Intelligent Predictive Maintenance (IPdM) in Forestry: A Review of Challenges and Opportunities

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Abstract: The feasibility of reliably generating bioenergy from forest biomass waste is intimately linked to supply chain and production processing costs. These costs are, at least in part, directly related to assumptions about the reliability and cost-efficiency of the machinery used along the forestry bioenergy supply chain. Although mechanization in forestry operations has advanced in the last 20 years, it is evident that challenges remain in relation to production capability, standardization of wood quality, and supply guarantee from forestry resources because of the age and reliability of the machinery. An important component in sustainable bioenergy from biomass supply chains will be confidence in consistent production costs linked to guarantees about harvest and haulage machinery reliability. In this context, this paper examines the issue of machinery maintenance and advances in machine learning and big data analysis that are contributing to improved intelligent prediction that is aiding supply chain reliability in bioenergy from woody biomass. The concept of "Industry 4.0" refers to the integration of numerous technologies and business processes that are transforming many aspects of conventional industries. In the realm of machinery maintenance, the dramatic increase in the capacity to dynamically collect, collate, and analyze data inputs including maintenance archive data, sensor-based monitoring, and external environmental and contextual variables. Big data analytics offers the potential to enhance the identification and prediction of maintenance (PdM) requirements. Given that estimates of costs associated with machinery maintenance vary between 20% and 60% of the overall costs, the need to find ways to better mitigate these costs is important. While PdM has been shown to help, it is noticeable that to-date there has been limited assessment of the impacts of external factors such as weather condition, operator experiences and/or operator fatigue on maintenance costs, and in turn the accuracy of maintenance predictions. While some researchers argue these data are captured by sensors on machinery components, this remains to be proven and efforts to enhance weighted calibrations for these external factors may further contribute to improving the prediction accuracy of remaining useful life (RUL) of machinery. This paper reviews and analyzes underlying assumptions embedded in different types of data used in maintenance regimes and assesses their quality and their current utility for predictive maintenance in forestry. The paper also describes an approach to building 'intelligent' predictive maintenance for forestry by incorporating external variables data into the computational maintenance model. Based on these insights, the paper presents a model for an intelligent predictive maintenance system (IPdM) for forestry and a method for its implementation and evaluation in the field.

Keywords: intelligent predictive maintenance (IPdM); big data analytics; chipper; machine learning; operator fatigue; remaining useful life (RUL)

1. Introduction

Energy consumption is rising year by year with rapid population growth and economic development. Growing concerns about energy security and global warming triggered by greenhouse gas (GHG) emissions from fossil fuel consumption have motivated

more researchers to investigate developing sources of renewable energies including wind turbines, solar panels, bioenergy, hydropower, geothermal, and ocean energies [1]. With a great sense of responsibility, several nations have established a formal commitment to boost the proportion of renewable energy [2]. In recent years, renewable energy production has rapidly shifted into a profitable business, as evidenced by the numerous initiatives that have risen [3]. Among all types of renewable energy resources, over the last two decades, bioenergy has been under intense investigation with notable research efforts in different countries to define and measure sustainable practices [4].

In forestry, trees are logged and transport to the timber company. Only a small portion of the whole tree is utilized as a valuable timber for the furniture, construction etc., leaving the remainder of the trees such as branches, leaves, bark, and tops for either paper, biomass energy, or other uses. Biomass feedstock can be obtained from agricultural residues, low-value material from industrial processes, municipal solid waste (MSW), wood, forest residues, energy crops, animal manure etc. [5,6]. These residues remain on the sites after the completion of the harvesting operations. A forest biomass supply chain is a combination of organizations, human resources, activities, information, and biomass resources (bulk residues, chips, bundles) involved in delivering residues from suppliers to customers. It consists of the transformation of trees or tree components into a finished product (e.g., chips for power generation, liquid fuels) that is transported to the end customer. These activities include the harvesting, collection, pre-processing (e.g., chipping, grinding), storage, and transportation from supply to demand points. Each of these activities has its sub-categories, for example, pre-processing includes drying, palletization, ensiling, and pyrolysis [1].

Since the cost of the energy product provided from biomass is moderately low (i.e., 0.16 € per kg for wood pellets [7]), to make this resource cost-efficient and viable, its supply chain from collection, transport, storage to distribution (logistics) must be efficient and well defined and optimized [8]. Modelling is an important phase in understanding the supply chain process that leads to enhanced supply chain efficiency. Thus far, investigations that utilize supply chain models have focused on assessing specific supply chain scenarios, usually to minimize cost. However, the most considerable fraction of biomass energy cost generated comes from logistics operations [9,10]. A reliable logistics strategy is essential for all supply chain elements to operate harmoniously and ensures that the whole system functions as efficiently as possible [11,12]. Logistics optimization has been recognized as a unique chance for growth, profitability and competitiveness for organizations [13]. Emerging mobile machinery in biomass supply chain such as mobile wood chipper and mobile pyrolysis systems provide an effective way to deal with biomass logistics [14], as these units can be located close to feedstock sources or moved throughout a large region with biomass resources [15]. This creates a dual benefit, as reducing biomass accumulation in forest ecosystems reduces forest fire risks, and pyrolysis products are easier to store, handle, and transport than raw biomass [16].

Despite the benefits, the repair and maintenance costs of the chipper and pyrolysis machines are the major barrier that limits their efficiency and productivity [5]. Although some research [17] ignored the effect of maintenance and downtime cost in productivity of machinery during the operation, others estimated the costs associated with forest machinery maintenance (e.g., feller-buncher, forwarder, skidder, processor etc.) vary between 20% and 60% [18–24] of overall costs. In 2019, Spinelli et al. [18] indicated that chipper repair and maintenance may represent between 1.5% and 29% of total production cost. They declared that repair and maintenance costs are complicated to calculate as the rate, scale, and severity of breakdowns are inherently variable [25], and different repairmen or operators may record various cost figures for the same maintenance activity [26–28]. Many factors could increase the frequency and severity of failures and reduce safety, such as careless equipment storage, poor preventive maintenance, and low quality of prior repairs [18]. The latter being generally affected by time pressure that derives from the seasonal character of operation [29]. One solution to overcome the problem is to develop and perform a suitable maintenance plan for critical components of machinery.

Over the last few decades, the concept of maintenance has evolved from a corrective approach (repair tasks after a failure) to a preventive strategy (schedule maintenance plan to reduce the breakdown) [30]. In the last two decades, with the accelerated growth of computer science and emerging Internet of Things (IoT) technologies, maintenance strategies have revolutionized from preventive maintenance (schedule-based maintenance) to predictive maintenance (PdM). Remaining Useful Life (RUL) is the time left for a machine/component to offer its operative capabilities before a crash [25]. The maintenance planner or decision-maker use this metric to plan the actual time that machinery needs maintenance. Therefore, an accurate RUL prediction of critical assets is an important challenge in predictive maintenance (PdM) to improve reliability, elude breakdown, and diminish the maintenance costs [31]. Several studies reported the beneficial effect of PdM system that could lead to a sustainable supply chain such as avoiding unnecessary maintenance and estimate remaining lifetime [32], deep reductions in greenhouse gas emissions [33], reduce fuel and lubricants consumption [32], enhance maintenance safety [34], maintenance costs, and the availability of spare parts, avoid losing valuable production time [35], and make the supply chain more resilient. Nowadays, emerging big data and cloud-computing trends, offer a potential approach to enhance capture and analysis of a huge amount of data to deliver intelligent predictive maintenance with data inputs coming variously from maintenance archive data, sensor-based monitoring, and on-board devices on machinery. However, predictive maintenance regimes are only good as the quality of the input data [36], and the accuracy of the models depend on the relationships between these data and the predictions being produced. Although many researchers have acknowledged the importance and impact of external factors in RUL accuracy [37,38], it has not yet been seriously and practically addressed. The first reason could be the lack of infrastructure and process capability to store, process, and analyze the data collected from machine itself and external factors [39]. The other reason might be the researchers' perspective on solving the problem, as using advanced IoT technologies and smart sensors, cause ignorance of other potential data sources like external factor data.

This paper aims first to review the current machinery maintenance strategy in the forest sector, particularly chipper machines. In this research work, the operator fatigue during the operation are two potential external factor data that will be added to the standard IPdM model. Therefore, these two external factors will be studied in the literature review. The paper further presents a conceptual framework for developing intelligent predictive maintenance (IPdM) using big data technologies, machine learning algorithms, and Internet of Things (IoT) technologies. The model will used for design, implementation, and evaluation in biomass supply chain forestry. Lastly, according to the results, hypotheses will be suggested to improve the maintenance strategy in forestry. The paper is divided into six subsections. In the maintenance history, we first briefly describe the maintenance revolution. Then, the different maintenance models will be explained in the following section. Finally, the current chipper maintenance method will be described.

2. Maintenance

According to the Oxford Dictionary, maintenance is "the process of preserving a condition or situation or the state of being preserved" [40]. Maintenance is used essentially for anything worth repairing instead of replacing with a new one. It is not only used in manufacturing processes but also to railways, vehicles, computers, and so on. Machines, equipment, and devices production have always been subject to wear and repair and maintenance requirements. Along with the improvement of manufacturing, there has been a growth of maintenance. As far back as humankind began making devices that fulfilled their needs, maintenance was required. Repair and maintenance records (dated 600 B.C) can be seen in ancient Egypt document states a stoppage of supply of cedarwood needed to maintain the sacred boat of Amun Ra [41]. There was a considerable advance in worker productivity from the first Industrial Revolution due to new agriculture methods, advanced

machinery, and other field cultivation methods. All this led to countries' industrialization, transforming the agrarian country into an industrial one [42].

The Industrial Revolution had other significant impacts on society as well. England's population multiplied while the mortality rate decreased, thanks to improved hygiene, less hunger, and improved medical care. Urbanization formed, with large urban industrial centers with factories, new roads, railroads, and bridges attracting people from rural areas. Then, Manchester, Liverpool, Birmingham and Glasgow developed into the most progressive cities. The method of "letting the device work until its breakdown" was the first that humankind commonly employed. On first sight, it is the most comfortable and straightforward way of maintenance. Machines were relatively simple, and therefore there was no need for a technician who would know how to fix it, at the initial stage. Even nowadays, according to Bloch and Geitner [43], over 55% of people still practice corrective maintenance. With the growing complexity of machines, especially after the beginning of the first Industrial Revolution, different maintenance methods have been developed to reduce costs and improve the environment and operators' safety.

2.1. Maintenance Models

Companies and industries have adopted various maintenance approaches and policies to diminish maintenance expenses and enhance their productivity and risk management. The concept of maintenance has evolved over the last few decades from a corrective approach [44,45] (maintenance actions after a failure) to a preventive approach (maintenance actions to prevent the failure) and recently, key industrial manufacturers have invested in predictive maintenance (PdM) to maximize the availability of machine parts and equipment uptime and deploy maintenance more cost effectively [46]. Unlike traditional models, PdM is designed to monitor the actual condition of the equipment to alert the system in advance and determine whether maintenance will be required. Fault detection and condition monitoring are critical components of PdM and can potentially eliminate catastrophic equipment failures in industrial manufacturing. Through the measurement using sensors, unknown or abnormal patterns, events, or failures can be predicted using anomaly detection technology [47]. Condition-Based Maintenance (CBM) is a relatively maintenance model (Aligned with Industry 4.0 and digitalization) that has been utilized to plan for maintenance action based on the condition of the machines and to prevent failures by solving problems in advance. It uses sensors to monitor the performance of a system or a critical component and a measurement system to control and evaluate signals. In such techniques, signal data are used to forecast the RUL of the component unit through the relation between the historical data and real-time condition monitoring information collected from the in-field unit. Breakdown or failure is then determined as the occasion when a CM signal enters a prespecified failure threshold. As can be seen from Figure 1, there are three main types of maintenance methods, which will be described in the following subsection.
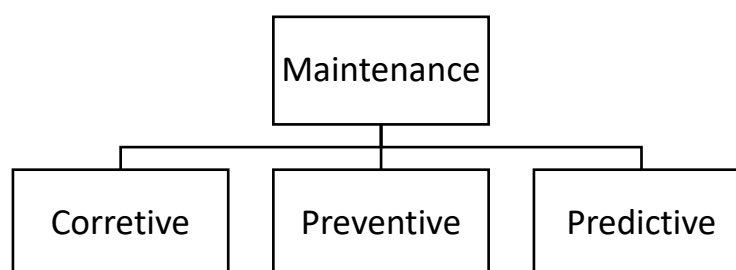
Figure 1. Three popular maintenance models.

2.1.1. Corrective Maintenance

In the Industrial Revolution, operators and workers were responsible for machinery and equipment maintenance, known as corrective maintenance (CM). CM is performed when the process or machine has a critical halt, and machine failure has already occurred.

Production is halted as long as the maintenance takes time, causing a reduction in production and a rise in costs. The repair time cannot be predicted, and in the worst-case scenario, the failure can affect the other elements, further increasing the repair time. Therefore, corrective maintenance is mainly employed in an environment where machinery breakdown does not impact the production. This strategy is based on the assumption that the costs sustained for downtime and replacement in case of breakdowns are fewer than the investment required for the maintenance program [48]. This approach may be economical when faults occur rarely. However, the frequency and different types of breakdowns may remarkably raise the plant's downtime cost and the cost of equipment.

Figure 2 illustrates the functionality of corrective maintenance of machinery for a period of time. The *X*-axis and *Y*-axis showed the level of machine health and operation time, respectively. In the first 12 months of machinery operation, the machine's health condition reduced from excellent to average health and then the failure occurred. Accordingly, the maintenance crew were present to identify the failure and order the machine's spare parts. This procedure typically takes a lot of time, and during the maintenance, the production is down. Generally, the maintenance fleet is not able to repair the machine carefully and accurately because they are under tremendous pressure to repair the machinery as soon as possible. Many cases and incident reports have demonstrated the risk of injury or death associated with maintenance activities [49]. The next failure of machinery occurred after six months, which indicated that there is no pattern in the failure of the machines, and an incident can happen anytime. Therefore, the maintenance crew must be available and prepared for the upcoming failure. The main disadvantages of corrective maintenance are that the production is stopped, the spare part is not available and must be purchased, the repairman is under great stress to repair the machine, the possibility of injury or death is high during the maintenance phase, the failed component might cause a failure of other parts, the nature of breakdown might be unknown, the scale of damage is large, and the overall cost is extremely high (e.g., machine maintenance and production down).
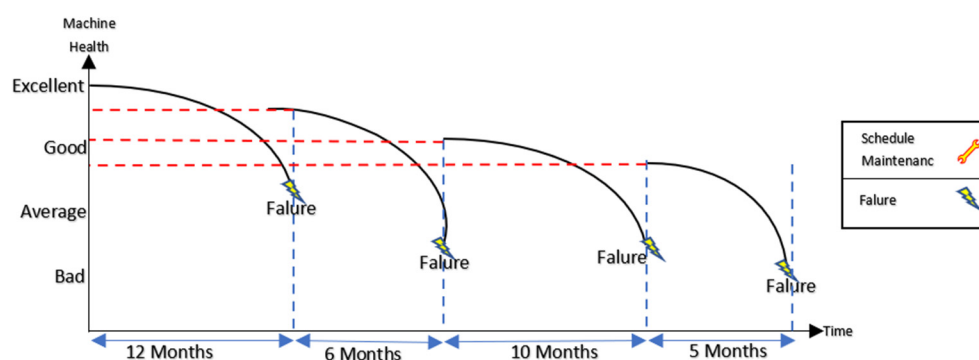
Figure 2. Repair and maintenance strategy using the corrective maintenance method.

2.1.2. Preventive Maintenance (PM)

At the beginning of the 20th century, industries began to add maintenance activities to their business plans, and maintenance managers started to transform from solving failures to preventing them, a process known as preventive maintenance (PM). PM is based on periodic reviews of the system with the aim of preventing unplanned breakdowns and failures [50]. This maintenance method is typically used outside the production time. The objective of this type of employed maintenance is to reduce or eliminate the accumulated deterioration through periodic checks and replacement of parts [51]. Preventive maintenance is enacted to identify any anomalies or malfunctions in the elements of a system. This method is regularly performed visually and physically on the machine [52–56]. This maintenance method requires the strong administration and development of a plan that must be performed by qualified staff. Besides, if it is not precisely used, there will be a failure, which will cause damage and increase costs.

As can be seen in Figure 3, regular maintenance is applied every three months to avoid machinery breakdown. However, the failure might take place before or after the scheduled maintenance time. As a result, arranging the maintenance program long before failure can lead to unwanted maintenance costs, and postponing the maintenance can increase the risk of breakdown. Compared with corrective maintenance, preventive maintenance is much safer in terms of human injury and is reliable and cost-effective. However, for many industries with complex machinery and systems such as aviation, marine, mining and power energy industries, the method is still costly and requires a lot of improvements. Diniz, Carlos Cézar Cavassin, et al. [57] used the World Class Maintenance (WCM) models to estimate availability of mechanics, oil consumption (hydraulic/engine), and maintenance costs as a basis for preventive maintenance. They observed a 5% increase in the availability of mechanics and a 60% decline in oil usage. However, the cost of maintenance increase by 3% as a result of new machinery investment and the training of mechanics.
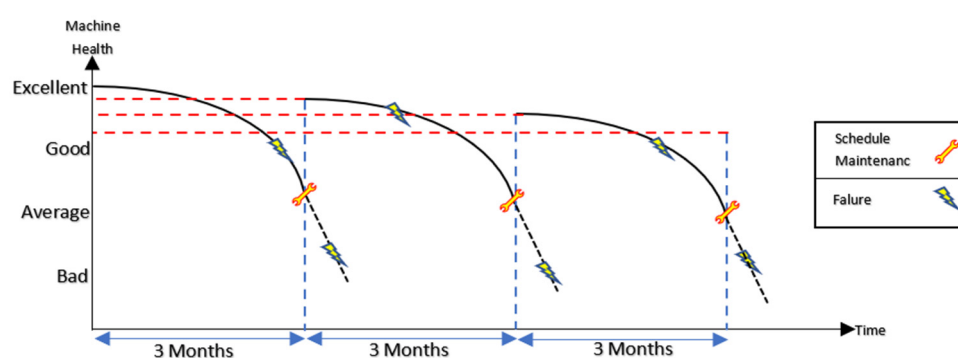
Figure 3. Repair and maintenance strategy using the preventive maintenance method.

2.1.3. Predictive Maintenance (PdM)

In the last two decades, with the accelerated growth of computer science and emerging IoT technologies, maintenance strategies have revolutionized from preventive maintenance to predictive maintenance (PdM) [58–60]. Recently, key industrial manufacturers have invested in PdM to maximize the availability of machine parts and equipment uptime and deploy maintenance more cost effectively [46]. The possibility of conducting predictive maintenance contributes to reducing machine downtime and costs and improving the control and quality of production [61–64]. Unlike traditional preventive maintenance, PdM is designed to monitor the actual condition of the equipment to alert the system in advance and determine whether corrective maintenance will be required. Fault detection and condition monitoring are critical components of PdM and can potentially eliminate catastrophic equipment failures in industrial manufacturing. Through measurements using sensors, unknown or abnormal patterns, events, or failures can be predicted using anomaly detection technology [47]. Condition-Based Maintenance (CBM) is a new maintenance model (Aligned with Industry 4.0 and digitalization) utilized to organize maintenance activities based on the machines' status and limit breakdowns by solving the barriers in advance. It uses sensors to monitor the performance of a system or a critical component and measurement system to control and evaluate signals. In such techniques, the data of CM signals are adopted to anticipate the RUL of the component unit through the relation between the archive data and real-time data obtained from the in-field machines. The breakdown is then determined as the incident when a CM signal exceeds the failure threshold.

There are different maintenance strategies aimed at enhancing the prediction accuracy of RUL. The PdM approaches organized into the following four levels according to their basic methods, i.e., knowledge-based methods [65,66], physics model-based approaches [67–69], data-driven (statistics-based, pattern recognition, or artificial intelligence (AI) and models based on machine learning algorithms) [70–73], and hybrid approaches. RUL is the time remaining for a component/part to fulfil its operative capabilities before a crash. Using the Internet of Things (IoT) and connected technology, it is feasible to observe

the health of a system by performing continuous measurements, performing analytics, and predicting its future degradation and RUL of equipment [74–79]. An accurate RUL prediction of critical assets is an important challenge in PdM to improve reliability and safety, avoid fatal breakdown, and reduce maintenance costs. Several studies reported the beneficial effect of PdM systems that could lead to a sustainable supply chain by avoiding unnecessary maintenance and estimating the remaining lifetime of a machine part [32], reducing greenhouse gas emissions [33], reducing fuel and lubricant consumption [32], enhancing maintenance safety [34], overseeing the maintenance costs and availability of spare parts [80], avoiding valuable production time [35], and making the supply chain more resilient. Figure 4 shows that most of do not occur immediately, and usually there are some degradation symptoms from the normal state to failure. Hence, the actual conditions and trends should be estimated and predicted during the degradation process, and relevant maintenance actions should be considered before breakdown occurs [81]. From Figure 4, it is clear that the machine was initially in a healthy condition. Over time, its health reduced. The fault occurred after passing the "Good" machine health indicator and from that point, the machine's health began to degrade, as indicated by the dashed lines. The machine or component broke down after 135 days and the optimum maintenance plan was enacted right before the failure. However, in the real-world, the prediction is inaccurate and could take place sooner or later.
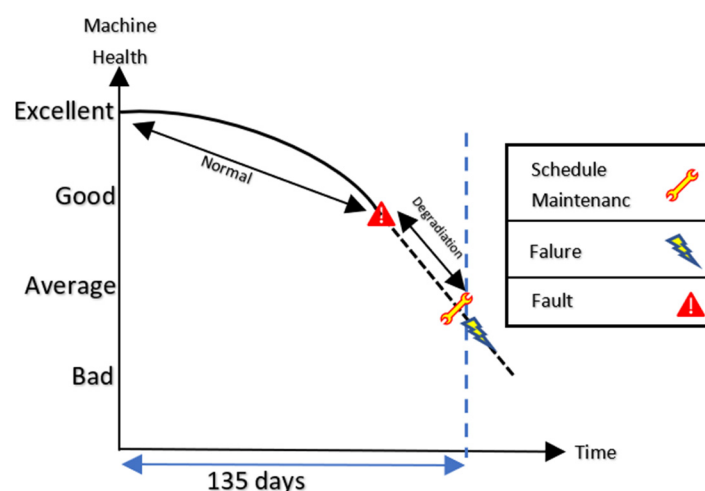
Figure 4. Machinery health conditions in the predictive maintenance model.

Although there is a huge interest in using PdM method in diverse industries [82], some researchers and industries have reported that PdM is expensive [83,84], complex [85], and has difficulty obtaining reliable and accurate RUL prediction [86,87]. In 2005, Li et al. [88] asserted that the complexity of the manufacturing environment and PdM technology and information technology limitations are significant challenges to implementing a predictive maintenance system. Kombe (2009) [89] pointed out that the placement of sensors and the proper interpretation of data by personnel are major challenges. Mondal et al. (2013) [90] emphasized high costs as the principal disadvantage in the selection of the predictive maintenance policy. Tiago et al. (2020) [61], in their review article, declared that several challenges and opportunities are needed to be addressed including real time-based PdM application [91,92], most of the tests applied in PdM use simulation benches [93], linking the PdM to the production process [91], a vision of the computing within Industrial applications. Sutrisno et al. [94] compared three methods for estimating the remaining useful life of ball bearings. The methods used several features for tracking degradation and three different approaches for estimating RUL. The limited amount of training data led to high uncertainties among all three approaches. The authors also mentioned the multiple challenges in analyzing the data, including limited training samples, no information about failure modes, no fixed failure threshold, and a wide range of failure times. Despite new

solutions for data-driven RUL prediction using advanced deep learning and big data technologies, Ren et al. [95] declared that significant challenges, such as optimal feature selection and extraction, and efficient feature compression, need more exploration. In another study Ellefsen et al. [96] stated that the accuracy of RUL predictions based on data-driven methods strongly depends on the quality of the constructed run-to-failure training data labels. Li et al. [97] used an ensemble prognostics method to classify the stages of the whole degradation process utilizing locally weighted linear regression, and then determined the optimal degradation-dependent weights by reducing cross-validation training errors (only during offline training). Lastly, they selected the degradation-dependent weights to the member prognostic algorithms of an ensemble. They stated that the accuracy of partitioning the entire degradation process into multiple degradation stages needs improvement. In order to address the aforementioned challenges, a new generation of maintenance strategy emerged, dubbed Intelligent PdM.

2.1.4. Intelligent Predictive Maintenance (IPdM)

Emerging big data, the internet of things (IoT) concept, and cloud computing are exponentially increasing processing and storage capabilities. With data inputs coming variously from maintenance archive data, sensor-based monitoring, and external contextual variables, big data analytics offers a potential approach to enhance capture and analysis of these data to deliver an accurate failure prediction of machineries and components. Some researchers have integrated these tools with artificial intelligence methods and machine learning approaches, calling their models "intelligent". For example, in El Kihel et al. [98] implemented intelligent predictive maintenance tools to optimize industrial energy performance through different vibration, energy, and temperature parameters in real-time. Pech et al. [99] put forth a Smart and Intelligent Predictive Maintenance (SIPM) system derived from the full-text analysis of associated papers. They investigated several research papers related to PdM and IPdM and collected their methods and approaches. "Sensor/smart sensors" and "Big Data" are two major keywords that have been used by the researchers in IPdM. In [100], Michal et al., mentioned that the "implementation of Industrial Internet of Things (IIoT), Condition Monitoring, Big Data, Cloud computing, virtual and augmented reality in maintenance methods will significantly improve the effectiveness and quality of manufacturing processes and eliminate human factors". They proposed an approach to provide intelligent predictive maintenance control by visualizing varying types of information using augmented reality. Mateusz Marzec et al. [101] investigated various machine-learning techniques and proposed a procedure to automatize the intelligent predictive maintenance process. There are many research studies regarding the design and implementation of IPdM approaches in the literature and the majority of them characterized the models based on the following technologies [100,102–108]:

- Autonomous Robot
- Big Data
- Cloud Computing
- Industrial Internet of Things
- Cybersecurity
- Augmented (AR) and Virtual Reality (VR) technologies

As researchers have mentioned regarding IPdM systems, new technologies play a key role in revolutionizing systems from PdM to I(intelligent)PdM. We can store and analyze much more data with new technologies to improve prediction accuracy, but this does not necessarily mean the data quality will change much in this revolution. IPdM regimes are only good as the quality of the input data that they use and the accuracy of the assumptions underpinning the relationships between these data and the prediction algorithms being produced. For example, different data quality measures such as the experience and age of operators, environmental changes, operator behavior/fatigue, weather conditions, slope, etc., could make the condition of the machinery in operation clearer. Although many researchers have acknowledged the importance and impact of external factors in RUL

accuracy [109–111], it has not yet been seriously and practically addressed. The first reason could be the lack of infrastructure and process capability to store, process, and analyze the data collected from machine itself and external factors. The other reason might be the researchers' perspective on solving the problem, as most research is based on using advanced algorithms and techniques, enriching collected data, and taking advantage of high-precision sensors to improve the RUL performance and accuracy.

This paper aims to design a conceptual framework to develop an intelligent predictive maintenance (IPdM) model using external factor data for chipper machines. In the following section, the external factors data will be described.

2.2. Forest Machinery Maintenance

It has been noted that the harvest system mechanization leads to higher levels of productivity in the supply chain. A disadvantage is that as mechanization improves, costs also increase [112]. Cost and safety are two major criteria in the repair and maintenance of harvesting and biomass machinery in forestry. Repair and maintenance, fuel, and labor costs describe as the three highest costs for transport companies. The overall forest machinery cost was estimated from 20% to 60%, depending on different factors such as machinery age, usage, operator experience, vegetation, weather condition during the production, maintenance strategy etc. [18–24]. The right maintenance plan, enhancing decision-making in maintenance, and performing work properly can cause cost reductions, boost efficiency, and advance vehicle reliability. It is usually inefficient when the machine is idle, as it decreases its operating hours per year. An unplanned breakdown in forestry not only delays delivery but can also cause damage to the whole supply chain. According to recent studies, unplanned downtime induced by an inadequate maintenance plan diminishes a plant's overall productive capacity by up to 20% and costs about $50 billion each year [113]. Unplanned downtime attributes to the time the element/machinery is unavailable due to unscheduled maintenance in the form of breakdowns. Unplanned downtimes conflict with the maintenance function and result in costs for a fleet. This is typical for all system elements, including electrical breakdowns, mechanical breakdowns, accidental damage [114]. A higher availability can be accomplished by regularly replacing components. However, this strategy can be costly, not only because of regular observations but also because of components costs. Hence, failure prognostics and flexible maintenance are vital for fleet managers [115]. Effective maintenance is also profitable from sustainable development, as heavy forest machinery are also significant polluters [116].

The other important issue that could rise during the maintenance of forest machinery is safety. An estimated 13.7 million people are employed formally in the forestry sector worldwide, and millions more are engaged informally, particularly in developing countries [117]. In fact, accident reporting systems are infrequently available in the forestry sector in developing countries [118]. Forestry has been known in many countries as an industry with high percentages of work-related injury [119–122]. Although the number of accidents has not been recorded in global data, it is likely (using agriculture as a guide) that the number of injuries in professional forest operations worldwide exceeds 170,000 per year [117]. Forestry industries have a higher rate of accidents compared with other sectors where comparative statistics are available [123–125]. Fatigue related to long working hours, sleeplessness, fast-paced and intensive work along with financial pressures and inadequate training [126] could lead to logging injuries [121,127]. Melemez [118] (2015) ranked personal factors (32%) and organizational factors (22%) as the two most major causes of fatal forest harvesting accidents in the Western Black Sea region of Turkey. Wang et al. [128] stated that loggers incur 26% more injuries than the average industrial worker, and are 19 times more likely to be killed on the job. Several research studies have been conducted to minimize forestry accidents and identify the leading cause of accidents as well as the best prevention methods. In this research study, the chippers' maintenance activities were identified as one of the main causes of different injuries and fatal death in

forestry operation. We believe that implementing the IPdM system would improve the maintenance regime and enhance safety in this industry.

2.2.1. Chipper

The production of renewable energy resources (e.g., biofuels, wind turbines, solar cells etc.) is fundamental for sustainable development [129]. Various nations have committed to improving renewable energy sources. Recently, renewable energy production has rapidly converted into a valuable business. The European Union has established new aims for biomass utilization by encouraging all members to increase biofuel usage [3]. Nevertheless, biofuel prices are comparatively low and could make the biomass supply chain risky [130]. The potential development and expansion of the biofuel sector primarily rely on efficiency in the supply chain to avoid increasing fuel costs [131].

The wood fuel supply chain system consists of multiple steps. The initial phase, which is the costliest one, consists of converting green waste into woodchips. The chipper machine is responsible for accomplishing this task. Various chippers and grinding systems are adopted for different biomass sources, including branches, leaves, and whole trees [132]. Chippers are divided into two main categories based on their functionality and usage, including household and industrial chippers. While the first chipper category is driven by farm tractors, the second category is self-propelled machinery and built-in machines. In terms of mobility, the device is divided into two categories: fixed and movable with disc and drum tools [133]. Mobile woodchippers are now available for different purposes in a wide range of sizes and configurations to convert the branches and tree trunks into chips, thus making them easier to transport [134]. Mobile chippers are placed on a trailer or transported using the tractor, truck, or forwarder. Industrial chippers generally deliver high productivity, quality, and fuel efficiency significantly when the settings are appropriately adjusted. In 2006, Naimi et al. [135] reviewed different commercial-scale size reduction units, chipping systems, and performance properties for woody biomass. The carrier engine (e.g., tractor) could provide the power chipper required during operation or be provided with an independent engine. It can be seen from the Figure 5 that there is also another type of mobile chipper with an autonomous motor.

(**a**)

(**b**)

Figure 5. (**a**) displays mobile chipper during operation, and (**b**) illustrates where the autonomous motor of chipper with red color [136].

2.2.2. Chippers' Maintenance

According to the literature [137], fuel consumption, depreciation, and repair and maintenance costs are the main chipper costs. The chippers perform a cumbersome task, and high wear and tear of their components is unavoidable [2]. Therefore, in order to avoid the failures of the chippers machine, regular maintenance is crucial. However, the maintenance cost estimation is complicated, as the frequency and severity of failures are variable, and the maintenance cost for two seemingly identical chippers could be different [18]. Moreover, the local maintenance costs of parts and labor could affect operators records for the same maintenance intervention [138]. Although there has been different research work on chipper costs in fuel consumption and depreciation [139], repair and maintenance costs are less considered a cost element. However, the chipper maintenance cost, especially some

particular components such as chipper knives and anvil, play a vital role in the overall agricultural and forestry equipment expense. In 2001, Spinelli and Hartsough [140,141], in their survey, declared that chippers operators report more extensive maintenance demands than the rest of their fleet in agriculture. Spinelli et al. [18] stated that the chipper repair and maintenance cost is between 1.5% and 29%, including fuel and labor. Besides, maintenance cost is the main reason that the machinery is replaced with a new one after the optimum replacement age [142]. As the frequency and severity of machinery failures increase, supply chain productivity goes down. Different companies design different plans to overcome the maintenance challenge to meet the expected productivity.

3. External Factors

In recent decades, due to advances in science and technology and demand for cost effectiveness in supply chains, a great number of PdM methods have been introduced to optimize the prediction accuracy of machinery failure and enhance performance [143–145]. A considerable amount of research papers used laboratory and benchmark data sources to design, implement, and evaluate their methods. Generally, researchers used archive data (e.g., machine and component information, stored sensor data, maintenance history etc.) and real-time sensor data as primary inputs. However, some researchers argue that there are some other types of elements that could impact the prediction accuracy of models. Recent advances in psychology and the cognitive sciences have shown that emotions (such as fear, anger, distraction, stress, and fatigue) play a significant role in a person's behavior [146]. The study of automobile drivers' behavior has attracted a lot of research attention, and studies are being conducted to discover the crucial factors that contribute to road accidents and that can potentially affect a person's ability to drive safely [147]. Driving behavior is regarded as a complicated system in which the environment, driver, and vehicle influence factors. Other elements are fatigue, drowsiness, distraction, memory, workload, traffic, vehicle safety features, and discomfort caused by long driving hours, training, and experience [148]. Numerous researchers in the field of psychology believe that drowsiness and fatigue are the leading causes of road accidents. Other vital factors in road accidents are drunk driving and driving at a high speed. Accordingly, driver behavior detection is emerging as a growing research interest in the real-time monitoring of driving states [149].

Despite the importance of external factors in RUL prediction accuracy, research in this field is still very limited. A number of studies have argued for the importance of external factors and their possible impact on the failure of machinery and components [49]. Most of the present research on condition monitoring signals imply that components have similar attributes, function under similar external conditions, or that external factors do not affect the failure and degradation process [150,151]. This hypothesis may not be true in the real world. Machinery and components perform under diverse conditions (e.g., locations, pressures, weather condition, and speeds), the degradation of functioning units can considerably decelerate or accelerate. Temperature and humidity are the two influential external factors that Ren et al. [152] pointed out that affect RUL prediction accuracy of battery use. Aydemir et al. [153] indicated that sensor measurements are influenced by external factors, including environmental noise, sensor position, and operation conditions (e.g., load), and each machine must to be characterized individually. Kontar et al. [37] proposed a nonparametric framework for modelling the evolution of condition monitoring (CM) signals under different external factors. According to the authors, external factors can significantly affect the development of CM signals in real-life applications, incorporating the effect of such external factors will improve the overall prediction of RUL accuracy. In 2014, Marinelli [154] employed an artificial neural network (ANN) model to predict the condition level of earthmoving trucks. The authors utilized capacity, age, kilometers travelled, and maintenance level of trucks as predictors for the condition level of these trucks. The performance of the model was compared with the corresponding prediction accuracy of the statistical method of dissociation analysis (DA). Yang and Makis (2010) propose an approach to detect and localize the occurrence of gear failure for a gearbox that

operates under different load conditions [155]. In the following subsection, two important variables including human (e.g., operator fatigue, experience, age), and environment factors will be described in the transportation system.

It has been purported that workers are becoming a source of bottleneck for enhanced productivity in forest industries [156,157]. Therefore, the investigation of the motives behind the operators' performance is essential. The value of particular human traits for forestry work performance has been studied for over 60 years [158,159]. There are many traits that have been described as important for successful harvesting work, such as concentration, decision making, memory, motivation, motor coordination, pattern recognition, planning capacity, logic reasoning, and spatial perception [160–162]. In Sweden, human screening during work was used in the 1960s. However, this approach's popularity declined as the use of psychological tests to evaluate a person's suitability to perform a task began to be examined in the 1970s [158]. Human screening has been applied in Brazil [163], and as an entry test for some training programs in Sweden [158]. There are some other factors that directly or indirectly affect a person' performance and reduce productivity, including fatigue, stress, and worker retention with longer hours and low pay.

Operator Fatigue in Forestry:

According to the Forest Safety Code of Tasmania (2020), "Fatigue is a state of tiredness or exhaustion that results in a degree of impairment. This impairment may be physical and/or mental and can result in an increased risk of workplace errors or accidents" [164]. In the harvesting operation, the extension of the working day has the potential to significantly influence an operator's performance and safety. It can cause problems with the accumulation of fatigue and its impact on behavior connected to maintaining safe working practices, like the failure to keep attention and the tendency to take risky short cuts [165]. The number of working hours has been linked to increased fatigue and tiredness and performance degradation, which is more significant at night [166]. Dinges (1995) [167] and Spurgeon et al. (1997) [165] asserted that tiredness and fatigue could relate significantly to performance loss and increased risk of accidents. There has been limited literature investigating the role of fatigue in accidents and injury among forestry operators despite the financial consequences and dangerous nature of forestry work in different regions worldwide. Most research to date has focused on the effect of the physical workload. Fibiger and Henderson [168], in their research on physiological workloads, argued that tree fellers could not maintain the expected high energy expenditure level over a 7-h workday. In 1994, Parker and Kirk [169] stated that most forest tasks are much physically demanding with planting, pruning, and chainsaw operation being the higher physiological workload tasks, and machine operation being the lowest physiological workload task. It is described that incident rise just before the first break in the day's work, which is believed to correspond with a reduction in workers' energy levels and increasing fatigue [170–172]. According to the [164], In the forest field, ISO31000 fatigue likelihood scores are designed to measure the level of workers' fatigue during their shift activities. The chipper operators' fatigue during operation and maintenance scored 3 in Table 1, which indicates a moderate level. However, fatigue conditions can change to a high level when operators have inadequate rest quality after their shifts, night shift, and extended shifts, or if working conditions change due to the harsh terrain and climate, consecutive shifts, insufficient rest between shifts and during shifts, and work with high physical demands. The likelihood of individual fatigue and the severity of consequences are two factors that help measure the risk in forestry.

In many parts of the world, the forestry industries are constantly looking for ways to improve the performance of their wood supply systems in order to compete in the global wood products marketplace. Shift extension and multiple shift forest operations are not new concepts in forestry to meet the growing demand for increased production efficiency and overall pecuniary returns [173]. Generally, according to the literature, several aspects can affect forest productivity and safety [173], such as human factor [174] (operator experience [175], age, health condition, education level [175], and operator fatigue [176]); the work objective (tree form and volume); the slope and terrain situations, shift work [173];

and machine maintenance practices [177–179]. In this research work, we argue that there is a possibility that chipper operators' fatigue could increase the acceleration of wear and tear of the chipper components, which could lead to an unpredicted breakdown during the operation. Therefore, an IPdM model will be offered to extract the operator fatigue data during chipper operation, and then feed this data along with archive and sensor data to the machine learning model to predict the breakdown event.

Table 1. Chipper operator fatigue rate during operation and maintenance activities.

Role	Sub Classification	Activities	Fatigue Consequence Rating (from 1–5)
Machine Operator	Machine Operator	Chipper	3
Machine Operator	Manual Tasks	Inspections, maintenance etc.	3

4. Conceptual Model for Design, Development, and Evaluation of IPdM Model

According to the literature, there are two maintenance management systems in forestry companies: run-to-failure and scheduled check. In this research work, a state-of-the-art intelligent predictive maintenance (IPdM) system will be introduced as an alternative to overcome the maintenance cost and improve the safety of chipper operators. This study aims to provide a conceptual framework for developing IPdM system for the maintenance of mobile chippers machinery in a forest company. In general, the framework first uses different sensor and embedded machinery devices to monitor and detect the fault in the critical component of the chipper. Then, the current condition of machinery and parts are transmitted to the detection engine system to identify the anomaly in real-time. Data will be stored in a database for further processing and automate analysis. Since the data collected have the volume, variety, and velocity characteristics, traditional computing system are incapable of processing and analyzing the data. To overcome this challenge, a novel approach based on big data technologies, cloud, machine learning algorithms, and the Internet of Things (IoT) will be adopted to ensure the efficiency, scalability, and availability of the system.

This research study argues that the current maintenance platforms cannot capture external factors that might affect machinery breakdowns, like operator fatigue. Although external factors might cause machinery failure and safety issue, research study focus on this research objective is still rare. A conceptual IPdM framework will be proposed to consider the effect of external factors on prediction accuracy. As represented in Figure 6, the proposed architecture contains the following modules:

Data Sources: Three types of archives, sensors, and telemetry data are considered for this experiment. Two methods are commonly used to store archive data in forestry, including computer-based (Excel sheet, software) and paper-based. A great deal of information is recorded such as machinery number and type, spare part availability, maintenance crew names and skills, breakdown date and time, breakdown type, maintenance time duration, operators start and end work, and operators' rest time. In this research work, archive data will be used in two phases of the analysis. First, some information such as time and date of previous failure, failure causes, operators who were responsible at the moment of failure incident, the number and types of replaced spare parts, could help us better understand the nature of failure in the chipper machine. Second, the archive data could be fed into machine learning algorithms to improve the accuracy of RUL. Lastly, these data could be used to design and develop a simulation model to compare the current maintenance strategy with the IPdM model.

Distributed Message System: Develops a streaming data pipeline with horizontal scalability and high throughput characteristics to distribute real-time data from the chipper machinery to the pre-processing and analyzing modules. Many open-source distributed messaging queue applications exist, such as Apache Kafka, Apache Flume, Apache Sqoop, and RabbitMQ [39].
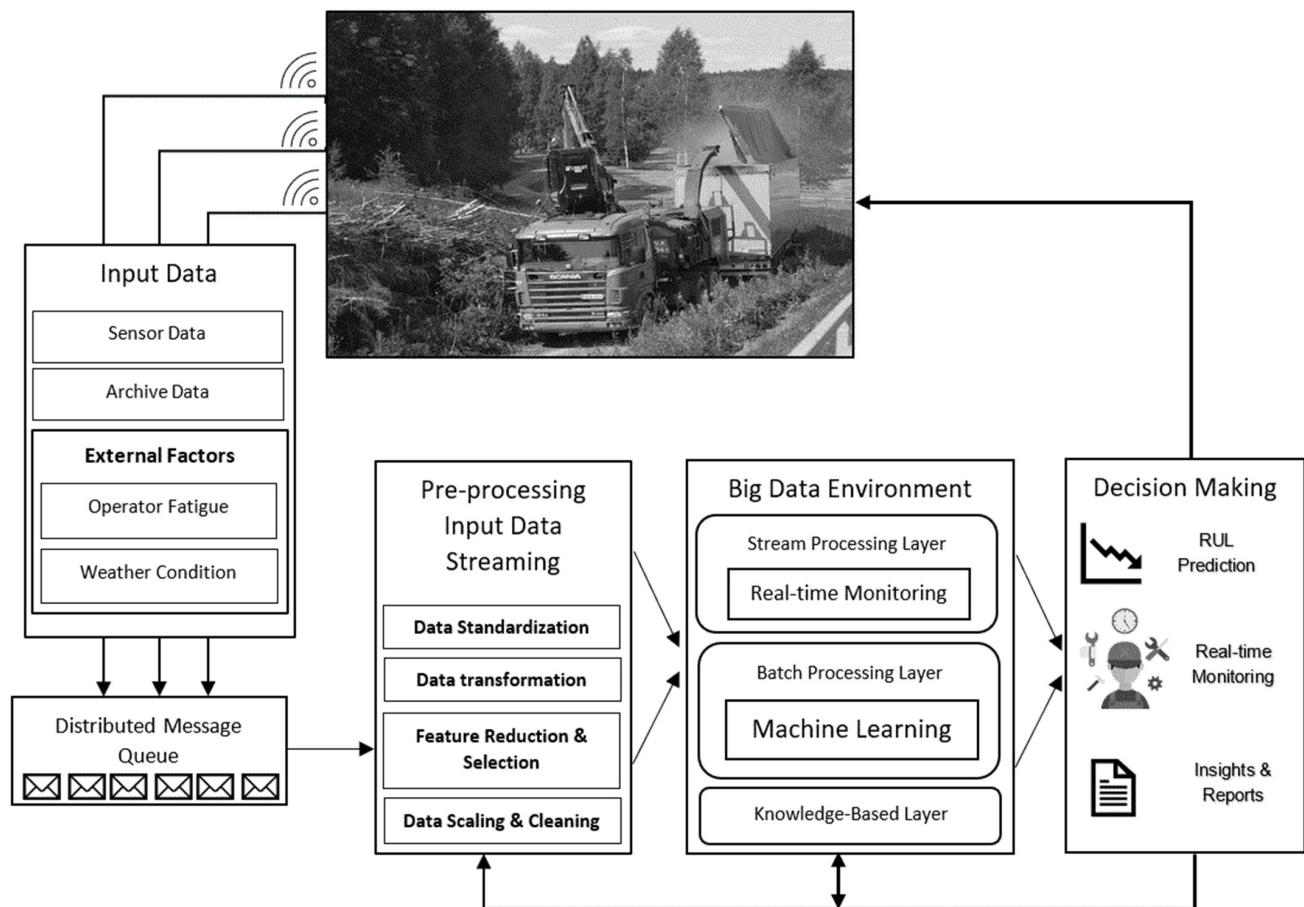
Figure 6. Conceptual IPdM framework for biomass forestry.

Data Preprocessing: The pre-processing step is an essential part of architecture as it converts the raw data sources to meaningful information that could be used to improve data analysis and assist in the decision-making processes. The raw data are incomplete, noisy, and inconsistent and must be cleaned using data cleaning techniques. The nominal data (categorical variables) in archive datasets need to be transformed into numeric variables. One-hot encoding as feature transformation techniques would be a suitable option for this operation, but the challenge is that the amount of numeric variables become too large and complex to be analyzed [180]. The Autoencoder method is a possible solution to achieve low-dimension and robust data. Data Scaling is another pre-processing activity to redefine the attribute value scale into a smaller range to process rapidly. The replacement method replaces attribute values with low-level values that can be easier to understand by a machine. Lastly, the volume of data is reduced to a manageable size to achieve more effective detection. There are different methods to perform this task, including unnecessary filter data, feature selection and data clustering, data compression, and selecting representative data instead of the whole data [181].

Big Data Environment: The model requires the processing capability to analyze vast amounts of batch and real-time data instantaneously. However, big and complex data cannot be handled utilizing traditional techniques. Therefore, we have introduced the Big Data Environment module to process and analyze data (with the characteristics of volume, velocity, and variety) coming in streaming format and apply machine learning algorithms to predict the RUL of the critical chipper component on a scalable distributed-computing platform based on big-data technologies. The Stream Processing Layer transforms the streaming data obtained from different sources into the standardized format in order to be used for quick decision and real-time monitoring the condition of chipper. The Batch Processing Layer uses pre-processed data and predicts the RUL of the chipping machine

based on the machine learning algorithm. The results of the analytics then are stored on the distributed Knowledge Base Layer for further analysis and visualization applications. Apache Hadoop, and Apache Spark framework are two popular big data platforms could be used to deal with big data challenges. Apache Spark [182], developed at UC Berkeley AMPLab, is a large data-parallel computing framework that provides rapid in-memory computing on a distributed system. Spark streaming is an essential component of Apache Spark that uses the in-memory capability to process data in real-time. Accurate and quick decision making based on machine learning technologies require high response speed that spark streaming could provide this capability [183]. Spark MLlib is a scalable machine learning library that provides different algorithms based on distributed implementations. PySpark could be used as a programming interface, combining the simplicity of Python and the power of Apache Spark.

Decision Making: The decision-making segment is responsible for providing clear insight and guidance for assessing the status of the chipper. The data analysis results are numeric and must be understandable by maintenance decision-makers. Therefore, three visualization techniques, including interactive dashboard, real-time notifications, and insights report, are adopted. The interactive dashboard supports maintenance decision-makers and chipper operators to understand the analytics outcome on graphs, including current and predicted machinery health conditions, the remaining useful life of each component, and maintenance schedules. Additionally, the occurrence of critical events can be communicated via SMS, e-mail in real-time. The system should allow decision-makers to produce daily, weekly, or monthly reports based on their requirements.

In Figure 6, the overall picture of IPdM model is described. Now, the details of how to measure the chipper operator fatigue and how to evaluate the new IPdM will be discussed. In the next subsection, we briefly describe the method that could be used to obtain and extract the operator fatigue data from chipper operator activities.

4.1. Operator Fatigue Extraction

Fatigue is a qualitative type of data and there is no solid method to collect this value. Therefore, we must collect and analyze different data to provide the fatigue value. To do so, three subsections have been designed, including data collection, data pre-processing, data analysis.

4.1.1. Data Collection

The fatigue management (FM) rule is an essential tool of the National Heavy Vehicle Regulatory (NHVR) [184] as it seeks to increase safety during heavy vehicle operation in Australia. In forest industries, fatigue management has a great influence on operation safety, so some forest industries in Australia have employed monitoring systems to gauge the work/rest activities and sleep patterns of forest workers [184,185]. As can be seen from Figure 7, the first phase of this model involves data collection from the chipper operator daily shifts and measuring how the level of fatigue goes up and down base on the hours of work/rest time. The operator action can be seen in several aspects, including work (chip/hour), rest, moving distance, travel time, and operational delay. In order to extract the operator fatigue during a workday of chipper operators, different types of data need to be extracted from machinery such as chipping, travelling, and operators' rest time. Cadei et al. [186] collected chipper truck telemetry data from GSM/GNSS Teltonika FM3612 receiver to evaluate wood chipping operation efficiency. They extracted useful information from the devices including date-time stamp, chipper location (latitude and longitude), travelling and engine speed of chipper, temperature of the engine, and fuel consumption. Similar to Cadei et al., we use same telemetry device, and a web-server application for a remote acquisition of data could be designed and developed. The data collected could help us to extract the following feature from machinery to measure operator fatigue:

- Operator working: (Travelling Speed < 1 km/h) AND (Engine Speed > 1500)
- Chipper in move: (Travelling Speed > 1 km/h) AND (Engine Speed > 0)
- Operator resting: (Travelling Speed = 0 km/h) AND (Engine Speed = 0)
- Operational delay: (Travelling Speed = 0 km/h) AND (Engine Speed < 1500)
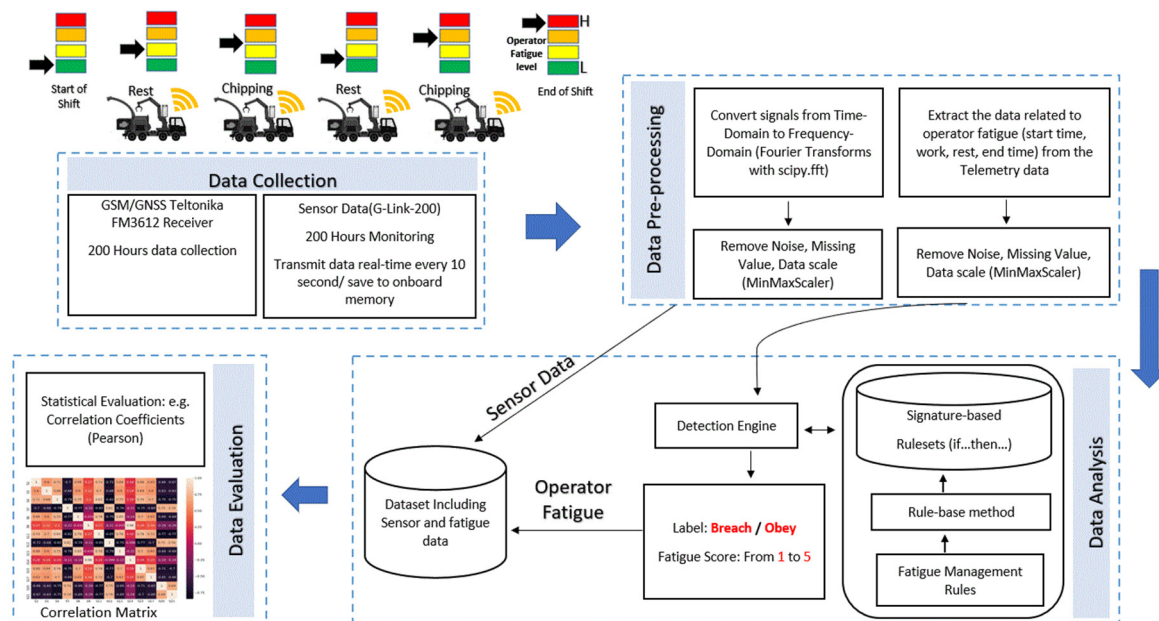
Figure 7. Correlation between operator fatigue and vibration sensor data.

4.1.2. Data Pre-Processing

The collected data are in text format, so different pre-processing methods are required to convert these data to the valuable data that could be used for analytics. The raw collected data from the GSM/GNSS Teltonika FM3612 receiver might contain various errors because of human, computing, and transmission faults. These errors include missing characteristics, incorrect values, or consistent format. Data transformation generally consists of normalization and generalization. Data scaling is another pre-processing activity to redefine the attribute value scale into a smaller range to process data rapidly. The replacement method replaces attribute values with low-level values that can be easier to understand by a machine. Lastly, the volume of data will be reduced to a manageable size to achieve more effective detection. There are different methods to perform this task, including unnecessary filter data, feature selection and data clustering, data compression, and selecting representative data instead of whole data.

4.1.3. Data Analysis

The system designed in this section was inspired by the architecture of intrusion detection systems (IDS) [185]. According to the specification of fatigue regulation and characteristics of the driving dataset, the rule-based approach can be recognized as the most powerful choice to develop the signature database. A signature-based IDS detection operation relies on comparing input data characteristics with a signature database. The system's output can define whether an operator obeyed or breached the forest fatigue regulations for every shift, along with their working progress. Notably, it is designed as a set of provisions of max-work and min-rest corresponding to each time frame, such as 5.5 h or 8 h. Thereby, the rule-based technique will ideally consider every rule clause under the form of "IF ... Then". Using the rule based model [185], fatigue management rules and regulations in forestry transform into the rulesets. Therefore, the work/rest time of the chipper operator could be checked by rulesets in the detection engine, and the operator

fatigue level becomes identifiable; we can say whether the operator obeyed or breached the fatigue regulation.

An anomaly-based approach is applied to evaluate driver performance and investigate unusual operator fatigue in a particular working period. Monitoring the performance of operators is an essential task since there is a possibility of chipper breakdown. In this case, the operator would receive the obey label even though the reason the operator stopped working is not "rest". Therefore, we need to ensure whether the operator meets the production goal and whether their performance is good enough. Thus, these abnormal data points can clarify their operating performance. Notably, they can show which day a driver had their best and their worst performance. The core technique of the module is a univariance statistics-based outlier detection method. The input dataset for this module, the driver profile, contains multiple significant attributes that are produced from raw dataset created by the driver fatigue manager application.

4.2. The Correlation between Operator Fatigue and Sensor Data

The wear and tear of critical components and the operator's fatigue status should be monitored and measured simultaneously. This helps to identify whether the collection of the operator fatigue data could impact the acceleration of chipper failure. In general, operator fatigue is monitored during the operation, and when the level of fatigue exceeds the threshold, the vibration signals' pattern could be checked to see whether it changes or not. Any correlation between operator fatigue data and vibration sensor data could help to improve the prediction accuracy of RUL. Figure 7 shows different steps and tools required to measure the correlation between operator fatigue and vibration sensor data.

As mentioned earlier, accelerometer sensors and operator fatigue data (external factor data) collect from the chipper machine. In the Section 4.1, we explained the way chipper operator data could be obtained. Therefore, in this part, we discuss data collection using vibration sensors and how to measure the correlation of operator fatigue with vibration sensor data. The G-Link-200 accelerometer sensor could be a suitable option for monitoring the critical component. Its measure range is between ± 2 g and ± 40 g, which could cover the vibration frequency of the chipper machine. This sensor has already been tested and was designed to monitor machinery in rugged environments like forestry and mining industries. In the pre-processing step, as the sensor data are time series (time-domain format), they need to be converted into frequency-domain. A Fast Fourier Transform (FFT) algorithm [187] will be used to transform time-domain accelerometer sensor data to frequency-domain data in pre-processing phase. The data pre-processing phase also involves performing standard data preparations such as missing value imputations, data aggregation at the hourly level, and outlier detection and treatments. In this phase, several types of pre-processing methods will be employed for data cleaning, data normalization, feature extraction, feature selection, and feature integration.

The operator fatigue data is integrated with the vibration sensor data, and in the evaluation phase the correlation of fatigue and vibration sensor data could be evaluated in different states using correlation methods such as Pearson's correlation coefficient [188] and correlation matrix.

4.3. IPdM Development and Evaluation

The success of the correlation test will lead us to the next step, where the IPdM model will be proposed, and a method for the evaluation will be presented. Figure 8 demonstrates different steps required to consider implementing the IPdM model. In this step, archive data are integrated with the vibration sensor and operator fatigue data. Different preprocessing techniques are applied to data to ensure the quality of the data. The proposed IPdM is developed based on different machine learning algorithms, and the accuracy and performance of each of them will be evaluated. According to the literature [189], the neural network approach (e.g., CNN, FFBPN, RNN, LSTM) seems to be a promising solution to predictive maintenance problems. The Root Mean Square Error (RMSE) [190] will be

selected as an evaluation metric to measure the accuracy and the algorithm performance. The RMSE is calculated by taking the square root of the average squared differences between the actual and predicted values. This value can represent the estimation of the standard deviation σ of a typical collected value from the model's prediction. In other words, a lower RMSE value means a more accurate prediction. The prediction could also be evaluated based on K-fold cross-validation, precision, recall, and false positive rate (FPR). The expression of RMSE is:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)}{n}} \tag{1}$$
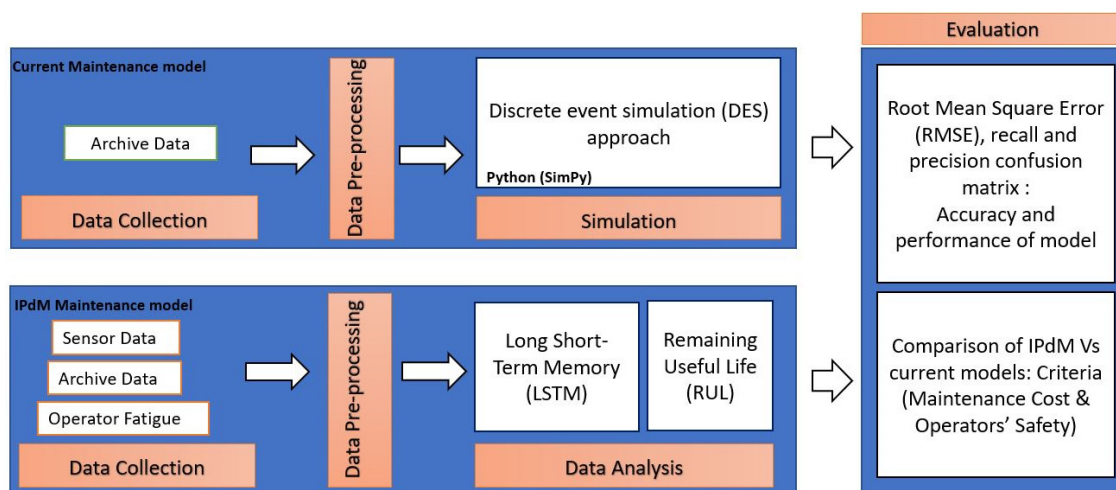
Figure 8. Different step to develop and evaluate the IPdM model in forestry.

In the Section 4, we already discussed the reasons why the proposed model designed based on big data technologies. Since the volume, variety, and velocity of data are large scale, a normal computer will not be able to handle the processing and analyzing part. Therefore, state-of-art big data technologies are adopted to take care of the data challenges.

However, the RUL obtained from the analysis part needs to be evaluated. Maintenance cost and safety are two criteria that will be evaluated based on two models. In the second phase, the evaluation of the IPdM will be accomplished through simulation using archive data to measure the potential improvements in "remaining useful life" and potential impact on safety. First, the discrete-event simulation method [191] will be used to build a contemporary maintenance method (integration of preventive and corrective model) in forest harvesting using archive data (maintenance records) related to the maintenance of chipper. The simulation model will be developed using Python (simply library) and Python API TensorFlow, an open-source software library for numerical computations using data flow graphs. The maintenance cost and operation safety will be compared between two maintenance models to determine whether the IPdM model could offer any improvement to the forest supply chain. Another possible system evaluation could be to compare the IPdM model with and without the integration of external factors to measure the impact of external factors on the accuracy of the prediction model.

This research work investigates forestry supply chains intending to examine the possibility of promoting the prediction accuracy of RUL on chipping machinery. The results generated by this research directly enhance the quality of information that can be applied in decision-making for scheduling machinery maintenance in the forestry industry. Providing this system could leads to a sustainable supply chain in the forest biomass sector which can avoid unnecessary maintenance and estimate the remaining lifetime of critical components, lead to deep reductions in greenhouse gas emissions, reduce fuel and lubricants consumption, enhance maintenance safety, maintenance costs, and the availability of spare parts, avoid valuable production time loss, and make the supply chain

more resilient. Additionally, it is expected that the outputs of this research will contribute to supporting the forest industry and government to promote sustainable production, protect precious forests, and improve product safety.

5. Conclusions

This paper aims to highlight the importance of the external factor variables in intelligent predictive maintenance models. We argued that predictive maintenance regimes are only as good as the quality of the input data that they use and the accuracy of the assumptions underpinning the relationships between these data and the predictions being produced. With data inputs coming variously from maintenance archive data, sensor-based monitoring and external contextual variables, big data analytics and cloud platforms offer a potential approach to enhance the capture and analysis of these data to deliver intelligent predictive maintenance. In this research, the challenges and opportunities for designing, implementing and evaluating an IPdM system for forestry will be examined in the context of contemporary research literature. Various external factors might influence machinery failure, including operator behavior/fatigue, weather condition, terrain surface(e.g., slope), etc. Among all these variables, there is limited research on the effect of operator fatigue on machinery failure. This research has shown how operator fatigue data collect from chipper truck telemetry data can improve the RUL prediction and evaluate the efficiency of wood chipping operations. This conceptual model could help researchers implement IPdM in the dynamic environment (e.g., forestry, mining, road construction) to reduce maintenance costs and improve safety.

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