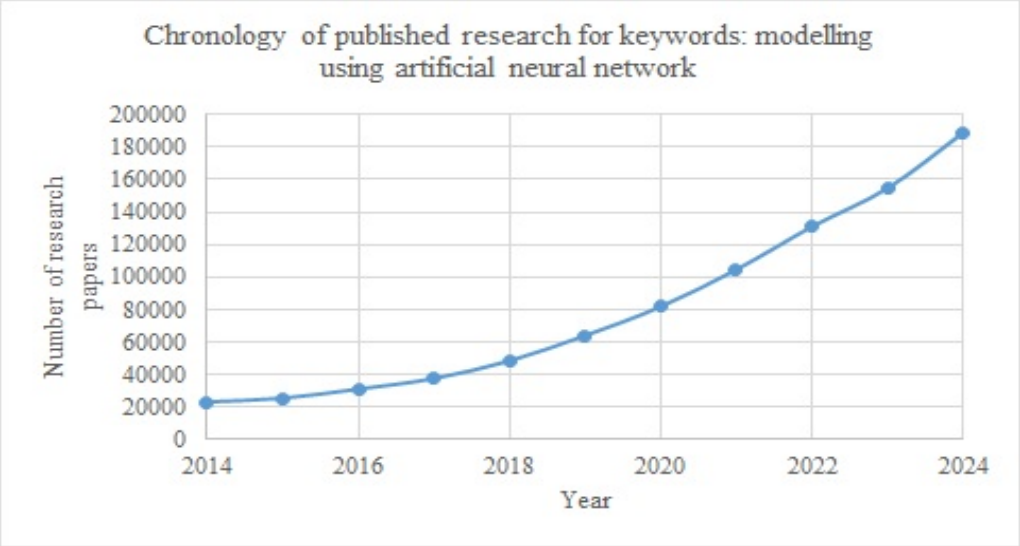


FIGURE 1: Trends in publications where ANN was used for modelling purpose

The graph in Fig. 2 was generated using the Scopus [19] platform, covering the ten-year period from 2014 to 2024. The keywords used in the search were "artificial neural network" and "mining." As depicted in the graph, there has been a clear upward trend in the number of scientific publications focusing on the application of ANNs within the mining sector. This growth indicates a rising interest among researchers in leveraging machine learning techniques, particularly neural networks, to address complex challenges in mining operations. The increasing number of studies suggests that ANNs are being progressively integrated into various aspects of mining research, including predictive maintenance, resource estimation, process optimization, and safety monitoring. This trend underscores the growing acceptance of ANN-based methodologies as viable and effective tools for improving efficiency, reliability, and decision-making in mining-related applications.

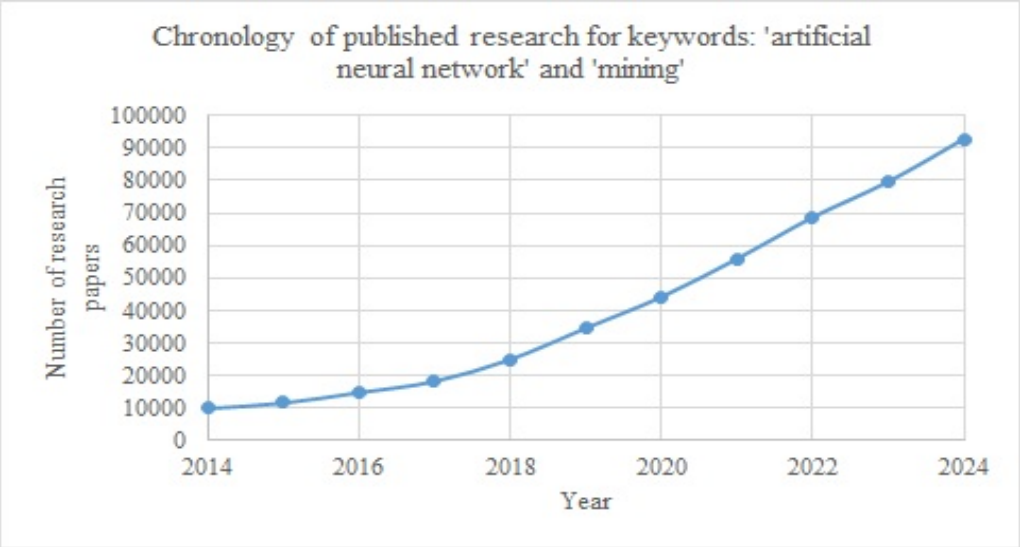


FIGURE 2: Trends in publications where ANN was used for research in mining sector

The graph in Fig. 3 was generated using the Scopus platform [19] for the period spanning from 2014 to 2024, using the keywords "predictive maintenance" and "artificial intelligence." The results clearly illustrate a consistent and notable increase in the number of publications related to the application of AI in predictive maintenance. This rising trend reflects a broader shift in industrial and academic research toward data-driven and intelligent maintenance strategies aimed at minimizing unplanned downtimes, optimizing asset utilization, and enhancing operational reliability. When considered alongside the graphs in Figs. 1 and 2, which respectively highlight the general adoption of artificial neural networks for modeling and their application within the mining sector, Fig. 3 further narrows the focus by demonstrating how these technologies are being increasingly applied to predictive maintenance tasks. Together, these three figures collectively establish both the widespread applicability of ANNs and their growing relevance in the specific context of mining equipment reliability and proactive maintenance planning.

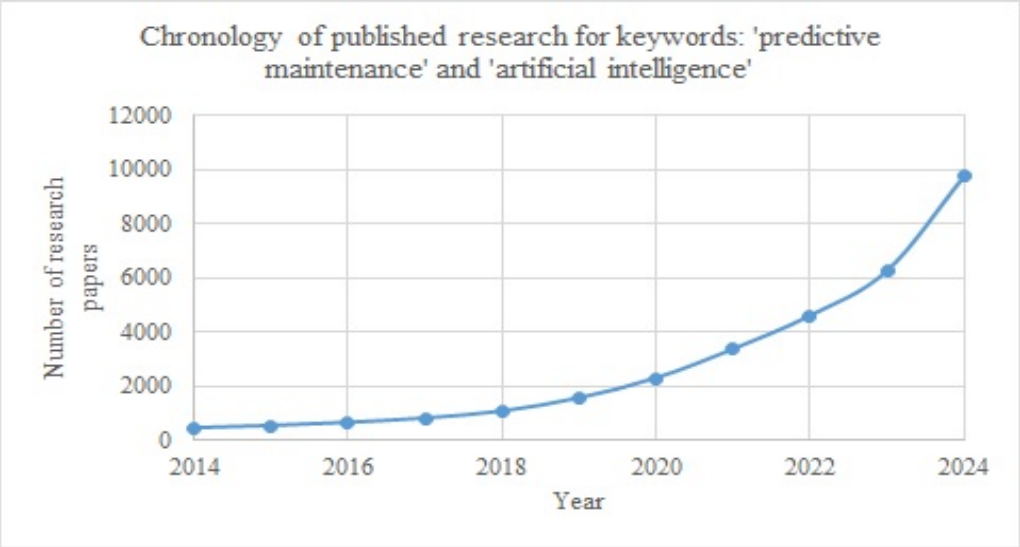


FIGURE 3: Trends in publications where ANN was used for research in mining sector

Considering all three graphs presented in Figs. 1 to 3, the use of machine learning tools for modeling conveyor belt (CB) damage is supported in the presented thesis. AI-enabled predictive maintenance not only helps mine operators mitigate breakdowns caused by CB failures but also improves resource management through timely repairs and refurbishments. Method for predicting future failure sizes in conveyor belts under various operating conditions during material transportation at mines is discussed in the presented thesis. Past failure records of CBs used at two different mines—surface lignite mine in Poland, and surface limestone mine in Poland, were used to train an artificial neural network (ANN), which was then employed to predict future failures of CBs under specific operating conditions at mines.

The dissertation consists of the following chapters:

Chapter 1. Characteristics of conveyor belts and modeling approaches for wear and failure analysis

This chapter begins with an introduction to conveyor belts, their construction, operating principles, and significance in continuous material transportation systems at mining sites. It then presents a comprehensive literature review on the wear and degradation mechanisms of conveyor belts during material transportation operations, with particular emphasis on parameters contributing to belt failure in harsh mining environments. Based on the results of literature review, an Ishikawa diagram is introduced as a systematic tool for conducting root-cause analysis, enabling the identification and categorization into key groups of parameters that influence conveyor belt deterioration —people related parameters, belt and belt splices related parameters, conveyor related parameters, environment related parameters, parameters related to organizational activities and transport material related parameters.

The chapter then transitions into a discussion on the rationale for employing data-driven approaches, emphasizing the limitations of traditional methods and the advantages of using machine learning algorithms, particularly artificial neural networks (ANNs), in modeling complex, non-linear patterns of conveyor belt damage. The integration of domain knowledge, historical failure data, and advanced predictive techniques forms the foundation for developing effective condition monitoring and predictive maintenance systems in modern mining operations.

Chapter 2. Introduction to machine learning and their application in predicting conveyor belt damage

This chapter provides an overview of machine learning principles with a focus on Artificial Neural Networks (ANNs), particularly Long Short-Term Memory (LSTM) networks. It introduces the theoretical foundations of LSTM architectures and their relevance to time-dependent data. The chapter then presents the specific use case scenario of applying LSTM networks to the predictive maintenance of conveyor belts in the context of the current thesis. Additionally, it reviews selected case studies from existing literature. It discusses potential implications and advantages of approach where LSTM models are implemented with a single time step.

Chapter 3. Dissertation scope, research objectives, and methodology

This chapter outlines the problem statement and states the existing research gap, establishing the foundation for the study. It clearly defines the main goal along with utilitarian goal and presents the methodological framework adopted in the thesis. A structured roadmap of the thesis is introduced, dividing the methodology into distinct stages. Each stage is described in detail, supported by a flow process chart that visually represents the sequence of operations. Subsequent sections elaborate on each step of the methodology, ensuring clarity and coherence in the overall dissertation approach.

Chapter 4. Predictive modeling of conveyor belt failures based on visual inspection data

This chapter presents the failure records collected from the surface lignite mine in Poland and demonstrates how the proposed methodology—based on LSTM neural networks—can be applied to predict future failure sizes in conveyor belts under varying operational conditions. It evaluates the predictive performance using failure data which were recorded at the mine using subjective human visual inspections. The results highlight the influence of data type on prediction accuracy and provide practical insights into how the methodology can be implemented in real mining environments. The findings are further supported by an analysis of database characteristics and associated parameters that justify the predicted outcomes.

Chapter 5. Magnetic diagnostic system for conveyor belt health monitoring

Each method of recording conveyor belt failures has its own advantages and limitations. Having previously discussed the constraints associated with failure data obtained through human visual inspection, this chapter introduces the advanced diagnostic system known as DiagBelt+, which offers a more objective and precise approach to condition monitoring. This chapter presents the operating principles and functionality of the DiagBelt+ system, highlighting its operational benefits and significance in conveyor belt diagnostics. A literature review is included to summarize traditional visual assessment methods for belt wear and to emphasize the necessity of advanced diagnostic systems like DiagBelt+. The chapter outlines the advantages and key areas where DiagBelt+ contributes to more accurate and efficient monitoring of conveyor belt conditions.

Chapter 6. Predictive modeling based on failure records from the DiagBelt+ system scans

This chapter plays a crucial role in demonstrating the adaptability of the developed methodology across multiple types of failure-recording databases. It presents the characteristics and structure of the utilized datasets, including the distribution of independent variables and relevant features such as belt segment length. The chapter also discusses how these parameters may influence the prediction outcomes under specific operating conditions. Additionally, it includes two-year-ahead failure predictions and provides a comparative analysis with regression-based results to assess the feasibility and reliability of the ANN-generated forecasts.

Conclusion

The work was concluded with a summary in which a comparative analysis of prediction results obtained from two distinct failure-recording databases: human visual inspection and the DiagBelt+ system. The objective of the comparison is not to determine which method of failure recording is superior, but rather to evaluate how the developed methodology for predicting future conveyor belt failure sizes performs when applied to different types of data. The chapter also discusses the practical implications of utilizing each type of database. It concludes by emphasizing that the methodology has been successfully validated across both datasets, confirming its readiness for practical implementation in mining operations.

Chapter 1

Characteristics of conveyor belts and modeling approaches for failure analysis

1.1 Overview of belt conveying systems in coal mining

In a Conveyor belt system (CBS) there are multiple Belt loop (BL) in a system. BL in a CBS comprises multiple medium-length or short rubber belt segments (BSs), ranging from a few dozen to several hundred meters in length. These segments allow for the targeted replacement or repair of damaged sections within the BL, thereby reducing maintenance costs. The belt segments are connected by splices to create a continuous loop, as shown in Fig. 1.1. This Fig. shows a schematic representation of a belt conveyor system, commonly used in industries like mining for transporting bulk materials. The diagram is split into two parts, a top view (plan) and a side view (elevation). Each part highlights important components and concepts related to the conveyor belt's structure and operation. In the top section, the conveyor belt is shown looped around two large pulleys, the tail pulley on the left and the head pulley on the right. These pulleys guide the movement of the belt. The head pulley is typically connected to the drive unit, which powers the motion of the belt, causing it to rotate in a continuous loop. The tail pulley is usually passive and allows the return portion of the belt to loop back to the start. The belt is divided into belt segments labeled BS_1 to BS_7, which stand for belt sections. These sections represent different lengths or pieces of the conveyor belt that may have been joined together during installation or maintenance.

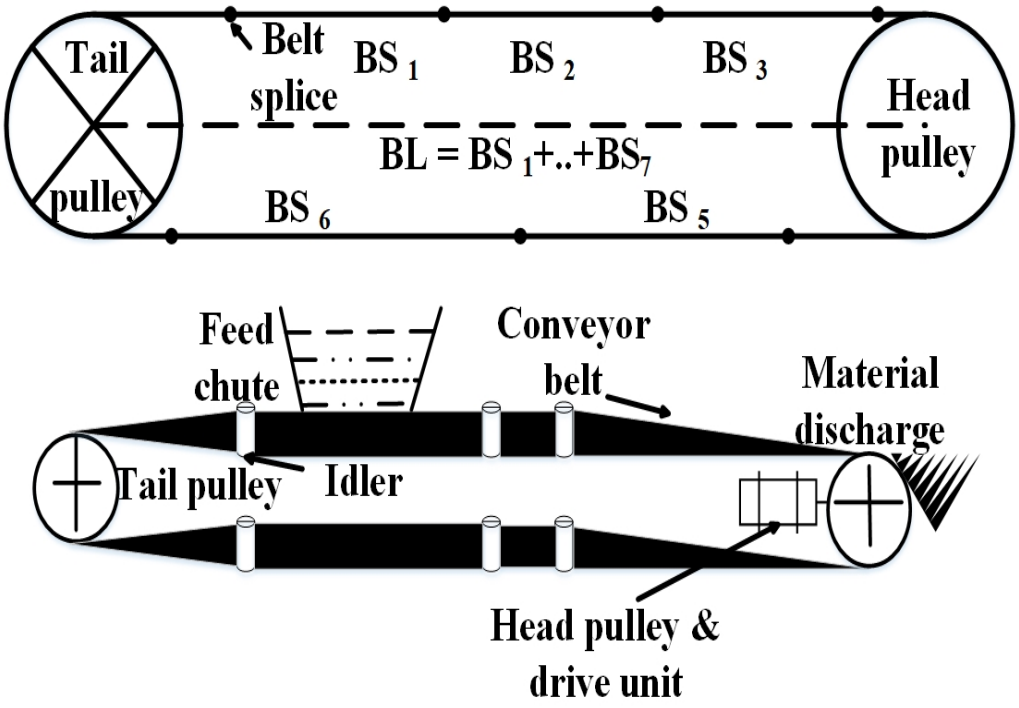


FIGURE 1.1: Schematic representation of a belt conveyor system

One of the notable features in the diagram is the belt splice, a joint where two belt segments have been connected. Splices are critical as they can be weaker points and may influence belt durability [20], [21]. The total length of the belt is represented by BL, which is the sum of all the individual belt sections: BL = BS_1 + BS_2 + ... + BS_7. The lower portion of the diagram presents a side elevation of the conveyor system. Material is loaded onto the belt via a feed chute, which directs the bulk material from a higher point down onto the moving belt. As the belt travels, it is supported by rollers called idlers. These idlers prevent sagging and help keep the belt aligned. As the belt moves toward the right, the material is transported along its length until it reaches the end at the head pulley, where it is discharged—typically into another system, pile, or processing unit. The material discharge is shown at the right end, where the contents carried by the belt are released due to the belt bending around the head pulley. In summary, this image provides a clear visualization of how a conveyor belt system operates, showing key components such as pulleys, belt segments, splices, idlers, and the material flow path from loading (feed chute) to unloading (discharge).

There are primarily eight different types used across various industries. Roller bed type of conveyor belt [22], [23] utilizes rollers placed beneath the belt, reducing friction and making it easier to move heavy loads. The arrangement of idlers forms a trough-shaped cross-section, facilitating the transport of larger material volumes while minimizing material spillage to the sides. The spacing between rollers can be adjusted based on the weight of

the materials being transported. This system is ideal for long-distance transportation or when goods need to move across different elevations. Its ability to support heavy loads makes it popular in industries like warehousing and packaging.

Flat belt conveyors [24], [25] are among the most widely used systems in industries for transporting light- and medium-weight materials. They consist of a flat, continuous belt made of various materials such as rubber, fabric, or synthetic fibers. These systems are commonly found in manufacturing, assembly lines, and airports. Their simplicity and flexibility make them suitable for both horizontal and inclined transportation.

Modular belt conveyors [26], [27] are designed with individual interlocking segments or modules, often made of hard plastic. These segments can be easily replaced or repaired without requiring the entire belt to be changed. Modular belts are ideal for conveying products in industries like food processing, where cleanliness and ease of maintenance are important. The open structure allows for easy cleaning and drainage.

Cleated belt conveyors [28], [29] have vertical cleats or barriers spaced evenly along the belt. These cleats help transport materials at steeper inclines, preventing the products from falling back. Cleated belts are often used in industries that handle loose materials, such as agriculture or food processing, as they can transport materials like grains, vegetables, and powders efficiently.

Curved belt conveyors [30] allow products to be transported around a corner while maintaining the orientation of the material. This type of belt conveyor is useful in industries where space is limited, or production lines need to follow a particular path. They are commonly used in packaging and sorting applications where materials need to be directed to different sections of a facility.

Inclined or declined belt conveyors [31], [32] are used to move products between different elevations. They can be equipped with cleats to hold the material in place as it moves uphill or downhill. These systems are ideal for transporting items from ground level to a higher platform or vice versa, and are often used in industries like construction and agriculture. Sanitary and washdown conveyor belts are designed for environments where hygiene is a priority, such as food processing and pharmaceuticals. They are made from materials that resist contamination and can be easily washed down or sanitized. These systems often feature stainless steel frames and belts made from FDA-approved materials to ensure cleanliness.

Special conveyor belts [33] are customized for unique industrial needs. These can include belts designed to withstand extreme temperatures, belts with magnetic properties for moving metal parts, or belts made from materials resistant to chemicals. These belts are often found in industries such as aerospace, mining, and waste management, where traditional belts would not suffice. Main types of conveyor belts used in mining industries are steel cord conveyor belts, textile reinforced conveyor belts, chevron conveyor belts, pipe conveyor belts, heat resistant conveyor belts, flame-resistant conveyor belts, wire-mesh conveyor belts and aramid conveyor belts.

Steel Cord (ST) Conveyor Belts [34] are reinforced with steel cords, - providing them with high tensile strength and durability. These belts are ideal for long-distance transportation and heavy-duty applications in mining, where they can handle high loads and resist impact. They are often used in high-stress environments, such as underground mines or large-scale open-pit mines.

Textile Reinforced Conveyor Belts [35] use layers of synthetic fabric (like polyester or nylon) to provide flexibility and strength. These belts are commonly used in medium-duty mining operations, such as coal transport, where the belt needs to be durable yet flexible enough for varying load conditions. They are also suitable for shorter distances.

Chevron conveyor belts [36] have a raised pattern or cleats on their surface, which helps to move materials up steep inclines. These belts are particularly useful in mining operations where bulk materials like sand, gravel, or coal need to be transported uphill without slipping back. The cleats also improve grip on uneven terrain.

Pipe conveyor Belts [37], [38] are designed to transport materials in a fully enclosed, tube-like shape. This system prevents spillage and protects the material from external environmental factors like wind or rain. Pipe conveyors are commonly used in mines where minimizing environmental impact is crucial, and material loss must be avoided.

Heat-resistant conveyor belts [39] are used in mining operations where materials are transported at high temperatures, such as in metallurgical processes or areas with high ambient temperatures. These belts are made from materials that can withstand extreme heat without degrading, ensuring they can continue functioning in tough environments.

Flame-resistant conveyor belts [40] are specifically designed to reduce the risk of fire, making them essential in underground mining operations, particularly in coal mines where methane gas and coal dust are present. These belts are treated with flame-resistant materials to improve safety and reduce the risk of combustion.

Wire mesh conveyor belts [41] are used in applications that require high durability and strength, especially for moving abrasive or sharp materials. These belts are made of metal wires woven together, making them suitable for transporting heavy, rugged materials in harsh mining environments.

Aramid conveyor belts [42], [43] are reinforced with aramid fibers, which are known for their strength and lightweight properties. These belts provide a balance between high tensile strength and reduced weight, making them ideal for long-distance material transport in mining. They offer excellent resistance to impact, cutting, and wear.

The method developed in this thesis was applied to a steel cord conveyor belt database obtained from both mines—lignite and limestone mines. Therefore, examining the construction and operational characteristics of this type of belt provides essential insights and supports a deeper understanding of the predicted results.

1.2 Construction and operational characteristics of ST conveyor belts

The Fig. 1.2 illustrates the internal structure of a steel cord conveyor belt, detailing its key components and design features. The "cover carry side" refers to the upper rubber layer of the belt that comes into direct contact with the transported material. The "core rubber" is the layer that binds and protects the steel cords within the belt structure, providing flexibility and durability. "Fabric reinforcement" consists of textile layers embedded within the rubber to enhance tear and impact resistance. The "cover pulley side" is the bottom rubber layer of the belt, which comes into contact with pulleys and rollers during operation. The "cord diameter" indicates the thickness of individual steel cords, while the "cord pitch" defines the distance between adjacent steel cords. The steel cords are arranged in alternating "left twist" and "right twist" directions to ensure structural balance and minimize belt deformation during operation. "Edge rubber" is the lateral rubber protection along the belt edges, preventing wear and contamination. This construction ensures the belt's strength, flexibility, and resistance to mechanical stress during heavy-duty use in mining and other industrial environments.

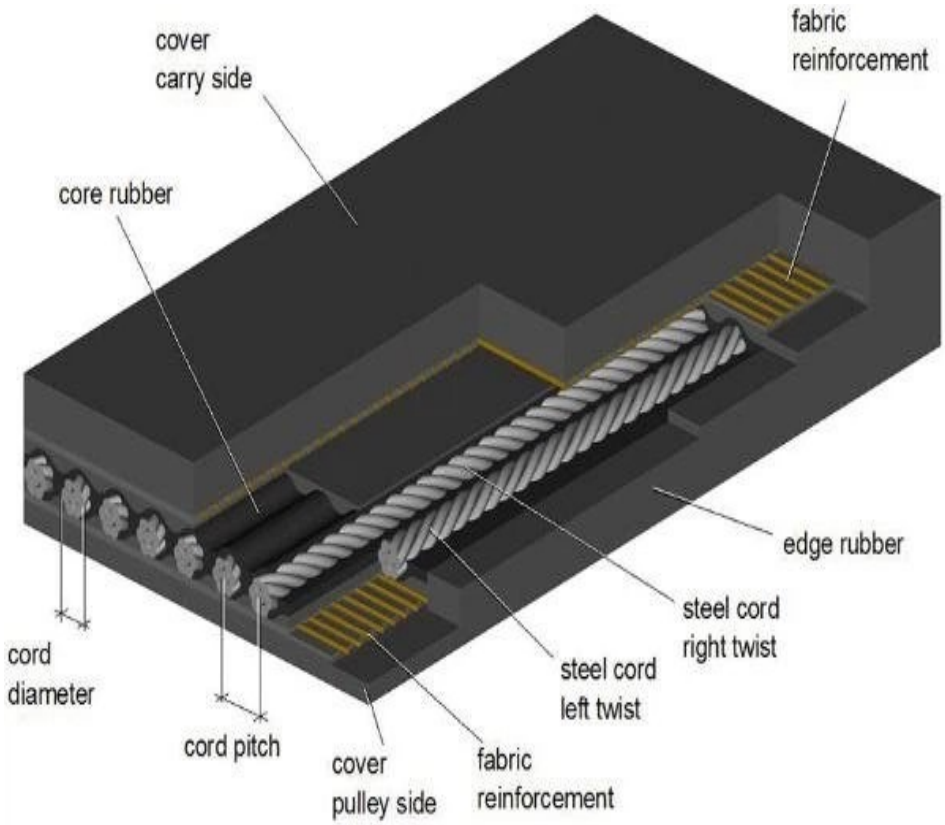


FIGURE 1.2: Steel cord conveyor belt construction [44]

Steel cord conveyor belts possess several notable features that make them highly suitable for demanding industrial applications. One of the primary characteristics is their high tensile strength, which allows them to carry heavy

loads efficiently over long distances. Researchers Błażej et–al.noted that belts rated up to ST-5000 (5000–kN/m) are standard in high-capacity systems, though in-situ monitoring often reveals that tensile strength is overestimated without proper diagnostics–[45]. In addition, these belts exhibit low elongation, meaning they stretch minimally under tension [46]. This ensures consistent performance throughout operation and helps reduce the frequency and cost of maintenance. Another key attribute is their flexibility [47], which enables the belts to bend around smaller pulleys compared to traditional fabric-reinforced alternatives. This enhances their adaptability in compact or complex conveyor systems. Steel cord belts are also recognized for their exceptional durability, offering strong resistance to impact, wear, and adverse environmental conditions. Finally, from a safety perspective, these belts can be manufactured in flame-retardant and heat-resistant variants, making them suitable for specific high-risk applications where thermal resistance and fire protection are essential.

Understanding the construction and operational characteristics of steel cord conveyor belts provides the foundation for evaluating their performance under various industrial conditions. However, even with advanced design features and high-strength materials, the long-term efficiency and safety of these belts depend significantly on how they are maintained.

1.2.1 Maintenance practices for steel cord belts

Maintenance practices for steel cord conveyor belts are essential to ensure their reliability, safety, and extended service life. One of the primary aspects involves regular inspections and visual checks to detect signs of surface wear, mechanical damage, or abnormal belt behavior such as misalignment or slippage. Magnetic tools are employed to measure the belt's thickness, while X-ray scanning is used to identify internal defects, including broken or corroded steel cords within the core [48], [49]. Particular attention should also be paid to edge wear, as frayed or uneven edges may indicate tracking or alignment problems [50].

Proper belt tensioning is another critical factor, as it facilitates effective frictional engagement and the reliable transfer of driving force from the drive drum to the belt [51], [52]. Maintaining optimal tension is necessary to avoid issues such as excessive elongation or slippage. Insufficient tension may result in sagging, increased resistance to movement, overheating of the drive drum which in extreme cases can lead to fire hazards—poor tracking, and higher energy costs. Conversely, excessive tension can make the belt more susceptible to mechanical damage, longitudinal tearing, and increased wear due to heightened resistance.

Alignment and tracking must be consistently maintained to ensure the belt runs true along its intended path. Misalignment can cause uneven wear, edge fraying, and inefficient operation [53]. Regular adjustments and monitoring of tracking systems are essential to minimize resistance, energy consumption, and unnecessary belt strain.

Pulleys and idlers also require systematic maintenance. Pulleys should be examined for lagging wear or surface damage, while idlers must be checked for free rotation [54]. Those with damaged or seized bearings should be promptly replaced to prevent localized wear and belt distortion[55].

The condition of belt splices is equally important. Splices should be periodically inspected for signs of wear, separation, or structural weakening. If deterioration is observed, the affected joints should be reinforced or replaced to avoid sudden failure during operation[56], [57].

Cleaning and lubrication contribute significantly to overall belt health. The belt and the surrounding conveyor components must be kept free of debris to reduce abrasive wear. Pulleys, idlers, and moving parts should be adequately lubricated to ensure smooth operation and reduce frictional losses.

Lastly, environmental protection measures should be in place to safeguard the conveyor belt from harsh operating conditions. Using appropriate covers or enclosures helps defend against the damaging effects of extreme temperatures, high humidity, corrosive chemicals, and other external threats, thereby extending the functional lifespan of the belt system.

Despite the implementation of comprehensive maintenance practices, steel cord conveyor belts remain susceptible to various forms of damage due to operational stresses and environmental influences. Understanding the typical modes of failure and degradation is therefore essential to developing effective diagnostic strategies and targeted interventions that mitigate unplanned downtime and extend belt service life.

1.2.2 Common modes of failure and degradation

Understanding and addressing the root causes of failure in steel cord conveyor belts is essential to prevent recurring issues and ensure reliable operation. Common modes of failure include surface wear, steel cord breakage, cord corrosion, splice failure, edge damage, and cover delamination, each with distinct causes, detection methods, and preventive strategies.

Surface wear typically results from abrasion caused by conveyed materials and the accumulation of external debris. It is usually detected through visible thinning of the top cover or the appearance of surface cracks, while preventive measures include the use of wear-resistant rubber covers and routine cleaning of the belts and the surrounding conveyor structure to minimize abrasion [58].

Steel cord breakage often occurs due to overloading, sudden tension spikes, or bending around pulleys with diameters that are too small for the belt's design. These faults are commonly detected using non-destructive techniques such as X-ray or magnetic inspections—specifically, tools like the DiagBelt system developed at Wrocław University of Science and Technology—enabling precise identification of broken cords within the belt core. Prevention focuses on respecting load limits and selecting pulleys that meet standardized belt specifications [58], [59].

Cord corrosion is frequently caused by the ingress of moisture or chemical exposure through compromised cover layers, leading to steel cord weakening or breaks as evidenced by magnetic-core inspection data. Preventive strategies include manufacturing belts with corrosion-resistant steel cords (e.g., zinc coatings) and prompt repair of damaged covers [58].

Splice failure, resulting from improper splicing techniques, fatigue loading, or environmental effects, manifests as visible separation or cracking at the joint. Effective prevention incorporates rigorous quality-control during splice construction and scheduled inspections to identify structural weaknesses before they lead to operational failure [57].

Edge damage is commonly associated with belt misalignment, contact with conveyor structure, or uneven loading. Frayed or delaminated edges typically signal misalignment, which can be mitigated by precise belt tracking and reinforcing edges with robust materials [58].

Cover delamination arises from bonding failure between rubber layers due to aging, heat, or manufacturing defects. It becomes visible through peeling or bubbling and can be avoided by selecting high-quality belts with proven bonding processes and avoiding extreme environmental exposure [58].

To comprehensively reduce the risk of failure, best practices for steel cord conveyor belts include implementing a preventive maintenance schedule and utilizing condition-monitoring tools such as the DiagBelt magnetic inspection system [49]. Early detection of internal damage enables timely corrective measures, while training maintenance staff to recognize early warning signs and collaborating with manufacturers ensures that maintenance strategies are tailored to operational environments. Advanced diagnostic technologies offer real-time monitoring capabilities and support non-destructive evaluation of issues such as cord breakage, corrosion, splice deterioration, and cover separation [58], [60].

Advanced diagnostic tools

Advanced diagnostic tools play a crucial role in monitoring the condition of steel cord conveyor belts and enabling early detection of internal damage or structural defects. Among these tools, X-ray inspection systems are widely used due to their ability to penetrate the belt and produce high-resolution images of its internal structure, allowing for the identification of broken cords, corrosion, and other hidden defects [61], [62].

Ultrasonic testing is another effective method, which involves sending ultrasonic waves through the belt material and analyzing the reflected signals to detect anomalies. This technique is particularly useful in locating delamination between layers and identifying cracks or voids in the rubber cover or steel cords. A specific implementation, such as the BeltSonic system [48], measures the distance between the ultrasonic emitter and the belt surface. While it can detect holes or fractures, its sensitivity is limited to areas directly under sparse emitter points.

Magnetic flux leakage (MFL) technology is used to assess the condition of the steel cords within the belt [49], [56]. In this method, magnetic fields are applied to the cords, and sensors measure any distortions in the field, which

may be caused by broken wires or corrosion, indicating structural compromise.

Infrared thermography [63], [64], [65] involves the use of infrared cameras to capture thermal images of the belt surface. By detecting abnormal heat patterns, this technique can reveal areas of increased friction, slippage, or misalignment, often indicating mechanical wear or impending failure.

Embedded RFID systems [66] represent a modern and intelligent approach to belt monitoring. These systems incorporate RFID tags with integrated sensors directly into the belt structure to collect real-time data on parameters such as tension, temperature, and belt usage, enhancing predictive maintenance capabilities.

Acoustic emission monitoring [67] detects high-frequency sound waves generated by the formation or propagation of micro-cracks, delamination, or steel cord breakage. By analyzing these acoustic signals, maintenance teams can pinpoint developing issues before they result in operational failure.

Three-dimensional laser scanning [68] provides a precise measurement of the belt's surface contour. By projecting laser beams across the belt surface, this technique identifies deformations, irregularities, or abnormal wear patterns that may not be visible through conventional inspections.

Finally, vibration analysis [69], [70] involves measuring the vibration signals produced by the conveyor system during operation. Variations in these signals can indicate imbalances, misalignment, or damage in the belt itself or in key components such as pulleys and idlers, enabling timely intervention and repairs.

Many of these diagnostic tools are increasingly integrated with advanced digital platforms that support predictive maintenance and real-time monitoring. Many of these diagnostic tools are increasingly integrated with advanced digital platforms that support predictive maintenance and real-time monitoring. This integration not only enhances the accuracy and speed of fault detection but also enables proactive decision-making, reduces unexpected downtime, and extends the operational life of machinery. Moreover, real-time data analytics allow maintenance teams to prioritize tasks efficiently, minimize maintenance costs, and improve overall system reliability and productivity.

Integration with digital systems

Internet of Things (IoT) [71] sensors [72] play a key role by continuously collecting data on critical parameters such as belt tension, operational speed, and wear. This continuous flow of information enables timely detection of irregularities and facilitates proactive decision-making. Artificial intelligence and machine learning algorithms are employed to analyze the collected diagnostic data, allowing for accurate prediction of potential failures and the generation of maintenance recommendations based on historical patterns and real-time inputs. Additionally, centralized monitoring systems consolidate data from various diagnostic tools to provide a holistic and comprehensive view of the conveyor belt's health, enhancing operational efficiency and minimizing unplanned downtime.

The preceding sections have outlined the primary factors contributing to belt degradation, current diagnostic technologies used for condition assessment, and best practices for maintaining the integrity of steel cord conveyor belts. To further contextualize these aspects, it is essential to examine the state of research in this domain. The subsequent section presents a comprehensive literature review focused on conveyor belt wear and failure mechanisms, highlighting recent advances, key findings, and existing knowledge gaps in the field. This literature review establishes the foundational basis for an Ishikawa diagram as shown in Fig. 1.5, presented later in this chapter and offers a comprehensive analysis of the key parameters contributing to conveyor belt damage at mining sites. The parameters influencing conveyor belt (CB) damage, as identified in the literature review, are not intended to support a specific conclusion or validate a particular hypothesis. Instead, they serve to delineate a distinct set of contributing parameters that underlie CB degradation during operation in mining environments.

1.3 Literature review on conveyor belt wear and failure

Conveyor Belt Systems are critical to maintaining operational efficiency at mining sites, but they operate under harsh conditions, often exposed to abrasive materials, high loads, and varying environmental factors, making them prone to wear and unexpected breakdowns, which can result in significant financial losses [73]. CBs are the most valuable and essential components of the entire CBS, enduring various operational loads that lead to wear and damage [7], [8]. During the loading, delivery, and transport processes, belt loops and their segments are subjected to destructive forces from sharp objects and heavy impacts [4], [74].

The wear resistance of the outer rubber covers, which account for a substantial portion of the belt's thickness, plays a crucial role in determining their service life. Both steel cord and multiply belts have at least 70% of their thickness covered by rubber, significantly impacting manufacturing costs [75]. Fedorko et al. [76] observed that damage to conveyor belts often begins with penetration through the top cover, eventually affecting the carcass and underlying layers, as shown in Figs. 1.3 and 1.4. Cerny et al. [77] emphasized that frequent intense loads exacerbate this wear. Early identification of such damage through regular monitoring can prevent further deterioration, with proactive repairs avoiding costly breakdowns. In some cases, damaged sections of the belt must be removed, shortening the overall belt length.



FIGURE 1.3: Damaged conveyor belt [78]



FIGURE 1.4: Damaged conveyor belt patch [78]

Loading and discharging bulk materials primarily affect the top layer of the belt, with 80% of wear occurring on the top cover and 20% on the bottom cover [79]. Shorter belts endure more cycles, while longer belts experience fewer due to their greater loop length. Friction from drum surfaces and idlers, which are in direct contact with the bottom cover, also contributes to wear. Abrasion of belt covers can generate fine rubber particles that may negatively impact the environment. Although research on this issue hasn't specifically focused on CBSs, similar studies on tires have been conducted [80]. The extent of belt cover wear can be measured using systems like Beltsonic [79], with punctures at feed points accelerating the process.

Studies such as those by Babiarz et al. [81] highlight the significant challenges faced by Polish lignite mining sites, including machinery damage and

costly repairs from unanticipated failures. Research has shown that proactive maintenance and predictive diagnostics can enhance productivity and yield economic benefits. Implementing monitoring, diagnostics, and prediction techniques to anticipate belt failures is therefore crucial for improving production output in plants utilizing CBSs.

A skilled workforce is essential for successfully operating any production site at its optimal condition. The influence of human-related factors on failures is indirect; however, deficiencies in maintenance practices, care, or personnel qualifications can accelerate the progression of failure development. For instance, neglecting to patch cuts in the conveyor belt can facilitate water ingress, leading to corrosion. Similarly, failure to remove accumulated materials from bottom idler sets can exacerbate abrasion. In certain cases, improper installation can directly contribute to failures; for example, inadequate support at loading points can increase the frequency of failures. Overall, these factors primarily affect the rate at which failures occur rather than serving as direct causes. Several research studies confirm this, suggesting that the critical factor in belt deterioration is not solely the quality of the product itself but also the selection process [55], [82], [83].

Molnár et al. [84] investigated the effects of two-body and three-body abrasive conditions by employing the ISO 4649 and ASTM G65M testing methods, respectively. Their findings revealed several key observations. The central region of the conveyor belt exhibited a comparatively smoother surface, whereas the rim region showed significant cracking. It was also observed that sharp-edged abrasive materials had a particularly destructive impact on the belt. The study demonstrated a correlation between abrasion rates and tensile strength based on regression analysis. Furthermore, tear strength emerged as the most influential parameter in the ASTM G65M testing method. The authors emphasized the importance of selecting an appropriate testing procedure, noting that the ISO 4649 method, which relies on a two-body abrasion mechanism, may not accurately represent real-world operational conditions. In contrast, the ASTM G65M test, based on a three-body abrasion mechanism, was considered more representative of the actual fatigue and wear experienced by conveyor belts in practical applications.

The nature of damage inflicted upon the belt is contingent upon several factors, including the material properties of the belt itself, the characteristics of the transported materials, and the operational conditions [85]. Each transported material (coal, overburden, mixture) possesses its own unique composition of properties, leading to distinct types of damage to the rubber belt. Throughout the journey from loading point to dumping point, materials are in constant contact with the CB, and various factors contribute to damage, such as the quantity and size distribution of the material, high throughput and impact velocity, abrasive nature of the material, improper loading causing pitting, relative density, sharp edges of raw materials, and continuous operation time of material transportation. The CBs used at mining sites endure heavy-duty payloads continuously, underscoring the need to assess their influence on both the upper layers of the CB and the overall system itself.

Furthermore, within the entire conveyor belt system, issues like material carry back (accumulation of dust and transported material on idler rolls and pulleys over time) and belt mis-tracking are among the primary causes [86], which can lead to disruptions in material movement at mining sites. Consequently, considering all the potential factors that can impact the condition of the CB, premature wear is often observed [87]. Sharp and rough surfaces accelerate the wearing out and eventual destruction of rubber parts over time. Xie et al. [88] and Chen et al. [89] discuss wear and fault detection in their respective works.

Overloading [90] occurs when the conveyor belt is subjected to more - weight than it is designed to handle. This can lead to mechanical strain and operational inefficiencies. It can be caused by incorrect estimation of load capacity, improper loading practices, and lack of monitoring systems. It affects the belt by belt sagging, increased wear and tear, motor overload, and potential system failure. The load significantly influences the durability of conveyor belts [91] and energy consumption [92]. A portion of the energy required to transport material on a conveyor belt is dissipated through impact damage, wear, and deformation of the belt. Consequently, the energy consumption per kilogram of material per kilometer of transportation decreases when the conveyor operates at full load. Impacts from falling material are more detrimental to an empty belt compared to a loaded one, as the material already present helps absorb and distribute the impact force. However, overloading leads to spillage and increased wear, particularly from idlers rotating under the stress of excessive material load. Blockages [93] happen when materials accumulate and obstruct the conveyor belt's movement. It can leed to belt break, sudden failures as tearing the belt off. Cumulative failures are wearing of covers and increasing number of cables cuts, increasing length of corrosion (lack of metal) or increasing are of failuer (hole in the belt cord - several cables cut in one place). This can cause a sudden halt in operations and damage to the belt. it can be caused by large chunks of coal or debris, inadequate material flow control, and malfunctioning transfer points. Impact it can have are operational downtime, belt damage, and increased maintenance efforts to clear the blockage.

The damage to the CB during operation can be categorized into two distinct types: (i) occasional or local damage, and (ii) repeated or linear damage. Occasional damage occurs in limited sections of the belt, while linear damage is distributed along the entire length of the belt loop. Continuous damage, associated with the belts age and the number of cycles it undergoes during operation, also influences the number of impacts on the belt and, consequently, the degree of damage. Researchers[94], [95] have noted that damage often starts at the top layer of the CB and then expands to the carcass and bottom layers. Regular monitoring of the upper layer of the rubber belt can help minimize damage to the steel cord. Belt-related parameters such as insufficient cover thickness, resistance to abrasion, and puncture resistance also play decisive roles. Additionally, the importance of the wearing process in rubber products under constant intensive loads has been highlighted by Cerny et al [77]. Bajda et al. [6] highlighted the correlation between the

length of the CB and its operating time, along with the impact on belt reliability, which diminishes with an increased number of belt splices and segments within the belt loop. They indicated that a higher number of belt segments in the loop leads to lower reliability, causing periodic emergency down-times and consequently higher operating costs. The addition of extra splices to the belt loop decreases the reliability of the entire belt, as the durability of the splice is lower compared to that of the belt itself [12]. Therefore, the number of belt splices within the loop, along with their design and build quality, significantly influences the performance of the belt loop [77]. Bajda et al. [6] also noted that the age of belt segments could be up to 71 months, resulting in a 12.7% increase in the number of belt segments and splices. As the average belt age approached that of disassembled belts, there was a 19% increase in the sections and splices of the conveyor belt. Frequent changes to belt sections and splices led to an increased number of splices and sections in the belt loop, incurring higher costs. To mitigate this, they suggested replacing either the entire belt section or the damaged portion of the belt up to the splice. Another crucial comparison highlighted by them was the average duration of downtime for belt failures, which can typically be resolved within 10 hours, compared to belt splices, which require 70.71 minutes and 93.9 minutes, respectively. Monitoring and diagnosing belt and splice conditions [87], [96], [97], [98] can minimize such down-times, reducing losses and enabling mining sites to operate at optimal capacities. Solutions to counter the increasing risk of breakdowns due to belt aging and the number of splices are already being implemented by mines [12], [13], [14].

The operational and maintenance parameters can be categorized into two distinct sub-categories, low budget constraints and human error. Low financial budgets constrain the availability of other resources on production sites, leading to a chain reaction: imbalance or shortage of skilled and unskilled human resources (often due to lack of training) $\rightarrow$ lack of tools and equipment (such as computer systems and spare machinery parts) $\rightarrow$ absence of diagnostic equipment $\rightarrow$ poor design and improper installation of energy-absorbing devices. Human error constitutes the next major subsection within the operational and maintenance category, encompassing avoidable errors and lapses in effort. Such oversights result in low-quality repairs, inadequate maintenance frequency, surveillance, and poor or absent database management of events occurring at mining sites. Human error is a significant factor in decision-making and policy implementation at production sites and can often be controlled in the majority of cases. The disparity between the expected life of a belt segment and its actual service life in the field until complete failure occurs is concerning.

Manufacturing defects in conveyor belts can significantly impact their performance, durability, and safety. Material-related deficiencies, as noted by Bortnowski [90], may arise from the use of substandard rubber compounds or metal components during production. These defects create inherent weak points within the belt structure, increasing the likelihood of premature failures. The consequences of such material flaws include reduced belt lifespan, more frequent repair interventions, and heightened safety risks within the

operational environment.

In addition to material quality, workmanship issues also play a critical role in determining belt reliability. According to Bortnowski [90] and the EN 14051:2012 standard [99], poor manufacturing practices such as improper splicing techniques and flawed assembly processes can compromise the structural integrity of the belt. These workmanship-related shortcomings can result in an elevated risk of belt failure, increased maintenance expenditures, and unplanned interruptions to industrial operations, all of which underscore the importance of adhering to stringent manufacturing standards and quality control protocols.

Incorrect conveyor belt alignment [100] during installation can cause mistracking and uneven wear. Increased maintenance efforts, reduced belt life, and potential safety risks are the impacts it can have. Inadequate tensioning[101] of the belt during installation can lead to slippage and inefficient power transmission. It can result in reduced operational efficiency, increased wear on the belt, and potential motor overload. Lack of training [102], [103], [104], insufficient training for personnel handling the conveyor systems can result in improper use and handling, contributing to failures. Increased risk of operational errors, higher maintenance costs, and reduced system reliability are the impacts of it. Ignoring manufacturer guidelines [102], [103], [104], failure to adhere to the manufacturer's operational guidelines and load specifications can lead to overloading and subsequent failure. Mechanical strain, increased wear and tear, and potential system breakdown are some of the possible outcomes of it.

Inappropriate design specifications [90], [105], incorrect design specifications, such as improper belt width, tension, idler set and spacing, speed, or material selection, can lead to operational inefficiencies and premature failures. Their impact could be Increased operational costs, frequent breakdowns, and reduced belt life. Inadequate lubrication [106], lubrication is crucial for the smooth operation of moving parts in the conveyor system. Inadequate lubrication can lead to increased friction and eventual failure of components. It can be caused by neglecting regular lubrication schedules, using inappropriate lubricants, and lack of access to lubrication points. Increased wear on bearings and rollers, potential overheating, and mechanical breakdowns are few of the impacts it can have. Poor maintenance practices [107] include neglecting regular inspections, failing to replace worn out parts, and not adhering to maintenance schedules. Lack of maintenance personnel, insufficient training, and budget constraints are some of the possible causes of it. It can impact such as escalation of minor issues into significant failures, increased downtime, and higher repair costs.

Belt mis-tracking [90], [108], it occurs when the conveyor belt veers off its intended path, causing it to run off-center. This can lead to significant damage, including edge wear and tearing. Causes of belt mis-tracking could be misalignment of the belt, damaged idlers, improper loading of materials, and structural defects in the conveyor system. Impact of the belt mis-tracking could be increased maintenance costs, reduced belt life, and potential safety hazards. Belt slippage [90] happens when the drive pulley fails to maintain

adequate traction with the belt. This can result in a loss of power transmission and inefficient operation. Possible causes of it are inadequate tension, worn-out lagging on the drive pulley, and contamination on the belt surface. It can create impact such as reduced conveyor efficiency, increased wear on the belt, and potential overheating of the drive motor. Belt tear [61] are significant structural damages that compromise the integrity of the belt. These can be longitudinal or transverse tears caused by external forces. It can be caused due to sharp objects falling onto the belt, excessive material buildup, and improper maintenance leading to weakened belt areas. Impact it can have includes immediate shutdown of the conveyor system, high repair costs, and potential safety risks to workers.

Poor environmental consideration [109], failure to account for environmental factors during the design phase, such as temperature variations- humidity [110], and chemical exposure, can lead to accelerated degradation of conveyor components. Higher maintenance costs and reduced reliability of the conveyor system are few possible impacts it can have. Corrosion [111] is the degradation of metal components of the conveyor belt system (CBS) due to exposure to moisture and chemicals. This is particularly problematic in humid or chemically aggressive environments and temperature differences. It is caused by exposure to water, coal dust, and acidic or alkaline materials, ambient temperature changes commonly found in mining environments. Weakening of structural components, increased risk of mechanical failure, and higher maintenance costs are the impacts it can generate. Wear and tear [90], [112] refer to the gradual degradation of the conveyor belt due to continuous use and exposure to abrasive materials. Constant contact with coal and other abrasive materials, improper maintenance practices, and high operational speeds are the causes. Their impact can result in reduction in belt life, increased frequency of replacements, and higher operational costs.

The current service lifetime from the mounting date often deviates from expectations. Repairing machines in remote mining facilities is challenging due to the lack of spare parts and skilled workforce. Zimroz et al. [113] underscore the importance of environmental and ambient working conditions. Operating conditions at mining sites differ significantly from other production sites. Extreme temperatures, chemical exposure, and humid conditions exacerbate the effects of saltwater seepage from underground sources. Additionally, continuous mining activities result in high dust exposure in the environment. These factors contribute to accelerated aging and surface wear of rubber belts. Rainfall also adversely impacts mining operations, facilitating the wear process on rubber belts. Research has established that UV radiation is another important variable that contributes to wear processes. After identifying all the parameters influencing conveyor belt damage during material handling through the literature review, the author developed an Ishikawa diagram to analyze the cause (various factors affecting the damage) and effect (damage to the conveyor belt).

The operational costs of mines can be minimized by maintaining optimal conditions and implementing effective strategies [12], [13], [14]. The

performance of specific materials is closely tied to operating conditions, determined by the expertise of human resources at the mining site. Human involvement plays a crucial role in belt deterioration, influenced by both the quality of materials and the accuracy of their selection [55], [82], [83]. Material properties, transported material, and operating conditions interact significantly to affect belt wear [85]. Zimroz et al. [113] stressed the importance of ambient working conditions during mining operations.

The insights gathered from the literature review have provided a structured understanding of the diverse factors contributing to conveyor belt wear and damage in mining operations. Based on this analysis, the author has categorized the root causes into six primary groups. These categories reflect the multifaceted nature of belt degradation and serve as a foundation for deeper analysis of failure mechanisms during material transfer processes in mines.

1.3.1 Six major cause categories of parameters contributing to conveyor belt damage

People related parameters

Human-related factors strongly influence the reliability and effectiveness of conveyor belt systems. Low availability of skilled workforce—remote location, particularly in remote mining locations, impairs timely maintenance and limits access to critical diagnostics. Limited staffing often causes reactive rather than proactive maintenance strategies, raising the likelihood of unplanned failures [114], [115]. Incorrect use and installations including improper belt tensioning, misaligned idlers, and faulty splice installation leads to uneven wear patterns, increased energy consumption, and early belt failure, as these errors covers and splice areas. Lack of experience or rotation of service includes lack of experience of frequent rotation of service personnel disrupts continuity in maintenance practices. When personnel change often, knowledge transfer is hindered, reducing the likelihood of detecting subtle pre failure signals and undermining consistent inspection protocols. The selection of incompatible testing methods for conveyor belts—such as reliance on visual inspection alone instead of advanced diagnostic tools (e.g., magnetic or X-ray scanners)—can result in missed internal damage and delayed detection of critical conditions [70], [115]. Wrong selection of CB material—strength, construction for operating conditions contains, the wrong selection of CB material, in terms of strength and construction relative to operating conditions, impairs belt resilience. Choosing belts with insufficient tensile strength or inappropriate core types (e.g., textile instead steel-cord) can result in rapid degradation when exposed to heavy loads or high-impact scenarios. Poor personnel—low salary, less trainings translates poor personnel conditions, including low salaries and inadequate training, diminish workforce motivation and reduce the adoption of standardized maintenance procedures. This often leads to shortcuts, skipped inspections and improper handling of critical operations, impacting the belts overall durability and safety.

Transported material related parameters

The characteristics of the material being transported are pivotal in determining conveyor belt wear and performance. Sharp-edged material impacts, such as elongated or crushed rock fragments, lead to punctures and gouges in the belt cover, progressively weakening the structure [116]. High product density increases the normal force on the belt, which—when combined with abrasion—accelerates surface fatigue and core degradation [117]. Type of material—coal, overburden, mixture of materials exhibit varied wear behaviors; coal is generally less abrasive than rocky overburden, while mixed material streams result in unpredictable loading patterns [118].High throughput of material subject the belt to more frequent loading cycles, elevating cumulative fatigue and progressive wear [118], [119]. High abrasivity of material, such as silica-rich ores, increase sliding and impact wear through abrasive mechanisms [117], [120].

High relative impact velocity—when material hits the moving belt at high speed—amplifies impact energy, causing harsher damage to the cover layer [121]. Likewise, pitting from improper loading—due to material depositing in concentrated spots—induces localized stress, forming pits and cracks on the belt surface. The relative density of materials influences line-load and dynamics, with denser materials raising tension and energy absorption requirements [119]. Distribution & the lump size of carry material on the grain curve foster edge wear, tracking issues, and micro-cracking due to non-uniform load paths [119]. High presence of large lumps in the grain curve acted upon by high drop heights further intensifies impact damage, leading to deep indentations or tears [116]. Finally, continuous operation time under transport conditions without adequate rest or cooling cycles accelerates degradation through sustained mechanical fatigue and thermal buildup [118]. Together, these parameters define a complex interplay of geometric loading, material properties, and operational dynamics, all of which must be incorporated into predictive models for accurate maintenance planning and belt life estimation.

Belt and belt splices related parameters

Number of cycles at present (high # of impacts) indicative of high-impact frequency, directly correlates with belt fatigue. Each passing load cycle induces bending and stress at splices, edges, and cords, while repeated impacts (high numbers of impacts) exacerbate internal breakdown, as evidenced by studies on NDT detection of fatigue zones in belt cores [122]. Closely related, BS expected age & age at failure (%, months)—measured as percentages or months—serve as critical predictors in lifespan models. Research from Wroclaw University shows that splice strength diminishes over time, lowering the mean time between failures (MTBF) under prolonged use [6]. Current age of the BS (from the first installation)—also informs residual service life. Older belts lose resilience due to rubber hardening and diminished bonding layers [115]. Belt parameters: too low cover thickness, resistance to abrasion, puncture resistance markedly increase wear and vulnerability to puncture or tearing; standards like ISO 9856 quantify these factors [123]. The distinction between new or used BS matters—reused cores may have compromised

internal structure, causing inconsistent performance [115].

Incompatible splice construction and properties, including layer mismatch, improper step configuration, or compound incompatibility, lead to weak joints that significantly reduce splice efficiency and accelerate edge fatigue [124]. Additionally, shorter belt segment length & high number of splices in the belt loop is detrimental—an increased splice count introduces more potential failure points, reducing overall belt integrity [6]. Finally, weak construction quality of belt and splice—such as inadequate adhesion, poor vulcanization, or uneven layer alignment—significantly reduces dynamic splice strength and increases wear; laboratory studies report splice efficiencies as low as approximately 50–60% under such conditions [99].

Parameters related to organizational activities

Organizational factors significantly determine the operational reliability and maintenance efficiency of conveyor belt (CB) systems. Insufficient frequency of maintenance, surveillance increases the risk of unnoticed wear and misalignment, often resulting in catastrophic failures due to accumulated damage [125]. Poor quality of repairs, including substandard splice work or improper component replacements, compromises the belt's structural integrity and accelerates failure modes [126]. Poor database management of belts and events—such as lack of systematic logging of belt usage, failures, and repair actions—impairs trend analysis and forecasting, undermining proactive maintenance planning [90]. Imbalance of specialist and non-specialist man power, where routine tasks are performed by inadequately trained workers, leads to misdiagnosis, improper repair decisions, and inconsistent belt care.

Lack or not enough trainings for maintenance staff diminishes their ability to correctly adjust tension, perform diagnostics, or install splices—leading to recurrent breakdowns. Usage of compromised rubber parameters: strength, abrasiveness, hardness, where belts featuring substandard strength, poor abrasion resistance, or wrong hardness specifications are deployed, shortens lifespan and heightens wear susceptibility [126]. Poor quality spare parts, such as low-grade rollers or splice kits, introduce premature wear and cause frequent malfunctions [125]. Lack of diagnostic equipment—like magnetic scanners, thickness gauges, or X-ray tools—limits the early detection of failures and impedes condition monitoring [90].

Lack of computer aided management systems prevents efficient scheduling, record keeping, and maintenance optimization, often leading to reactive rather than predictive actions [125]. Poor design and improper installation of energy absorbing devices (e.g., impact beds or chute liners) means excessive impact forces are unmitigated at load points, causing punctures, accelerated wear, and material spillage [126]. These organizational shortcomings collectively undermine technical strategies and negate the benefits of predictive maintenance frameworks, emphasizing the need for robust management processes and trained personnel to support system longevity and performance.

Conveyor related parameters

The conveyor's operational mechanics profoundly influence belt performance and longevity. High relative velocity of the receiving belt and falling material intensifies impact forces, promoting puncture and cover damage; this has been rigorously demonstrated in impact-resistance studies through statistical correlation between belt damage and relative impact speed and height [127], [128].

High difference in theoretical and real capacity of material transportation such as when belt feeders or loading chutes are miscalibrated—lead to overloads, energy inefficiencies, and belt strain, a phenomenon observed in mining-driven energy efficiency studies. Tension in the splices, speed, bend radius, tracking jointly significantly regulate stress profiles and fatigue zones across the belt; research demonstrates how bend radius and idler spacing influence tension distribution and failure risk . Belt loop length, belt segment length affect dynamic loading and vibration modes; longer belt runs have been shown to suffer increased stress accumulation and lower resilience under dynamic conditions [129], [130]. Incompatible inclination of the belt and angle of impact from the falling material—particularly in chutes with steep drops—contribute to gouging and accelerated wear; studies show chute redesign reducing damage when impact angles are aligned with belt movement [131]. Wrong dimensions of the belt: thickness, length, width can cause mismatching with pulley sizes and idler geometry, leading to edge cracking and structural fatigue. Transfer points: High height of the material drop, lack of energy absorption, high acceleration of material—especially high drop heights lacking energy-absorbing features, produce high acceleration impacts that increase penetrating and bending stresses; experimental dynamic absorption models quantify how impact forces concentrate energy in these zones [132]. Poor & incompatible design: wrong dimensions, lack of covers, loading point design geometry—impairs material flow and support, causing accelerative loading, spillage, idler damage, and misalignment. Empirical modeling underscores the need for accurately designed conveyor structures to prevent localized stress and belt damage.

Environment related parameters

Environmental conditions significantly influence the durability and operational efficacy of conveyor belt systems. Extreme temperature conditions, both high and low, can degrade belt performance by altering material properties. Elevated temperatures accelerate thermal ageing, leading to rubber stiffening and reduced elongation capacity, while sub-zero temperatures cause brittleness and cracking under load [133]. Chemical exposure and salt water introduce corrosive elements that can deteriorate internal steel-cord structures and damage rubber bonding layers, weakening splice integrity over time [134]. Similarly, faster ageing of CB due to elevated temperatures involves thermally induced oxidative processes that break down polymer chains, a phenomenon intensified when combined with UV (ultraviolet) and ozone exposure . High dust exposure, especially from abrasive particles like coal or mineral fines, exacerbates surface wear and promotes ingress into cracks, further compounding mechanical fatigue . High humidity, Rain, quality

of surrounding air particles introduce moisture that penetrates the belt carcass, causing swelling of textile plies, promoting corrosion, and giving rise to tracking issues and delamination [135]. Finally, exposure to high UV radiation levels and ground-level ozone triggers photochemical degradation of rubber surfaces, leading to ozone cracking, loss of tensile strength, and premature failure—even indoors under fluorescent lighting [136].

Following the identification of relevant parameters through a comprehensive literature review and expert consultations with mining site personnel—who contributed experiential knowledge of parameters observable only through on-site practice—these factors were systematically incorporated into a root cause analysis. The outcome of this analysis is presented in the form of an Ishikawa diagram, as shown in Fig. 1.5. This approach facilitates the systematic linkage of categorized causes to the observed damage in the conveyor belt. After enlisting all the parameters into the Ishikawa diagram, the quantifiable parameters were identified and then their availability has been checked within the database. The parameters used for different databases are mentioned in the chapters 4, 6 and are summarized in Tables 4.1, 4.2, 6.1, and 6.2.

1.3.2 Failure classification and root cause analysis

The Ishikawa diagram, also known as the Fishbone diagram or Cause-and-Effect diagram, is a widely utilized tool for systematically identifying and organizing potential causes of a problem in order to uncover its root causes. It was developed by Kaoru Ishikawa, a pioneer in the field of quality management, and was first introduced in his book Guide to Quality Control [137]. The diagram visually resembles the skeleton of a fish, with the main problem placed at the "head" and major cause categories branching out like "bones." These categories commonly include Methods, Machines, Materials, People, Environment, and Measurement, which help guide the exploration of all potential contributing factors.

The Ishikawa diagram plays a fundamental role in quality management and continuous improvement efforts. It is particularly effective in structuring brainstorming sessions, enabling teams to visually map out all possible causes of a problem in a comprehensive and organized manner. This structured approach ensures that both obvious and hidden root causes are examined, making the analysis more robust and reliable [138]. The main components of the diagram include the problem statement, which is placed at the head, followed by main cause categories and their associated sub-causes, forming a hierarchical structure for detailed cause-and-effect evaluation.

Its utility in root cause analysis is further emphasized by its broad application across a wide range of sectors. In healthcare, it is used to analyze medication errors and improve patient safety [139]; in environmental science, it aids in understanding complex issues such as water pollution [140]; in engineering, it contributes to failure analysis and design optimization [141]; and in information technology, it supports software development and debugging

processes [142]. The versatility of the Ishikawa diagram is also reflected in its widespread adoption in manufacturing and service industries [143].

Because of its simplicity, flexibility, and effectiveness, the Ishikawa diagram remains a vital tool in modern problem-solving and quality improvement strategies. As research and technology continue to advance, this diagram continues to evolve and adapt, maintaining its relevance and value in promoting operational excellence across disciplines.

The scientific goal of this dissertation is to develop an artificial intelligence (AI)-based method for predicting future failure sizes in conveyor belts under various operating conditions during material transportation at mines. To support this objective, an Ishikawa diagram was developed as part of the research framework, serving as a structured analytical tool for identifying and categorizing the root causes of conveyor belt failures. After the introduction and discussion of the potential applicability of the Ishikawa diagram, Fig. 1.5 illustrates how this method can be implemented in the context of a conveyor belt system in a mine, with a particular focus on identifying material handling-related damage as the root cause of belt failure.

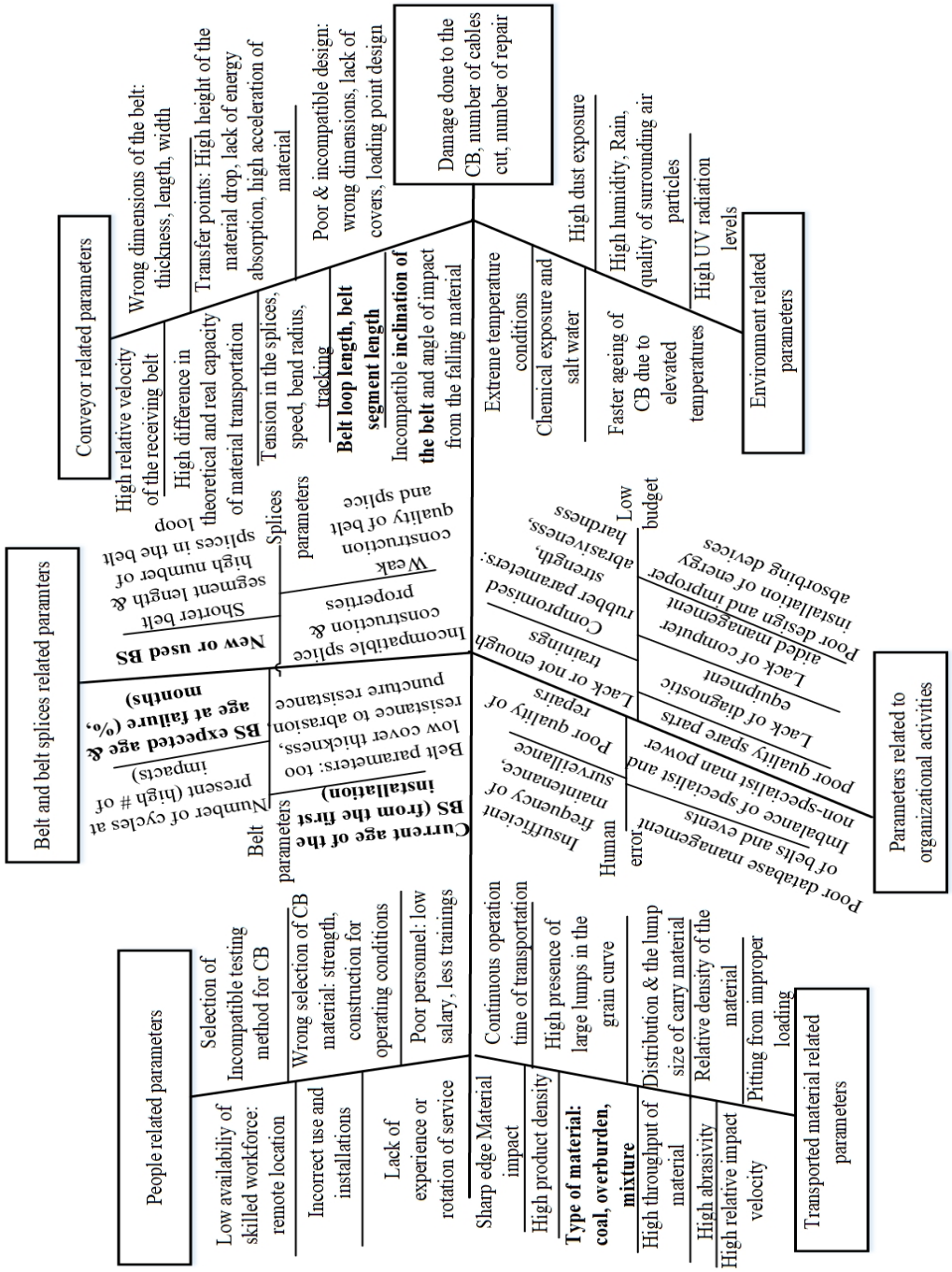


FIGURE 1.5: Ishikawa diagram for parameters affecting conveyor belt damage [144], [145]

The categorization of parameters in the Ishikawa diagram provides a comprehensive foundation for understanding the multifactorial nature of conveyor belt degradation. While qualitative analysis is essential for identifying and grouping failure sources, quantitative modeling is necessary to forecast degradation patterns, evaluate risk, and support data-driven decision-making. Building on the established cause-effect framework, the subsequent chapter explores various approaches to modeling conveyor belt degradation.

Chapter 2

Selection of intelligent methods for predictive maintenance

2.1 Background on predictive failure methods

Various modeling approaches have been employed to analyze conveyor belt systems (CBSs) and their degradation under mining conditions [55], [146], [147], [148]. Statistical methods have been used to identify inter-dependencies between input and output variables at mining sites, offering insights into the operational parameters contributing to both major and minor belt damage [149], [150]. However, these traditional techniques often fall short when applied to systems characterized by nonlinearities, high dimensionality, and noise. For instance, linear models can be mispecified in the presence of nonlinear interactions, which may result in biased or inconsistent estimates in complex settings [151]. Additionally, when the number of variables exceeds the available observations, classical regression models become unstable or undefined unless supplemented with regularization or dimensionality reduction techniques [152].

Intelligent methods have become the standard in equipment failure prediction because they enable proactive, accurate, and cost-effective maintenance even in complex, data-rich industrial environments. As a result, organizations achieve higher reliability, lower operational risks, and improved asset performance. Support for these benefits is well documented:

- AI-powered predictive maintenance can reduce unplanned downtime by up to 30%, cut maintenance costs by 25%, and extend equipment lifespan by 20–40%, significantly enhancing reliability and asset utilization [153], [154], [155], [156].
- Deloitte and industry reports confirm that predictive maintenance implementations produce 5–15% reductions in facility downtime, 5–20% increases in labor productivity, and more efficient asset management workflows, leading to cost savings and operational resilience [157].
- Machine learning models excel at detecting subtle, nonlinear failure patterns from high-dimensional sensor data, enabling more precise and earlier interventions compared to traditional rule-based or statistical methods [158], [159], [160].

Moreover, as described in chapters 4 and 6, presented thesis has high-dimensional data with evident nonlinear associations, as demonstrated in Tables 4.3, 6.5, and 6.4. Techniques such as artificial neural networks (ANNs) [125], [161], [162], [163] and random forests [130] are particularly effective in capturing complex noisy high dimensional nonlinear relationships among operational parameters.

Presence or suspicion of non-linear relationships

Artificial neural networks should be considered in scenarios where correlation coefficient such as Pearson correlation coefficient suggests the absence of linear relationships, yet domain knowledge or exploratory analysis indicates potential non-linear or multivariate associations. Additionally, ANNs are highly appropriate when the goal is to construct predictive models that integrate both linear and non-linear patterns across multiple variables. A low or near-zero Pearson correlation coefficient typically indicates the absence of a linear relationship. However, this does not preclude the existence of a strong non-linear association (e.g., exponential, parabolic, or sinusoidal). ANNs are particularly well-suited to capturing such non-linear dependencies due to their flexible, non-parametric learning capabilities [164], [165]. Modeling inherently complex systems, in various domains—such as biological processes, financial systems, or environmental dynamics—relationships between variables are often non-linear and highly intricate. ANNs can model these systems more effectively than linear statistical methods [166], [167].

Scenarios involving noisy or high-dimensional data [168]

Noise tolerance—ANNs often demonstrate greater robustness to data - noise compared to traditional linear models, as their architecture enables learning of underlying patterns even amidst stochastic variability. High-dimensional data analysis—in cases where datasets contain a large number of variables, identifying significant correlations using conventional statistical approaches can become intractable. ANNs excel in these settings by learning latent representations and complex feature interactions that are not readily apparent through pairwise correlation analysis.

To validate the relevance and effectiveness of this approach, it is crucial to examine whether AI-enabled predictive modeling, particularly using ANNs, has already been applied in real-world mining environments. Such case studies provide practical insights into the feasibility, performance, and benefits of these advanced modeling techniques in addressing operational challenges in the mining sector.

2.1.1 Case studies of AI-enabled predictive modeling in mining environments

ANNs have proven highly effective in predictive modeling of conveyor belt damage in mining environments, addressing limitations of conventional - threshold based and manual inspection systems. One notable case at the lignite mine in Poland utilized magnetic diagnostics combined with ANN-supported decision systems to assess steel-cord core damage, extending belt

life and improving refurbishment precision from 70% to over 90% [169]. Researchers from Wrocław University of Science and Technology were directly involved in this DiagBelt+ project, demonstrating the practical success of ANN-driven diagnostics in a real-world brown coal mine.

Another study conducted by Bzinkowski et al. [170] implemented strain sensors on conveyor rollers and trained ANN and other machine learning (ML) models to detect overloads and local damage with classification accuracies reaching 100% under lab conditions. The ability of ANNs to learn complex patterns from noisy, high-frequency signals gives them a clear advantage in dynamic industrial conditions. Similarly, in Chinese underground mines, a dynamic Bayesian approach integrated with ANN components modeled failure modes such as misalignment, slippage, and tearing, allowing preemptive maintenance decisions [171]. On-device neural inference techniques using compact convolutional networks have even enabled real-time anomaly detection on low-power microcontrollers, supporting distributed predictive maintenance across long conveyor systems [172].

Predictive Modeling of Conveyor Belt Deterioration in Coal Mines Using AI Techniques [144]. The study highlights the use of AI techniques to model and predict wear and damage in CBs, specifically within the context of a coal mine in, Poland. The study focused on developing five ANN models to forecast damage and wear, using a dataset of 1112 entries that included variables such as belt age, number of repairs, and the number of cable cuts. These models were designed to predict various outcomes like the number of repairs and the cumulative impact of cable cuts under different operating conditions. The research demonstrated that AI tools could effectively predict belt deterioration, enabling proactive maintenance strategies that reduce unplanned downtime and associated costs. By integrating AI into conveyor belt monitoring, the study suggests that mines can significantly enhance operational efficiency and minimize financial losses due to unexpected belt failures [144].

Predicting the availability of continuous mining systems using long short term memory (LSTM) neural network [173]. The published work discusses case studies and research on conveyor belt failures and AI-driven solutions. One of the highlighted case studies is from the open pit Drmno in Serbia, which focuses on predicting the availability of continuous mining systems using ANNs. The study demonstrates the limitations of traditional analytical methods and shows how ANNs can improve predictive accuracy for system failures. Data from the electric power industry of Serbia were used to train a LSTM neural network model, which predicted failures in conveyor belts, bucket-wheel excavators, and other components of the mining system. The LSTM model, combined with simulations, significantly enhanced predictive maintenance, reducing unplanned downtimes and improving system availability. Through various statistical evaluations, the ANN-driven model proved to offer greater predictive power than traditional methods in modeling failures and forecasting maintenance needs [159], [174].

Evaluation system of curved conveyor belt deviation state based on the

ARIMA–LSTM combined prediction model [175]. The LSTM neural network was used in the study to predict conveyor belt deviation during material transportation in curved sections. The LSTM model was specifically chosen because it addresses the issue of vanishing gradients in recurrent neural networks (RNNs), making it suitable for long time-series prediction tasks, such as conveyor belt monitoring. In this thesis, deviation data from the conveyor belt were used to train the LSTM model, allowing it to learn patterns and predict future deviations based on past data. The model's architecture included input gates, forget gates, cell states, and output gates, which help in efficiently capturing long-term dependencies between different states of the conveyor belt system. The LSTM networks ability to predict deviations helped optimize belt performance and enabled proactive maintenance, reducing the likelihood of belt device.

These case studies collectively highlight how ANNs contribute to reduced downtime, extended equipment life, safer operations, and overall maintenance cost savings. Their ability to handle high-dimensional sensor data, learn temporal dependencies, and generalize across diverse operating conditions makes them indispensable in the mining sector's shift toward Industry 4.0 [176] and intelligent asset management.

2.2 Artificial intelligence algorithms and their selection

The computer science—engineering field AI [177] incorporates the concept of ANNs. AI refers to the broader concept of machines or systems simulating human intelligence. This includes tasks like problem-solving, reasoning, learning, and language understanding. AI, ML, Deep Learning (DL) all three are interconnected as shown in Fig. 2.1.

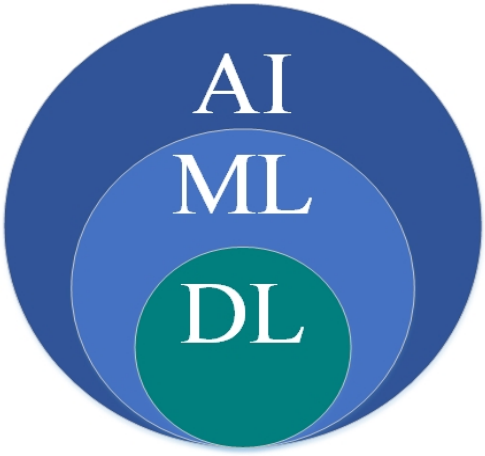


FIGURE 2.1: Artificial intelligence, machine learning, deep learning set as a whole

In recent years AI , ML [178], and DL [179] have emerged as transformative technologies across various industries. ML is a subset of AI that enables systems to learn from data, identify patterns, and make decisions with minimal human intervention. It involves training algorithms to improve their performance on tasks through experience, allowing them to adapt and make accurate predictions based on new data. Machine learning offers a powerful set of tools for analyzing large volumes of data generated by CBSs [144], [180], [181]. By applying ML algorithms, it is possible to develop predictive models that can anticipate failures, optimize maintenance schedules, and enhance overall system performance [181], [182]. Within ML, DL has revolutionized complex data processing by employing multi-layered neural networks to model intricate patterns and relationships. DL is a further subset of ML that involves neural networks with many layers (hence "deep"). These networks mimic the human brain and are particularly effective for complex tasks like image recognition, speech processing, and natural language understanding [183].

ANN is a fundamental component of artificial intelligence and machine learning, engineered to recognize patterns, make decisions, and predict outcomes based on input data [15], [183], [184], [185]. ANNs are one possible machine learning option that can contribute into studying multivariate (transportation) systems [186], [187] like CBS. By leveraging past data, ANNs can model complex relationships (between input variables—operating conditions and output variables—damage to the CB) within the system, providing valuable insights and future predictions to enhance maintenance and operational strategies. Structure of artificial neural networks consists of neurons, layers, weights—biases and activation function.

Neurons[15], [184], [185] serve as the fundamental processing units of an ANN. Each neuron receives inputs, processes them, and generates an output. A neuron combines the input data with a set of weights, adds a bias, and then passes the result through an activation function to produce the final output. Layers [188] are of three types which are, input layer, hidden layers, output layer. Input layer is the first layer of the network, where the input data is fed into the system. Each node in this layer represents a distinct feature of the input data. Hidden layers are located between the input and output layers. Hidden layers perform the main computations, each hidden layer contains multiple neurons, and the networks depth is determined by the number of hidden layers. Output layer generates the final output of the network. The number of nodes in this layer corresponds to the number of desired output classes or values.

Weights [188], are parameters within the network that transform input data within neurons. Each connection between neurons has an associated weight, determining the strength and direction of the input signal. Biases are added to the weighted sum of inputs before passing through the activation function. They enable the activation function to be shifted to the left or right, which is crucial for learning complex patterns.

Activation functions [189], [190] determine whether a neuron should be activated. They introduce non-linearity into the network, enabling it to learn more complex patterns. Common activation functions include Sigmoid, Tanh, ReLU, Swish. Sigmoid produces outputs between 0 and 1, useful for - probability-based outputs. Tanh (hyperbolic tangent) [191] outputs range from -1 to 1, centered around zero, making it beneficial for zero-centered data. ReLU (rectified linear unit) [192] outputs the input directly if it is positive; otherwise, it outputs zero. It helps to mitigate the vanishing gradient problem [193]. Swish [194] is non-monotonic, meaning it doesn't always increase with X, unlike ReLU or sigmoid. It allows small negative inputs to pass through, which can help avoid dying neurons (an issue in ReLU). It retains smoothness and differentiability across all input values, which benefits optimization during training.

The working mechanism of ANNs can be simplified into forward propagation learning, and backpropagation learning. Forward propagation [195] involves passing the input data through the network to obtain the output. In each layer, a neuron computes a weighted sum of its inputs, adds a bias, and applies an activation function to generate an output. This process continues from the input layer, through the hidden layers, to the output layer, where the final prediction or classification is generated. Learning (training) [196] an ANN involves adjusting its weights and biases to minimize the error between its predictions and the actual target values. A common approach to training involves supervised learning, where the network is trained on a labeled dataset. Each example in the dataset consists of an input and its corresponding correct output. Backpropagation [195], [197] is a fundamental algorithm for training ANNs. It functions by propagating the error backward from the output layer to the input layer, adjusting the weights and biases to minimize the error. The process involves, calculating the error at the output layer, using the derivative of the activation function to determine the gradient of the error with respect to each weight, and adjusting the weights and biases in the direction that reduces the error, typically using an optimization algorithm like gradient descent.

Types of neural networks

Feedforward neural networks [198], the simplest type of ANN where connections between nodes do not form cycles. Information moves in one direction—from input nodes, through hidden nodes (if any), to output nodes. Variants of FFNNs are single-layer perceptron (SLP) and multi-layer perceptron (MLP). SLP [199], [200] is the simplest form of ANN, with a single layer of neurons. MLP [200], [201] consists of multiple layers (input, hidden, and output layers), allowing the network to learn complex patterns. Convolutional Neural Networks (CNNs) are a type of MLP, but they are not standard MLPs or fully connected networks. CNNs [202] are specialized in processing grid-like data structure such as image and video recognition. They use convolutional layers to automatically and adaptively learn spatial hierarchies of

features from input images.

Recurrent neural networks are not SLPs or CNNs — they are a distinct type of MLP specialized for sequential data. RNNs [203] are designed to recognize sequences and patterns in sequential data. They have connections that form directed cycles, allowing information to persist across steps. Variants of RNNs are simple RNN, LSTM (used in the dissertation) and, Generative adversarial networks (GANs). Simple RNN is a basic form with short-term memory. LSTM addresses the problem of vanishing gradients in RNNs, allowing the network to learn long-term dependencies. Gated recurrent unit (GRU) is a simplified version of LSTM with fewer parameters. GANs [204], [205] consist of two neural networks, a generator and a discriminator, that compete against each other. Used for generating new, synthetic instances of data that can pass for real data.

Challenges and limitations associated with ANNs

Despite several well-recognized challenges and limitations, artificial neural networks (ANNs) remain a valuable and effective tool for modeling conveyor belt damage. One of the primary concerns is the substantial data requirement associated with ANN training—these models typically need large, high-quality datasets to achieve reliable performance [206]. In scenarios where data are insufficient, the model may underperform or produce misleading results. Additionally, training deep or complex ANN architectures can demand significant computational power, often requiring access to specialized hardware such as graphical processing units (GPUs) [207].

Another critical limitation is the issue of interpretability. ANNs are frequently criticized for being "black boxes," offering little transparency into their internal decision-making processes [208], [209], [210]. This lack of explainability can hinder trust and adoption in high-stakes industrial environments. Furthermore, ANNs are prone to overfitting, especially when the training data are limited or not representative of real-world variability [211], [212]. Overfitting results in excellent performance on training data but poor generalization to unseen scenarios, which must be controlled through regularization techniques and cross-validation. Ethical concerns have also been raised regarding ANN use in sensitive domains, where biases embedded in the data may propagate unfair outcomes and reduce accountability [213].

Nevertheless, these challenges do not negate the advantages of ANNs for predictive tasks in complex industrial systems. In the context of conveyor belt damage modeling—where nonlinear patterns, temporal dependencies, and multivariate sensor inputs often exist—ANNs have demonstrated superior predictive capability compared to traditional statistical approaches [149]. With proper preprocessing, architecture design, and validation strategies, their application can significantly enhance failure detection and maintenance forecasting, ultimately improving operational reliability and reducing downtime [170].

Comparison of commonly used artificial intelligence algorithms for predictive maintenance tasks is shown in the Table 2.1, highlighting their temporal modeling capabilities, interpretability, training complexity, and suitability for long-term sequential data. LSTM is shown to be particularly effective for applications requiring modeling of time-dependent degradation patterns.

Assessment of algorithm suitability for conveyor belt damage detection

The algorithms compared in Table 2.1 differ not only in their structure and temporal modeling capabilities but also in how well they align with the unique demands of conveyor belt fault detection. Conveyor belt systems in mining environments generate multivariate data which evolve over time. Damage often develops gradually, making temporal modeling a critical requirement. LSTM networks are particularly effective in this setting due to their ability to learn long-term dependencies and handle noisy, multivariate input. This makes them well-suited for detecting slowly progressing faults (e.g. belt wear or splice degradation) that may not be evident in short time windows. LSTMs trained on raw sensor data have shown superior performance over feature-based baselines in industrial fault prognostics tasks [214]—and have been widely used in predictive maintenance applications [159]. In conveyor belt-specific contexts, machine learning–based digital twins employing LSTM-driven models demonstrated high precision and accuracy in fault prediction under real operating conditions [182].

GRUs offer a simplified alternative to LSTM with lower computational cost, while still addressing vanishing gradient issues. Several case studies report that GRUs can outperform LSTMs for medium-length sequences, though LSTMs retain an edge for long sequence modeling [215].

Despite their speed and interpretability, feedforward neural networks (FFNNs) and random forests lack intrinsic mechanisms for modeling temporal dependencies. Consequently, they rely heavily on handcrafted temporal feature engineering—such as lag features, moving averages, trend indicators—to approximate sequence dynamics. This approach can easily overlook subtle temporal patterns that are critical for early fault detection in conveyor belt systems [216], [217], where degradation processes unfold over time and require capturing nuanced sequential dependencies.

CNNs (1D convolutional neural networks) can extract local patterns in time-series signals (e.g., sudden vibration peaks) and have been successfully applied to conveyor motor data using time-series imaging techniques [218]. However, unless integrated with sequential modules (e.g., CRNN architectures), they remain limited in long-term temporal reasoning.

Despite their strength when provided with engineered features, XGBoost and other tree-based models do not inherently model sequential context. They are commonly used as high-performing baseline classifiers in predictive maintenance literature; however, their effectiveness relies heavily on careful temporal feature engineering, such as lagged variables or rolling statistics, to capture sequence dependencies. This dependency on manual feature design introduces risks—subtle temporal dynamics essential for early fault detection (like gradual conveyor belt wear) may be overlooked if relevant lagged patterns are not engineered properly [219], [220], [221].

Algorithm	Temporal Modeling	Interpretability	Training Complexity	Common Applications	Comparison with LSTM
LSTM (Long Short-Term Memory)	Excellent (long-term dependencies)	Low	High	Sequential data, RUL prediction, anomaly detection	Best suited for multivariate time-series with long memory
FFNN (Feedforward Neural Network)	None	Moderate	Moderate	Failure classification, health scoring	Cannot model sequences or time-dependencies
GRU (Gated Recurrent Unit)	Good (short–medium memory)	Low	Lower than LSTM	Time-series forecasting, sensor fusion	Faster than LSTM, slightly less accurate for long sequences
CNN (1D Convolutional Neural Network)	Limited (pattern detection)	Low	Moderate	Signal classification, vibration analysis	Better for local patterns, weaker in capturing long-term time steps
Random Forest	None	High	Fast	Condition classification, feature ranking	Easier to interpret, but no temporal awareness
XGBoost	None	High	Moderate	Failure classification, regression tasks	High accuracy, but needs handcrafted temporal features
Autoencoder (unsupervised)	Moderate (depends on design)	Low	High	Anomaly detection from raw sensor streams	Good for detecting unknown faults, but harder to train
ARIMA / SARIMA	Short-term	High	Simple	Linear time-series forecasting	Good for stationary data, poor with nonlinear dynamics
Transformers	Excellent (attention-based)	Very Low	Very High	Long-range forecasting, text/log analysis	State-of-the-art, but often overkill for small industrial datasets

TABLE 2.1: Comparison of machine learning algorithms for predictive maintenance tasks

Transformers and other attention-based architectures demonstrate a strong ability to model long-range temporal dependencies, which makes them highly suitable for time-series analysis tasks. However, these models typically require large amounts of data and significant computational resources to perform effectively. As such, their deployment in industrial predictive maintenance—particularly for systems like conveyor belts—remains largely experimental. Compared to more established architectures like LSTM networks, transformers are still in the early stages of application in this domain. For example, a recent survey on transformers in time-series analysis emphasizes their capability for handling complex dependencies but also points out the challenges related to resource intensity and data volume requirements [222]. In parallel, transformer-based frameworks such as T4PdM, which have been applied in the fault diagnosis of rotating machinery, show promising accuracy but remain at the proof-of-concept stage rather than being widely deployed [223]. Similarly, modern transformer implementations like TQRNN, proposed for industrial machine health prognosis, underscore both the potential and the current limitations of these models in real-world manufacturing scenarios [224]. Thus, while transformers offer a powerful modeling approach, their use in conveyor belt damage prediction is still evolving and not yet as established or practical as recurrent neural network–based methods such as LSTMs.

Autoencoders—especially unsupervised variants—are effective for detecting anomalies in datasets with stationary behavior over short-term cycles. By learning to reconstruct normal operating conditions, they flag deviations via elevated reconstruction error, making them useful for early fault detection in controlled environments like rotating machinery vibration signals [225], [226]. However, their generalizability is limited in highly dynamic industrial systems—for example conveyor belts—where degradation follows nonlinear, non-stationary patterns that evolve over extended timeframes.

ARIMA and SARIMA models offer reliable performance in contexts with well-behaved, stationary time series and predictable seasonal trends. They assume constant statistical properties and linear dependencies, making them suitable for short-term forecasting tasks [227]. Yet, when applied to complex industrial systems with irregular, nonlinear behavior, these classical models struggle to adapt, as noted in discussions questioning their effectiveness for sporadic memory patterns and irregular dynamics [228], [229]. Consequently, while these techniques provide strength in niche scenarios, they lack robustness for broader predictive maintenance applications in evolving industrial environments.

Standard RNNs, while conceptually capable of sequence modeling, often struggle with retaining information over long time horizons due to their limited memory capacity. In contrast, LSTM networks have demonstrated the ability to model complex temporal relationships in predictive maintenance tasks involving multivariate sensor data [144], [170], [230], [231]. This

is especially relevant for conveyor belt systems where damage may accumulate gradually due to a combination of mechanical, operational, and environmental factors over hours or days. Considering the critical need to model long-range, multivariate temporal patterns and operate under noisy real-world conditions, LSTM networks currently represent the most robust and scalable solution for conveyor belt fault detection. LSTM networks—a specialized form of RNN are particularly well-suited for time-series modeling tasks where long-term dependencies exist, such as in mining environments where damage accumulates over extended operating cycles. Unlike traditional FFNNs, which assume independence between inputs and are thus limited in capturing temporal dynamics, LSTMs are equipped with memory cells and gating mechanisms (input, forget, and output gates) that allow them to selectively retain or discard information across time steps. This structure enables LSTMs to overcome the vanishing gradient problem common in standard RNNs, allowing them to model long-duration dependencies more effectively [214].

Despite these strengths, LSTM networks are not without limitations. They require significant computational resources for training, particularly when working with large input sequences and multivariate data. Additionally, their internal operations remain relatively opaque, limiting interpretability and explainability—especially in industrial applications where model transparency can be critical [175], [232]. Tuning LSTM hyperparameters is also non-trivial, and overfitting can occur if regularization techniques are not carefully applied. However, when balanced against their demonstrated - strengths—such as robust handling of long-term dependencies, resilience to noise, and effective modeling of non-linear sensor interactions—LSTMs remain one of the most capable neural architectures for condition monitoring in conveyor belt systems.

Moreover, in multivariate environments where interactions among operating conditions and their impact on to the conveyor belt damage evolve over time, LSTMs enable context-aware modeling. Their memory structure supports learning across varying operational conditions, allowing for early detection of gradual failure patterns before sharp anomalies occur [214], [233], [234], [235]. While other models may offer certain computational or interpretability advantages, the nature of damage progression in conveyor systems— characterized by subtle, time-dependent trends—makes LSTMs especially suitable. Therefore, despite their limitations, LSTMs offer a compelling balance of accuracy, flexibility, and robustness for predictive maintenance in the mining sector.

2.3 Fine-grained temporal resolution using LSTM neural network

LSTM networks were introduced by Hochreiter and Schmidhuber in 1997 [236] and have since become a cornerstone in the field of deep learning, particularly for sequential data processing tasks such as natural language processing, time series forecasting, and speech recognition. LSTM neural networks are a type of recurrent neural network [203] specifically designed to overcome the limitations of traditional RNNs, particularly in handling long-term dependencies and mitigating the vanishing gradient problem [193]. This limitation is addressed in the LSTM model through the incorporation of three gates—input gate, output gate, and forget gate, as depicted in Fig. 2.2. These gates allow the LSTM network to selectively forget outdated information and incorporate new information. The gates selectively update this cell state, allowing the network to maintain a memory of relevant information while discarding irrelevant details [237]. The effectiveness of updating old and new memories is influenced by the chosen time delay (a time delay of one was selected in this study) in the data used for training the LSTM neural network. For instance, in a time series consisting of five time steps (t_1 to t_5), with a time delay of three steps, the information flow in the LSTM network would progress as follows: $(t_1, t_2, t_3) \rightarrow (t_2, t_3, t_4) \rightarrow (t_3, t_4, t_5)$. In the presented thesis, the LSTM model was implemented using the Google Colab platform [238], with the Python programming language [239], [240] for code execution. Python libraries such as TensorFlow [241], [242], NumPy [243], [244], Keras [245], [246], pandas [247], [248], Matplotlib [249], [250], and scikit-learn [251], [252] were utilized for programming tasks.

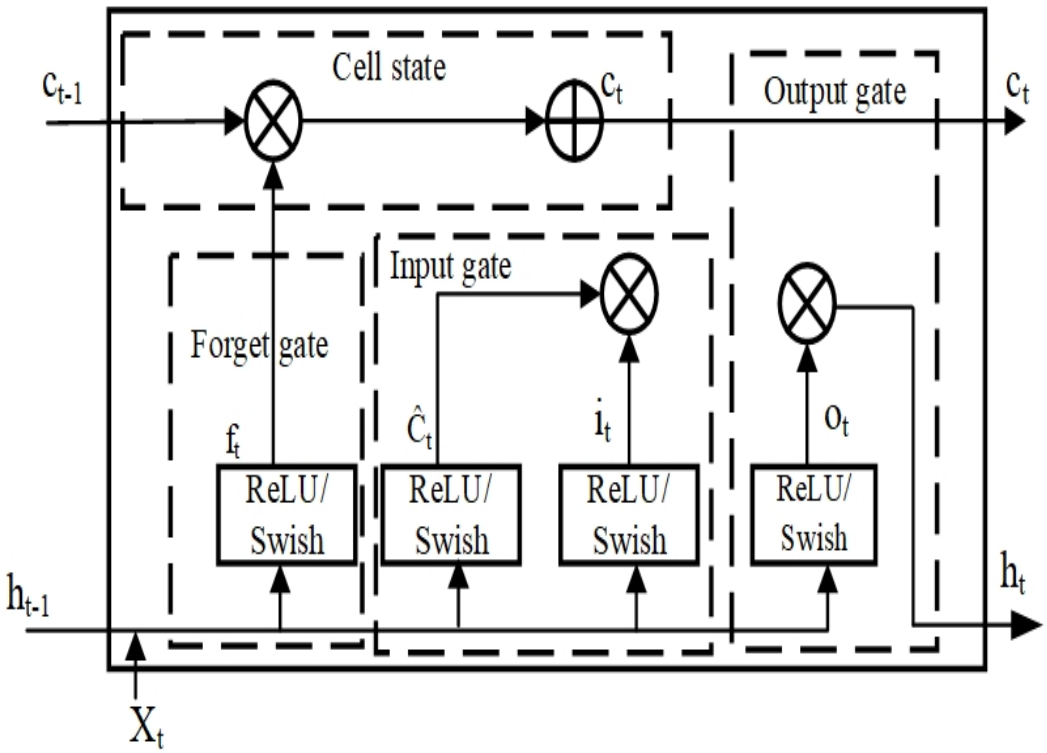


FIGURE 2.2: An Architecture of LSTM

Referring to the LSTM architecture illustrated in Fig. 2.2: t = time-step, c_t = cell state information, f_t = forget gate at t, i_t = input gate at t, c_{t-1} = previous time-step, $\hat{C}_t$ = value generated by the tanh function, h_t = hidden state, h_{t-1} = previous hidden state, o_t= output gate state, X_t = input at the particular time, Input gate = controls the extent to which new information flows into the cell state, Forget gate = determines what portion of the previous cell state should be retained, Output gate = regulates the information output from the cell to the next hidden state.

To further clarify the data flow in an LSTM neural network, where the system is modeled using a total of sixteen parameters as an hypothetical example (11 input parameters—X_1 to X_{11} and 5 output parameters—Y_1 to Y_5), the data flow follows the path which is illustrated in Fig. 2.3.

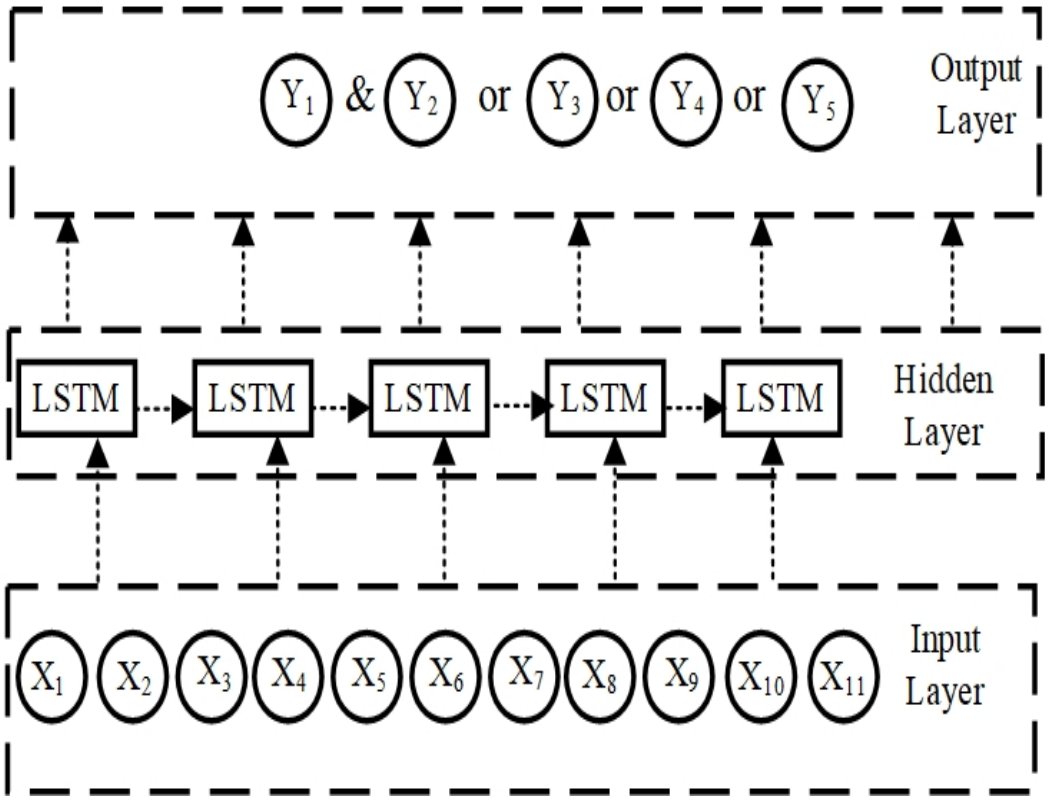


FIGURE 2.3: An example of data flow in LSTM network

Following the description of the LSTM network architecture and its internal data flow, following focuses on the model's practical applications. Emphasis is placed on identifying use cases that align with the predictive maintenance objectives outlined in this dissertation. By examining relevant use case scenarios, especially those pertaining to sequential data modeling, the applicability of LSTM architectures in addressing the challenges associated with conveyor belt failure prediction in mining operations can be thoroughly evaluated. This contextual understanding provides a critical link between model design and its functional deployment within the scope of the dissertation.

Use-case scenario of LSTM neural network for the presented thesis

In the context of the present study, a single time-step configuration was adopted for the LSTM neural network. This means that the model processes and updates its internal state based on one data point at a time. Such a configuration is commonly referred to as fine-grained temporal resolution and has distinct implications for both model performance and computational requirements.

Using a single time-step allows the LSTM to capture fine-grained temporal dependencies, which is particularly beneficial in applications where the detailed structure of sequential data is critical (e.g. pressure-signal classification on conveyor belts) [180]. Examples include speech recognition, music

generation, and high-frequency financial or sensor data analysis. By processing one data point at a time, the network can learn subtle variations and localized patterns that might be overlooked with larger time-steps. Within the context of the datasets utilized in this dissertation, it is of primary importance to capture the temporal progression at each time step, as the evolution of damage between consecutive inspections or scans provides a critical basis for evaluating the influence of specific operational conditions in the mines on conveyor belt degradation [60], [144]. Furthermore, learning dependencies at individual time-steps allows the model to identify short-term dynamics and transitions that are essential in fine-grained sentiment analysis, event detection, or signal classification.

Despite its strengths, the single time-step configuration introduces several challenges. One of the primary drawbacks is the increased computational burden. Since the model must update its state and perform computations for each data point independently, training becomes time-consuming and resource-intensive, especially for long sequences [253]. This can significantly reduce batch processing efficiency, as the potential for parallelization diminishes when time-steps are not grouped [216]. Additionally, while the model can capture short-term dependencies effectively, it may struggle with learning long-term dependencies. Although LSTMs are designed to mitigate the vanishing gradient problem inherent in traditional RNNs, the risk still exists when dealing with very long sequences. Recent inputs may dominate the state updates, leading to loss of earlier context over time [254]. Overfitting is another concern associated with fine-grained temporal resolution. Processing data at a very detailed level may cause the model to learn noise rather than signal, particularly in cases where the dataset is noisy or when the model capacity is high. Regularization techniques, such as dropout, are necessary to counteract this risk and maintain generalizability [255].

The selection of time-step size in LSTM networks should be informed by the specific requirements of the application and the nature of the dataset. For tasks that demand high temporal resolution—such as real-time signal processing or environmental monitoring—a single time-step may be advantageous, offering fine-grained prediction capability at the cost of increased computational overhead and slower training throughput [256], [257]. However, for problems that involve longer-term patterns and broader temporal dependencies, a coarser time-step (e.g., aggregating data in chunks) often yields more efficient training without sacrificing accuracy. For instance, multi-timescale LSTM architectures streamlining multiple temporal resolutions can preserve performance with reduced training time and shorter input sequences [258]. When implementing fine-grained time-steps, sufficient model capacity and computational infrastructure are essential to prevent overfitting and control training duration [259]. In summary, setting the time-step to one in an LSTM network provides high-resolution temporal modeling capability but introduces trade-offs in computational efficiency and robustness.

The decision should be carefully balanced against task objectives, data characteristics, and available resources to achieve optimal performance.

This chapter has established the theoretical basis for artificial neural networks (ANNs) and their extension into long short-term memory (LSTM) models, highlighting their suitability for representing time-dependent behavior in conveyor belt systems. It also presented the rationale for using AI-based predictive modeling to forecast conveyor belt damage under real operating conditions, thereby defining the methodological framework for the subsequent chapters. Through such predictive capabilities, maintenance strategies can be significantly optimized, reducing unplanned downtime and operational costs [260]. Building on this foundation, the subsequent chapter defines the scope of the dissertation, articulates the specific objectives pursued, and details the methodological framework adopted to develop and validate the methodology.

Chapter 3

Dissertation scope, objectives, and methodology

The literature review has shown that conveyor belts in mining operations are subject to a combination of mechanical wear, material degradation, and operational stresses, with surface damage and splice failures identified as the most frequent causes of downtime. While numerous studies have applied statistical, acoustic, thermal, and image-based diagnostic methods to detect belt damage [54], [70], [261], [262], most approaches are limited to reactive or short-term condition monitoring and rarely address the progression of damage over time [70]. Furthermore, existing machine learning models, although increasingly adopted for equipment fault detection, often rely on small, domain-specific datasets and lack adaptability to varying mining environments, such as those in brown coal and limestone extraction [144], [169], [182], [263]. This gap highlights the need for a robust, data-driven predictive framework capable of modeling not only the occurrence but also the development of conveyor belt failures, enabling timely maintenance decisions and minimizing unplanned stoppages.

3.1 Main objectives

The scientific objective of this dissertation is to develop an artificial intelligence (AI)-based method for predicting parameters associated with conveyor belt failures, including damage size and occurrence metrics, by utilizing operational characteristics and historical maintenance records obtained from mining environments. The developed method generates predictions of future damage-related parameters, which have the potential to be applied as decision-support inputs in maintenance planning. If implemented within operational practice, these predictions could contribute to enhanced maintenance scheduling and, consequently, to improvements in operational reliability. The reviewed literature indicates that, despite significant advances in conveyor belt diagnostics—ranging from image-based damage detection to machine learning-based fault classification—existing systems remain largely reactive, domain-specific, and limited in their ability to predict the progression of damage under varying operational and environmental

conditions [60], [70], [144]. Studies on brown coal and limestone mining environments highlight that harsh operating conditions, coupled with heterogeneous material handling, produce data patterns that are complex and unique, often requiring tailored feature extraction and model adaptation strategies [60], [169]. Furthermore, the interdisciplinary integration of mechanical diagnostics, sensor data processing, and artificial intelligence remains underexplored, particularly in the context of real-time monitoring systems capable of supporting predictive maintenance decisions [182], [264]. These findings underline an emerging industrial need for robust, adaptable predictive maintenance systems for conveyor belts—an area where the present dissertation contributes by addressing data complexity, cross-disciplinary challenges, and the economic and safety implications of unplanned belt failures [263].

The novelty and suitability of this dissertation for doctoral-level research arise from five interconnected factors. First, there is a clear emerging need in the mining industry for predictive maintenance methods that not only forecast the occurrence of failures but also predict the size and extent of impending damage. While existing approaches provide failure timing estimates, predicting failure size remains largely unexplored, yet it is crucial for selecting appropriate maintenance and repair strategies. Second, data complexity and uniqueness present a significant challenge. Conveyor belts operate in harsh mining environments where wear, mechanical stresses, and variable operational conditions impact lifespan. Developing an AI model capable of handling heterogeneous and often incomplete datasets—integrating sensor readings, historical maintenance records, and operational parameters—requires advanced methodologies beyond standard predictive maintenance. Third, the research involves a substantial interdisciplinary challenge, combining artificial intelligence, data science, materials engineering, mining engineering, and mechanical diagnostics. Effective integration of machine learning and deep learning techniques with domain-specific expertise in conveyor belt mechanics is still underdeveloped, requiring both theoretical advancement and practical validation. Fourth, there is strong potential for real-time application. A system that can deliver reliable, real-time predictions of failure size would significantly improve operational efficiency. Achieving this goal requires models capable of continuous learning from incoming data streams—a capability that remains an open research problem for complex machinery such as conveyor belts. Finally, the economic and safety implications are substantial. Reducing unplanned downtime lowers operational costs, while accurate failure size prediction enhances worker safety by allowing proactive maintenance scheduling and hazard prevention. Collectively, these aspects position the research within an interdisciplinary context that addresses a defined gap in the literature and leverages complex, multi-source data to develop and evaluate predictive methods relevant to mining operations.

This dissertation presents a predictive model for conveyor belt failure-related parameters in mining operations, developed using operational sensor

data and historical repairs-maintenance records collected from the mine. The proposed approach employs a long short-term memory (LSTM) neural network to model the temporal dependencies in belt wear and damage progression, enabling the prediction of both the occurrence and size of impending failures. The model architecture is designed to handle heterogeneous time-series inputs—including belt usage hours, loading conditions, environmental parameters, and recorded defect characteristics—allowing it to capture complex degradation patterns specific to brown coal—lignite and limestone mining environments. The methodology follows a sequential workflow supported by best practices in the literature: raw operational data are preprocessed to remove noise and handle missing values, following approaches for cleaning mining sensor datasets outlined by Błażej et al. [265] and Jurdziak et al. [60]; relevant features are extracted and normalized based on statistical and signal-processing techniques used in conveyor diagnostics [70], [264]; the processed data are split into training, validation, and test sets, as recommended for time-series modeling in predictive maintenance [144], [182]; the LSTM model is trained with optimized hyperparameters, leveraging architectures proven effective for sequential equipment monitoring [144], [263]; and its predictive performance is evaluated using metrics such as mean absolute error (MAE), root mean square error (RMSE), and prediction accuracy for failure size classification, consistent with prior works in conveyor belt wear prediction and industrial prognostics [144], [169]. This structured and literature-grounded approach ensures that the developed model is both technically robust and operationally relevant to the mining context under investigation.

The utilitarian goal of the thesis is to improve the operational efficiency of mines by developing an AI-based predictive maintenance system for conveyor belts. Preventive repairs based on predicted condition can prevent advanced damage and emergency downtime in conveyor belts, while also enabling more efficient resource allocation, extending belt service life, and improving safety to ensure smooth operations in mining environments.

To achieve the objectives outlined—the main scientific goal and the utilitarian goal, a structured and methodical dissertation approach was essential. The complexity of the problem, along with the interdisciplinary nature of the proposed solution, required a carefully planned sequence of stages that could systematically address the research gap and validate the effectiveness of the developed methodology. In this context, the roadmap illustrated in Fig. 3.1 was devised and followed throughout the course of the dissertation.

3.2 Methodological framework

The work presented in this dissertation follows a structured roadmap, moving from the identification of the problem through the formulation of the solution to its validation. Each phase builds upon the preceding one, with

clear links between stages that connect the research design to both the scientific objectives and the practical outcomes addressed in the thesis. Fig. 3.1 shows description of the key stages of the chosen methodology. The detailed content of the each chapter mentioned in the roadmap is already described earlier in the introduction of the thesis .

Literature review on the thesis subject

The initial phase of the thesis work involved a literature review focusing on conveyor belt systems used in mining operations, with particular attention to their mechanical characteristics, common failure modes, and maintenance challenges. This review facilitated the categorization of deterioration causes into six groups, as illustrated in an Ishikawa diagram as shown in Fig. 1.5, in Chapter 1. Additionally, previous works applying machine learning techniques to industrial equipment diagnostics were examined. This review established the foundation for understanding the current state of research and the limitations of existing predictive maintenance strategies for conveyor belts used in mines.

Necessity of research, identification of research gap and its solution

The analysis of available literature revealed a gap in the development of AI-based models capable of predicting the future progression of conveyor belt failures using operational data from mining sites. Existing approaches either lacked detail or relied on limited datasets, often overlooking the dynamic and harsh conditions encountered in mining environments. To address this gap, the dissertation develops a predictive modeling approach based on long short-term memory (LSTM) neural networks, designed to capture temporal dependencies and degradation patterns in conveyor belt operation. The method integrates multi-source time-series data—such as belt usage hours, loading conditions, and environmental parameters—with historical defect records to forecast both the occurrence and size of future failures. The model architecture, data processing pipeline, and training procedures are described in sections 2.2 and 2.3 of Chapter 2. The development process includes experimentation with different network architectures, training algorithms, and hyperparameters (Table 4.10). Model performance is evaluated using error metrics such as MAE, as detailed in sections 4.2 and 6.2 and Tables 4.10 and 6.7.

Streamlining and upgrading the research methodology to eliminate bottlenecks

During the initial modeling phase, the dataset created from human visual inspection of conveyor belts was used. The datasets contained human errors and missing values, pre-processing was required, as outlined in the flow process chart in Fig. 4.1 and 6.1. Subsequently, lists of input (Table 4.2 and 6.1) and output variables (Table 4.1 and 6.2) were constructed, as detailed in Chapter 4 and 6. While this dataset provided valuable insights, it exhibited limitations due to the subjectivity and inconsistency of manual inspection processes. Human-based evaluations are prone to error, lack standardization, and may fail to detect subtle or internal damage patterns. To overcome these challenges and enhance the reliability of the modeling, the

methodology included the incorporation of the DiagBelt+ diagnostic system. This system uses sensor-based scanning to detect and classify belt damage with high resolution and consistency. The resulting dataset provided a more detailed basis for model training.

Comparison of prediction results between two datasets and validation of the developed models

Following the development of predictive models based on both dataset, a comparative analysis was carried out to assess their performance, as detailed in Sections 4.3 and 6.3. In accordance with standard modeling practice, this phase necessitated rigorous validation of the trained models using historical data to evaluate their predictive accuracy and generalization capability. The prediction results obtained from the model trained on the human visual inspection data were systematically compared with those derived from the model utilizing the DiagBelt+ diagnostic system. The predicted values were then compared with the actual recorded data from the mine, and the results were analyzed using three performance indicators. Indicator A represents the percentage of total prediction instances with a relative error of less than 50% compared to mine records. Indicator B represents the percentage of total instances with a relative error between 50% and 100%, and Indicator C represents the percentage of instances with a relative error greater than 100%. The comparison between the predicted values and the recorded values at the mine is illustrated in Figs. 4.5, 4.6, 4.7, 4.8,4.9 and 6.6, 6.7, 6.8, 6.9, 6.10. Comparative prediction results are presented in section 4.3 and 6.3, with detailed results in Tables 4.13, 4.14, 4.15, 4.16, 4.17 and 6.8, 6.9, 6.10, 6.11. The comparison highlighted the reliability of the developed method and its applicability in different mining site where data collection is done using different approaches. This validation step was crucial in confirming the robustness of the proposed methodology and its applicability for predictive maintenance in mining operations.

Prediction of the next phase

The final stage of the dissertation involved utilization of the trained model to generate predictions for the next phase of conveyor belt operation. These forecasts serve as a foundation for proactive maintenance planning, enabling mine operators to anticipate critical failures before they occur. By delivering real-time predictions of future failure sizes, the developed method supports decision-making processes that enhance safety, reduce unplanned downtime, and extend the service life of conveyor belt systems. This predictive capability aligns directly with the scientific and utilitarian goal of the dissertation.

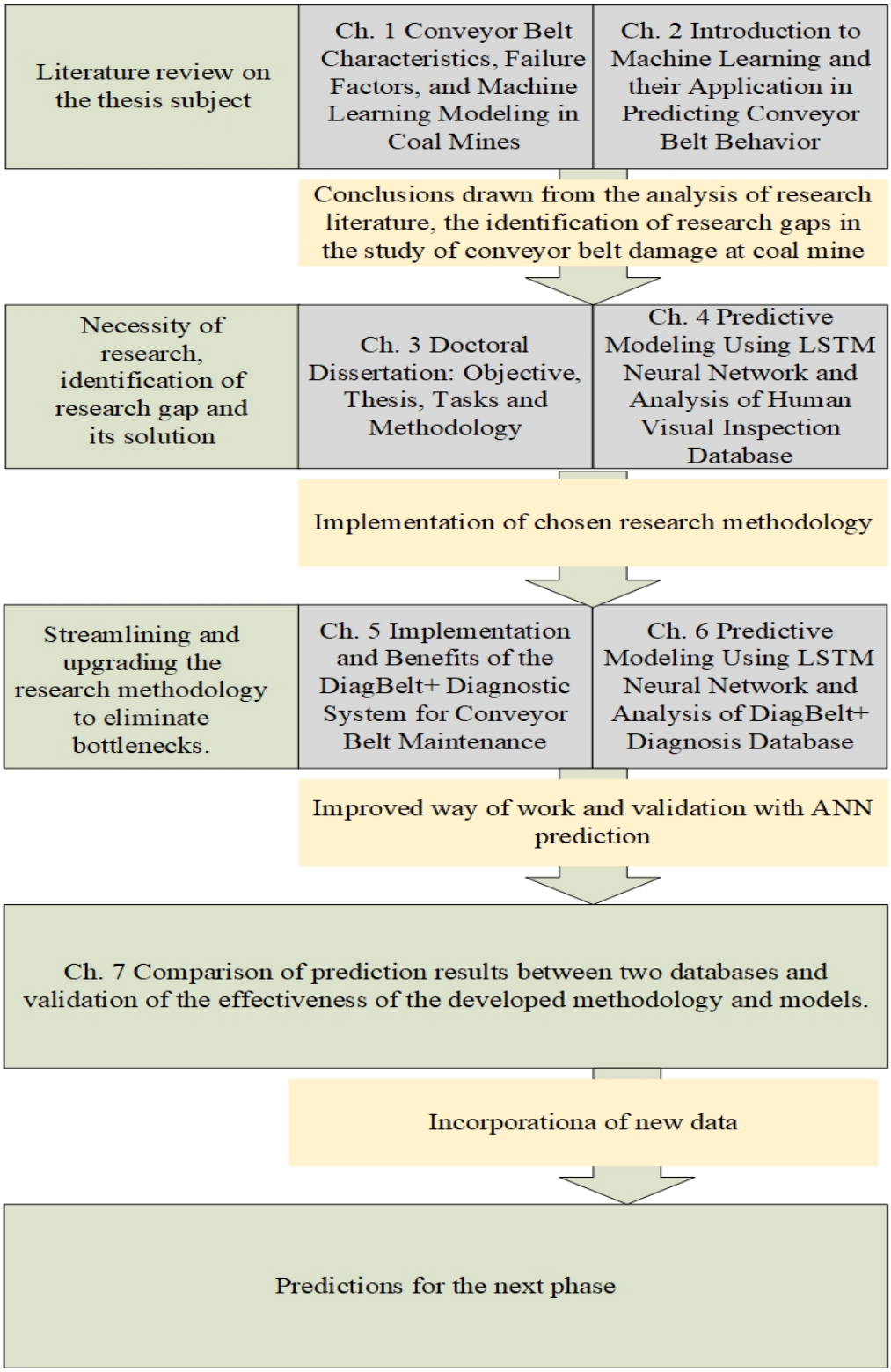


FIGURE 3.1: Road-map of the thesis

Having presented and described the overall roadmap of the thesis along with its key stages, it is essential to outline how these stages were operationalized through a detailed sequence of methodological actions. The Fig.

3.2 presents the "flow process chart of operations for the developed methodology", which visually and systematically depicts the step-by-step execution of the developed method. The chart shows the sequence of actions from the initial literature review, through data acquisition and preprocessing, to the modeling and prediction of conveyor belt damage using the developed LSTM models. It also indicates dependencies between stages, the order of data flow, and the transitions from conceptual planning to implementation.

Start—"Literature review on conveyor belt damage in mines, followed by the creation of an Ishikawa diagram."

A literature review was conducted to identify the potential causes of conveyor belt failures in mining environments. Based on these findings, an Ishikawa diagram was developed to systematically classify failure factors. This step is not purely descriptive; it directly informed the structure of the dataset by linking operational variables (as listed in Tables 4.2 and 6.1) with the observed degradation mechanisms in the field—an approach supported by failure-mode analyses in mining contexts [55], [266]. These mechanisms include poor belt alignment, carryback, wear, and roller failures—common root causes highlighted in industry case studies [267], [268].

Steps 1 & 2—Collection of data measured at mine & Checking and pre-treatment of data

Real-world multi-year datasets were obtained from Polish lignite and limestone mines. The data included records of conveyor belt damage parameters such as location, dimensions, and repair actions, as well as corresponding operational variables. One dataset was collected through routine human visual inspections, while the other was acquired using the DiagBelt+ diagnostic system, which employs non-contact scanning to detect and measure belt damage. Unlike previous studies that often use laboratory-generated or synthetic data, this dissertation works exclusively with raw operational mine data under real conditions. A tailored preprocessing pipeline was developed to handle mining-specific challenges: irregular sampling intervals, sensor dropouts, and environmental noise caused by dust and vibration. This pipeline integrates statistical outlier detection with temporal interpolation strategies optimised for long-sequence time series.

Steps 2 & 3—Checking and pre-treatment of data & Select dependent (output) variables and independent (input) variables

Variables were selected by first incorporating domain knowledge from experienced mining engineers to identify operational and damage-related factors of practical significance, and then applying mutual information ranking to statistically evaluate and prioritize features based on their relevance to the predicted failure parameters. This dual approach ensures both physical interpretability and predictive strength, avoiding the “black box” criticism

common in mining AI applications.

Steps 3 & 4—Select dependent (output) variables and independent (input) variables & Generate training-testing datatsets for ANN

The target output variables are mentioned in the Tables 4.1 and 6.2 and input variables in Tables 4.2 and 6.1. Selection was performed through a hybrid approach combining mining engineering expertise with mutual information analysis, ensuring both physical interpretability and predictive significance. To prepare the data for temporal forecasting, the dataset was split into training and testing subsets using a time-aware partitioning strategy that preserves chronological integrity. This avoids the leakage of future operational states into the training process, a known but often neglected source of bias in industrial AI research. In addition to conventional one-step-ahead forecasting, the methodology incorporated recursive multi-step modeling, where the output of the LSTM at time t was iteratively fed back as an input for predicting subsequent time steps (t+1,t+2,...). This approach allows the model to generate longer-horizon forecasts of failure size development, capturing the progressive nature of belt degradation. Such recursive modeling has been scarcely applied in mining-related AI studies, and its integration here enables the assessment of how prediction uncertainty accumulates over time — a factor critical for maintenance scheduling in real-world operations.

Steps 4 & 5—Generate training-testing datatsets for ANN & LSTM parameters selection: neurons, batch size, activation function, optmizer

Hyperparameters (neurons, batch size, activation functions, optimizers) were tuned using a multi-objective grid search that balanced prediction accuracy with computational efficiency to meet near-real-time constraints. The training epochs were determined using an adaptive early-stopping criterion tied to changes in validation MAE rather than a fixed patience window.

Steps 6–9 — Training, error analysis, model refinement, storage

Training incorporated a loss function combining MAE with a temporal smoothness penalty, discouraging unrealistic short-term oscillations in predicted damage size — a methodological novelty addressing the high temporal autocorrelation in conveyor belt wear progression. Iterative refinement was guided by both statistical performance metrics and engineering constraints on allowable prediction error for maintenance scheduling.

Step 10 — Prediction and validation

Predictions were validated not only statistically but also against historical maintenance decisions from the mine, enabling an operational relevance check. This dual validation framework strengthens the scientific contribution by aligning algorithmic accuracy with real-world decision-making criteria.

This flowchart captures the iterative and data-driven nature of the dissertation methodology, emphasizing quality control at each stage, especially during model training and validation. It closely follows the decided goal of the dissertation and serves as a guide for replicating or extending the approach in future studies.

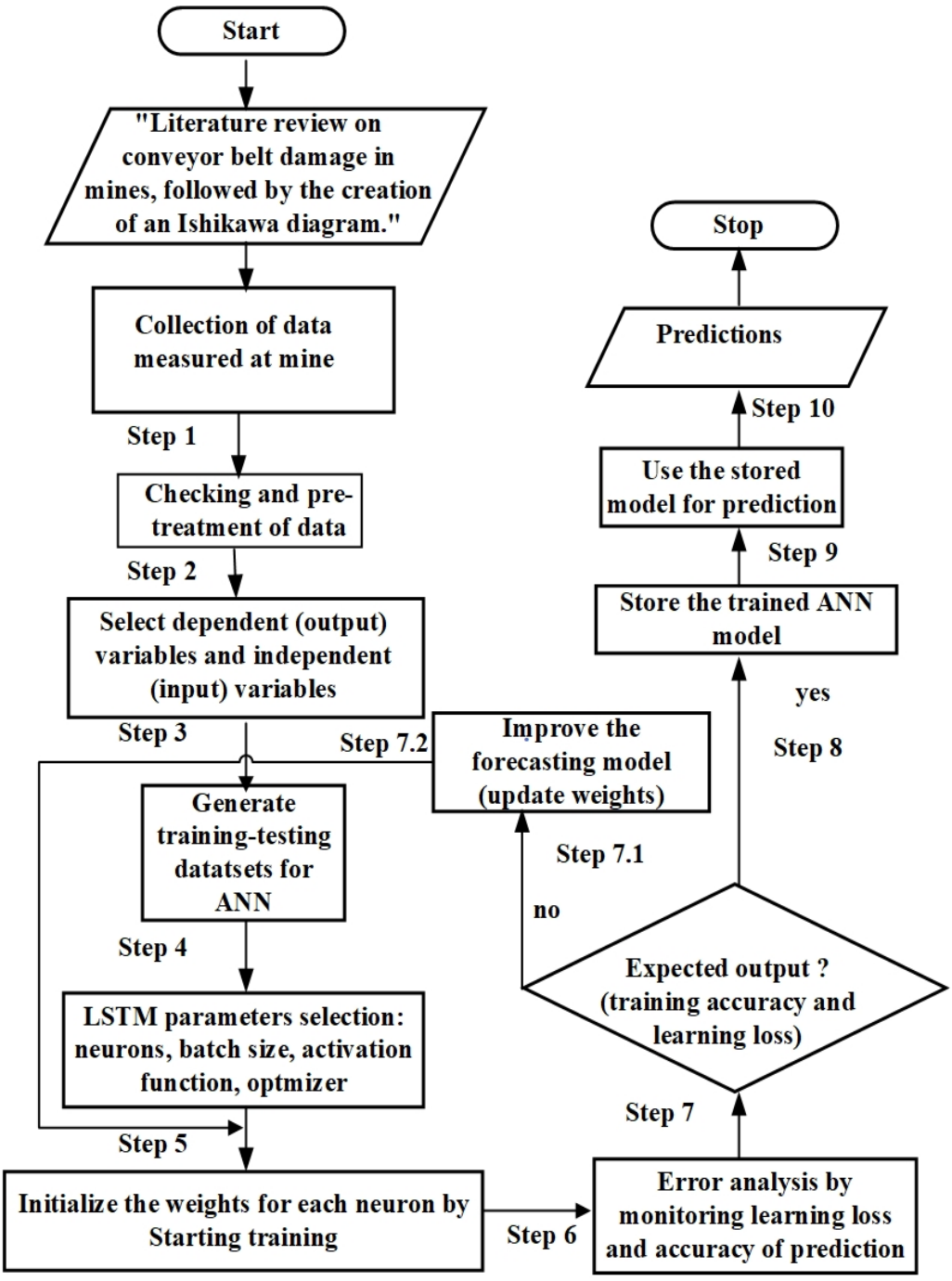


FIGURE 3.2: Flow Process chart of operations performed during the study

With the scientific objectives, scope, and methodological framework now established, the foundation is in place for the detailed examination of the

data on which the research is based. The next chapter introduces the datasets obtained from mining operations, describing their origin, structure, and variable composition, as well as the preprocessing procedures applied to prepare them for predictive modelling.

Chapter 4

Predictive modeling of conveyor belt failures based on visual inspection data

4.1 Description and characteristic of the visual inspection database

This chapter presents the description and characteristics of the human visual inspection database used in the development of the predictive model. The database, collected from surface lignite mine in Poland, contains detailed records of conveyor belt damage parameters, along with associated operational information. Analysing this database serves two purposes within the scope of the dissertation: first, to document the structure, origin, and content of the data, ensuring transparency and reproducibility; and second, to prepare the data for modelling by selecting relevant variables and defining hyperparameters for the long short-term memory (LSTM) neural network. These steps are essential for demonstrating the model's capability to predict the target failure-related parameters based on real-world inspection records.

The database, consisting of 1,112 rows in a spreadsheet provides detailed information on operating conditions, failures, and repairs of belt loops. It includes information on 11 belt loops, covering 119 belt segments (BSs). Each segments details, such as purchase information, unique identification numbers (BS names), installation dates, splice activities, segment lengths, technical parameters, conveyor belt specifications, inclination, transported materials, dismantling dates (with reasons), and the final disposition of removed segments (whether discarded or sent for refurbishment), were meticulously recorded in database. Conveyor belt failure data (dates and locations) and repair details (dates, dimensions, and locations) were systematically documented by the maintenance crew through routine visual inspections and stored in the repair and failure spreadsheet database. The raw data provided valuable insights into the operational realities, particularly the effects of operating conditions on conveyor belt damage and service life. The selection of variables for this study was guided by an Ishikawa diagram, as depicted in the chapter 1. This diagram, developed through a literature review, and helped in identifying 16 key correlated parameters, including input variables (operating conditions) and output variables (conveyor belt damage) from the

quantitative database provided by the mine. The finalized database included the variables listed in Tables 4.1 and 4.2.

TABLE 4.1: List of dependent variables

Y_1	Age at current repair-standstill (months)
Y_2	Number of small repairs at current standstill
Y_3	Cumulative number of small repairs at current standstill
Y_4	Number of cable/s cut at current standstill
Y_5	Cumulative number of cables cut at current standstill

TABLE 4.2: List of independent variables

X_1	Belt loop length (meters)
X_2	Belt segment length (meters)
X_3	Transported material (0: coal, 5: mixture of coal and rock-sand, 10: overburden)
X_4	Inclination of the conveyor belt (0: flat, 10: inclined)
X_5	New or moved belt segment (new: 0, moved: 10)
X_6	Completed percentage life compare to human estimation
X_7	Age at previous repair-standstill (months)
X_8	Number of small repairs during previous standstill
X_9	Previous cumulative number of small repairs
X_{10}	Previous numbers of cable cut
X_{11}	Previous cumulative number of cables cut

The database included parameters representing operating conditions, denoted as X_1 through X_5. The degradation of the CB was recorded in terms of the number of repairs, cable cuts, and the age at each failure instance. Additional information, such as mounting dates, repair dates, and estimated damage areas on the rubber cover (assessed via visual inspections), were also included in the data obtained from the mine. Parameters X_6 through X_{11} and Y_1 through Y_5 were manually calculated based on individual repair or mounting instances. These instances were identified by repair dates or timestamps

indicating the mounting and removal of a belt segment (BS) on a specific belt loop (BL). The manual calculations were carried out outside the mining facility by the research group at the institute presenting these findings. After the manual calculations, removing null values and correcting human errors, the "genesis dataset" comprised 927 rows of records in a spreadsheet, with 16 columns representing parameters—11 input parameters and 5 output parameters. The genesis dataset was then divided into two subsets: a training dataset containing 717 rows (77.3% of the total) and a testing dataset with 210 rows (22.7% of the total). Both subsets were randomly sampled from the genesis dataset. Each of these subsets was further split into two groups—one for input parameters (X_1 to X_{11}) and one for output parameters (Y_1 to Y_5). This resulted in four distinct datasets: two for training the neural network model (one for input parameters and one for output parameters) and two for testing the trained neural network model (again, one for input parameters and one for output parameters). The process of creating these four datasets is illustrated in Fig. 4.1.

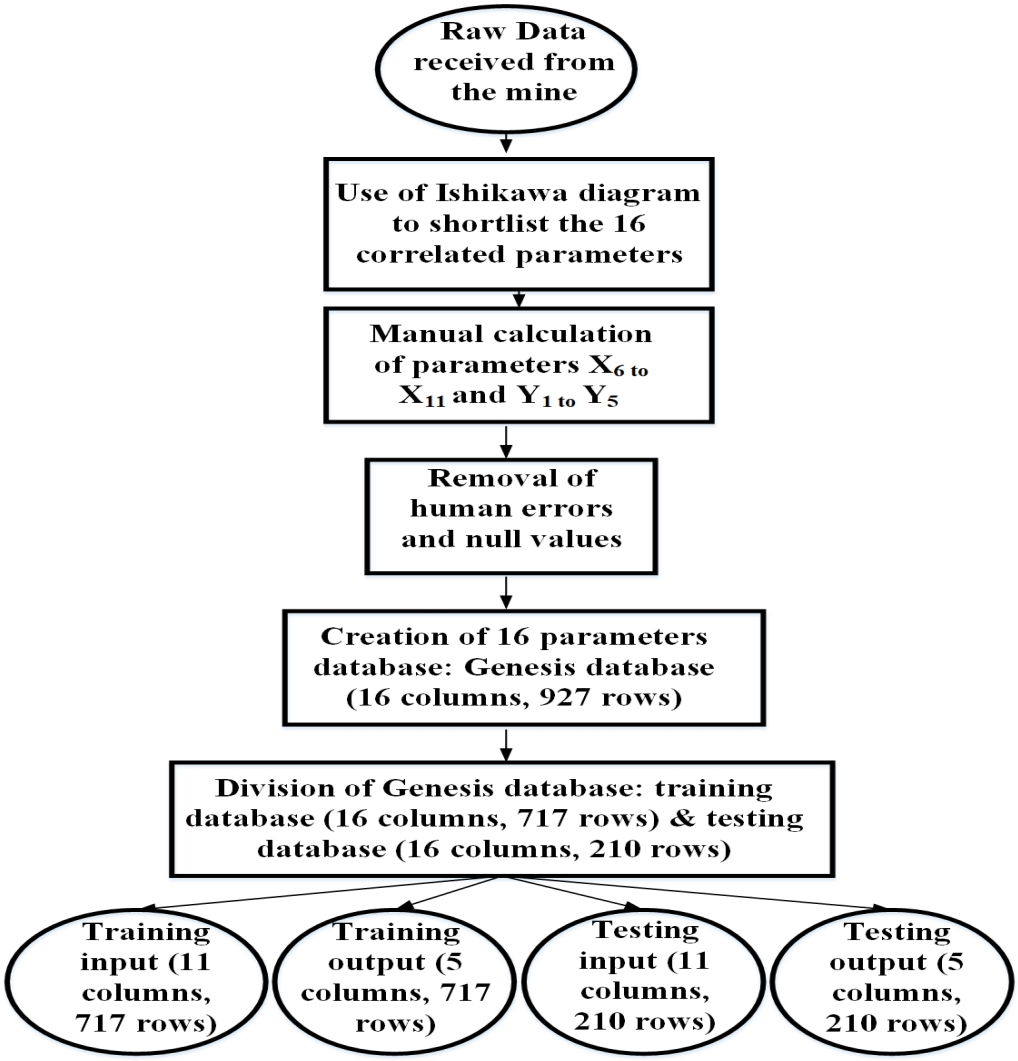


FIGURE 4.1: Flow process chart: testing and training dataset creation

Having examined the structure of the dataset obtained from the mine including the sixteen variables selected for modeling conveyor belt damage—and detailed the creation of four distinct datasets for training and testing purposes, it is now important to assess the nature of the data itself. Specifically, determining whether the relationships between the variables are linear or non-linear, which provides crucial context for selecting an appropriate modeling approach. As discussed in earlier chapters, artificial neural networks (ANNs) are generally more effective than traditional conventional methods when handling datasets characterized by non-linear dependencies. To support this, the Pearson correlation matrix shown in Table. 4.3 which illustrates the linear correlations among the input and output variables.

The Pearson correlation coefficient (r) [269] is a statistical measure that quantifies the strength and direction of a linear relationship between two variables. It ranges from -1 to +1. A value of +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no linear correlation.

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	Y_1	Y_2	Y_3	Y_4	Y_5
X_1: Belt loop length (meters)	1.0															
X_2 : *Beltsegmentlength(meters)*	-0.1	1.0														
X_3: Transported material (0: coal, 5:mixture of coal and overburden) 10: overburden	0.1	0.1	1.0													
X_4: Inclination of conveyor belt (0: flat, 10: inclined)	-0.7	0.2	-0.3	1.0												
X_5: New or moved belt segment (new:0, moved:10)	-0.2	0.0	0.0	0.2	1.0											
X_6: Completed percentage life compare to human estimation	0.1	0.1	-0.5	0.3	-0.1	1.0										
X_7: Age at previous repair-standstill (months)	0.3	0.0	-0.2	-0.1	-0.2	0.5	1.0									
X_8: Number of small repairs at previous repair-standstill	0.0	0.1	0.2	0.0	0.1	-0.2	0.3	1.0								
X_9: Previous cumulative number of small repairs	0.0	0.1	0.4	-0.1	0.0	-0.1	0.2	0.3	1.0							
X_{10}: Previous number of cable cut	-0.1	0.1	0.2	0.1	0.2	-0.2	0.1	0.5	0.2	1.0						
X_{11}: Previous cumulative number of cable cuts	-0.1	0.1	0.4	0.0	-0.1	0.0	0.2	0.3	1.0	0.3	1.0					
Y_1:Age at current repair-standstill (months)	0.5	-0.1	-0.5	-0.2	-0.3	0.7	0.7	-0.1	0.0	-0.2	0.0	1.0				
Y_2: Number of small repairs at current standstill	0.1	0.0	0.3	-0.1	0.2	-0.3	-0.1	0.1	0.3	0.1	0.3	-0.2	1.0			
Y_3: Cumulative number of small repairs at current standstill	0.0	0.1	0.4	-0.1	0.0	-0.1	0.2	0.4	1.0	0.2	0.9	0.0	0.4	1.0		
Y_4: Number of cable/s cut at current standstill	-0.1	0.0	0.2	0.0	0.2	-0.3	-0.1	0.0	0.1	0.1	0.2	-0.2	0.6	0.2	1.0	
Y_5: Cumulative number of cable cuts at current standstill	-0.1	0.1	0.4	0.0	0.0	-0.1	0.2	0.3	0.9	0.3	1.0	-0.1	0.4	0.9	0.3	1.0

TABLE 4.3: Pearson correlation matrix for all variables

Having reviewed the process of creating the four datasets and analyzed the Pearson correlation matrix to identify cases where the use of ANNs is justified, it is now worth exploring the structure and composition of the data itself. It offers a closer look at how the dataset is organized—illustrating for example, the distribution of belt segments by length, their classification according to current operational age, and the number of segments present within each belt loop. These characteristics provide essential contexts regarding the operating conditions at the lignite mine and they are critical for interpreting the model's inputs and performance.

It is advisable to investigate the discrete pool of operating conditions and properties of BSs within each BL, as the specific configuration of BSs in a given BL requires tailored working conditions to ensure performance aligns with the expectations set by mine operators. A clear understanding of these configurations is essential for accurately modeling conveyor belt behavior under real-world conditions. To illustrate the structure of both the input and output datasets used in the modeling process, representative examples are provided in Tables 4.4 and 4.5.

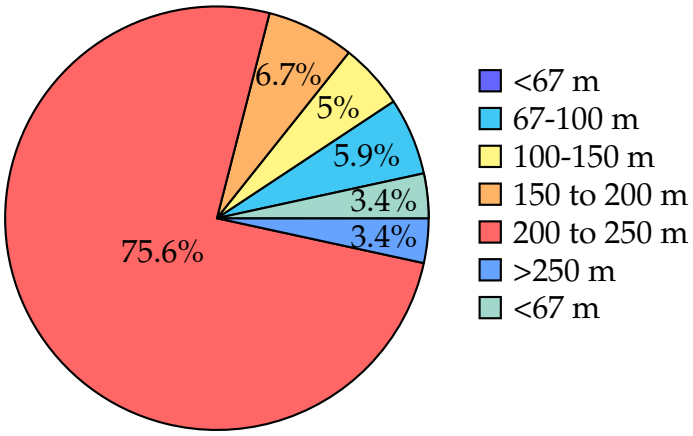


FIGURE 4.2: Belt segment length comparison in genesis dataset

As shown in Fig. 4.2, over 75% of the records in the genesis dataset feature BSs with lengths exceeding 200 meters. This is particularly important for making predictions about BSs shorter than 200 meters, as shorter segments are often older and more likely to have been shortened due to the removal of damaged portions, which is less common with newer belts.

Of the 119 total BSs, 107 (90%) were either newly purchased or relocated from another BL, while 11 (9.2%) were refurbished once, and only 1 (0.8%) was refurbished twice. In the genesis dataset, consisting of 927 rows, BSs used for the first time (installed after purchase) made up 51.6% of the rows (478 rows), while moved BSs (those used on at least two conveyors, often with a hidden history of damage) represented 48.4% of the rows (449 rows). In terms of the number of BSs, 78 (65.5%) were previously used and relocated from another BL, whereas 41 (34.5%) were newly installed.

Coal (lignite) accounted for only 13.4% of the data in the genesis dataset,

Belt loop	Belt segment	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
BL1	BS2	2975	142	0	0	0	96.7	88.2	5	5	7	7
BL4	BS31	2451	233	10	0	10	19.4	7.7	2	14	5	23
BL4	BS33	2451	210	10	0	10	13.9	4.9	3	6	5	28
BL8	BS66	1045	247	5	0	0	36.7	5.2	3	3	4	4
BL11	BS112	3524	247	5	0	10	116.7	69.8	2	7	3	14

TABLE 4.4: An example of input variables dataset

Belt loop	Belt segment	Y_1	Y_2	Y_3	Y_4	Y_5
BL1	BS1	27.9	3	3	4	4
BL4	BS33	7.7	2	26	2	92
BL6	BS57	44.9	5	15	2	36
BL6	BS59	1.8	4	4	7	7
BL7	BS62	2.6	3	3	7	7

TABLE 4.5: An example of output variables dataset

while a mixture of coal, sand, and rock made up 62.2%, and overburden represented 24.4%. If prediction errors are lower for coal compared to other materials, it suggests that coal exhibits greater consistency in handling during transportation and loading-unloading processes. As a result, conveyor belt damage during coal transportation becomes more predictable under specific operating conditions. In contrast, predictions may be more challenging for overburden and coal-overburden mixtures due to the greater variability in rock and sand grain sizes and their sharpness-roughness, compared to coal, which is relatively softer and more uniform.

Additionally, it is noteworthy that over 85% of the records in the genesis dataset pertain to flat belt inclination positions, while 14.3% involve inclined positions. This bias in the data suggests that predictions for inclined belt loops require particular scrutiny. The mechanisms of material impact and damage to the conveyor belt differ significantly between inclined and flat conveyor loop positions, especially during material loading-unloading and transportation operations.

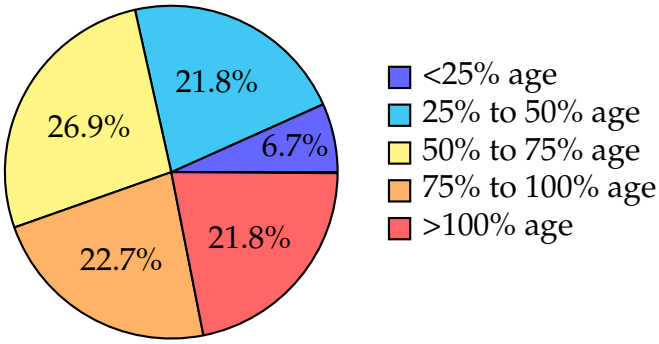


FIGURE 4.3: % records share in genesis dataset for Age at present compared to expected age by miners at the time of installation

Each BS has a life expectancy estimated by operators based on previous service life averages and belt quality at the time of installation. The percentage of life completion for each BS at the time of its removal from the loop, as shown in Fig. 4.3, is crucial for understanding the frequency of repairs and cable cuts. Older belts are more prone to critical damage, leading to their removal from the belt loop.

Furthermore, the BL length and the total number of BSs used in each BL

as shown in Fig. 4.4, are important factors when investigating the operating conditions and their impact on BS damage during operations. A BL with BSs of equivalent lengths suggests that both the BL and BSs are relatively new, as over time, critically damaged small sections of the BSs are removed and reintroduced after refurbishment. This approach reduces maintenance costs for the entire BS and facilitates repair work on smaller damaged patches within a larger BS.

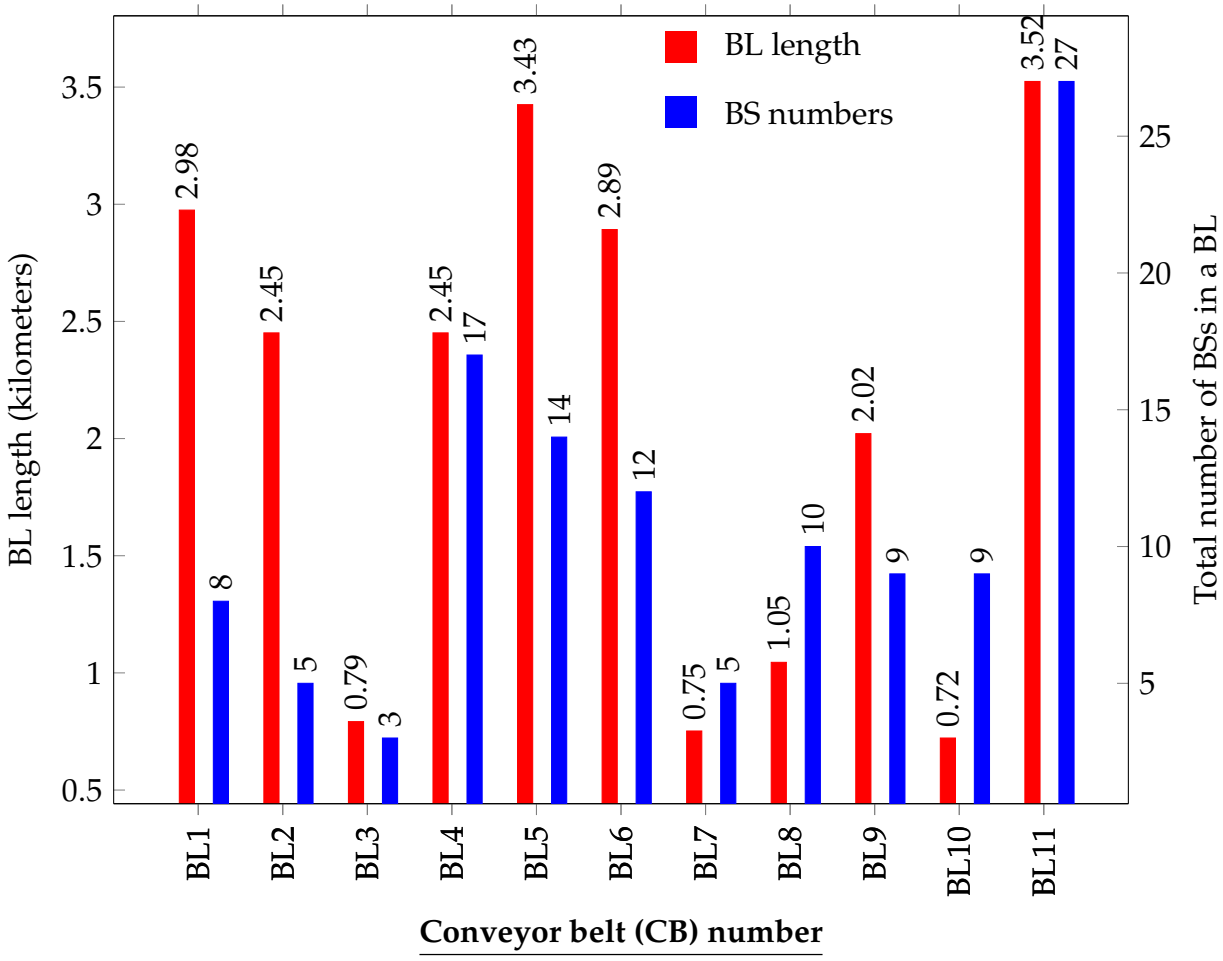


FIGURE 4.4: BL length and total BSs in each BL

After reviewing the composition and structure of the generated dataset—comprising both input and output parameters, it is now appropriate to move toward the core predictive and analytical phase of this dissertation. The subsequent section focuses on the modeling of conveyor belt wear using ANNs, applying the developed methodology to the real-world dataset. This step is critical for evaluating the predictive capabilities of the ANN models and assessing their effectiveness in capturing complex relationships inherent in the operational data.

4.2 Modeling using neural network

The process of creating the training and testing datasets is outlined in the flow process chart shown in Fig. 4.1. To investigate the influence of selected input parameters on these key output variables, five distinct ANN models were developed. Each model used the same set of eleven input parameters (X_1 to X_{11}) mentioned in the Table 4.2, while varying the combination of output parameters being predicted. A summary of these models is provided in Table 4.6.

TABLE 4.6: 5 main models designed during presented study

Model	Input parameters	Output parameters
Model 1	X_1 to X_{11}	Y_1 and Y_2 (age & number of small repairs)
Model 2	X_1 to X_{11}	Y_1 and Y_3 (age & cumulative number of small repairs)
Model 3	X_1 to X_{11}	Y_1 and Y_4 (age & number of cable/s cut)
Model 4	X_1 to X_{11}	Y_1 and Y_5 (age & cumulative number of cables cut)
Model 5	X_1 to X_{11}	Y_1 (age at current standstill)

To evaluate the performance of each of the five models (referred to as Model 1 to Model 5), three distinct variations of the training-testing datasets (V_1, V_2, V_3) were created. The 11 BL and 119 BSs were divided as shown in Tables 4.7 and 4.8. Each variation (V_1, V_2, V_3) was formed using different sets of belt segments, leading to unique combinations of input and output data rows in the training and testing datasets. These variations were derived exclusively from the 'genesis dataset', resulting in different training and testing configurations for each variations. This approach will help assess the prediction performance of the models under varying operating conditions, allowing the trained model to be recognized as a reliable method for predicting the deterioration of CB for future use at the mining site. The creation of three variations resulted in a total of fifteen different models, as shown in Table 4.9.

TABLE 4.7: Total number of belt loop (BL) and belt segment (BS) distribution in genesis dataset and in different testing datasets

	V_1 dataset	V_2 dataset	V_3 dataset
BL & BS used for training	11 & 92	11 & 98	11 & 79
BL & BS used for testing	11 & 27	9 & 21	11 & 40

TABLE 4.8: Number of belt loop (BL) and belt segment (BS) distribution in genesis dataset and in different testing datasets

Genesis dataset	V_1 dataset for testing	V_2 dataset for testing	V_3 dataset for testing
BL1: BS1 to BS8	BL1: BS1, BS8	BL1: BS2	BL1: BS3 to BS7
BL2: BS9 to BS13	BL2: BS9 to BS11		BL2: BS12, BS13
BL3: BS14 to BS16	BL3: BS16		BL3: BS14, BS15
BL4: BS17 to BS33	BL4: BS27 to BS29 BS32, BS33	BL4: BS17	BL4: BS19 to BS26 BS28,
BL5: BS35 to BS47	BL5: BS47	BL5: BS46	BL5: BS34 to BS42 BS43,
BL6: BS48 to BS59	BL6: BS57	BL6: BS48	BL6: BS50 to BS56
BL7: BS60 to BS64	BL7: BS62	BL7: BS63, BS64	BL7: BS60, BS61
BL8: BS65 to BS74	BL8: BS71 to BS73	BL8: BS65, BS66	BL8: BS67, BS68
BL9: BS75 to BS83	BL9: BS81to BS83	BL9: BS75, BS80	BL9: BS77 to BS78
BL10: BS84 to BS92	BL10: BS84 to BS86 BS92	BL10: BS87	BL10: BS88
BL11: BS93 to BS119	BL11: BS102, BS103, BS112, BS115, BS116	BL11: BS93 to BS101 BS119	BL11: BS107,BS109, BS111, BS113 BS114,BS117,

TABLE 4.9: All 15 models designed during presented study

Model	Input parameters	Output parameters
Model 1.1-V_1	X_1 to X_{11}	Y_1 and Y_2
Model 1.2-V_2	X_1 to X_{11}	Y_1 and Y_2
Model 1.3-V_3	X_1 to X_{11}	Y_1 and Y_2
Model 2.1-V_1	X_1 to X_{11}	Y_1 and Y_3
Model 2.2-V_2	X_1 to X_{11}	Y_1 and Y_3
Model 2.3-V_3	X_1 to X_{11}	Y_1 and Y_3
Model 3.1-V_1	X_1 to X_{11}	Y_1 and Y_4
Model 3.2-V_2	X_1 to X_{11}	Y_1 and Y_4
Model 3.3-V_3	X_1 to X_{11}	Y_1 and Y_4
Model 4.1-V_1	X_1 to X_{11}	Y_1 and Y_5
Model 4.2-V_2	X_1 to X_{11}	Y_1 and Y_5
Model 4.3-V_3	X_1 to X_{11}	Y_1 and Y_5
Model 5.1-V_1	X_1 to X_{11}	Y_1
Model 5.2-V_2	X_1 to X_{11}	Y_1
Model 5.3-V_3	X_1 to X_{11}	Y_1

The importance of model and their variations has already been explained. The next step is to focus on the neural network parameters used in the study. During the study, various combinations of hidden layers and neurons were explored and compared. Combination 2, as detailed in Table 4.10, was selected for the neural network parameters, as it achieved the highest validation accuracy during long short term memory (LSTM) neural network training (with the maximum possible accuracy being 100%). The mean squared error (MSE) loss function was used, with the MSE value decreasing as training accuracy increased. Different batch sizes (2, 4, 8, 16) were tested across models, with a batch size of 16 being chosen, as other sizes did not significantly impact training accuracy.

TABLE 4.10: Selection of neurons and layers combination

Combination	Input layer neurons	Neurons × hidden layer	Output layer neurons	Batch size	Epochs	Accuracy % for training /validation
1	11	36×4	2	16	60	97/75
2	11	36×3	2	16	60	97/83
3	11	36×7	2	16	60	98/71
4	11	36×3	2	16	90	98/77

Variety of optimizers—including Adam, Nadam, Adamax, RMSprop, and stochastic gradient descent (SGD)—were utilized, alongside back-propagation,

to update the neural network's weights. Additionally, six activation functions were tested—ReLU, Swish, sigmoid, tanh, Leaky ReLU, and softmax. Based on the training accuracy and learning loss observed during different training instances, the optimizers Adam, Nadam, and RMSprop, as well as the activation functions ReLU and Swish, were finalized due to their superior performance. The ReLU activation function offers several key advantages in this study—(i) it is computationally simple, with a straightforward rectifier function compared to tanh and sigmoid functions, which require exponential calculations. (ii) it promotes representational sparsity by outputting true zero values for negative inputs, enabling hidden layers in neural networks to have one or more true zero values. (iii) its linear behavior simplifies the optimization of the neural network when the behavior is linear or nearly linear, thereby avoiding vanishing gradients. (iv) it is well-suited for training deep neural networks. Additionally, the Swish activation function aids in data normalization, leading to faster convergence and more efficient learning in the neural network. It is also suitable for deep neural networks, enabling small gradient updates during training, which is crucial for effective backpropagation in deep networks.

With the neural network parameters finalized, the LSTM models were trained and tested using the various dataset combinations described earlier (V_1, V_2, V_3). During the training phase, the ANN identified complex, nonlinear correlations between the input and output parameters, which were subsequently stored in a hierarchical data format (.h5) file. The trained models were then employed to predict conveyor belt performance under various potential future operating conditions, with particular focus on output variables mentioned in the Table 4.1. This modeling phase enabled a evaluation of the neural networks' predictive performance under different data configurations. The subsequent section presents the results of these training and testing iterations, followed by a detailed discussion aimed at assessing the accuracy, reliability, and practical relevance of the developed models in forecasting conveyor belt wear and damage.

4.3 Results and discussion

Past records of selected input and output variables were utilized to predict the future behavior of the conveyor belt. The discussion on the varying proportions of different operating conditions and belt segment properties in the genesis dataset is described in section 4.1. Tables 4.11 and 4.12 illustrate the distribution across three versions of training and testing variations (V_1, V_2, V_3), each using different combinations of BSs. The distributions presented in these tables helps explaining the specific behavior of the models during predictions. By analyzing variations V_1, V_2 and V_3 it becomes clear that different numbers of used BSs were employed, allowing to correlate the representation of specific categories in the genesis dataset with their distribution in these variations. This analysis supports the conclusion that the trained

models are robust and applicable to future operating conditions beyond any specific range of operating or BS conditions. Instances numbered from 0 to 210 correspond to comparisons for variation V_1, instances 211 to 420 correspond to comparisons for variation V_2, and instances 421 to 630 correspond to comparisons for variation V_3.

To assess the predicted results for models mentioned in Tables 4.13, 4.14, 4.15, 4.16, 4.17:, three indicators were used—indicator A, B, and C and their basis of creation was relative error. Moreover, the models were highlighted in green color whose performance was comparatively better than other models.

Relative error formula:

$$\frac{|Predicted\ values\ by\ ANN - Values\ recorded\ by\ human\ visual\ inspection|}{Values\ recorded\ by\ human\ visual\ inspection} \times 100$$

A: % of 210 predictions instances having relative error <50% compared to mine records

B: % of 210 predictions instances having relative error between 50-100% compared to mine records

C: % of 210 predictions instances having relative error >100% compared to the records

Green color: models with better prediction results comparatively based on indicators and median value.

Figs. 4.5, 4.6, 4.7, 4.8 and 4.9, illustrate the results for all models referenced in Tables 4.13, 4.14, 4.15, 4.16, and 4.17. These figures indicate that trends were accurately predicted in most cases, and seasonal patterns were generally consistent with the mines historical data for most belt segments. Moreover, interpretation of all models (including all variations—V_1, V_2, V_3) prediction behavior is provided in the subsection 4.3.1.

TABLE 4.13: Prediction results in % for model 1 (age & number small repairs) indicating share for indicators A, B, C

Parameters	Activation function	Testing dataset version	Optimizer	Median value of relative error	A	B	C
Age	ReLU	V_1	Nadam	60	47	11	40
Repairs				45	53	34	11
Age	ReLU	V_2	Nadam	27	65	9	25
Repairs				29	71	21	7
Age	ReLU	V_3	Nadam	47	51	18	30
Repairs				46	50	19	31

TABLE 4.11: Share of the different parameters status-condition in different testing datasets

Parameters status-condition	V_1	V_2	V_3	Difference between maximum and minimum
$\leq$ 200 m BS length	24.8%	15.2%	10.9%	13.9%
$>$ 200 m BS length	75.2%	84.8%	89.1%	13.9%
Transported material: coal	10.9%	9.6%	8.5%	2.4%
Transported material: mixture-coal and sand, rock	51.9%	49.5%	52.8%	3.3%
Transported material: overburden	37.2%	40.9%	38.7%	3.7%
Belt position: flat	84.2%	86.2%	84.8%	2%
Belt position: inclined	15.8%	13.8%	15.2%	2%
Belt condition: new	47.2%	84.8%	62.4%	37.6%
Belt condition: moved from another BL	52.8%	15.2%	37.6%	37.6%
Age at current repair $\leq$ 60 months	77.6%	87.1%	79%	9.5%
Age at previous repair >60 months	22.4%	12.9%	21%	9.5%

TABLE 4.12: Share of the different parameters status-condition in different training datasets

Parameters status-condition	V_1	V_2	V_3	Difference between maximum and minimum
$\leq$ 200 m BS length	10.3%	13.2%	14.4%	4.1%
$>$ 200 m BS length	89.7%	86.8%	85.6%	4.1%
Transported material: coal	6.8%	7.3%	7.5%	0.7%
Transported material: mixture-coal and sand, rock	52.8%	53.6%	52.6%	1%
Transportred material: overburden	40.4%	39.1%	39.9%	1.3%
Belt position: flat	85.6%	85.0%	85.6%	0.6%
Belt position: inclined	14.4%	15%	14.4%	0.6%
Belt condition: new	52.8%	41.9%	48.4%	10.9%
Belt condtion: moved from another BL	47.2%	58.1%	51.6%	10.9%
Age at current repair $\leq$ 60 months	82.5%	79.6%	82%	2.9%
Age at previous repair >60 months	17.5%	20.4%	18%	2.9%

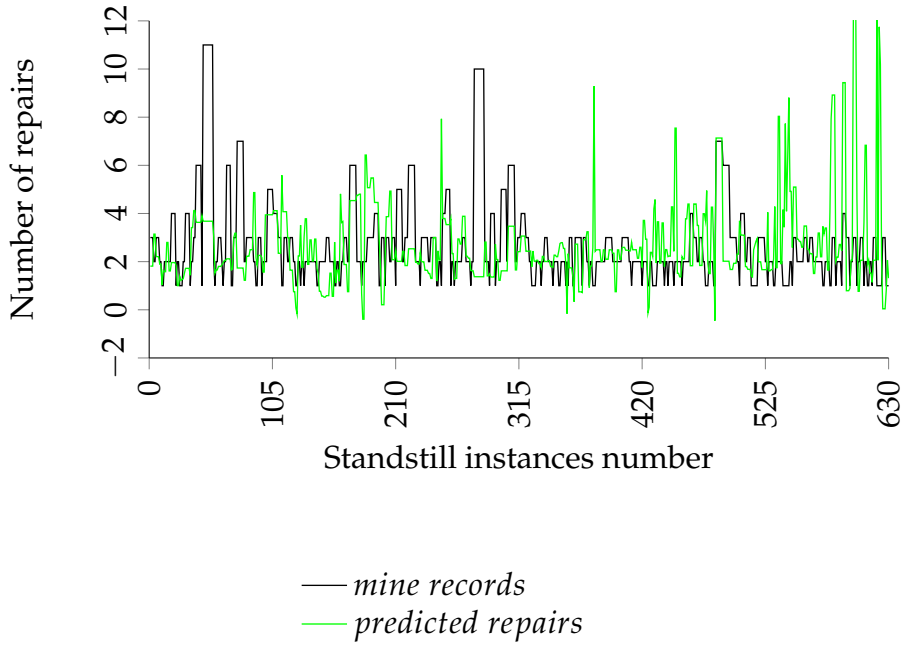


FIGURE 4.5: Predicted numbers of repairs vs repairs recorded at mine (models: 1.1-V_1, 1.2-V_2, 1.3-V_3)

Table 4.13, 4.14 and Figs. 4.5, 4.6 show that in both models 1 and 2, variation V_2 demonstrated comparatively superior values for indicator A. However, in model 2, the prediction results for variations V_1 and V_3 revealed a significant decline in indicator A values. Notably, BL2 and BL3 were excluded from the testing dataset for variation V_2. It is possible that BL2 and BL3 encountered significant issues, as noted by the mine operators during specific instances, which could have affected the recorded number of repairs.

Additionally, as shown in Tables 4.8 and 4.7, version V_2 had the highest number of BSs for training and the lowest number of BSs for testing.

TABLE 4.14: Prediction results in % for model 2 (age & cumulative number of repairs) indicating share for indicators A, B, C

Parameters	Activation function	Testing dataset version	Optimizer	Median value of relative error	A	B	C
Age	Swish	V_1	Adam	40	53	15	31
repairs				111	24	23	51
Age	Swish	V_2	Adam	33	62	15	21
Cumulative repairs				31	80	15	3
Age	Swish	V_3	Adam	55	48	17	34
Cumulative repairs				131	22	19	57

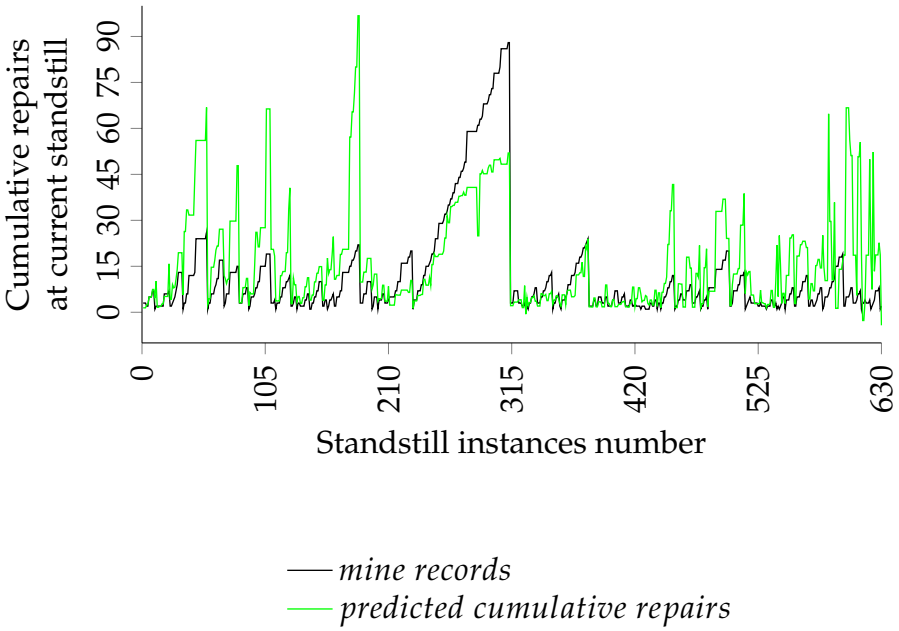


FIGURE 4.6: Predicted numbers of cumulative repairs vs cumulative repairs number calculated from mine data (models: 2.1-V_1, 2.2-V_2, 2.3-V_3)

TABLE 4.15: Prediction results in % for model 3 (age & number of cable/s cut) indicating share for indicators A, B, C

Parameters	Activation function	Testing dataset version	Optimizer	Median value of relative error	A	B	C
Age	Swish	V_1	Adam	49	50	29	19
Cable cuts				52	46	26	26
Age	Swish	V_2	Adam	28	59	11	29
Cable cuts				56	49	28	22
Age	Swish	V_3	Adam	36	62	14	22
Cable cuts				34	62	16	21

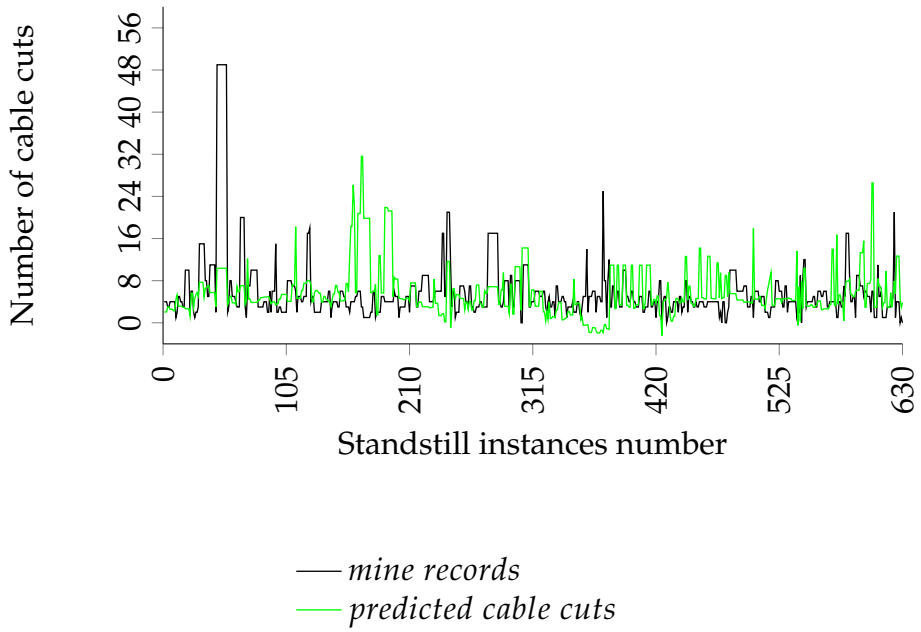


FIGURE 4.7: Predicted numbers of cable cuts vs cable cuts recorded at mine (models: 3.1-V_1, 3.2-V_2, 3.3-V_3)

In contrast to the results for models 1 and 2, as shown in Tables 4.13 and 4.14, the results for model 3, presented in Table 4.15 and Fig. 4.7 indicate that variation V_3 has comparatively better values for indicator A than variations V_1 and V_2. Additionally, the results for model 4, outlined in Table 4.16 and Fig. 4.8 show that variation V_2 has the lowest value for indicator C (2.8% for the cumulative number of cable cuts), while variation V_1 has the highest values for indicator A.

TABLE 4.16: Prediction results in % for model 4 (age & cumulative number of cable cuts) indicating share for indicators A, B, C

Parameters	Activation function	Testing dataset version	Optimizer	Median value of relative error	A	B	C
Age	ReLU	V_1	RMSprop	26	70	9.5	20
Cumulative numbers of cable cuts				55	43	31	25
Age	ReLU	V_2	RMSprop	33	58	12	28
Cumulative numbers of cable cuts				52	43	54	2.8
Age	ReLU	V_3	RMSprop	42	54	18	27
Cumulative numbers of cable cuts				107	23	22	55

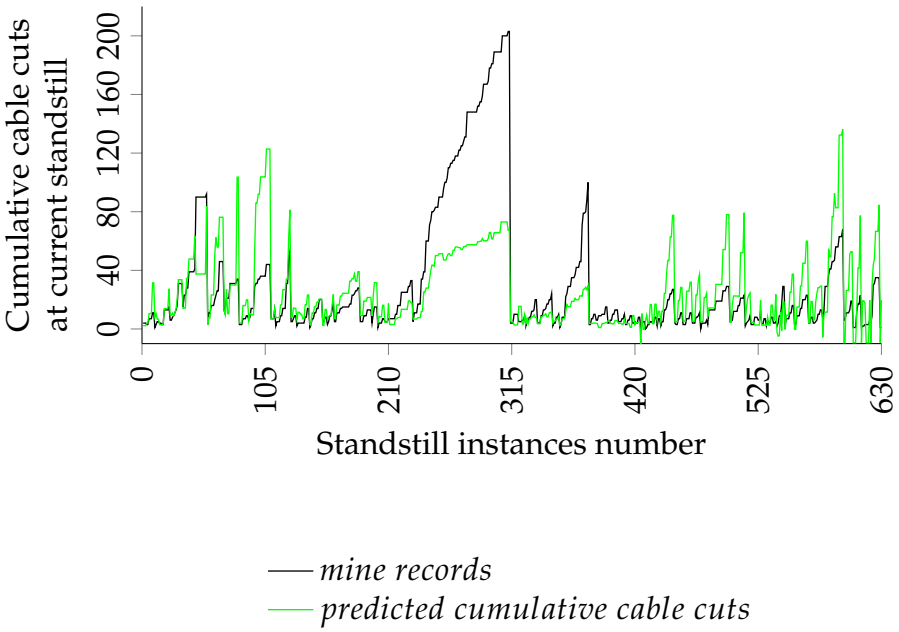


FIGURE 4.8: Predicted numbers of cumulative cable cuts vs cumulative numbers of cable cut calculated from mine data (models: 4.1-V_1, 4.2-V_2, 4.3-V_3)

TABLE 4.17: Prediction results in % for model 5 (age at current repairs-standstill) indicating share for indicators A, B, C

Activation function	Testing dataset version	Optimizer	Median value of relative error	A	B	C
ReLU	V_1	Nadam	36	65	12	21
ReLU	V_2	Nadam	27	58	16	24
ReLU	V_3	Nadam	22	66	6.2	28.2

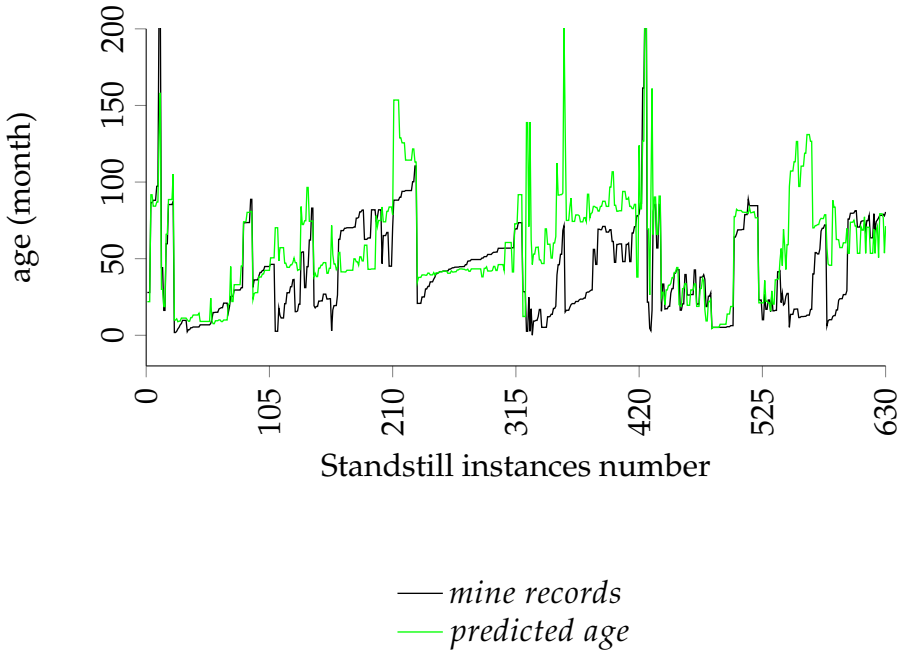


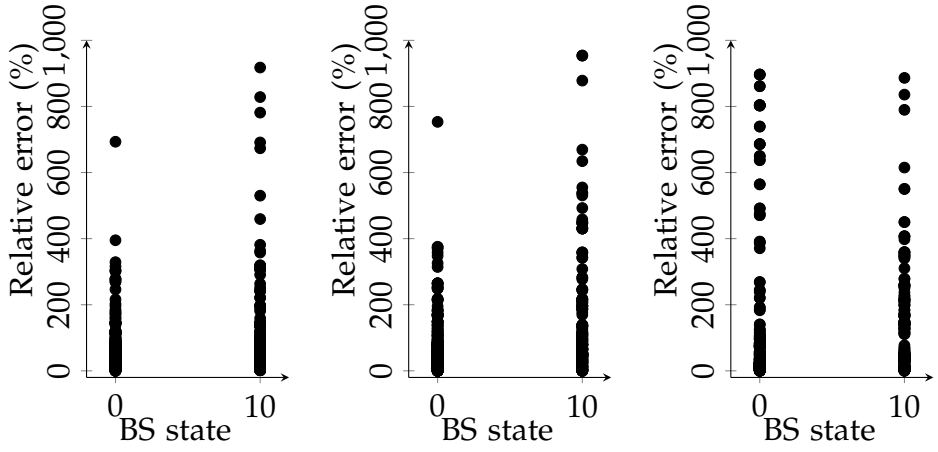
FIGURE 4.9: Predicted age vs age recorded at mine at specific instance of standstill (models: 5.1-V_1, 5.2-V_2, 5.3-V_3)

As shown in Table 4.17 and Fig. 4.9, all variations—V_1, V_2, and V_3 exhibit indicator A values exceeding 55% for model 5, suggesting that model 5 is reliable and can be used for future operating conditions. Additionally, Table 4.17 and Fig. 4.9 demonstrates that using a single output variable leads to improved prediction accuracy compared to models that require correlating two variables with the input set.

In summary, when considering the range between the highest and lowest values for indicator A across the prediction results for models 1 through 5, as detailed in Tables 4.13, 4.14, 4.15, 4.16, 4.17 and Fig. 4.5, 4.6, 4.7, 4.8, 4.9 it becomes clear that no specific variation of the training-testing dataset (V_1, V_2, V_3) consistently outperforms or underperforms the others. Therefore, the best-performing models, highlighted in green in the mentioned tables, can be utilized for specific targeted variables to assess conveyor belt performance under future operating conditions.

4.3.1 Interpretation of models behavior

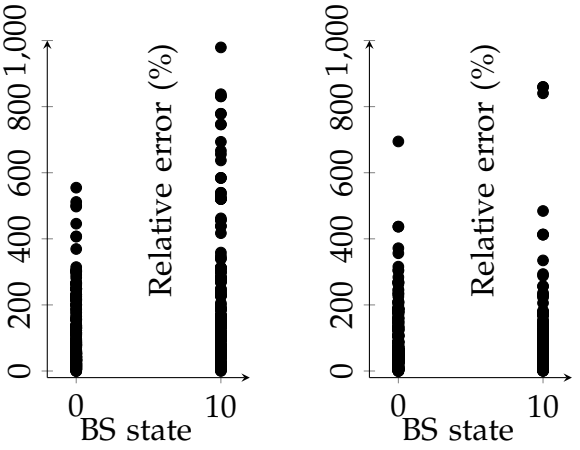
BSs that were moved from another BL show high relative errors in predictions across all models, as depicted in Fig. 4.10. These BSs, which have been repaired and reintroduced (and are then categorized as new), have already undergone a portion of their expected service life at the time of installation. This indicates that these BSs have hidden histories of repairs and damage that were not communicated to the AI model. Consequently, high relative errors for this category are expected, making it difficult for the AI model to accurately predict the total number of repairs and cable cuts, as well as estimate the age of new BSs.



(A) models: 1.1-V_1, 1.2-V_2, 1.3-V_3

(B) models: 3.1-V_1, 3.2-V_2, 3.3-V_3

(C) models: 5.1-V_1, 5.2-V_2, 5.3-V_3



(D) models: 2.1-V_1, 2.2-V_2, 2.3-V_3

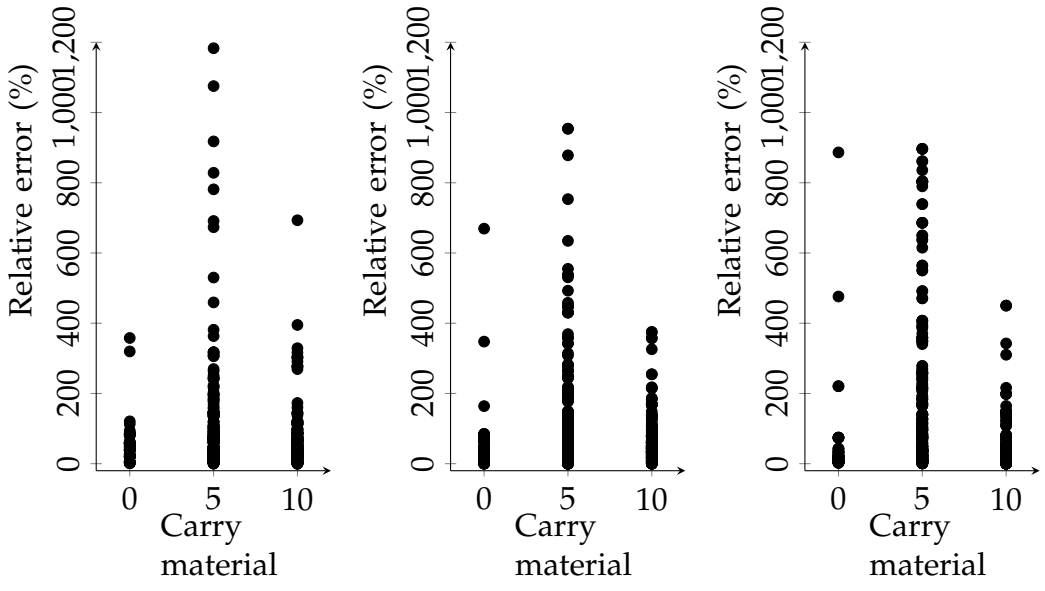
(E) models: 4.1-V_1, 4.2-V_2, 4.3-V_3

FIGURE 4.10: Belt segment (BS) state (new: 0, moved from another BL: 10)
impact on predictions for different models

Furthermore, there is no standardized rule for dismantling a specific BS from the BL; such decisions are primarily based on human judgment, experience, and the availability of resources for maintenance and replacement.

As discussed in earlier sections, another factor contributing to the high relative error and the outstanding number of errors could be the disproportionate record distribution in the genesis dataset. Specifically—(i) 90% of BSs (107 BSs) belong to the first use after purchase or were moved from another BL, while only 10% (12 BSs) are refurbished. (ii) in the genesis dataset, 65.5% of BSs (78 BSs) were moved from another BL, while 34.5% (41 BSs) were new.

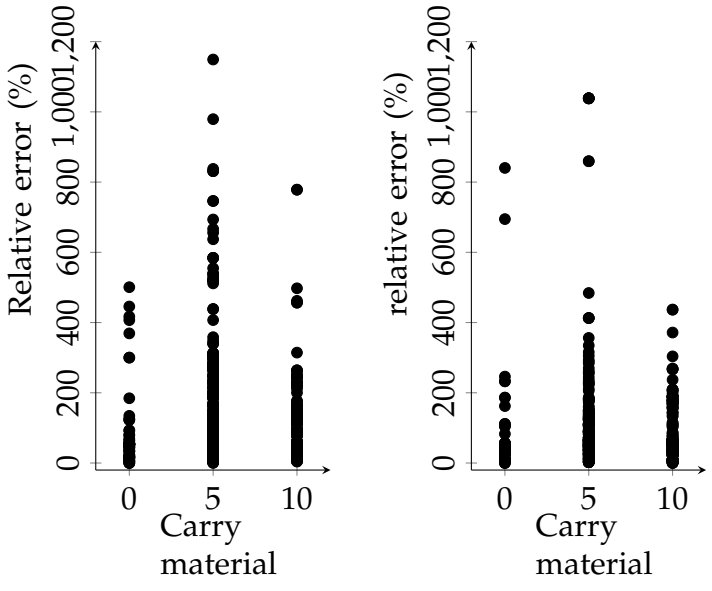
(iii) of the 927 rows in the genesis dataset, 478 rows (51.6%) pertained to new BSs, while 449 rows (48.4%) related to moved BSs.



(A) models: 1.1-V_1, 1.2-V_2, 1.3-V_3

(B) models: 3.1-V_1, 3.2-V_2, 3.3-V_3

(C) models: 5.1-V_1, 5.2-V_2, 5.3-V_3



(D) models: 2.1-V_1, 2.2-V_2, 2.3-V_3

(E) models: 4.1-V_1, 4.2-V_2, 4.3-V_3

FIGURE 4.11: Transported materials (0: coal, 5: mixture of coal and rock-sand, 10: overburden) impact on predictions for different models

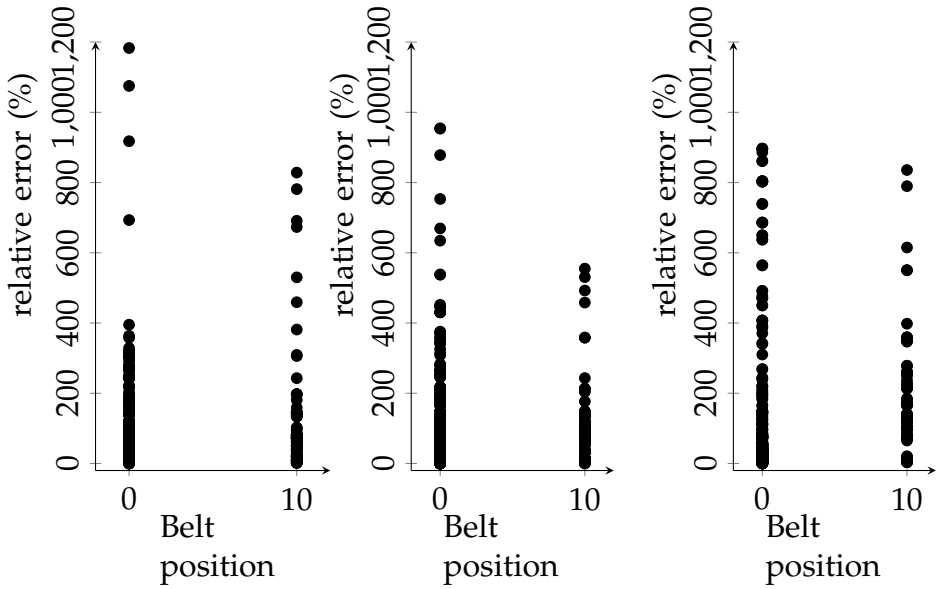
Regarding the material carried on the CB, a mixture of coal and overburden accounted for the highest relative error in predictions, as shown in Fig.

4.11. Coal exhibited the lowest relative error, followed by overburden. This suggests that coal is more uniform in material handling during transportation, whereas the mixture of coal and overburden involves varying proportions of each, with the grain size and wear capacity of overburden changing over time. As a result, it is evident that relative errors are higher for this category.

Relative errors in predictions for belt positions (flat or inclined) are illustrated in Fig. 4.12. Across all models, there is a consistent pattern, with a higher number of prediction points exceeding a 100% relative error threshold for flat belts compared to inclined ones. Interestingly, inclined belts account for less than 15% of the records in the genesis dataset. The angle of impact is a critical factor in material transportation, influencing the extent of damage to the CB caused by the material. Despite the significant disparity in record share between flat and inclined belts, the latter consistently exhibited lower relative errors across all models. This may be because inclined conveyor positions reduce uncertainty regarding the angle of impact, leading to more uniform damage patterns during material handling.

BL length also demonstrated relative errors in line with expectations, as shown in Fig. 4.13. While some individual cases showed the highest relative errors for BL longer than 2.4 kilometers (km), overall, instances with relative errors exceeding 100% were more frequent for BL shorter than 2.4 km. Notably, Model 5, which incorporates belt age, showed a higher incidence of relative errors for BL lengths under 1.2 km. This trend is attributed to the fact that 75% of the records in all three versions (V_1, V_2, and V_3) of the testing and training datasets correspond to belts aged less than 60 months. Shorter and younger BL necessitate more frequent changes of the BS during operations due to the higher number of cycles they undergo compared to longer BL. This suggests that key factors, such as the number of repairs and cable cuts that determine the service life of the belt (as modeled in Model 5), led to higher relative errors during training, which are reflected in the prediction results. This can be traced back to human decision-making, where specific damages and BS shifts for repairs are recorded based mainly on regular "visual inspections."

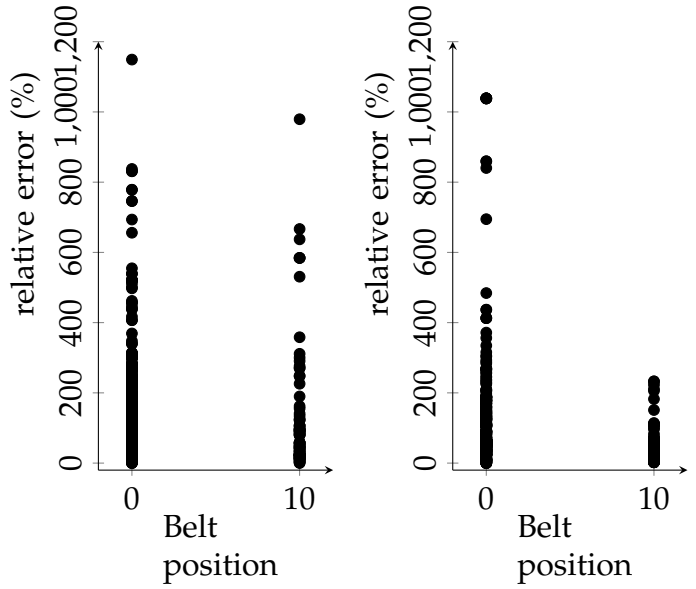
Furthermore, CB3, CB7, CB8, and CB10 were BL with lengths under 1,045 meters. Among these, CB10 and CB8 exhibited particularly high relative errors in predictions. In these cases, BS67 in CB8 and BS88 in CB10 were new BSs within their respective loops. This suggests that BSs without a history of prior failures are more prone to higher relative error rates in predictions. A likely contributing factor is human intervention, where the decision to remove a specific BS from a BL relies solely on expertise and experience, without any standardized rule to define a threshold for such removal. Additionally, cyclical visual inspections conducted at regular intervals in mining facilities often overlook minor damages to the conveyor belt unless they become significant enough to warrant inclusion in the next round of repairs and maintenance. Moreover, BS88 constitutes one-third of the total length of the CB10 belt loop, providing a larger surface area for material carry, which increases the potential for damage compared to shorter BSs.



(A) models: 1.1-V_1, 1.2-V_2, 1.3-V_3

(B) models: 3.1-V_1, 3.2-V_2, 3.3-V_3

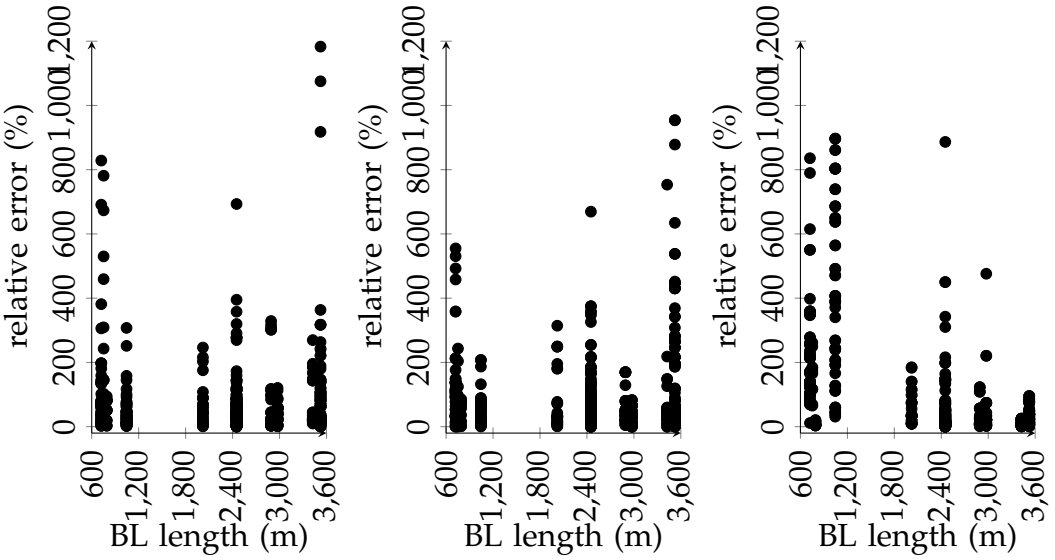
(C) models: 5.1-V_1, 5.2-V_2, 5.3-V_3



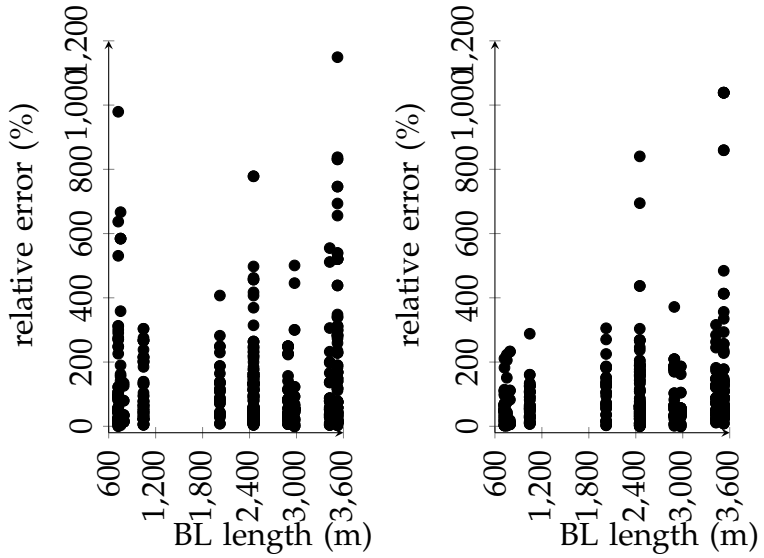
(D) models: 2.1-V_1, 2.2-V_2, 2.3-V_3

(E) models: 4.1-V_1, 4.2-V_2, 4.3-V_3

FIGURE 4.12: Conveyor positions (0: flat, 10: inclined) impact on predictions made by different models



(A) models: 1.1-V_1, 1.2-V_2, 1.3-V_3 (B) models: 3.1-V_1, 3.2-V_2, 3.3-V_3 (C) models: 5.1-V_1, 5.2-V_2, 5.3-V_3

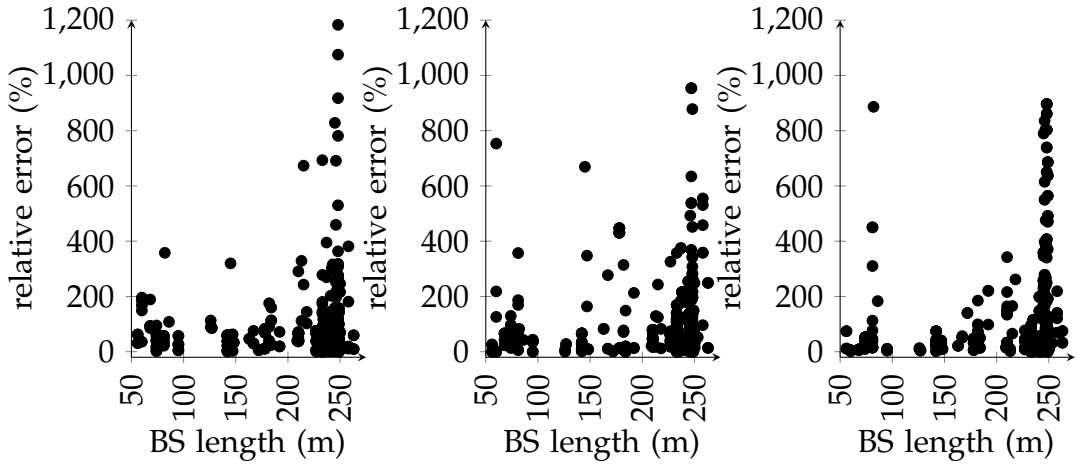


(D) models: 2.1-V_1, 2.2-V_2, 2.3-V_3 (E) models: 4.1-V_1, 4.2-V_2, 4.3-V_3

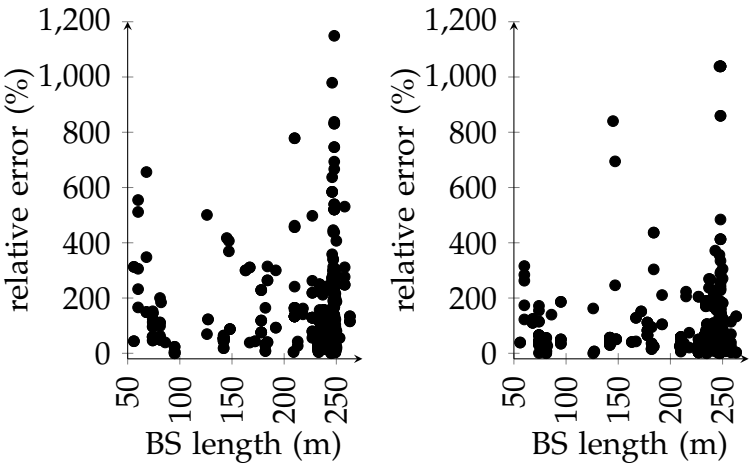
FIGURE 4.13: Belt loop (BL) length impact on predictions made by different models

The length of the BSs also significantly impacted the relative errors, as shown in Fig. 4.14. BSs longer than 225 meters had the highest frequency of relative errors overall. According to the percentage record shares presented in Tables 4.11 and 4.12, more than 75% of the total records in all versions of the testing and training datasets were for BSs longer than 200 meters. When damaged patches are removed from a BS, the overall length of the BS is reduced. A BS longer than 200 meters typically indicates that it is relatively new and that any damaged patches may not have been removed for repairs

and maintenance yet. As previously mentioned, the decision to remove BSs from a BL is entirely at the discretion of the mining operators. The lower relative errors observed for shorter BSs suggest that the models were more accurate in estimating the number of repairs and cable cuts, aligning more closely with the records from the mine than predictions for longer BSs. This implies that longer damaged areas introduce more uncertainties for the models. In conclusion, a more rigorous approach to recording failures is necessary, as relying solely on human visual inspection is insufficient.



(A) models: 1.1-V_1, 1.2-V_2, 1.3-V_3 (B) models: 3.1-V_1, 3.2-V_2, 3.3-V_3 (C) models: 5.1-V_1, 5.2-V_2, 5.3-V_3



(D) models: 2.1-V_1, 2.2-V_2, 2.3-V_3 (E) models: 4.1-V_1, 4.2-V_2, 4.3-V_3

FIGURE 4.14: Belt segment (BS) length impact on predictions made by different models

4.4 Conclusions and insights

Among the five highlighted models, the highest median relative error was 55%, and the lowest was 26%, while the highest value for indicator A was 80%, and the lowest was 43%. It was observed that BSs moved from one belt loop to another had high relative errors, indicating that hidden histories of the belt segments can significantly impact prediction accuracy. The model might incorrectly attribute the current operating conditions as the cause of the BSs behavior, which is not always the case. The study also found that predictions for flat belt positions had higher relative errors, likely due to the disproportionate record share between inclined (14.3%) and flat (85.7%) conveyor positions. A more diverse dataset covering different angles of impact could improve the accuracy, as each category requires specific data points to effectively map the correlations between variables. Notably, coal as a transported material resulted in the lowest relative errors, while a mixture of coal and sand-rock (overburden) led to the highest errors due to the uncertainty in the actual proportion of coal to overburden and the resulting frequency of large lumps in the transported material.

Shorter belt loops (less than 2.4 km) were associated with higher relative errors, as shorter loop lengths and younger BSs suggest more frequent changes. Additionally, shorter loops experience more cycles under the loading point than longer loops, increasing wear and tear. The number of BSs required to complete one belt loop also influences BS behavior, with higher damage expected in BSs that represent a larger share of the loops total length. Shorter BSs are typically older and have undergone more repairs, making their condition easier to predict. In contrast, failures in newer, longer BSs (over 225 meters) tend to be more stochastic, often due to extreme events like large rock lumps, leading to higher relative errors in AI model predictions.

It was discovered that no specific version (V_1, V_2, V_3) of the training-testing variants consistently outperformed the others across all models (1 to 5). Ideally, prediction results should not be sensitive to different dataset splits. However, further analysis revealed that relying solely on visual inspection and human decision-making for dismantling BSs is insufficient. This approach lacks a standardized rule, relying instead on subjective interpretations. Additionally, outliers in prediction results require closer attention, as factors from the BSs previous operation could influence its current behavior.

A more comprehensive approach is necessary, given that failure and repair data is currently based solely on visual inspections by mining employees. For a failure to be recorded and addressed during the next scheduled shutdown, it must be significant enough to pose a threat to operations. Smaller failures are often overlooked, as they are difficult to detect or too numerous to address individually during planned shutdowns. Consequently, the condition of a BS is assessed based on the recorded major failures and the segments age, reflecting the percentage of its expected operating time. Applying AI to such limited information has only partial success in predicting future events. While AI can predict failure events (e.g., moments of future failures,

cable cuts, and repairs) based on historical data, the current belt service management in the mine has not yet utilized such predictions. Instead, estimates are limited to when to replace entire BSs and calculating the total length of BSs needed to maintain uninterrupted conveyor operations. The data on performed repairs represents only a small portion of BS conditions, focusing on visible, significant failures that pose immediate risks.

Therefore, the implementation of diagnostic devices (e.g., magnetic or x-ray scanners) that can reliably detect both visible and hidden belt core damage could create a more robust dataset for AI model application. Subsequent chapter 6 integrates data from the implemented DiagBelt+ steel cord diagnostic system at the surface limestone mine in Poland. This inclusion will also showcase the applicability of the developed method in different kind of mines where data recording about the failure is carried out differently.

Chapter 5

Magnetic diagnostic system for conveyor belt health monitoring

This chapter provides a comprehensive overview of the DiagBelt+ system, emphasizing its role in addressing the limitations identified in the visual inspection database in the previous chapter 4. The subsequent chapter 6 employs a database generated by the DiagBelt+ system [96], [147], [270], [271], [272], [273] to predict the conveyor belt damage. Thus, learning about DiagBelt+ system is essential for understanding how advanced diagnostic systems can enhance data quality and reliability.

5.1 Operating principles and functionality of the DiagBelt+ system

Since the year 1979 magnetic diagnostic systems have been used to evaluate the technical condition of conveyor belts [274], [275], [276]. Initially, these systems generated an analog signal, aggregated for measuring circuits (belt strips) several tens of centimeters in width. The belts were scanned sequentially with one measuring head over several cycles or measured across the entire belt width at once using multiple measuring heads installed across the belt. However, this technique did not allow for the identification of individual defects only a few millimeters in size. The diagnostic system named DiagBelt has been developed for monitoring and diagnosing the technical condition of belt conveyor cores at Wrocław University of Science and Technology [57], [70], [277]. The developed system operates as a magnetic module within an intelligent, integrated conveyor belt diagnostics system [150]. The system comprises a data analysis program and a measurement belt provided by Beltscan System Pty, Southport, Queensland, Australia. It features the BeltGuard measuring bar, produced by BeltScan, an Australian company specializing in belt diagnostics since the 1970s. The compressed digital signal from a mobile measuring head with 112 sensors-coils placed at regular intervals of 25 mm (excluding neutral zeros indicating undamaged belt sections) is imported into a proprietary application called DiagBelt. Additionally, two permanent magnets are positioned above and below the examined belt, spaced approximately 35 mm from its covers as shown in the Fig. 5.1,

5.2, 5.3.

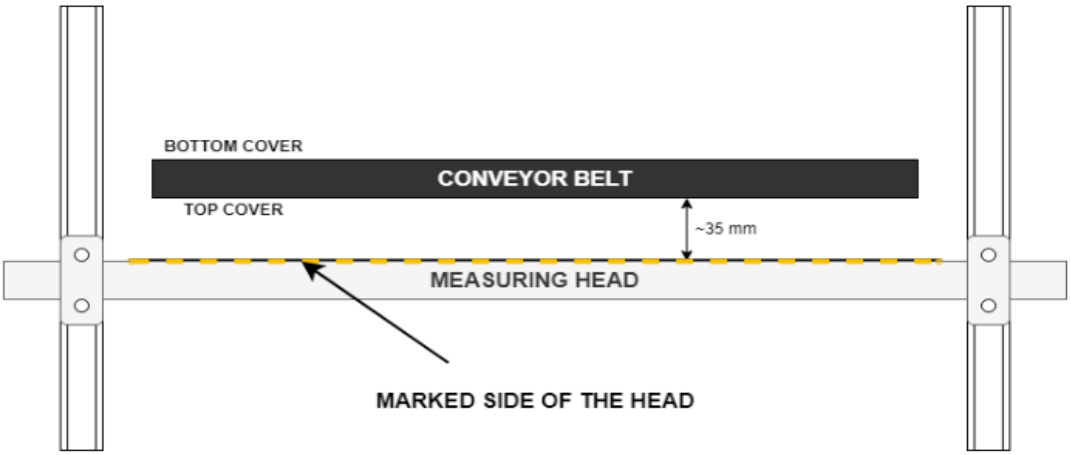


FIGURE 5.1: The mounting of the measurement head DiagBelt [265], [272]

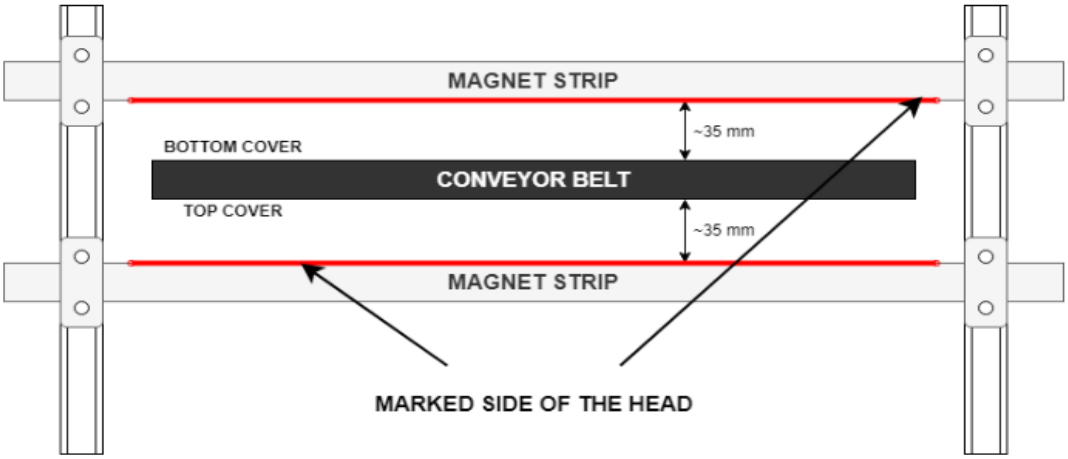


FIGURE 5.2: The mounting of conditioning heads DiagBelt on a lower pull [265], [272]

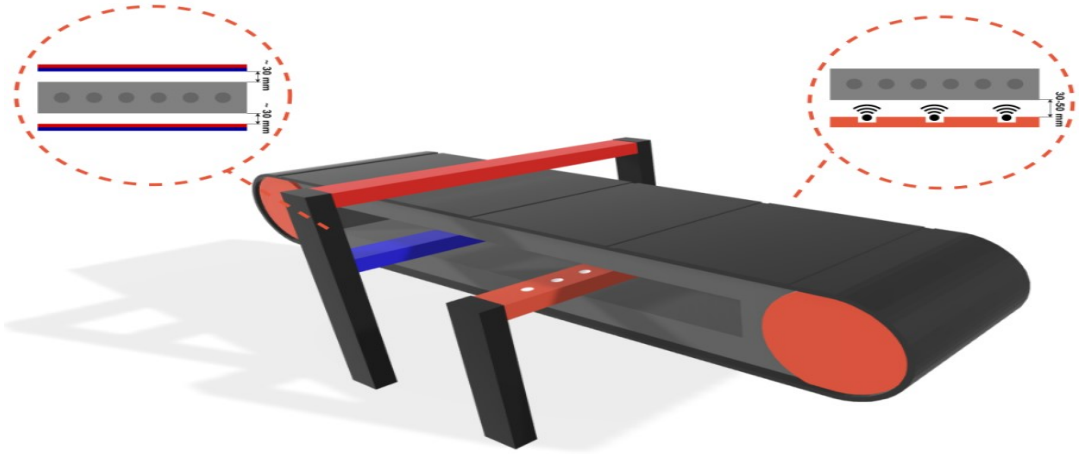


FIGURE 5.3: Schematic of the installation of the DiagBelt diagnostic system on a conveyor belt [273], [278]

This application forms the basis for analysing the condition of an entire belt loop as well as its individual sections and splices. The software is the successor to the HRDS system, which was used in a lignite mine located in Poland and based on the EyeQ measuring bar [279]. The new system's high-resolution measuring head, with a 2.5 cm wide measuring track, provides enhanced damage imaging and allows defects to be represented on a 2D plane as shown in Fig. 5.4, alongside the traditional single-dimensional signal found in various other magnetic systems with a wide measuring circuit (up to 40 cm). Furthermore, a high-resolution 2D image enables the identification of defect sizes and, with additional scans, the calculation of the damage area's growth rate along the belt's longitudinal and transverse axes as shown in the Fig. 5.4.

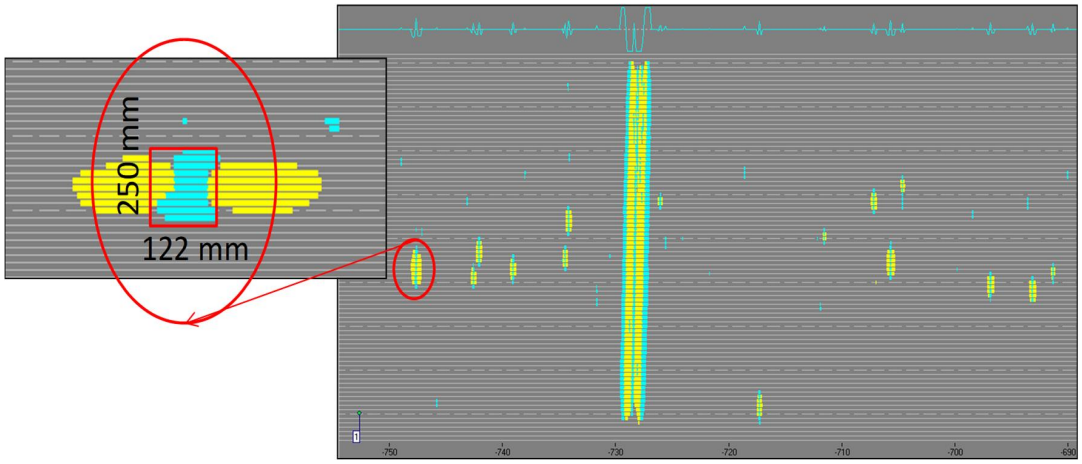


FIGURE 5.4: 2D image of belt defects with one defect zoomed and dimension-ed, along with a traditional 1D image [13]

The DiagBelt+ system operates as a diagnostic tool designed to monitor the condition of conveyor belts, specifically those reinforced with steel cords. The system employs a combination of magnetic and electromagnetic inspection techniques to achieve this. The DiagBelt+ system is designed to diagnose

the condition of steel cord conveyor belts by detecting and recording changes in the magnetic field that occur in the belt splice or areas where the belt core is damaged. Its primary function is to detect early signs of damage or wear in the belt's structure, enabling proactive maintenance and preventing catastrophic failures.

Principle of the DiagBelt+ System

The fundamental principle of the DiagBelt+ system is the non-destructive evaluation (NDE) [115] of conveyor belts using advanced magnetic and electromagnetic techniques. This non-invasive diagnostic method is developed to identify and analyse failures within the belt's core, ensuring the structural integrity and operational efficiency of conveyor systems. The DiagBelt+ system operates on the principle of magnetic induction. It involves magnetizing the core of conveyor belts, which are reinforced with steel cords, and detecting anomalies in the magnetic field caused by damage or discontinuities in these steel cords. This approach allows for the early detection of micro-damages, changes in the belt's core structure [278], and the assessment of overall belt health without interrupting the conveyor's operation. The entire system is designed to operate efficiently under various environmental conditions, withstanding temperatures ranging from -25°C to +70°C and humidity levels up to 95% [271],[60].

Elements of the system

Measuring Head—this head contains 90 coils spaced every 25 mm, allowing for precise recording of changes in the magnetic field. The system's head is 3 meters long and comprises 7 modules, each with 16 coils (sh shown in the Fig. 5.5), totaling 112 measuring channels [57]. This configuration enables measurements with a 25 mm resolution. The coils support bipolar measurements, and the measurement signals from the induction coils are amplified and transmitted to a recorder. Coil sensitivity and measurement frequency are set by the operator. The recorder collects data from the measuring bar, and a connected computer allows the data to be saved and exported as a CSV (Comma Separated Values) file. This data is then processed by a computer program designed in the LabView environment. Permanent Magnet Heads—two heads are used to magnetize the steel cords in the conveyor belt. Tachometer—measures the speed of the belt to ensure accurate data collection. Data Acquisition Module—collects and processes the magnetic data to detect anomalies. Magnetization, magnetic inspection—the system uses magnetic flux leakage (MFL) as the primary method for detecting damage. The system uses permanent magnet heads placed above and below the conveyor belt at equal distances (typically placed around 35 mm from the belt covers). A measuring head consisting of multiple inductive coils (90 coils spaced at 25 mm intervals along a length of 2250 mm) is used to measure the magnetic field strength (magnetic induction) generated by the magnetized belt core [265]. As the conveyor belt moves, it passes under a measurement head equipped with inductive sensors. This head contains 40 coils per meter

of active length, spaced at 25 mm intervals.



FIGURE 5.5: Module with magnetic coils[57]

Detection of Magnetic Field Changes

These magnetic heads magnetize the steel cords within the belt core creating a magnetic field around them. When a magnetic field is applied to the steel cords within the conveyor belt, any discontinuities, such as breaks or significant wear, cause a distortion in the magnetic field. These distortions are detected by sensors and interpreted as areas of potential damage [280]. By detecting these changes, the system can pinpoint areas of concern. It involves the use of electromagnetic waves to penetrate the belt and provide detailed information about its internal condition. Changes in the electromagnetic response can indicate different types of damage, including de-lamination, corrosion, and other structural issues. The data acquisition module captures this information, which is then analyzed to determine the condition of the belt. Sensors are placed along the conveyor belt to continuously monitor the magnetic flux. As the belt moves, the sensors capture data, which is then processed to identify anomalies indicative of core failures or significant wear. Magnetic diagnostics is effective in identifying issues that are not visible through routine visual inspections, such as internal cord damage.

Signal Collection and processing

The signals from the inductive coils are amplified, collected in a data acquisition module. The data is then transmitted to a computer for further analysis. The large amount of data generated by the system needs to be effectively processed and analysed. This requires robust software capable of handling and interpreting the data accurately [58]. The system processes the signals using a thresholding method where signals are converted to discrete values of -1, 0, and +1 based on their magnitude relative to predefined thresholds thmin and thmax. The complexity of the data analysis might require specialized training for the maintenance personnel to understand and act upon the diagnostic reports correctly. Two-dimensional (2D) image analysis requires less training effort compared to one-dimensional (1D) signal analysis. A 2D image facilitates easier localization of damage, and the detected area is directly proportional to the actual size of the damage. Moreover, magnetic systems can be employed to determine the dimensions of conveyor belt

splices.

Data Analysis and Reporting

The system generates a detailed report assessing the technical condition of the conveyor belt. This report includes parameters like the number of damages, number of splices, belt segments and loop length. It also creates a visual map of the conveyor belt showing the condition of different sections. Damage density is visually represented by colors from green, through yellow to red, allowing for easy identification of sections requiring repair. The system provides comprehensive reports and visual maps of belt conditions, aiding maintenance teams in making informed decisions. The visual representation of damage density allows for easy interpretation of the data and helps prioritize maintenance activities. The system allows for adjusting the sensitivity of the coils and the measurement frequency, enabling customized inspections based on specific needs. The results are saved in a comma separated value—CSV file, facilitating detailed analysis of the belt core's condition. The study examined belts with various parameters, including loop length, number of sections, nominal strength, width, age at the time of testing, and transported material, all operating under real conditions.

5.1.1 Operational benefits and importance of the DiagBelt+ system

The DiagBelt+ system is crucial for several reasons such as enhanced safety, reliability and cost efficiency, comprehensive analysis, non-invasive method, and their industrial applications, and extended belt life. Enhanced safety–reliability and cost efficiency—the system allows for the early identification of micro-damages and wear in the conveyor belts, which can prevent larger, more costly and catastrophic failures by planning proactive maintenance, reducing unexpected downtime and improving the efficiency of mining operations. The system aids in the proactive maintenance of conveyor belts. By identifying potential issues early, it allows for planned repairs and replacements, reducing downtime and preventing unexpected failures. This results in significant cost savings and extends the lifespan of the conveyor belts. This enhances the safety of operations in industries that rely heavily on conveyor systems, such as mining and manufacturing. Also, early detection of issues allows for planned maintenance, which is generally more cost-effective than emergency repairs. Moreover, implementation of the DiagBelt+ system reduces the need for extensive repairs and replacements, leading to significant cost savings. The ability to monitor the belt continuously and in real-time allows for better budget allocation and resource management. By identifying the specific sections of the belt that need repair, the system helps in reducing maintenance costs. Only the damaged sections need to be addressed rather than replacing the entire belt, which is both cost-effective and resource-efficient.

Comprehensive Analysis—the ability to customize inspection parameters and generate detailed reports enables thorough analysis of the belt condition. The system's high-resolution capabilities and 2D visualizations (3D visualizations is an option, it requires several scan on different sensitivity level) offer an in-depth view of the damage, facilitating precise maintenance decisions. Non-Invasive Method—the DiagBelt+ system's non-invasive nature means that it does not require disassembling or halting the conveyor belt, thereby minimizing operational disruptions. Industry applications—the system is used in various industries including mining (e.g., hard coal, lignite, limestone, copper ore, and any other material) where the condition of conveyor belts is critical for operational efficiency. Extended belt life—by maintaining the belt in optimal condition and preventing severe damage, the DiagBelt+ system helps extend the operational life of the conveyor belts. Regular monitoring and timely maintenance extend the service life of the conveyor belts. This is particularly important in industries where conveyor belts are critical to operations, such as mining and manufacturing.

Building upon the introduction of the DiagBelt+ system and its operational significance, the following section delves into a comprehensive review of the existing literature to contextualize its development within the broader evolution of conveyor belt diagnostic technologies. This literature review not only situates DiagBelt+ among traditional and modern diagnostic approaches but also critically examines its technical advantages, implementation challenges, and potential for integration with predictive maintenance and AI-based modeling. By synthesizing insights from prior research, this review lays the groundwork for understanding the technological and methodological advancements that inform the subsequent development of predictive systems for conveyor belt failure analysis.

5.2 Literature review

5.2.1 Summary of detailed literature review

Literature review on the DiagBelt+ system comprehensively highlights the evolution of conveyor belt diagnostics from traditional visual and analog techniques to modern, data-driven, non-invasive systems. The primary motivation for conducting this literature review was to critically evaluate the current state of conveyor belt diagnostic technologies, with a particular focus on the DiagBelt+ system. Traditional methods, such as visual inspection and analog signal analysis, have proven insufficient in accurately detecting and quantifying belt defects. By reviewing the capabilities and advantages of DiagBelt+, including its digital signal processing, non-destructive testing capabilities, and integration into predictive maintenance strategies, this review establishes a technical foundation for exploring data-driven approaches to belt failure prediction. Furthermore, the literature reveals the economic and operational benefits of adopting advanced diagnostics, highlights limitations

in current metrics used to assess belt wear, and supports the use of artificial intelligence—especially neural networks—as a promising direction for improving the accuracy of failure prediction models. This contextual background is essential for justifying the development of an AI based tool aimed at predicting failure size growth in conveyor belts, particularly in mining applications where reliability and efficiency are critical.

Summary of the literature review

1. Visual assessment for evaluating belt wear has been found deficient in accurately determining belt condition [13].
2. Traditional methods for evaluating belt condition relied on analog signals, which lacked the precision to accurately identify individual defects. In contrast, modern diagnostic systems like DiagBelt utilize digital signals, enabling detailed 2D imaging of defects for more precise analysis [58].
3. The DiagBelt+ system provides a non-invasive method to ensure the proper geometry of belt splices, thus enhancing their performance and durability [278].
4. To maintain conveyor belts integrity and prevent costly downtimes usage of non-destructive testing system known as DiagBelt+ system with regards to importance of regular and comprehensive diagnostics of damage and growth of existing damage over time to the belt conveyor [57], [60], [115], [280].
5. Conveyor belt splices are critical failure points, and while traditional diagnostic methods such as visual inspection and X-ray imaging have limitations, recent advances highlight magnetic diagnostics as a reliable non-invasive alternative. Modern systems like DiagBelt+ improve on earlier low-resolution approaches by enabling real-time, high-resolution visualization of splice geometry, offering greater accuracy and repeatability in splice quality assessment [122].
6. Re-testing every few months (frequency depend of belt condition and age) to monitor damage progression and estimate remaining belt life. Diagnostic systems like DiagBelt offer significant economic benefits by enhancing belt durability and minimizing waste. Despite some reluctance from mines to share detailed data, the potential savings justify wider adoption of such diagnostics. Continuous or periodic belt monitoring can lead to improved maintenance decisions, extending belt life and reducing costs [280] .
7. The authors recommend using damage density (defects per meter) and damage area per meter as more useful measures than total defects/area, since these account for changes in belt sections length [58], [278], [280].

8. The study found that the total number of defects per meter (failure density) and the total number of failures per belt section were insufficient metrics by themselves. In addition, the total surface area of defects offered a more comprehensive understanding of the belt's condition [58], [277], [278], [280].

9. The integration of diagnostic systems into maintenance strategies is crucial for optimizing conveyor belt operations. Predictive maintenance based on accurate diagnostics enhances the economic efficiency and sustainability of belt systems [60], [115], [278].

10. Neural networks, with their capacity to learn and adapt, present a highly effective approach to predictive maintenance in industrial environments [149].

11. The study [265] investigates the implementation of the DiagBelt+ diagnostic system at the lignite mine, highlighting its advantages over traditional visual assessments in evaluating belt wear. The findings demonstrate that parameters such as belt speed, cord diameter, and sensitivity thresholds strongly influence diagnostic accuracy, with the system providing notable technical and economic benefits.

5.2.2 Detailed literature review

Research works [58], [150], [270], [281], [282] collectively emphasize the progressive and often random nature of conveyor belt damage development, particularly in steel-cord belts, and how diagnostic and predictive methods can be applied to monitor this process. The doctoral research synthesized in this area reinforced the utility of such predictive methodologies by embedding them within broader frameworks of condition monitoring and maintenance planning, situating diagnostic data analysis as a key element of reliability-centered asset management [281]. The literature consistently emphasizes the time-dependent and progressive character of conveyor belt damage, with deterioration processes typically initiating in localized regions and subsequently propagating due to operational and environmental stresses. Early investigations into random deterioration processes demonstrated that defect development in belt cores follows stochastic yet progressive patterns, with concentrated clusters of failures accelerating under conditions of cover thinning, water ingress, and subsequent corrosion of steel cords. Such findings underscored the inadequacy of relying solely on aggregated condition indices, as these may obscure critical localized defects that pose immediate operational risks [150].

Subsequent advances in diagnostic technologies, particularly the refinement of magnetic sensing systems such as DiagBelt, have enabled more granular monitoring of defect initiation and progression. High-resolution imaging facilitated the identification and quantification of individual cord failures and their temporal development in both longitudinal and transverse directions, revealing that cracks propagate not only along the steel cords but also

across the belt axis due to bending stresses and puncture-induced damage. Longitudinal data series derived from repeated scans over several years permitted the derivation of measures such as defect density per meter, total defect area, and mean defect size. Regression analyses of these measures enabled not only the projection of future belt states but also the assessment of the economic rationality of different replacement policies [58]. Recent work by Jurdziak et al. [60] further demonstrated that damage progression in steel cord belts follows linear growth patterns. Their study, based on repeated DiagBelt+ scans in a lignite mine, proposed aggregated measures of damage per meter that improve comparability between belt segments of varying lengths. Damage extent (both length and width) increased linearly with time, but the rate of this increase varied depending on the age of the belt segment at the time of the first scan [60], [282]. These findings are directly relevant to the present thesis, which builds upon this predictive approach by developing an AI-based model capable of forecasting failure size development in conveyor belts under different mining conditions. In this way, the integration of traditional regression analysis with modern predictive tools contributes to more accurate maintenance planning and improved belt lifecycle management.

Forecasting approaches have subsequently been developed to extend beyond descriptive analyses, with regression-based models applied to DiagBelt diagnostic data offering quantifiable predictions of remaining belt lifetime. Both linear and quadratic models have been evaluated, though linear regression often produced more accurate forecasts, particularly for longer operating periods. These studies highlighted the potential of predictive modeling to inform rational belt replacement strategies, thereby optimizing operational continuity and minimizing maintenance-related costs [70], [260], [270]. Crucially, the newly added study on trends in aggregated measures (DiagBelt+) demonstrates that short-term increases in defect extension along (EXx) and across (EYy) the belt are well approximated by linear functions between inspections, but that the slopes themselves increase systematically with segment age—captured by a quadratic regression of slope versus age. (later on in the chapter 6, forecast will be prepared with ANN and compared with regression methods). This reconciles linear month-to-month forecasts with life-cycle acceleration and directly informs rational, segment-level replacement scheduling (timing, counts, budgeting). The authors also point to multivariate extensions and AI once multi-conveyor, multi-time datasets accumulate.[282].

Collectively, these contributions establish a robust methodological foundation for predictive approaches to conveyor belt condition assessment. By integrating statistical characterization of defect randomness, regression-based lifetime forecasting, high-resolution diagnostic imaging, and sector-level trend

analyses, the literature demonstrates that belt deterioration is both progressive and multifactorial. The convergence of these research directions provides the empirical and methodological basis for the development of advanced AI-driven models, which hold the potential to further enhance the accuracy and applicability of forecasts of failure progression in conveyor belts used in large-scale mining operations.

The third part of the study [283] on steel cord conveyor belt failures focused on the temporal development of damage in belt cores, extending earlier analyses of their spatial distribution. Using repeated DiagBelt magnetic scans of 30 belt segments over several years in a Polish copper mine, the authors observed that failures tend to propagate more rapidly across the belt width than along its axis, mainly due to bending stresses and water-induced corrosion. To quantify these processes, they introduced diagnostic measures such as defect density, defect surface area density, and mean defect area, which were found to follow nonlinear growth patterns. Statistical regression indicated that defect density increases quadratically with time, defect surface density grows proportionally to the fourth power of time, and mean defect size follows a power function. These results highlight the accelerating nature of belt core degradation and demonstrate that predictive modeling based on repeated diagnostic measurements can support forecasting of remaining belt life and maintenance planning.

The monograph [115] explores the benefits of implementing advanced diagnostics and refurbishment strategies for conveyor belts within the framework of the circular economy. It emphasizes the importance of replacing conveyor belts on new ones, aligning with circular economy principles. The regular practice followed at lignite mine focuses on predictive replacements based on the condition of the belts. The diagnostics help forecast the wear state, allowing for the replacement of belt sections before they fail. This approach significantly improves the success rate of refurbishments and extends the operational life of their core which can be used 3 times (2 refurbishments). By reducing the reliance on new belts and enhancing resource efficiency, these strategies offer significant economic and environmental advantages. This comprehensive approach not only helps in managing costs and reducing waste but also ensures the reliability and longevity of conveyor belt systems, particularly in industries where they play a critical role. The DiagBelt system is specially useful in selecting belts for recondition increasing the recondition success rate.

The research article [277] provides a comprehensive analysis of conveyor belt damage, focusing on how proper loading and operation affect the belt's longevity and efficiency. The paper aims to identify and understand the characteristic features and locations of damage on the cross-section of conveyor belts. This helps in detecting abnormalities in conveyor systems, especially during the loading process at chutes. The study involved analysing seven

different conveyors to compare and investigate the distribution of belt damage across their cross-sectional profiles. The research utilized the DiagBelt system to scan conveyor belts in Polish mines. This detailed approach helped in understanding the distribution patterns of failures. The findings showed that the distribution of damage is often trimodal, with a higher concentration of failures in the central area of the belt. This uneven distribution is attributed to the conveyor's loading and support system design, as well as the material impact intensity. Edge wear and corrosion also contributed to failures at the belt's edges. This can help in making necessary adjustments to the material transport process, such as modifying loading points and conveyor parameters to achieve an even load distribution. The findings have significant implications for conveyor owners and operators. They enable a more effective assessment of conveyor belt conditions, proper design of conveyors and chutes, and the implementation of necessary corrective actions. This leads to minimized risk of failures through corrected loading point, extended belt lifespan due to even distribution (flat profile), and more efficient transportation processes—by reducing the energy losses associated with accelerating the transported material and minimizing the additional energy dissipation resulting from belt damage.

The study [149] focuses on evaluating the effectiveness of statistical analysis and neural networks in identifying failures in steel cord conveyor belts. Its objective was to develop and validate a method for early detection of belt core failures, thereby enabling predictive maintenance and extending belt lifespan. Data were collected using a measurement system that recorded multiple operational parameters of the belts. Statistical analysis was used to calculate confidence intervals and Pearson's correlation coefficients, while clustering techniques were applied to group different failure types. A neural network was then trained to identify patterns and anomalies linked to steel cord failures, and it demonstrated higher detection accuracy compared to traditional statistical methods. Importantly, this study marked one of the first systematic attempts to introduce artificial neural networks into conveyor belt diagnostics, initiating a research direction later developed at Wrocław University of Science and Technology (PWr). Subsequent work, such as Rzeszowska et al. [147], advanced this approach by applying clustering methods and self-organizing maps (SOM) to DiagBelt+ data, further confirming the potential of AI-based diagnostics in enhancing the precision and automation of belt condition monitoring. These developments emphasize the growing role of AI in predictive maintenance of conveyor belts, forming a foundation that the present thesis builds upon.

The assessment of conveyor belt splice integrity has been the subject of considerable research, as splices represent the weakest link in conveyor systems and are highly susceptible to both fatigue and sudden failure. Traditional diagnostic methods, such as visual inspection, are widely used due to their simplicity but cannot detect hidden internal defects, while X-ray imaging provides detailed internal visualization but is costly, stationary, and requires strict safety protocols. Mechanical and finite element approaches have

also been explored, though they are often limited to controlled conditions and computationally intensive analyses. More recently, IoT-based monitoring has been proposed, yet challenges remain regarding sensor durability and data integration in harsh environments. Among these methods, magnetic diagnostics have emerged as a promising non-invasive solution, capable of detecting cord discontinuities and splice geometry variations in real time. Earlier magnetic systems were constrained by low-resolution, one-dimensional signals requiring expert interpretation, but advances such as the DiagBelt and DiagBelt+ systems now allow two-dimensional visualization, higher resolution, and automated analysis, significantly improving the reliability and repeatability of splice evaluation under operational conditions [122].

In conclusion, the DiagBelt+ system represents a substantial advancement in conveyor belt diagnostics, particularly in mining environments where operational continuity and safety are critical. By utilizing magnetic sensing technology to detect internal defects in steel-reinforced belts, DiagBelt+ addresses the limitations of traditional visual inspections, offering high resolution, two-dimensional scans that enable early detection of critical cable damage. Its proven reliability in daily mine operations, combined with its ability to differentiate between surface corrosion and structurally significant cuts, makes it as a vital tool for informed maintenance planning including refurbishment and timely intervention. The comprehensive diagnostic data generated by DiagBelt+ forms a robust foundation for developing predictive models based on artificial intelligence. As such, the system not only enhances current diagnostic practices but also directly supports the broader objective of this thesis which improve conveyor belt reliability through data-driven failure prediction strategies.

Chapter 6

Predictive modeling based on failure records from the DiagBelt+ system scans

Following the evaluation of the DiagBelt+ systems specifications and operational capabilities, the system was employed to scan conveyor belts damage. The failure data extracted from these scans were subsequently utilized for the development and validation of an artificial neural network (ANN) model aimed at predicting conveyor belt degradation. Additionally, the model was used to forecast failure patterns up to two years into the future, with the goal of supporting proactive maintenance and repair planning.

6.1 Structure and characteristics of the dataset

To train the neural network models, data from the surface limestone mine in Poland was used. Historical data of selected input and output variables were analyzed to forecast the future wear of the conveyor belt. The genesis database included several parameters, such as belt dimensions, scan number, belt age in months at the time of scanning (measured from the installation date of the belt segment), belt section number and length, as well as the length and width of detected damage signals. Additional recorded parameters comprised the distance from the start and end of the signal to the nearest joint in millimeters, the channel of the signal start and end, the area of the detected signal, and the center position of the signal relative to both the left joint and the belt width.

The dataset consisted of a total of 929 records, with 534 rows (57.4% of total entries) (which belongs scan performed at 31.8 and 38.5 months) allocated for training and 395 rows (42.6% of total entries) (which belongs scan performed at 48.3 months) for testing. The selection of variables for this study was based on an Ishikawa diagram, as presented in Chapter 1. This diagram, constructed through a comprehensive literature review, facilitated the identification of 11 key correlated parameters, which are detailed in Tables 6.2 and 6.1 and an example of dataset is given in Table 6.3. Six parameters were selected as input features, while five were designated as output variables. The six input parameters characterize the attributes of the belt segments along

with their corresponding scan numbers. The five output parameters quantify the extent of damage sustained by the belt segments. Parameter X_3, Y_1 and Y_2 were manually calculated from the data generated by the DiagBelt+ system. X_3 parameter was calculated from the date of installation of the belt segments on the belt loop. Following a manual inspection of the DiagBelt+ database and subsequent calculations, the flow process chart outlining the database creation for training and testing was implemented, as presented in Fig. 6.1. The training and testing dataset creation flow process chart is same as that of mentioned in the Chapter 4 earlier.

TABLE 6.1: List of independent variables

X_1	Belt loop length (meters)
X_2	Belt width (millimeters)
X_3	Age at scanning instance (months)
X_4	Belt section length (meters)
X_5	Belt section number
X_6	Scan instance number

TABLE 6.2: List of dependent variables

Y_1	Density of failures per meter length of belt (calculated)
Y_2	Number of total failures for each section
Y_3	Damaged area (cm^2)
Y_4	X (length of the damage signal in millimeters)
Y_5	Y (width of the damage signal in millimeters)

X_1	X_2	X_3	X_4	X_5	X_6	Y_1	Y_2	Y_3	Y_4	Y_5
7200	1000	31.8	112.9	1	1	0.035	4	51.3	121	75
7200	1000	31.8	95.7	2	1	0.010	1	40.8	81	75
7200	1000	38.5	95.9	2	2	0.020	2	64.4	71	100
7200	1000	38.5	447.3	4	2	0.016	4	321.9	299	450

TABLE 6.3: An example of input-output variables dataset

Following the presentation of the input-output variable definitions and the process flow outlining the construction of the four datasets used for model training and testing, the next section focuses on examining the intrinsic characteristics of the data. This includes an analysis of the distribution of damage density as a function of belt age, as well as a comparative assessment of belt segment lengths and the corresponding number of recorded failures. The evaluation is performed across selected age groups (31.8, 38.5, and 48.3 months) to uncover trends and structural patterns within the dataset that may influence the behavior and performance of predictive models.

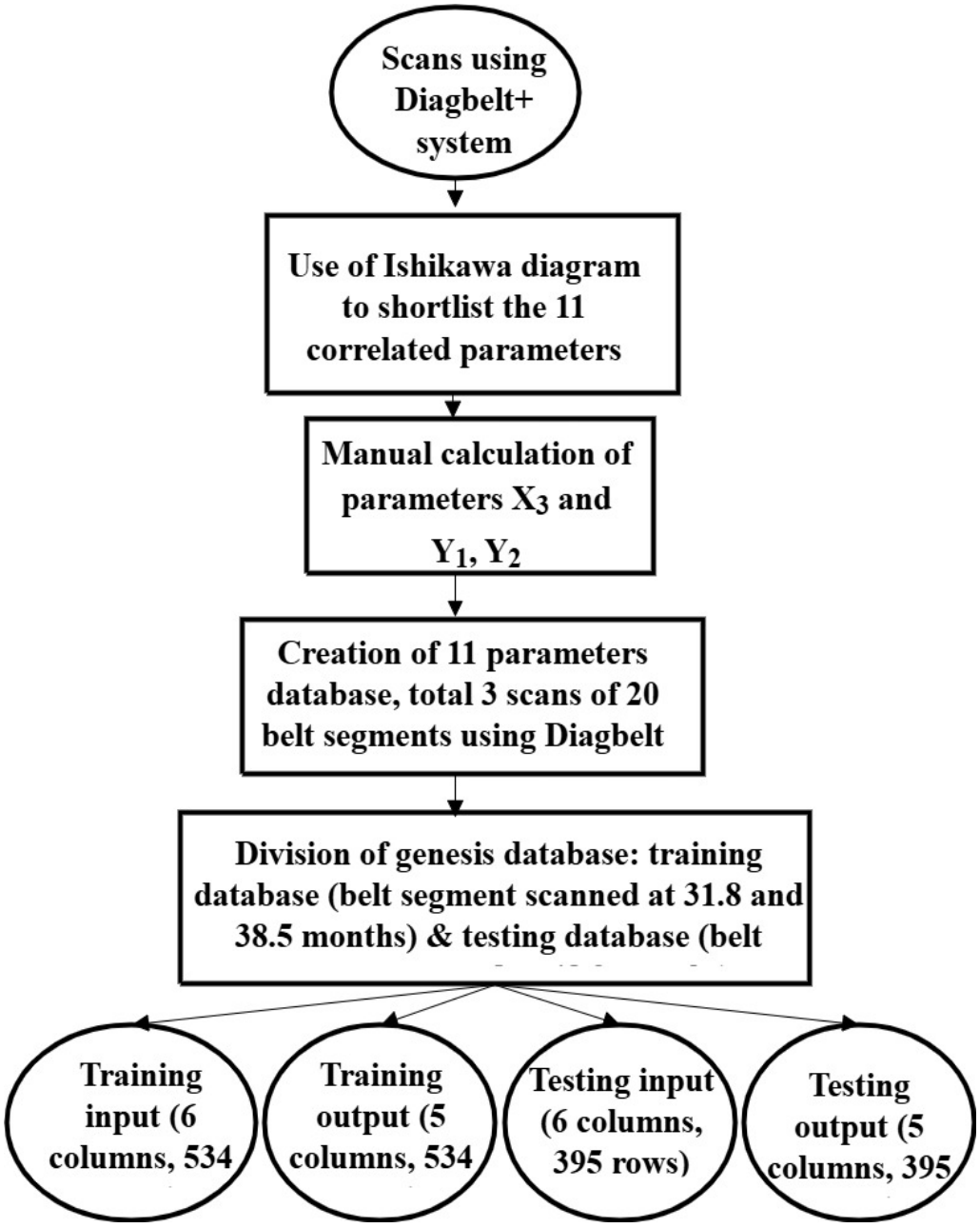


FIGURE 6.1: Flow process chart: testing and training database creation

All 929 records were part of a single belt loop having a total length of 7200 meters. The belt loop comprised of 20 belt sections, with individual segment lengths ranging from 59 meters (shortest) to 450 meters (longest). Detailed length comparison of all belt segments is provided in the Fig. 6.2 and 6.3.

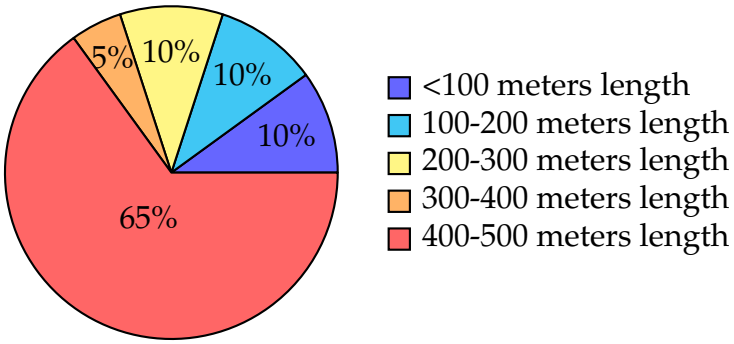


FIGURE 6.2: Belt segment length comparison in genesis database

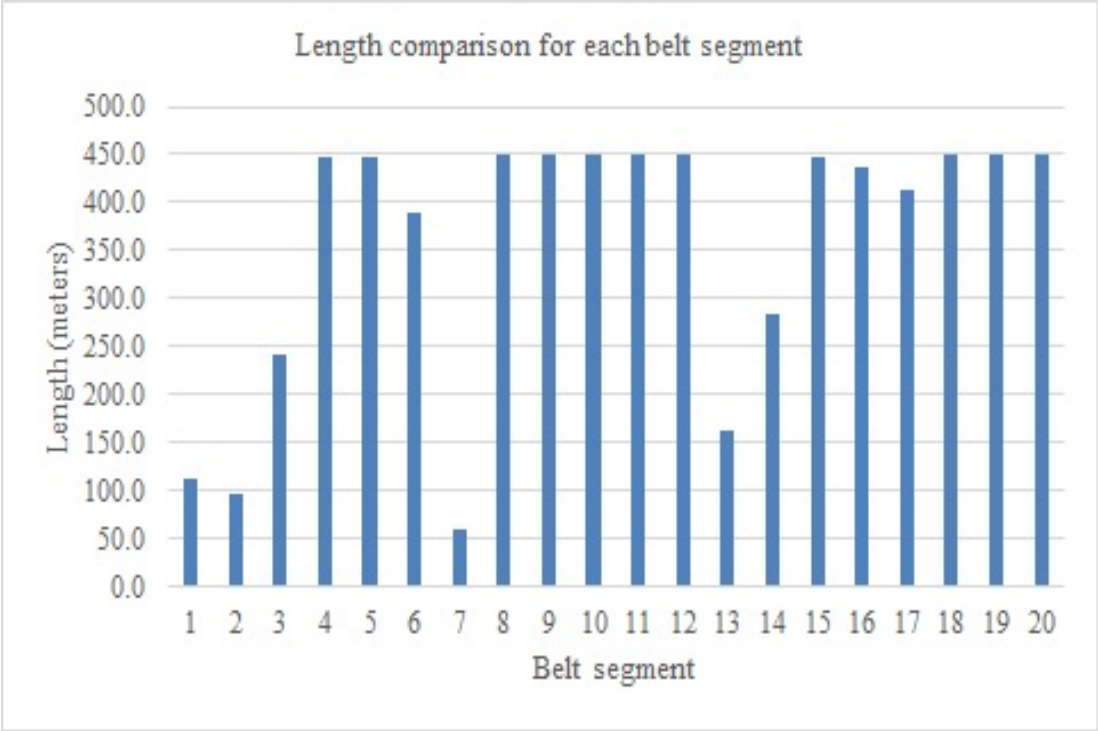


FIGURE 6.3: Comparison of belt segment lengths for individual segments in the Genesis database

Moreover, number of failures recorded to different scans are mentioned in the Figs. 6.4 and 6.5. Fig. 6.4 illustrates the increment of total failures for each belt segment over time, specifically at 31.8, 38.5, and 48.3 months. It is evident that the number of failures increases progressively with age across all segments. Notably, segments such as 1, 6, 9, 10, 12, and 16 show a particularly sharp rise in failures, with segment 9 reaching close to 48 failures by 48.3 months. This pattern indicates that the progression of failure is not

uniform across segments and suggests that certain segments are more prone to rapid degradation. When used in a neural network model, these segments—especially those with significantly higher failure counts—can disproportionately influence the learning process. If the model is not appropriately normalized, this could result in poor generalization, especially on segments that exhibit lower or more gradual failure behavior. Fig. 6.5 presents the damage density for each belt segment, expressed as failures per meter of belt length, over the same time intervals. This chart reveals a more normalized perspective on degradation by accounting for segment length. Some segments, particularly 6, 9, 10, and 12, maintain a high and consistently increasing failure density, while others remain relatively stable. The inclusion of damage density as a feature is particularly important for neural networks, as it mitigates the skewing effect caused by raw failure counts on longer belts. This measure allows the model to focus on the relative rate of degradation rather than absolute failure numbers, which are inherently length-dependent. However, segments with abrupt increases in density could still challenge the model if it is not trained to recognize or accommodate such nonlinear patterns.

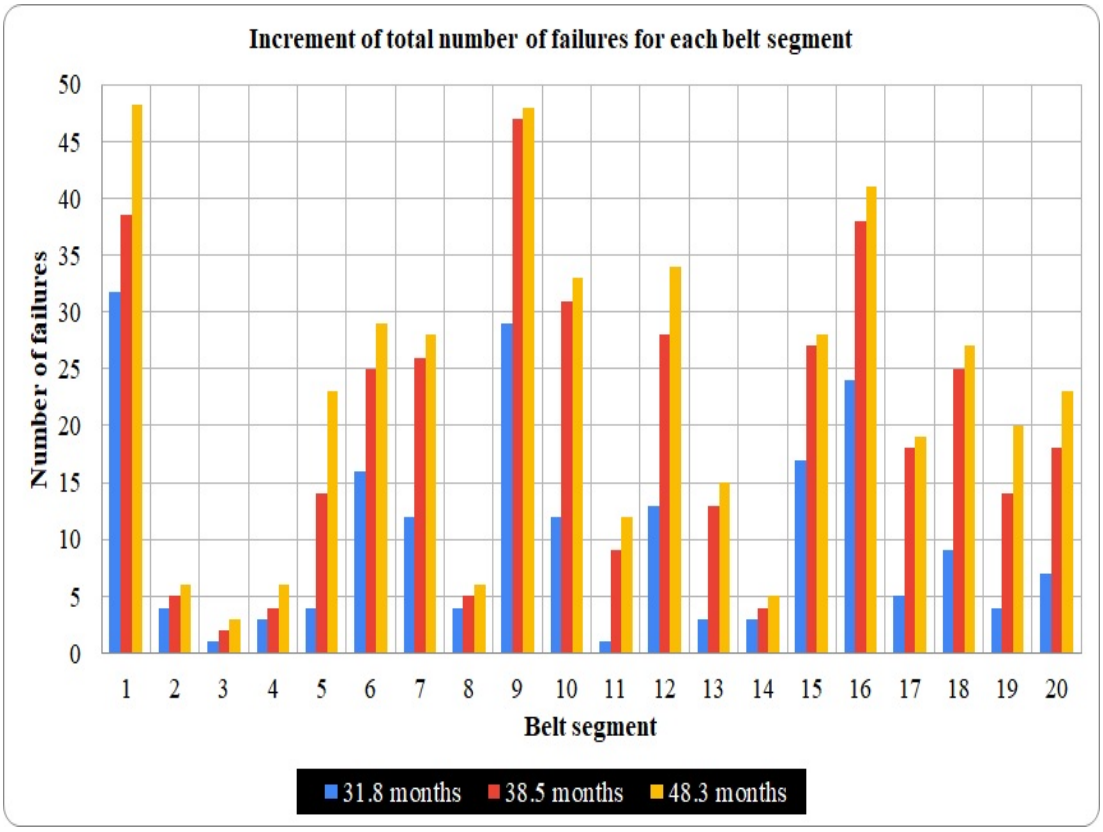


FIGURE 6.4: Total number of failures accumulation over time across different belt segment

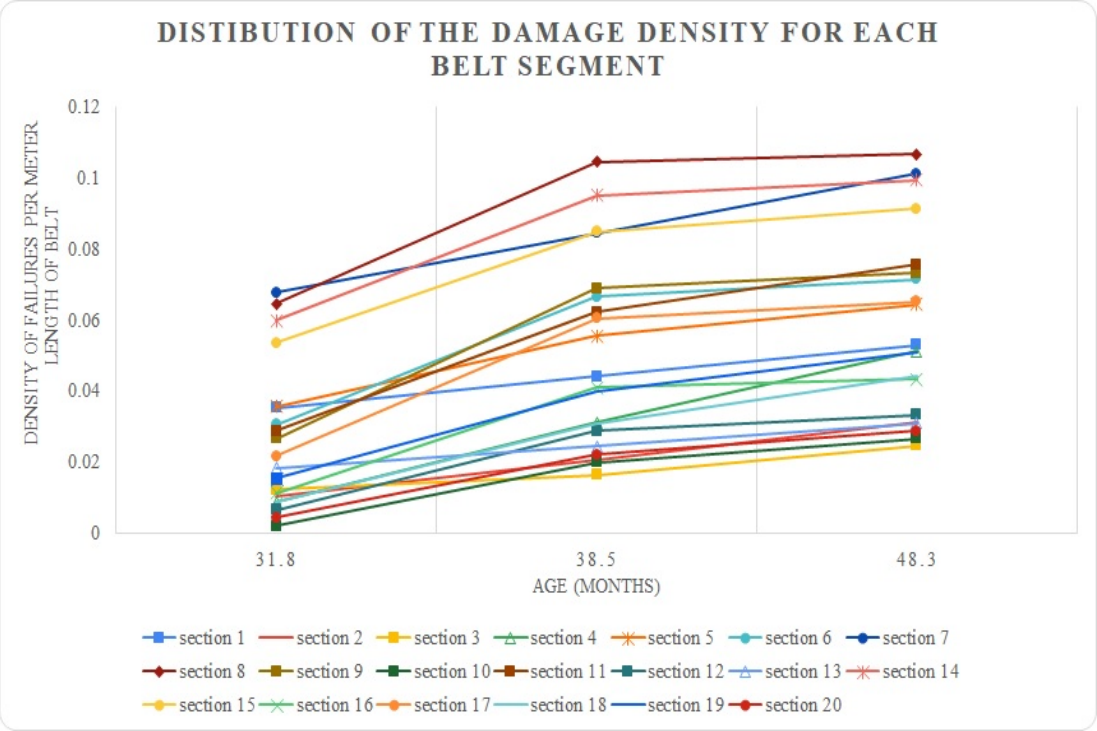


FIGURE 6.5: Trend of total number of failures for each belt segment

Fig. 6.3 compares the lengths of each belt segment, which range from around 59 meters to nearly 450 meters. Most segments (as also can be witnes in Fig. 6.2) are on the longer side, exceeding 400 meters, but a few, like segments 1, 2, and 7, are significantly shorter. Repairs, such as cutting off damaged sections or making a new splice in place—which can create a risk of breakage— often result in shorter belt segments, as cutting off belt fragments removes damaged parts of the belt and consequently leads to a lower recorded number of failures. This introduces a source of bias in the neural network, particularly if the model treats these shorter segments as equivalent to longer, unrefurbished ones. The network might underpredict the failures for long belts or misinterpret the historical behavior of short belts, as it lacks context regarding refurbishment or removal. Taken together, Figs. 6.2, 6.3, 6.4, 6.5 highlight the importance of carefully considering segment length, failure density, and time progression in designing and training neural network models. Incorporating failure density as a feature, recognizing the effects of repair, and potentially using time-series modeling to capture the evolution of damage could help improve model accuracy and robustness in future predictions.

Building upon the preceding section, which examined key structural attributes of the dataset—such as the distribution of damage density with respect to belt age and the relationship between belt segment length and the corresponding number of failures across different age groups (31.8, 38.5, and 48.3 months)—the subsequent analysis aims to further investigate the underlying statistical relationships within the dataset. To this end, an exploratory

data analysis is conducted to quantify the associations between the input variable representing belt age at the time of scanning and the various failure-related output parameters.

This includes the computation of Pearson correlation coefficient, as well as measures of central tendency (mean, median, and mode), providing a deeper understanding of data variability, skewness, and the nature of dependencies among variables. These insights form the basis for evaluating the suitability of predictive modeling approaches in the context of conveyor belt failure analysis.

Table 6.5 shows the Pearson correlation between the set of variables. Limitation and use-case specific scenarios of Pearson correlation coefficient has already been discussed in earlier chapter in 4.1. The Pearson correlation coefficient (r) is a statistical measure that quantifies the strength and direction of a linear relationship between two variables. It ranges from -1 to +1. A value of +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no linear correlation. Moreover, an exploratory data analysis as shown in the Table 6.4 was conducted to investigate the statistical relationships between the input variable X_3, representing the conveyor belt's age at the time of scanning, and all associated output variables indicative of belt failure characteristics. The analysis involved computing the Pearson correlation coefficient to assess the central tendency through the mean, median, and mode values for each output variable. The Pearson correlation coefficients were found to lie within the range of 0.55 to 0.71, suggesting moderate to strong positive linear relationships between belt age and the various failure-related outputs.

TABLE 6.4: Exploratory data analysis of the X_3 variable-age at scanning instance and all output variables

	Y_1	Y_2	Y_3	Y_4	Y_5
Pearson correlation co-efficient	0.71	0.63	0.55	0.59	0.58
Mean value	0.0337	11.93	785.05	830.95	1165
Median value	0.0289	6	377.93	442.5	537.5
Mode value	0	0	0	0	0

Furthermore, the descriptive statistics revealed notable differences between mean and median values within each output variable, which is a useful indicator of distributional skewness. For $Y_2 - Y_5$, the median values (6, 377.93, 442.5, and 537.5, respectively) were approximately half of their corresponding means (11.93, 785.05, 830.95, and 1165). This substantial disparity suggests the presence of strong right-skewed distributions, likely driven by extreme values or outliers in the failure data (as detailed in Table 6.4). By contrast, for Y_1 the median (0.0289) was 85.8% of the mean (0.0337), reflecting relatively lower skewness. Such skewness across most variables points to heterogeneity and non-normality in the dataset, both of which can significantly affect the performance and assumptions of conventional linear modeling techniques.

Variable	X_1	X_2	X_3	X_4	X_5	X_6	Y_1	Y_2	Y_3	Y_4	Y_5
X_1: Belt loop length (meters)	1.00										
X_2: Belt width (millimeters)	#DIV/0!	1.00									
X_3: Age at scanning instances (months)	#DIV/0!	#DIV/0!	1.00								
X_4: Belt section length (meters)	#DIV/0!	#DIV/0!	0.00	1.00							
X_5: Belt section number	#DIV/0!	#DIV/0!	0.00	0.49	1.00						
X_6: Scan instance number	#DIV/0!	#DIV/0!	0.94	0.00	0.00	1.00					
Y_1: Density of failures per meter length of belt	#DIV/0!	#DIV/0!	0.71	-0.02	-0.03	0.72	1.00				
Y_2: Number of failures for each section	#DIV/0!	#DIV/0!	0.63	0.37	0.11	0.64	0.85	1.00			
Y_3: Damaged area (cm^2)	#DIV/0!	#DIV/0!	0.55	0.28	0.08	0.56	0.85	0.95	1.00		
Y_4: X (length of damage signal in millimeters)	#DIV/0!	#DIV/0!	0.59	0.33	0.10	0.60	0.85	0.98	0.98	1.00	
Y_5: Y (width of damage signal in millimeters)	#DIV/0!	#DIV/0!	0.58	0.30	0.10	0.60	0.86	0.97	0.99	0.99	1.00

TABLE 6.5: Pearson correlation matrix for all variables

These statistical characteristics—non-linearity, skewed distributions, and strong monotonic but not strictly linear relationships—highlight the limitations of traditional modeling approaches, which typically rely on assumptions of linearity and normally distributed residuals. In contrast, artificial neural networks (ANNs) are well-suited for such complex modeling tasks, as they are capable of capturing non-linear dependencies and learning from high-dimensional, irregularly distributed data. Therefore, in light of the data's structure and correlation patterns, ANN-based modeling presents a more effective and reliable alternative for predicting conveyor belt failure progression, offering improved adaptability and accuracy compared to conventional methods.

6.2 Neural network modeling and forecasting

Using the generated datasets, 4 main models were created which are mentioned in the Table. 6.6. For training and testing purposes, data from three different scans were used, corresponding to 31.8 months for the first scan, 38.5 months for the second, and 48.3 months for the third. The first two scans (31.8 and 38.5 months) were utilized for training, while the third scan (48.3 months) was used to evaluate the predicted results of future.

TABLE 6.6: 5 main models designed during presented study

Model	Input parameters	Output parameters
Model 1	X_1 to X_6	Y_1 (density of failures per meter length of belt)
Model 2	X_1 to X_6	Y_2 (number of total failures for each section)
Model 3	X_1 to X_6	Y_3 (damaged area-cm^2)
Model 4	X_1 to X_6	Y_4 and Y_5 (length and width of damage signal in millimeters)

Various combinations of neural network operating parameters, as listed in Table 6.7, were evaluated. Subsequently, Combination 4 was selected for further use. Consistent with the previous chapter, where the modeling of the HVI database was conducted, three indicators—A, B, and C—were utilized to assess the performance of different models, as presented in Tables 6.8, 6.9, 6.10, and 6.11.

Relative error formula:

$$\frac{|Predicted\ values\ by\ ANN - Values\ recorded\ by\ DiagBelt+\ system\ |}{Values\ recorded\ by\ DiagBelt+\ system} \times 100$$

A: % of 210 predictions instances having relative error <50% compared to mine records

B: % of 210 predictions instances having relative error between 50-100% compared to mine records

C: % of 210 predictions instances having relative error >100% compared to the records

Green color: models with best prediction results comparatively based on indicators and median value.

TABLE 6.7: Selection of neurons and layers combination

Combination	Input layer neurons	Neurons × hidden layer	Output layer neurons	Batch size	Epochs	Accuracy % training/ validation
1	6	36×2	2	16	7	71/90
2	6	36×3	2	16	7	90/90
3	6	36×4	2	16	7	96/96
4	6	36×5	2	16	7	97/97
5	6	36×7	2	16	7	97/97

6.3 Results and discussion

For training and testing, data from three scans were utilized, with the first at 31.8 months, the second at 38.5 months, and the third at 48.3 months. The initial two scans (31.8 and 38.5 months) were used for training, while the final scan (48.3 months) served to assess the prediction results of future. Significant prediction errors were primarily observed for belt segment lengths ranging from 400 to 450 meters as it can be witnesses in Table 6.8, 6.9, 6.10, 6.11 and charts shown in Fig. 6.6, 6.7, 6.8, 6.9, 6.10. Shorter belt segments may have influenced the neural network weights, introducing bias in the predictions. This bias likely arises from the fact that shorter segments have often undergone repairs, such as cutting out damaged parts or making splices, whereas longer belt segments may still contain damaged areas and have not yet been repaired.

Refurbishment is carried out at Bestgum Sp. z o.o. [284] after the removal of an entire belt section that has been used but not excessively worn, or after the removal of a long belt segment (typically, segments shorter than 50 meters are not refurbished at Bestgum). The refurbishment process involves the removal of both covers (top and bottom) through milling, repair of broken cables, rust removal through grinding, application of liquid rubber, installation of new covers, and vulcanization. This process effectively produces a belt that is nearly new but retains its original, repaired core. It is important to distinguish refurbishment from belt shortening. Simply cutting out a damaged portion of the belt does not constitute refurbishment; rather, it reduces the belt's length. However, the overall condition of the refurbished belt section improves because the most deteriorated parts are removed and discarded. Having established the dataset structure, examined its characteristics, and reviewed the operational parameters of the ANN, the following section presents the prediction results generated by the ANN after training.

TABLE 6.8: The distribution across indicators A, B, and C in % based on belt failure density (Y_1) calculated from ANN-predicted failures

A	B	C
45	55	0

Referring to Table 6.8 and Fig. 6.6, few of prediction results exhibit a relative error below 30%, with no predictions exceeding the 90% relative error threshold. As illustrated in Figs. 6.3 and 6.2, most belt segments exceed 400 meters in length. However, the dataset includes a diverse range of belt segment lengths, spanning from 59 meters to approximately 450 meters, with failure densities ranging from 0.2 to 10.6 failures per 100 meters. Despite this variability, the model has demonstrated good performance in predicting the Y_1 parameter as number of outliers (indicator C) in the predictions are 0. However, the observed median relative error of 57.1% can largely be attributed to the limited dataset size and the number of available belt segments. A key factor influencing prediction accuracy is that only two scans

were available for training, both of which corresponded to the initial operational phase of most belt segments. The third scan, used for prediction, captured a later stage in the operational lifespan, during which the belt segments were more exposed to wear (due to already damaged top cover because of impacts of material being transported) and thus more susceptible to damage. In conclusion, given the constraints of the available dataset, the model has produced predictions without outliers for the Y_1 variable, effectively representing failure density per meter of belt length.

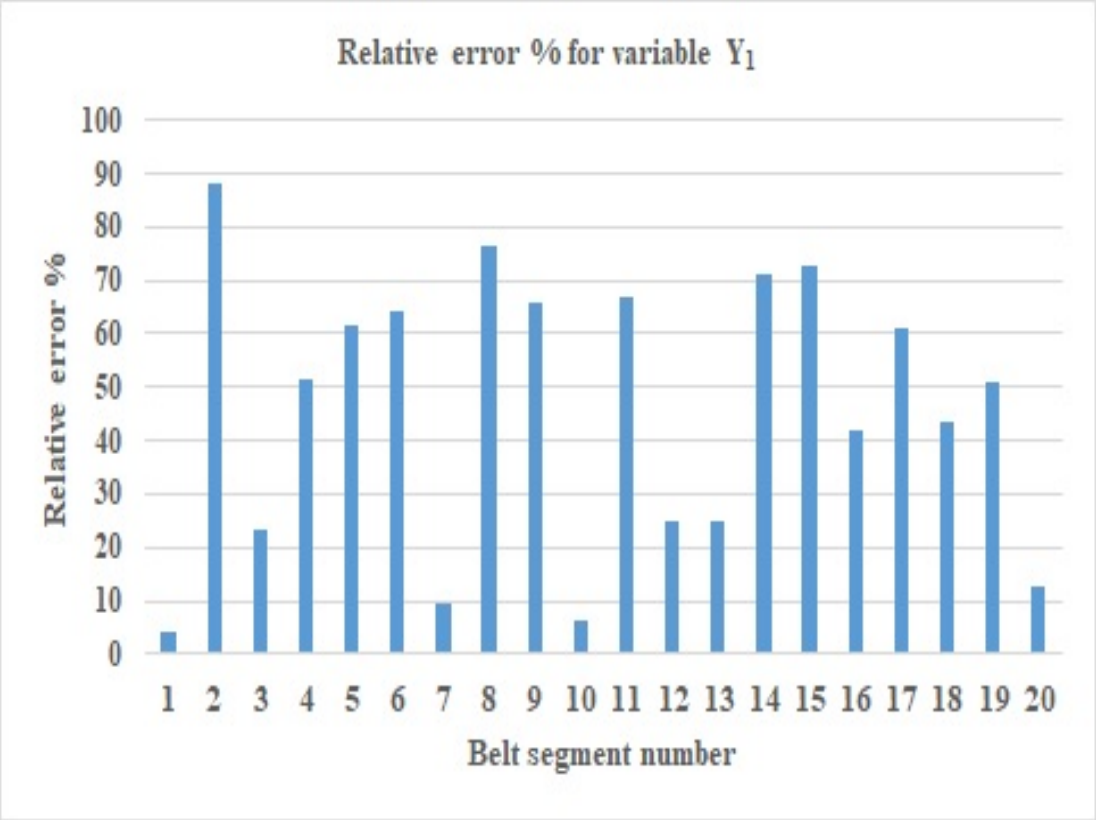


FIGURE 6.6: Comparison of failure density per meter predicted by the ANN and measured by the DiagBelt+ system

TABLE 6.9: Prediction results in % for model 2 (Y_2: number of total failures for each section) indicating share for indicators A, B, C

Activation function	Optimizer	Median value of relative error	A	B	C
swish	adam	79.4 %	25	75	0
ReLU	Nadam	98.5 % %	00	100	0
ReLU	RMSprop	51.05 %	45	55	0

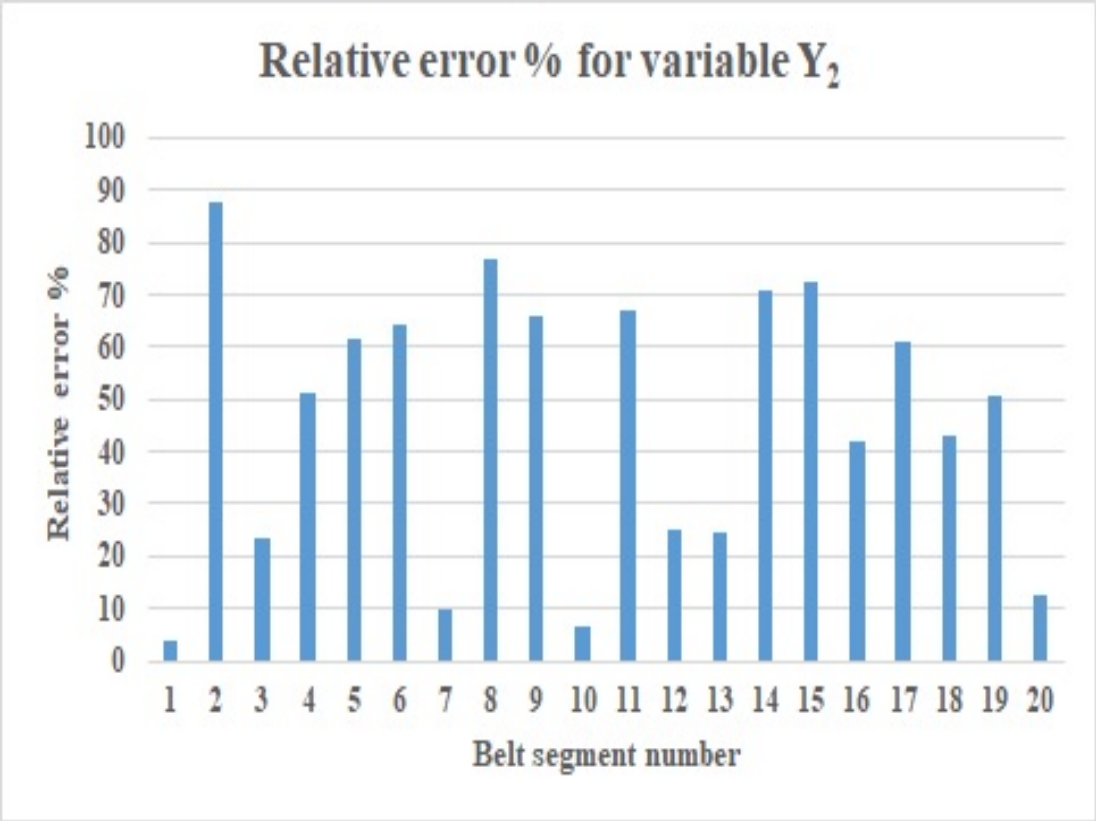


FIGURE 6.7: Comparison of predicted values generated by the artificial neural network and the DiagBelt+ system for the number of failures for each belt section

Following conclusions can be drawn from Table 6.9 and Fig. 6.7. Belt segments 1, 3, 7, 10, 12, 13, 16, 18 and 20 correspond to Indicator A in terms of relative error, while the remaining belt segments fall under Indicator B. Among the belt segments classified under Indicator A, segments 1, 3, 7, and 13 have lengths shorter than 250 meters, while segments 10, 12, 16, 18 and 20 exceed 400 meters. Notably, belt segments 1, 3, 7 and 13 are the ones shorter than 250 meters that fall under Indicator A, suggesting that the model struggled to establish accurate damage correlations for longer belt segments. A noteworthy observation is that the all of belt segments except belt segment 6 and 14 categorized under Indicator B have lengths exceeding 400 meters. Additionally, belt segments 6 and 14, both exceeding 250 meters in length, suggest that the model encountered difficulties in accurately predicting the total number of failures when belt length exceeded this threshold of 250 meters. This difficulty may also indicate that specific large chunks of rock may have fallen onto these segments, as larger belt areas present a greater surface exposure, increasing the likelihood of such impact events during material transportation. As previously mentioned, longer belt segments indicate that they have not yet been shortened by removing damaged and worn-out sections. This factor may contribute to increased uncertainty in failure predictions, as pre-existing worn-out patches are more susceptible to damage due to their weakened condition.

TABLE 6.10: Prediction results in % for model 3 (Y_3: damaged area cm^2) indicating share for indicators A, B, C

Activation function	Optimizer	Median value of relative error	A	B	C
swish	adam	98 %	0	100	0
ReLU	Nadam	99.9 %	0	100	0
ReLU	RMSprop	62.8 %	40	55	5

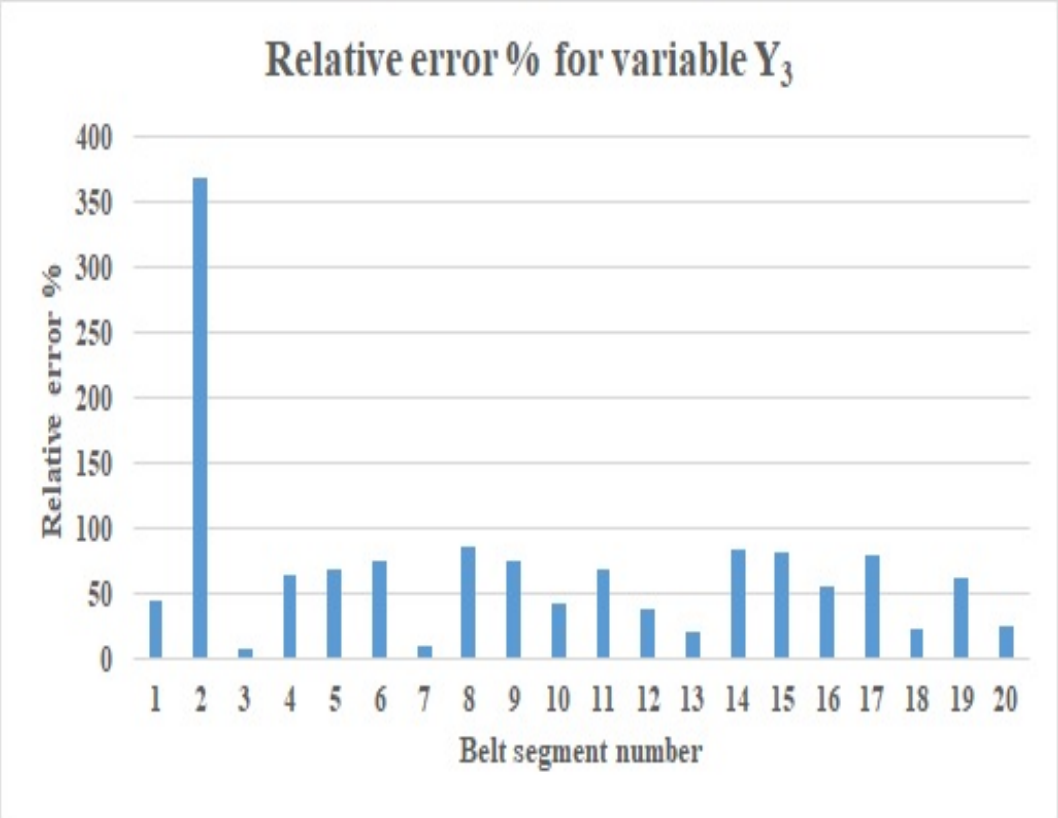


FIGURE 6.8: Comparison of predicted values generated by the artificial neural network and the DiagBelt+ system for the damaged area of each belt section

As evident from Table 6.10 and Fig. 6.8, the prediction accuracy of Model 3 has deteriorated compared to Models 1 and 2, with Indicator C accounting for 5% of the belt segments. Specifically, under Indicator C, belt segment 2—with an approximate length of 100 meters—is of particular interest. This suggests the occurrence of an irregular event, such as the accidental fall of a large rock, which may have been larger or sharper than the typical transported material. Apart from these cases, the relative prediction error was around 60%, indicating that despite variations in the characteristics and granular size of the transported material over time, the model performed well in estimating the damaged area. It is important to consider that damage severity can vary: in some cases, the damage may be deep enough to

reach the steel cord core while remaining relatively small in surface area, whereas in other instances, the damaged area may be extensive but limited to the cover layers without penetrating the steel cord region. Overall, the model has demonstrated strong performance, successfully limiting Indicator C values to only 5% of the belt segments. Given the high level of uncertainty associated with predicting damage area, this outcome reinforces the model's effectiveness in handling complex damage patterns.

TABLE 6.11: Prediction results in % for model 4 (Y_4: X length of damage signal in millimeters) indicating share for indicators A, B, C

Para-meters	Activation function	Opti mizer	Median value of relative error	A	B	C
X	swish	adam	99.7 %	0	100	0
Y			99.6 %	0	100	0
X	ReLU	Nadam	99 %	0	100	0
Y			99 %	0	100	0
X	ReLU	RMSprop	55.6 %	40	55	5
Y			61.5 %	35	60	5

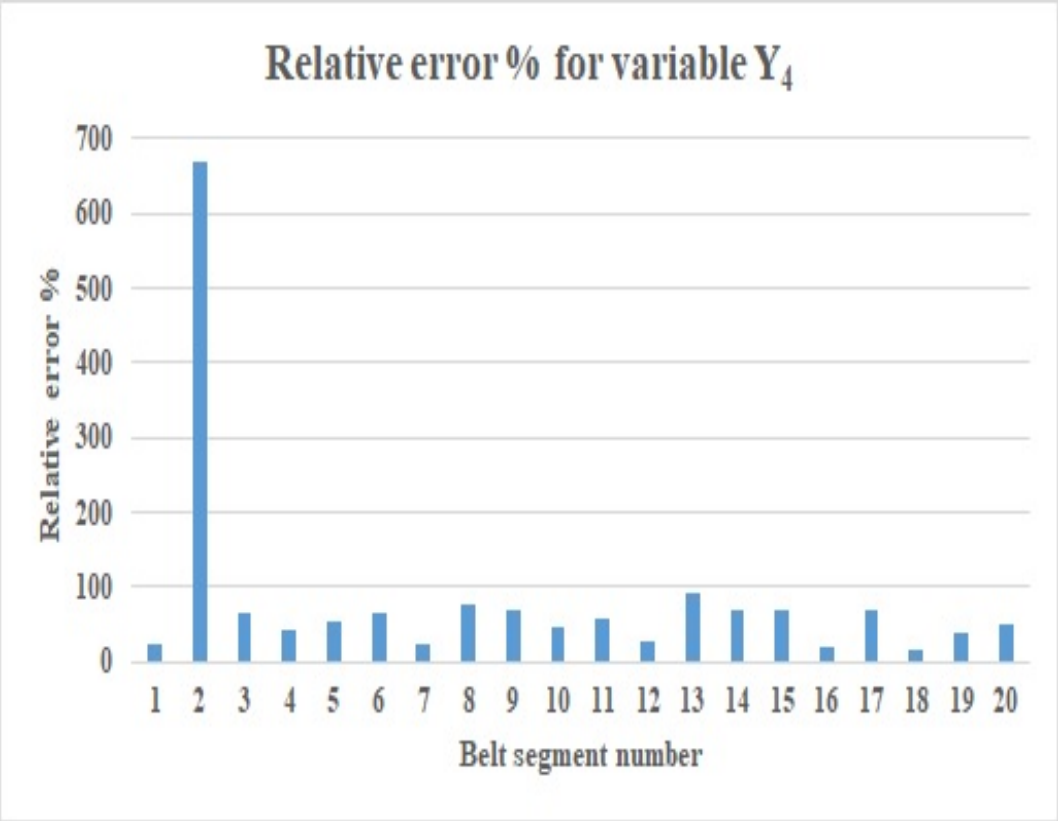


FIGURE 6.9: Comparison of predicted values generated by the ANN and the DiagBelt+ system for the length of the damaged signal in millimeters for each belt section

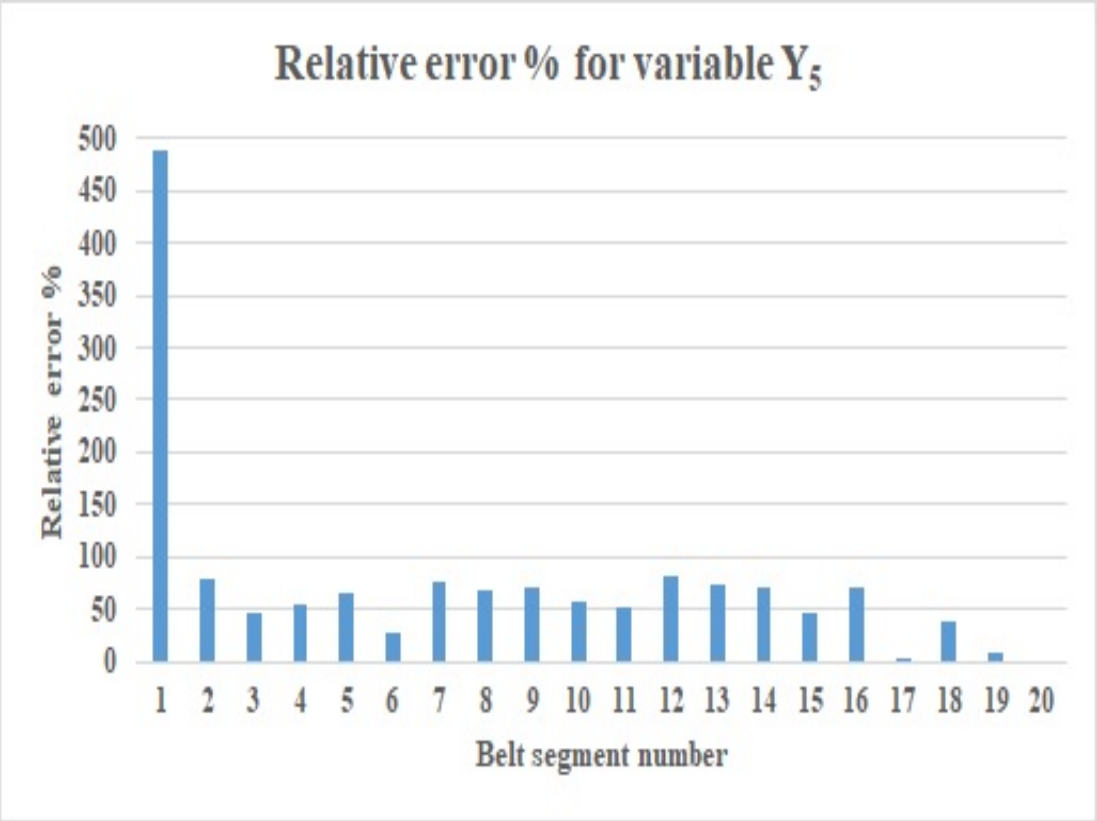


FIGURE 6.10: Comparison of predicted values generated by the ANN and the DiagBelt+ system for the width of the damaged signal in millimeters for each belt section

As observed in Table 6.11, Fig. 6.9, and 6.10, the trend of outliers observed in the previous model, where damaged areas were predicted, has persisted in the current model, which predicts specific damage characteristics such as length and width. Notably, belt segment 2 continues this trend, reinforcing the hypothesis that an irregular event may have occurred. Additionally, this belt segment has a length of less than 100 meters, which may have influenced the neural network's performance, given that only two belt segments in the dataset fall within this length range. This highlights the crucial role of data availability in the learning process of neural networks.

Furthermore, the median values of error in predictions for both parameters, Y_4 and Y_5, are approximately 55 % and 60%, aligning with the median values observed in Model 3. The underlying reasons for this behavior remain consistent with those identified in Model 3—damage depth and surface area can vary due to continuous fluctuations in the characteristics of the transported material over time.

6.3.1 Practical use of the developed forecasting methodology and its validation

To validate the applicability of the developed methodology and demonstrate its practical usefulness, predictions for future were generated for the surface limestone mine in Poland for the fourth-fifth scan under the hypothesis that it was conducted one and two years into the future after the last scan which was at 48.3 months (thus prediction were made for 60.3 and 72.3 months of age from the first installation date). The initial two scans (31.8 and 38.5 months) served as the training dataset, while the third scan (48.3 months) was used for testing by comparing the model's predictions with actual observations at this stage. After confirming that the model's performance aligned with expectations, the third scan (48.3 months) was added to the training dataset. The updated model was then utilized to forecast a future states at 60.3 and 72.3 months of age. As a result, the final training dataset comprised the first three scans, with predictions made for the condition at 60.3 and 72.3 months of age. The initial assumptions, including the length of the belt segments as well as the overall belt width and loop length, were maintained, with the belt loop length set at 7200 meters and the width at 1000 millimeters. Additionally, the set of independent input variables for predictions remained unchanged except the age—60.3 months and 72.3 months. An example of the training dataset used is given in the Table 6.12.

X_1	X_2	X_3	X_4	X_5	X_6	Y_1	Y_2	Y_3	Y_4	Y_5
7200	1000	0	112.9	1	1	0	0	0	0	0
7200	1000	0	112.9	2	1	0	0	0	0	0
7200	1000	31.8	112.9	1	2	0.035	4	360.6	321	450
7200	1000	31.8	95.7	2	2	0.010	1	40.7	81	75
7200	1000	38.5	113	1	3	0.044	5	561.6	446	700
7200	1000	38.5	95.9	2	3	0.020	2	64.4	71	100
7200	1000	48.3	113.3	1	4	0.052	6	571.3	456	950
7200	1000	48.3	96.1	2	4	0.031	3	65.5	72	125

TABLE 6.12: An example of input variables dataset

Predicted results of the future are provided in the Table 6.13 and 6.14, these results were predicted using the pre-trained models which are marked in green colors in the Table 6.8, 6.9 ,6.10, 6.11. Such predictions assist mine operators in optimizing inventory management and planning future maintenance or procurement of new belt segments or components in advance. Prolonged storage of pre-ordered spare belts or their elements, if not maintained under appropriate conditions, may lead to material degradation over time. Additionally, maintaining buffer inventory imposes financial constraints, as capital remains tied up in unused stock. The proposed predictive modeling approach using ANN enables operators to allocate financial resources more efficiently, ensuring that expenditures occur at the appropriate time when

Belt segment	Y_1	Y_2	Y_3	Y_4	Y_5
1	0.141002	15.9	1360	1652.4	2176
2	0.177726	17.077	1333.2	1635.4	2154.1
3	0.073743	17.857	1610.9	1794.6	2360.2
4	0.042214	18.94	2157.7	2100.8	2731.6
5	0.044687	20.102	2164.7	2110.7	2729.4
6	0.054433	21.312	1994	2032.6	2664.5
7	0.42272	25.088	1273.2	1605	2115.1
8	0.052706	23.741	2176	2098.7	2717.3
9	0.055452	24.974	2178.6	2101.1	2720.2
10	0.058135	26.168	2180.7	2106.7	2726.1
11	0.060668	27.306	2183.2	2116.7	2735.8
12	0.063074	28.389	2185.7	2128.5	2747.6
13	0.182478	29.439	1465.8	1726.8	2271.7
14	0.107658	30.342	1731.2	1853.3	2436.8
15	0.069371	31.151	2191.1	1931.8	2732.2
16	0.07266	31.86	2166.5	2141.7	2769.8
17	0.078468	32.447	2094.9	2134.6	2787.4
18	0.072832	32.896	2205.2	1929.9	2745.5
19	0.073685	33.217	2205.9	1937.9	2753.4
20	0.074091	33.406	2207.7	1953.2	2766.4

TABLE 6.13: Forecasted results over a 12-month period in future using pre-trained neural network models

replacement or maintenance is necessary. Furthermore, this approach facilitates proactive maintenance strategies, reducing instances where belt segments must be scrapped due to extensive damage. By implementing timely repairs, the risk of surpassing damage thresholds—beyond which segments become irreparable—is minimized,thereby enhncing the operational lifespan of conveyor belts.

Belt segment	Y_1	Y_2	Y_3	Y_4	Y_5
1	0.349	39.5	1548.8	1667.3	2455.7
2	0.393	37.733	1523.5	1641.6	2426.2
3	0.165	39.961	1809.3	1879	2662.4
4	0.072	32.269	2497.4	2472	3170.6
5	0.073	32.639	2504.1	2429.6	3130.9
6	0.073	28.558	2255.1	2245.8	2936.9
7	0.571	33.868	1475.8	1602.1	2369.3
8	0.074	33.347	2516.3	2386.4	3086.8
9	0.075	33.553	2519.5	2388	3088.8
10	0.075	33.736	2522.1	2394.9	3096.4
11	0.075	33.949	2525.2	2408.7	3111.4
12	0.076	34.166	2528.5	2428.9	3132.5
13	0.271	43.714	1685.7	1762.6	2580.5
14	0.109	30.861	1891.5	2051	2731.8
15	0.077	34.665	2535.3	2516.9	3223
16	0.076	33.405	2509.5	2493.1	3192.3
17	0.073	30.364	2421	2362.2	3088.1
18	0.079	35.649	2552.4	2304.4	3260
19	0.079	35.737	2553.3	2319.4	3279.1
20	0.080	35.952	2557	2334.5	3299.7

TABLE 6.14: Forecasted results over a 24-month period in future using pre-trained neural network models

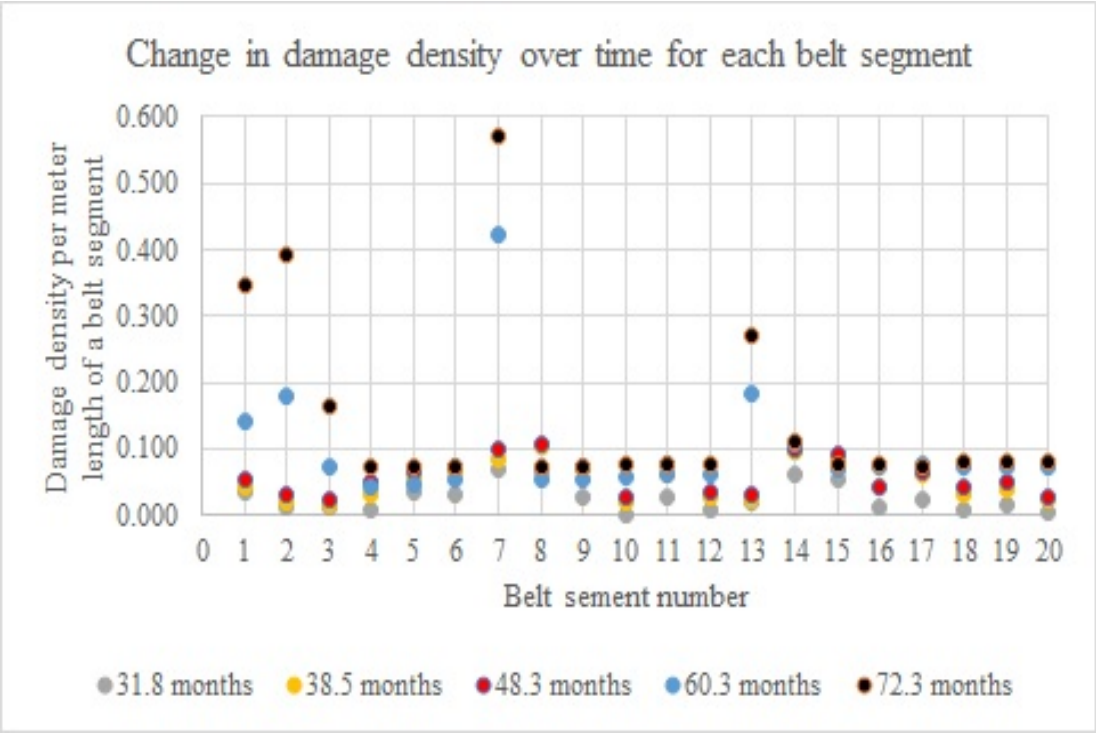


FIGURE 6.11: Change in damage density over time for each belt segment

As illustrated in Fig. 6.11, the predictions for 60.3 and 72.3 months generally maintained the increasing trend in damage density. However, there were three instances (two for 60.3 months) where this increasing trend was not sustained. For the entire belt loop length of 7,000 meters, the observed damage densities at 31.8, 38.5, 48.3, 60.3, and 72.3 months were 0.025, 0.052, 0.060, 0.085, and 0.126 failures per meter length of belt respectively. This indicates that despite the presence of three deviations in predictions, the overall forecasts for damage density align with expected trends, demonstrating that the ANN model was able to capture the future progression when values were aggregated across the full belt length.

It should be noted, however, that between the second and third scans the growth rate was much smaller than in the earlier period for a considerable number of belt segments (refer to Fig. 6.5). Several factors may explain this observation: repairs could have been performed on damaged belt sections, temporarily lowering the number of failures; the intensity of conveyor usage may have been reduced, resulting in lower loads; or the diagnostic device may have been installed in a slightly different configuration, producing smaller recorded signals. Furthermore, the use of only three scans to develop the regression model provides a very limited sample size, which restricts the statistical significance of inferences and contributes to the observed scale of prediction errors. Another important limitation is the absence of operational data such as the intensity of conveyor usage and the total transported mass between scans. Since only calendar time was used as a predictor, the model does not fully capture variations in belt loading conditions, which are directly related to the rate of failure development. As noted in prior studies [60], [285], failure density is a more robust indicator than calendar time, and predictive accuracy could be significantly improved if transported mass were available as an explanatory variable. Unfortunately, such operational records could not be obtained for either mines. The lack of these critical inputs limits the precision of long-term forecasts, even though the aggregated predictions still reflect the expected overall damage density trends.

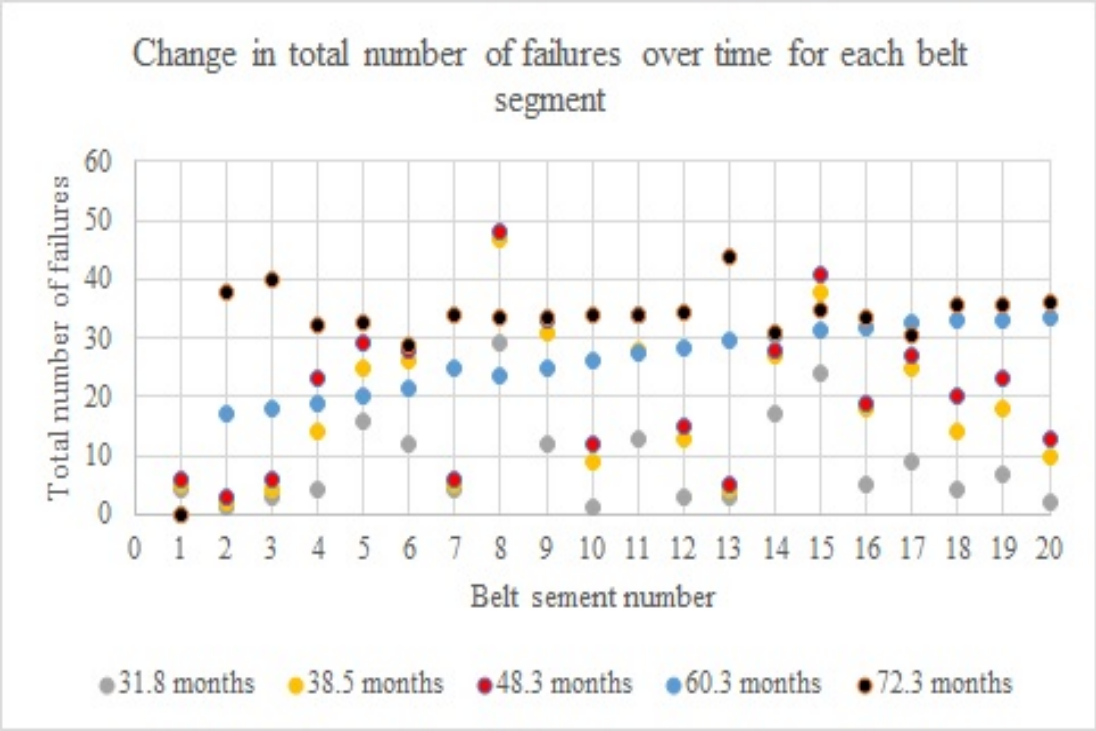


FIGURE 6.12: Change in total number of failures over time for each belt segment

As shown in Fig. 6.12, the number of damages increases over time. The total number of failures observed for the entire belt loop length of 7,000 meters was 173, 363, 419, 596, and 884 at 31.8, 38.5, 48.3, 60.3, and 72.3 months of age respectively. However, it is noteworthy that there were four instances where the predictions did not follow the expected increasing trend compared to the first three scans. Notably, three out of these four deviations corresponded to the age at 60.3 months. Despite these discrepancies, the model effectively compensated for these outliers when considering the entire loop length, as evidenced by the overall trend in failure counts across different time intervals. This further confirms that the ANN produced reliable predictions, reinforcing its applicability as a dependable tool for future planning.

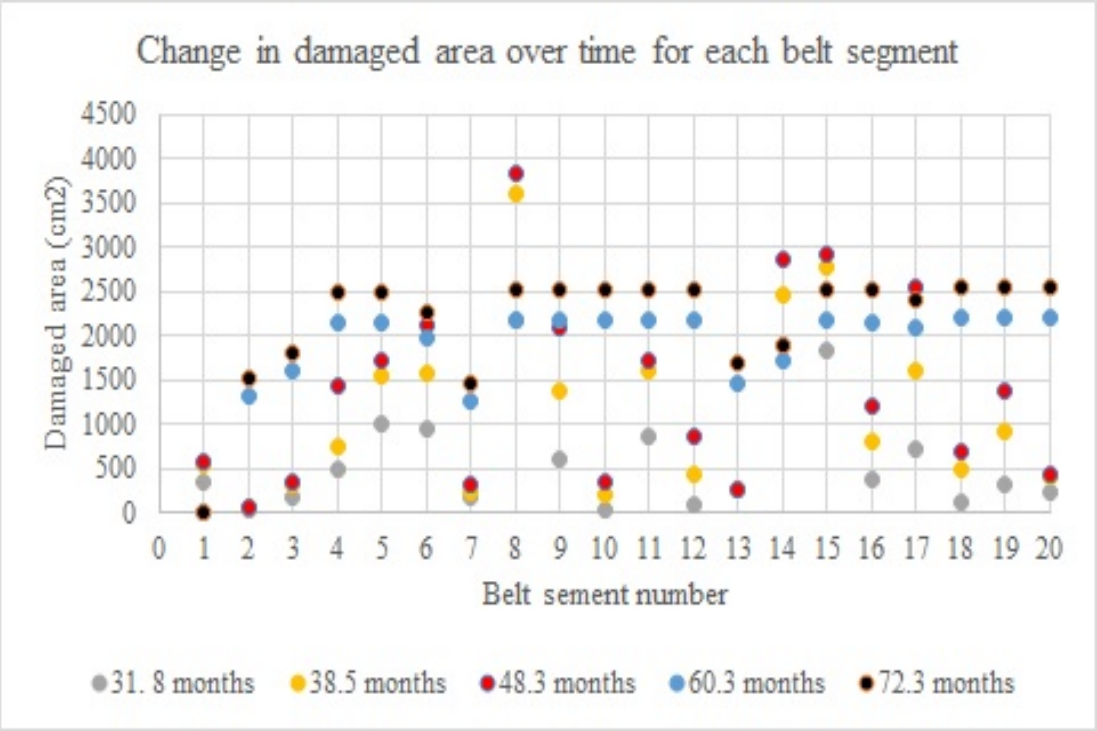


FIGURE 6.13: Change in damaged area over time for each belt segment

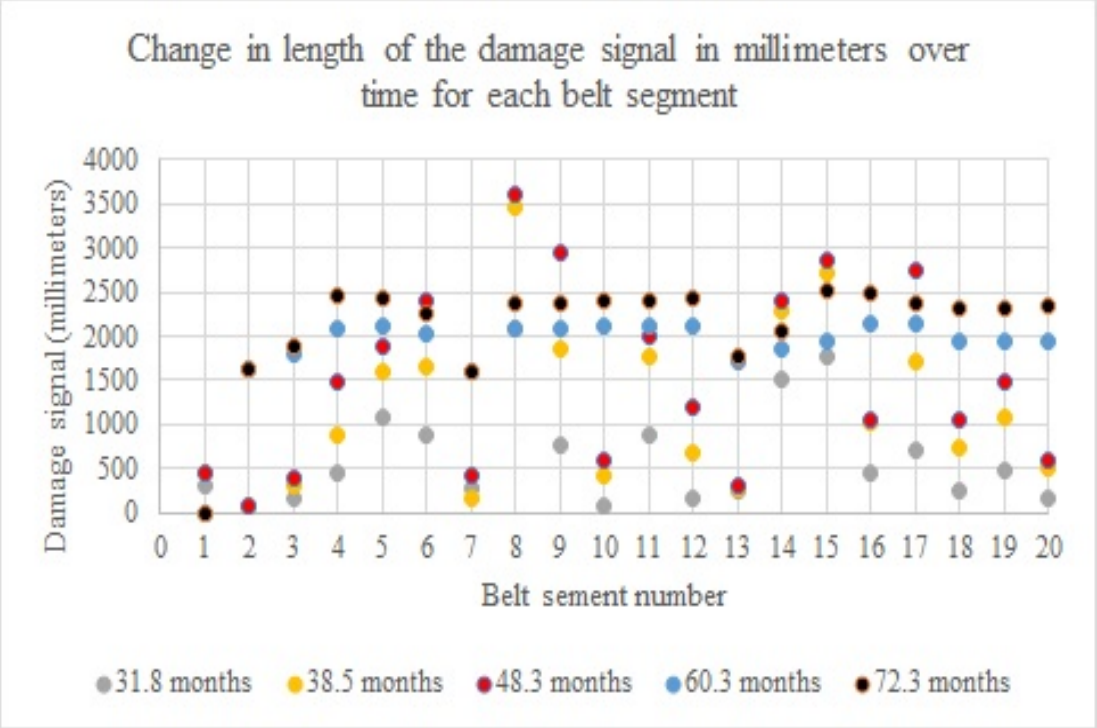


FIGURE 6.14: Change in length of the damage signal in millimeters over time for each belt segment

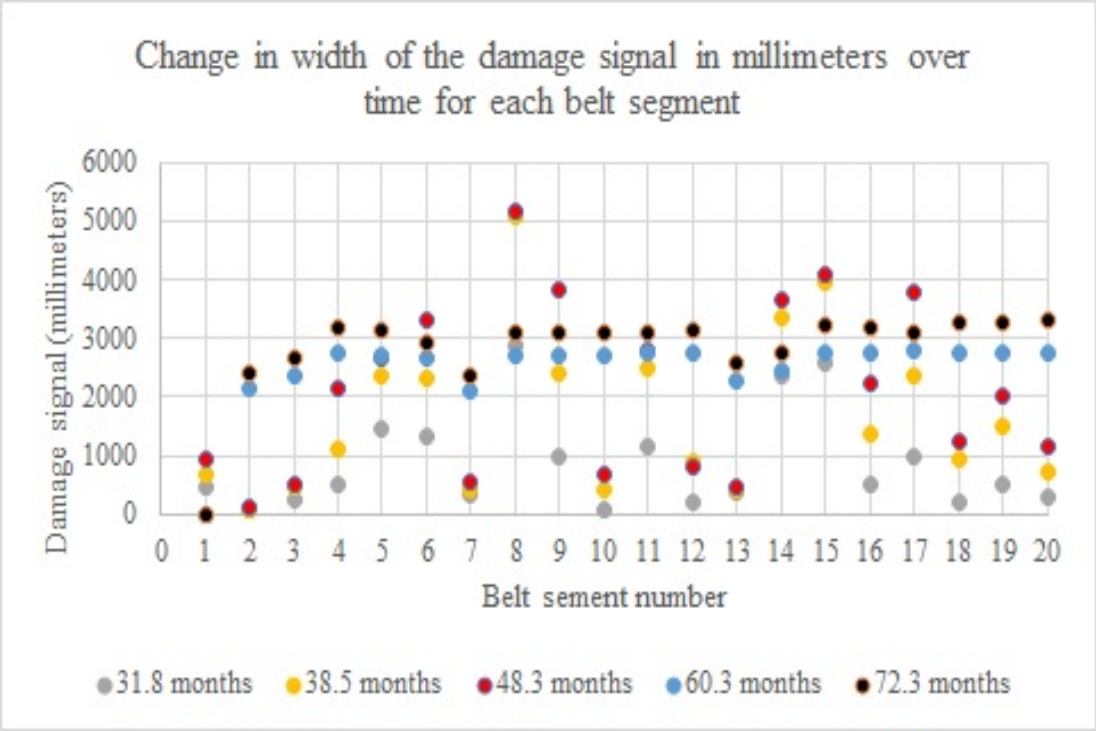


FIGURE 6.15: Change in width of the damage signal in millimeters over time for each belt segment

Damaged area comparison as shown in the Fig. 6.13 and damage signals are inherently interconnected, as the recorded damage signals serve as indicators of the resulting damaged area. As shown in Fig. 6.14 and Fig. 6.15, the model predicted 10 outliers for length-based signals and 14 outliers for width-based signals, where the damage signals did not exhibit an increasing trend compared to those recorded at 31.8, 38.5, and 48.3 months of age. Additionally, the total damaged area for the entire belt loop length was observed to be 12,819.87, 22,104.31, 27,879.96, 34,014, and 38,557.4 cm^2 at 31.8, 38.5, 48.3, 60.3, and 72.3 months, respectively which confirms that damaged area is in increasing trend. Without consistent information on chunk size, transport rate, and the frequency of material movement on the conveyor belt, it is not possible to reliably predict the area of damage, including both its length and width.

It is of particular interest to evaluate how the regression models align with the damage values recorded on-site by the DiagBelt+ system, as well as with the predictions generated by the ANN for 60.3 and 72.3 months. This comparison helps to assess the consistency and validity of the predicted values over time. The degree of convergence between the regression curve and the ANN-based forecasts offers insight into the reliability of the models. Figs. 6.16, 6.17 and 6.18 serve to confirm the plausibility of the predicted values and support the feasibility of the modeling approach, indicating whether the predictions are scientifically reasonable and coherent with observed damage trends.

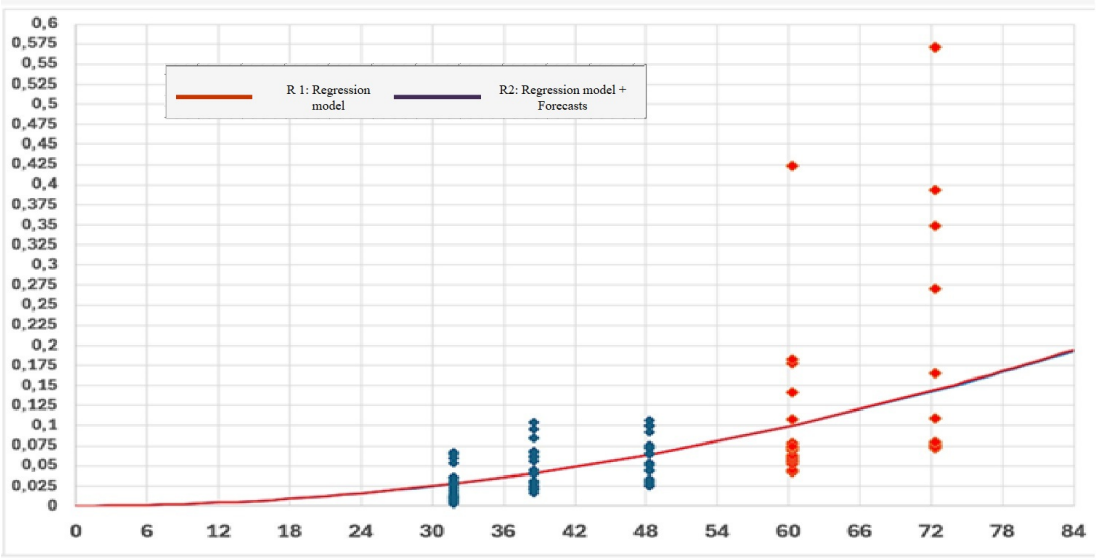


FIGURE 6.16: Comparison of failure density between predictions made by R1 and R2 models

Fig. 6.16 illustrates the regression models fitted to the measured damage densities of the conveyor belt, together with the extended predictions obtained through the hybrid approach combining regression and artificial neural networks (ANN). Both models exhibit a similar upward trend, which aligns with the expected pattern of increasing belt wear and accumulated damage as the conveyor system ages [130], [277]. The blue curve represents the regression model (R1), which was developed exclusively on the basis of three DiagBelt+ scans performed at 31.8 months, 38.5 months, and 48.3 months of belt operation. The additional red line represents the R2 model, which incorporates the ANN-based forecasts for 60.3 and 72.3 months along with DiagBelt+ scans. The scatter points show the actual observed and predicted data distributions across different time intervals. The diagram highlights that while the regression model for the average density alone provides a relatively smooth growth trend of damage density, the combined regression and ANN model introduces higher variability, particularly in the extrapolated ranges beyond 48.3 months. This behavior reflects the presence of outliers in the prediction stage, which is expected due to the lack of sufficient empirical belt scans at later stages of operation.

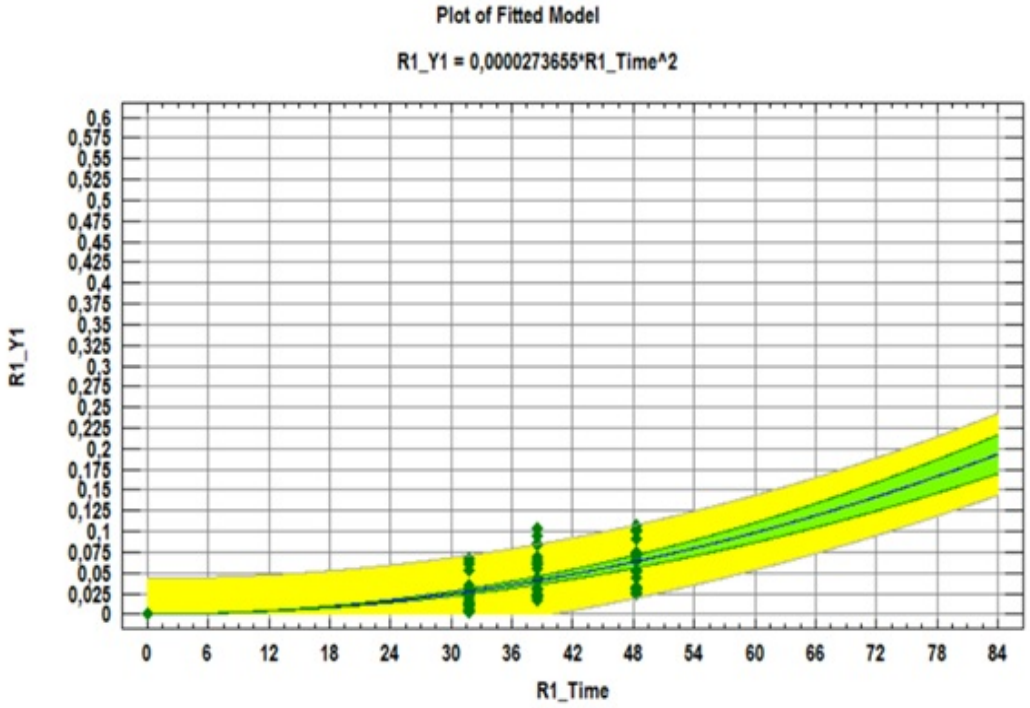


FIGURE 6.17: Quadratic regression model predictions for R1 model

X-axis (R1_Time): conveyor belt age in months.
Y-axis (R1_Y1): damage density per meter length of the belt.
Equation: the fitted model is quadratic: R1_Y1=0.0000273655 $\times$ ($Time^2$)
Green points: actual measured data points using DiagBelt+ system
Blue curve: fitted quadratic model (predicted mean damage density).
Green band: 95% confidence interval for the average damage density.
Yellow band: likely represents the 95% prediction interval, showing the expected range of individual future values.

The fitted model shown in Fig. 6.17 presents the fitted regression model (R1) with its 95% confidence intervals for predicted defect density values for individual belt segments. The regression function is quadratic in nature. The data points correspond to the DiagBelt+ inspections conducted at 31.8, 38.5, and 48.3 months, which formed the basis for model calibration. The green band represents the 95 % confidence interval around the fitted curve for the average density, while the wider yellow band depicts the 95% confidence prediction interval. The model indicates a gradual increase in damage density per meter of conveyor belt length with time, showing that quadratic regression sufficiently captures the progression of belt deterioration in the measured interval. Importantly, the prediction and confidence bands remain almost parallel across the analyzed time range, which means that uncertainty does not grow significantly with time and the confidence of predictions remains relatively stable. The growing uncertainty with the level of average density is depicted by slightly increasing green band, showing possible level of future average density.

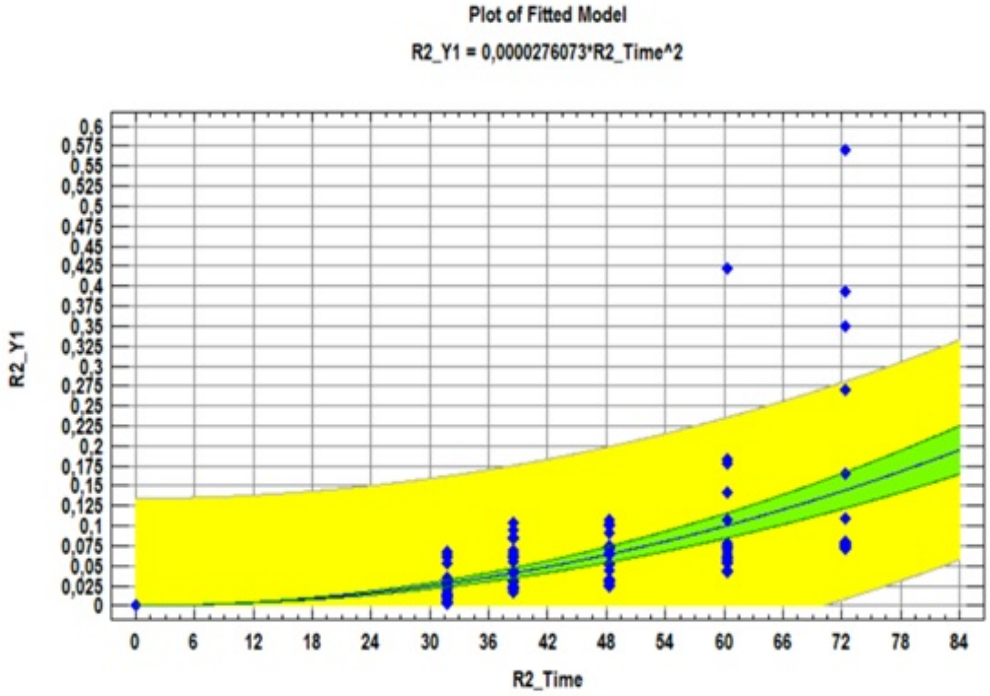


FIGURE 6.18: Quadratic regression model predictions for R2 model

Equation: R2_Y1=0.0000276073 $\times(Time^2)$
X-axis (Time): age of the belt in months (31.8, 38.5, 48.3, 60.3, 72.3 months).
Y-axis (Y_1): damage density per meter length.
Blue curve: fitted quadratic model (predicted mean damage density).
Green band: 95% confidence interval for the average damage density.
Yellow band: likely represents the 95% prediction interval, showing the expected range of individual future values.

The fitted curve as shown in 6.18 is accompanied by confidence (green band) and prediction intervals (yellow band), similar to the R1 case. However, unlike R1, this model integrates additional predicted data points for 60.3 and 72.3 months. These extended values provide a longer-term representation of damage density growth, but also introduce higher dispersion, as evidenced by the spread of blue points above and below the fitted regression curve. This reflects the ANN model's tendency to generate more variable predictions, particularly when operating in extrapolated ranges where no real scan data exist.

It is important to note that the DiagBelt+ system provided only three scans, and the time gaps between them were relatively short—approximately 7 months between the first and second scan, and 10 months between the second and third scan. Consequently, when predictions are extended to longer periods (e.g., 60.3 and 72.3 months), the likelihood of outliers naturally increases due to the absence of direct calibration data in those intervals. This

explains the larger scatter observed in the R2 model and emphasizes the challenges of long-term conveyor belt damage forecasting when relying on limited empirical measurements.

When comparing R1 and R2, it becomes evident that the regression-only model (R1) provides a smoother and more stable representation of belt damage density progression but remains limited in predictive scope because it only captures the period covered by the available DiagBelt+ scans. In contrast, the regression combined with ANN-based predictions (R2) enables extended forecasting up to 72.3 months, offering a more complete picture of belt deterioration over time. However, the incorporation of ANN forecasts introduces greater variability and a higher occurrence of outliers, particularly due to the scarcity of measured data for calibration in later periods.

From the perspective of predictive maintenance, R1 offers reliable insights within the observed data range, making it suitable for short- to medium-term planning. R2, on the other hand, extends the horizon of predictive maintenance by allowing forecasts beyond the measured period, albeit with a trade-off in terms of predictive uncertainty. The use of performance indicators A, B, and C further demonstrates that while ANN-based predictions can capture general trends, the reliability of these forecasts depends strongly on the density and continuity of input data. It is worth to notice than the yellow band (95% confidence interval for forecasts) is about +/- 95% over damage density average, what correspond to A+B errors classifications. Green band (95% confidence interval for the average) is about +/-18%, what is a 36% of class A errors. Developed at the beginning classification of errors is similar to the size of 95% intervals for the average and prediction limits. Therefore, combining regression and ANN models can enhance long-term predictive capacity, but careful interpretation of uncertainty bands and error indicators is essential before making operational decisions in mining belt maintenance strategies.

It is noteworthy and can be seen in the Fig. 6.13 that the ANN predicted 11 instances with lower damage area values compared to the first three scans at 31.8, 38.5, and 48.3 months of age. This suggests that the model encounters challenges in predicting large-area damages, as accidental damage caused by irregularly sized material chunks falling onto the belt is inherently unpredictable. However, despite this limitation, the overall damaged area continued to increase at 60.3 and 72.3 months, indicating that the ANN successfully predicts an increasing number of failures, particularly those of smaller area size. This trend is expected, as older belts become more susceptible to minor damages, while new belt segments can resist small-scale damage in their early stages, the belt cover deteriorates over time due to repeated impact cycles during material transportation. Based on Fig. 6.13, 6.14, and 6.15, it can be concluded that ANN models can serve as a valuable tool for future planning in mining operations, particularly for repair scheduling and inventory management.

Chapter 7

Conclusion

The scientific objective of this dissertation was to develop an artificial intelligence (AI)-based method for predicting parameters associated with conveyor belt failures, including damage size and occurrence metrics, using operational characteristics and historical maintenance records from mining environments. The achievement of this objective is evidenced in the results and discussion sections 4.3 and 6.3 in chapters 4 and 6, respectively, where the proposed AI method was successfully implemented at two distinct mining sites that employed different policies for recording failures. The research presented in this work has demonstrated the complete development and validation of the predictive methodology, following the procedure outlined in flow process chart in Fig. 3.2.

Intelligent methods for predictive maintenance were selected, with the long short-term memory (LSTM) neural network employed as the most suitable approach (as reasoned in the chapter 2, section 2.2 and Table 2.1) for modeling the time-dependent evolution of failures in conveyor belt. After training on the prepared datasets, the models demonstrated predictive performances across both mining environments as it can be seen in the Table 7.1. The model development included careful selection of network parameters, activation functions, optimizers, and evaluation measures, ensuring rigorous testing and reliable performance outcomes.

	Indicator A	Indicator B	Indicator C	Median value of relative error in prediction (%)
Human visual inspection database	64.4	17.84	16.84	28.6
DiagBelt+ database	41	56	3	33.2

TABLE 7.1: Comparison of prediction results between the HVI and DB+ databases—average predicted values across all models

The predictive modeling methodology was tested using two distinct - datasets— human visual inspection (HVI) and DiagBelt+ to validate its applicability under diverse operational conditions. The HVI database comprised 119 belt segments distributed over 11 loops, with loop lengths ranging from

722 to 3524 meters and segment lengths from 52 to 263 meters. In contrast, the Diagbelt+ (DB+) database included a single loop of approximately 7200 meters containing 20 belt segments, with lengths ranging from 59 to 451 meters. The patterns and rates of conveyor belt wear varied significantly between the two mining operations due to several key operational differences. First, the transportation speed of the materials differed notably—in the lignite mine, lignite was transported at approximately 6 meters per second, whereas in the limestone mine, limestone was conveyed at a slower rate of about 3.8 meters per second. This disparity in velocity likely contributed to variations in mechanical stress and wear distribution along the belt. Second, the number of operational cycles completed by the belts during the same net operating time differed substantially. In the limestone mine, longer belt loop and lower speed resulted in lower frequency compared to the shorter loop at the lignite mine. As a consequence, the belts at the limestone site experienced less frequent loading and unloading events, potentially slowing the wear process and influencing damage patterns differently than in the lignite operation. The frequency of belt loop circulation varied across the analyzed sites. In limestone mine, a complete belt loop occurred approximately every 30 minutes, whereas in lignite mine, the frequency was as high as every 10 minutes for a 3524 m loop, and proportionally shorter for conveyors of reduced length. In limestone mine, due to a change in transport direction, the same belt was transferred onto itself, effectively halving the interval between loadings to approximately 15 minutes. Although these differences are not substantial when comparing the longest conveyors, it is important to note that most conveyors in lignite mine are around 1 km in length, corresponding to a belt loop of approximately 2000 m and a circulation frequency of about 5 minutes.Together, these differences in transport speed and operational cycling contributed to distinct wear characteristics in each mining environment.

Furthermore, the failure registration methods varied in precision. The HVI system relied on human observation, which introduced subjectivity and the possibility of inconsistency. In contrast, the DiagBelt+ system employed automated scanning technology, offering higher precision and consistency in failure detection. In both cases, the AI-based predictive approach was implemented and validated, confirming the adaptability of the methodology to different materials, operating conditions, and failure registration methods. The DB+ dataset provided more accurate initial conditions, as the belt system was newly installed and began operation simultaneously. In contrast, the HVI database included belts transferred from other conveyors, complicating the assessment of their previous operational histories and introducing greater uncertainty. However, for newly installed belts within the HVI dataset, prediction results were notably reliable. Over time, as conveyor belts age, cover wear increases and the core becomes more susceptible to damage. Incorporating the time-dependent increase in average damage into the prediction model improved forecasting accuracy. The LSTM-based method effectively captured these dynamics. When comparing the prediction results, as presented in Table 7.1, the HVI dataset showed a lower median relative

error across all models. Specifically, Indicator A performed competitively on both datasets, while Indicator C exhibited significantly fewer outliers in the DiagBelt+ results. This suggests that although the HVI database facilitated broader generalization, the DB+ system provided more detailed and reliable damage insights, particularly in identifying localized core damage such as steel cord deterioration and failure depth. The results demonstrated that the LSTM models achieved competitive predictive performance across both datasets, thereby verifying that the procedure is robust and transferable across diverse mining environments.

Importantly, the second case study, using the DB+ dataset, highlighted the potential for future recursive applications of the methodology. As new data becomes available, the model can be retrained and refined to improve predictive accuracy over time, enabling continuous learning and long-term performance improvement. This confirms the forward-looking value of the proposed approach for integration into preventive maintenance strategies.The HVI system is less accurate compared to the DB+ system, yet it is easier to implement and more cost-effective, mainly because it does not require additional equipment. It had been used in mines for many years together with the Taśma program, developed in the mid-1980s, which contained information on conveyors, belt loops, belt sections, and splices. Records of belt damage and repairs (including material usage) were later documented in Excel files and, combined with the Taśma data, these formed the HVI database. Hence, the choice of failure recording method must balance accuracy requirements with available resources. From a modeling standpoint, even if initial damage is randomly distributed along the belt, damaged sections are more prone to further degradation due to mechanical weakening. Therefore, the likelihood of future damage is conditional on prior damage states. This supports a recursive modeling approach that updates segment conditions over time, enabling better failure forecasting. (The degradation process of conveyor belts has been characterized in the literature as a stochastic process appropriately modeled by a Markov chain [286]. In such a framework, the likelihood of transitioning to a future state depends solely on the current condition of the system, independent of past states or historical trajectories, and is defined by a set of discrete states supplemented by associated transition probabilities. This modeling approach has been applied, for instance, in the analysis of conveyor belt joint failures, where the wear of the rubber layer at the joint was treated as a continuous Markov chain parameter, enabling quantification of reliability and durability based on the state transitions of the wear variable [287]).

This dissertation presents a robust predictive modeling approach based on artificial neural networks—specifically LSTM, for forecasting conveyor belt damage in mining environments. The model was validated on two real-world datasets, demonstrating its adaptability across different materials, failure detection systems, and operational strategies. The results confirmed that the methodology allows mine operators to proactively manage maintenance

and repairs based on current belt condition and anticipated wear progression. The conclusions extend beyond the validation of the method itself. The findings indicate that the proposed AI framework can serve as a foundation for developing a preventive maintenance AI agent, which could be integrated into mine-specific diagnostic systems such as DiagBelt. Such an agent would enable automated damage prediction and maintenance scheduling on closed, site-specific datasets, thereby improving reliability and reducing downtime in large-scale material transport systems. In summary, the dissertation has achieved its primary objective of developing an AI-based predictive method for conveyor belt damage forecasting. The methodology has been successfully tested on two distinct datasets, confirming its effectiveness and adaptability. Moreover, the scalability of the approach provides a solid basis for further research and future advancements in predictive maintenance of conveyor belts.

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