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The logo consists of a series of vertical bars of varying heights on the left, followed by the word "SURVEY" in a blue, sans-serif font inside a rounded rectangular border.

# Wood Products Manufacturing Optimization: A Survey

SEYED MOHSEN HOSSEINI<sup>1</sup>, (Member, IEEE), AND ANGELIKA PEER<sup>1</sup>, (Member, IEEE)

Human-Centered Technologies and Machine Intelligence Laboratory, Faculty of Science and Technology, Free University of Bozen-Bolzano, 39100 Bolzano, Italy

Corresponding author: Seyed Mohsen Hosseini (seyedmohsen.hosseini@unibz.it)

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**ABSTRACT** The wood industry is a basic industry supplying primary materials to produce a wide range of products. The wood processing in sawmills bridges the transformation flow of raw materials to final products using machinery. Over the last decade, the global market for wood products has become highly competitive. As a result, sawmills are continually striving to improve their efficiency throughout their production process. Recent advances in automation systems and manufacturing technologies provide traditional sawmills with an unprecedented opportunity to be transformed into automated manufacturing plants to increase their efficiency. This opportunity motivates sawmill planners to adopt decision optimization technologies for enhancing their production yields. This transformation will support sawmills to remain resilient in current and future competitive markets. Although there is a vast amount of literature on decision-making in wood manufacturing in sawmills, a comprehensive overview of related approaches and findings with a special focus on optimization of decision processes is still lacking. The review firstly focuses on exploring opportunities provided by optimizing decision-making processes in the wood manufacturing along with associated roadblocks and challenges. Then, we explore methodologies adopted in the literature when aiming for the design and implementation of optimal decision-making systems. Finally, we provide references and guidelines for researchers and manufacturers interested in the topic, as well as formulate research gaps and recommendations for future research directions.

**INDEX TERMS** Autonomous production machines, automated wood processing, decision-making, decision support systems, optimization.

## I. INTRODUCTION

The forest industry plays a substantial role in the economic and social development of many countries, both at national and regional levels [1]. This industry provides a large set of base products for supporting the downstream value chain of different businesses such as pulp and paper, furniture, and construction [2], [3]. Wood products such as lumbers and plywood, and wood by-products and residues such as wood chips and sawdust, are among major products of forest industry accounting for a large portion of total exports of countries around the world, such as Argentina [4], [5], [6], Chile [7], [8], [9], Sweden [10], [11], [12], Canada [13], [14], [15], the United States [16], [17], [18], [19], and

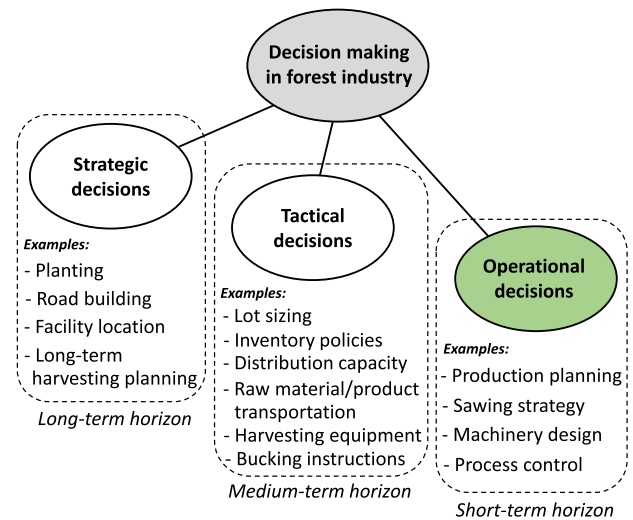
New Zealand [20], [21]. Despite an active participation in the value added to the industry of countries, poor or inaccurate decision-making processes over different steps of forestry planning, production and trade may lead to high production and transportation costs, losses, and eco-inefficiency. Consequently, this may critically affect the competitiveness of this sector [22].

In general, decision-making processes in the forest industry may include different aspects of wood-flow and delivery such as planting, harvesting, transportation, product processing, and marketing [23]. Hence, various decision support systems have been developed for forest supply chain management to improve decision processes [9]. According to spatial and temporal scales of decision activities, three decision-making levels can be generally defined in the forest industry, namely *strategic*, *tactical*, and

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*operational* [1], [24]. Strategic decisions generally refer to those decisions that should be made with long-term horizons (e.g., several decades), such as forest landscapes, biodiversity risks, preservation of species and the forest ecosystem, aiming at generating sustainable forestry, yields, and returns [25]. Some related examples include planting, long-term harvesting plans, facility locations and road design [26]. Instead, tactical decisions should be made with medium-term horizons (e.g., several months to few years) [25]. Decisions about harvesting equipment, bucking instructions, medium-term harvesting planning, and production logistics are some examples of tactical decisions [27]. Rather, the operational decisions consist in short-time horizons (e.g., real-time, daily, weekly, or up to one month), and are often highly detailed [24]. The decisions about sawmill production planning, production schedule, operation time, sawing strategy, manufacturing machines and corresponding controller design fall into this category [28]. Figure 1 illustrates the categories of decision tasks involved in the forest supply chain management. Although these three decision-making categories are intertwined (often hierarchically), their focus typically differs, in particular, in relation to beneficiaries [8], [24]. In fact, strategic decisions (and often tactical decisions) are usually made at the higher level, i.e., they are planned depending on regional and national policies, and usually take into account the interests of governments, forest owners, land managers, and transportation companies [29]. While such decisions are essential for maximizing sustained harvesting volumes, the increasing costs of production (including log prices, energy costs, etc.) along with the development of competitive wood product markets requires a special attention to the optimization of operational decisions at the sawmill level [1], [28]. In fact, in some cases, the beneficiaries' preferences can be incompatible. For instance, government regulations for reducing greenhouse gas emissions could negatively affect the benefits of private sawmills seeking their maximum profit, as such regulations may limit the sawmills' production capacities [30]. In addition, a sole focus on improving upstream decisions without considering downstream beneficiaries may result in missed opportunities to use the great potential of the production sector for contributing to the overall improvement of the forest supply chain management [5].

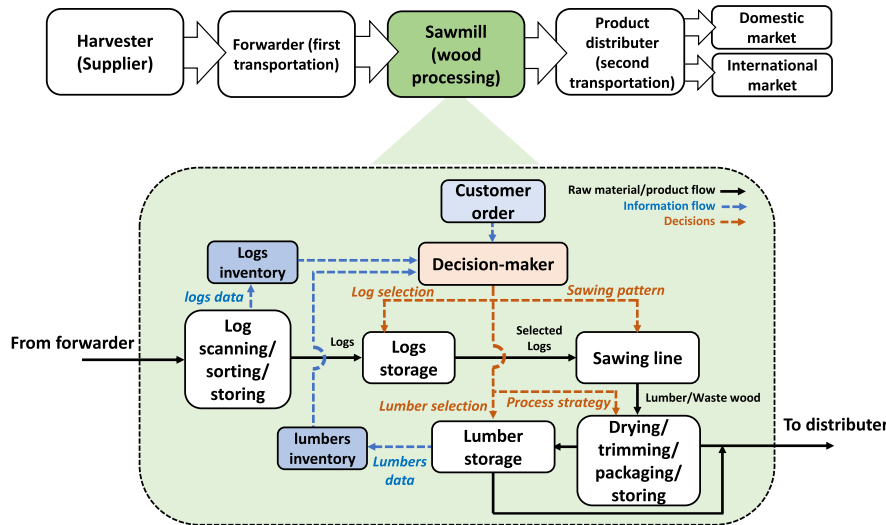
Responding to these needs, the concept of *sawmill operation optimization* targeting the optimization of operational decisions to be taken at the sawmill level is promoted. In this regard, optimization tools are widely used to support efficient and robust decisions in the manufacturing systems. By mathematically modeling the decision processes according to performance criteria and constraints, and by implementing optimization algorithms, decision makers in sawmills can improve their productivity while reducing costs and addressing uncertainty. In fact, the recent revolution in automation systems, industrial robots, and information and communication technologies along with advances in optimization and numerical analysis pave the way for supporting automated decisions on the wood processing in sawmills [11].



**FIGURE 1.** Three main categories of decision-making in forest supply chain management; (operational decisions: the focus of this survey).

In general, the manufacturing process includes log sorting, sawing procedure, production schedule, as well as lumber drying, grading, and storing [2]. Figure 2 shows the participating sectors contributing to the wood-flow in the forest industry, beginning at the harvest area in forests, while transferring to the sawmill through a forwarder company at the first transportation phase. After completing production processes, the final products should be distributed to the different available markets such as domestic or international markets through a transportation company. Focusing on the wood processing part in the sawmill (see Fig. 2), the logs received from the harvester are firstly scanned and sorted, and then stored in sheds, containers or warehouses. The logs data (e.g., diameter, length and quality) on the available log resources saved in an inventory database is provided to the decision-maker.

The decision process in sawmills is generally based on the expected market demand, mill capacity, and the availability of raw materials (e.g., logs) and stored products (e.g., stored lumbers) [31]. Indeed, according to the updated order information received from the customer, and the log and lumber inventory databases, the decision-maker can decide about the selection of required log characteristics for sawing, and controlling the sawing strategy over the sawing line [4]. The decision-maker should also decide about drying, trimming, and packaging procedures for the final products (e.g., lumbers, plywood, etc.), while storing the extra products if existed. Thanks to recent advancements in automation, control, and information technologies, most wood processing steps in sawmills can be performed in an automated fashion. Within our research context, we refer to *automation* as a variety of technologies supporting the wood production process automatically, such as computer-aided design and manufacturing systems, industrial robots, flexible manufacturing systems, computer numerical control machines, and decision



**FIGURE 2.** The wood-flow in wood products manufacturing from forests to markets, and the wood processing steps in sawmill level (wood processing in sawmills: the focus of this survey).

support tools [12]. In fact, in a modern sawmill, the concept of automation allows the decision-maker to apply intelligent strategies to the production processes for enhancing the final production yields in terms of production quality, quantity and cost [19]. As raw material costs generally represent the biggest portion of the total production costs in sawmills, maximizing the product yields from the sawing process is the core topic of relevant literature [20], [32]. Hence, finding an optimal sawing pattern which can maximize the production yields, while is feasible and computationally efficient is the main concern of sawmills' decision-makers to obtain the production objectives. In this regard, a general definition provided in [20] states the problem of finding an optimal sawing pattern as “to saw a log with certain parameters (log profile and defect core) into timber assortments so as to give a maximum return, given a table of timber assortments, their dimensions, and the prices for the various grades (or any other value for which the log has to be optimized, e.g. volume)”. In order to obtain maximum return or yield while fully meeting the product dimension and quality criteria, novel decision-making systems are expected to become the backbone of a more intelligent and sustainable wood processing system. Accordingly, significant research has been devoted to the design and implementation of such advanced decision-making approaches, with particular focus on finding optimal sawing patterns which can be implemented through smart machines and industrial robots. However, a review of the extensive body of studies on decision-making approaches for smart and automated wood processing is still lacking. We therefore perform a thorough exploration of this timely and relevant topic, with an emphasis on the potential opportunities and possible challenges, along with related methodologies for an efficient and holistic design of an automated wood processing system. This can spotlight future paths for researchers and practitioners.

#### A. PAPER OBJECTIVE AND CONTRIBUTION

A limited number of review papers are available in the literature discussing decision-making approaches for the forest industry management and their classification. The majority of existing reviews focuses on literature of high-level decision-making processes in forestry, mainly concerning strategic decisions. For instance, the study in [3] reviews the literature of forestry decision-making problems with a detailed look at the forest resource planning, including topics ranging from harvest scheduling to forest biodiversity conservation, sustainability, and related national/regional plans. Instead, the work in [33] presents a survey on forest management with a focus on potential impacts of risks and uncertainties implied by climate changes to decision-making processes. On the same line, a more recent review is presented in [23] on a set of forest management case studies where high-level decision-making techniques are applied in practice.

Some other aspects of decision-making in the forest supply chain management are further considered as topics of several earlier review efforts. A well-studied relevant area for instance is the optimization of transportation planning and logistics management in the wood supply and forestry industry. For example, the authors in [34] review existing transportation optimization methods for forest products considering decisions related to product flow, storage, pre-processing, as well as routing and scheduling of vehicles. A review presented in [30] analyzes different transportation methods for wood products to sawmills, focusing on a particular approach, namely discrete-event simulation.

Almost all the mentioned reviews point out that the decision-making processes involved in different steps of the forest products industry are constantly becoming more complicated due to the inter-dependency of different stakeholders and multiple conflicting criteria in the forest supply chain. Accordingly, realizing efficient decisions should not

only be pursued through optimizing high-level decisions, but should also be obtained through applying novel strategies to production process decisions at the sawmill level. Indeed, over the recent years, forestry research has been increasingly focused on effective resource use, optimal planning, and high productivity during production processes. An interesting literature review on the applications of digital twins and simulation tools to the production planning and control of sawmills is presented in [35]. Some of the opportunities and associated challenges are discussed, and a limited number of methods are reviewed. Another promising review of operational decision-support systems is provided in [36], focusing on increasing volume recovery from the wood sawing process in sawmills. Wherein, the authors present a short review followed by a mathematical formulation of the wood sawing process considering physical saw design factors (e.g., saw blade kerf) for improving lumber volume recovery and minimizing sawing errors. In [22], the review instead focuses on the challenges associated with simulation and optimization techniques for decision-making at the sawmill level (e.g., transportation and logistics domain), with a particular focus on artificial intelligence based optimization techniques.

As indicated before, the previous review papers mostly focus on high-level decision-making processes in forest products industry. When it comes to low-level decisions such as optimal operation of sawmills, research studies focus either only on specific aspects (e.g., as in [34] and [36]), or on specific approaches (e.g., as in [22] and [35]). Hence, there is an evident lack of a comprehensive survey on decision-making approaches designed for optimal operation of sawmills during material processing and product production steps.

This paper aims to fill this gap by reviewing key characteristics of existing decision-making approaches to obtain more flexible and smart sawmills. Firstly, the review categorizes and analyzes related literature by recognizing the prime opportunities and corresponding challenges ahead of automating decision-making processes in sawmills. More specifically, the first part of the review presented in Section II explores the actions that have been taken or have the potential to be considered within this context. After that, the second part of the review presented in Section III examines widely-explored methodologies that are applied to wood production systems to seize the opportunities while confronting challenges. Table 1 summarizes the contributions of this survey compared to some existing relevant surveys. We note that without losing overall coherence, one only interested in reviewing the presented methodological aspects can skip Section II and readily focus on Section III, and vice versa.

**B. LITERATURE SELECTION CRITERIA AND REVIEW METHODOLOGY**

In order to develop a comprehensive overview of the research topic, we employ a systematic search strategy based on some critical steps for finding the most relevant and

**TABLE 1. Foci of existing survey papers in the field versus foci of this paper.**

Ref.	Decision-making level	Survey focus
[3]	Strategic	Multiple criteria decision-making approaches to forest resource planning including harvest scheduling, forest biodiversity conservation, forest sustainability, forestation, risk and uncertainty
[33]	Strategic	Decision-making approaches for forest management under impacts of risks and uncertainties implied by climate changes
[23]	Strategic	Multiple criteria decision-making applications for forest management with a focus on real case studies
[30]	Tactical	Discrete-event simulation for supporting decisions in forestry sector including transportation of logs to sawmills, logistics, harvesting system, etc.
[34]	Tactical/Operational	Optimization of transportation planning and logistics management in the wood industry regarding product flow, storage, preprocessing, routing and scheduling of vehicles
[35]	Operational	Applications of digital twins in the wood industry at the sawmill level, focusing on operational production planning and control
[36]	Operational	A short review followed by a mathematical formulation of the wood sawing process considering physical saw design factors for improving lumber volume recovery and minimizing sawing errors
[22]	Operational	Optimization and simulation techniques for decision-making in sawmills yards with a focus on artificial intelligence based approaches
This paper	Operational	Identifying opportunities and challenges of automating decision-making processes in sawmills, and investigating widely-explored methodologies for seizing these opportunities while addressing the challenges

principal research publications. We begin by selecting a set of keywords and keyphrases to search for relevant literature including some more general keyphrases to the smart production such as “*automation in manufacturing*”, “*production planning*”, and “*autonomous production machines*”, and some specific keyphrases to the wood processing such as “*automated wood processing*” and “*smart sawing systems*”, alongside the keywords “*decision-making*”, “*planning*”, “*optimization*” and “*control*”. Accordingly, we select a large sample of related publications from important scientific databases, in particular Scopus-indexed journal and conference papers, books and chapters from *Science Direct*, *Springer*, *IEEE Xplore*, and *Taylor & Francis* databases. Then, for the resulting papers, we define three sub-frames associated with a time/citation filter as: “*f.1*” including the papers published during the last five years from 2017 to 2022, “*f.2*” including the papers published from 2011 to the end of 2016 and cited at least 5 times, and “*f.3*” representing the papers published before 2011 and cited at least 10 times. Accordingly, the review covers a wide range of related literature with threshold criteria referring to being up to date and/or being highly cited. In total, we review 119 publications (with the exception of review papers and fundamental sources), of which 36.9% were placed within frame *f.1*, 23.7% within frame *f.2*, and the remaining 39.4% within frame *f.3*. Figure 3 shows a statistical report of the literature surveyed in this



review clustered by publication years and/or the number of citations that they have received.

### C. PAPER STRUCTURE

To date, many research works have been published examining the use of simulation and optimization tools to support decision-making processes in the forest industry. Based on the extracted and filtered publications in the search and selection step, we focus on two major perspectives: (A) *opportunities and challenges* and (B) *methodologies*.

On the one hand, in terms of the opportunities regarded, all the surveyed works are grouped into three main categories: (Ao1) *economic profits* (including production efficiency improvement, energy cost saving, and space saving), (Ao2) *technical achievements* (including product quality improvement and process quality improvement), and (Ao3) *environmental incentives and penalty avoidance* (including manufacturing waste management and environmental footprint reduction). In addition, the possible related challenges that are tackled in the literature are grouped into four main categories: (Ac1) *financial limitations*, (Ac2) *technical feasibility*, (Ac3) *customer satisfaction*, and (Ac4) *uncertainty*.

On the other hand, we categorize all the selected research works in terms of the methodologies applied to the decision-making systems, namely: (B1) *Model-based mathematical programming*, (B2) *Search algorithms*, and (B3) *Artificial intelligence approaches*.

With respect to the two superordinate categories described above, the remainder of this paper is structured to follow a logical and coherent outline. The readers are firstly introduced to the main opportunities of automated decision-making in wood processing and the relevant challenges discussed in existing literature in Section II. The readers are then presented with the methodological discussion of the decision-making approaches in Section III. Section IV discusses two use cases to illustrate how to model and implement different decision-making processes in real sawmill production systems by relating them to opportunities and challenges (Section II) as well as decision-making approaches (Section III). Section V concludes the review with research gaps and recommendations on future research directions.

## II. OPPORTUNITIES AND CHALLENGES

There are several studies confirming that most sawmills worldwide undergo inefficient operations with high amount of raw material wastage [37]. For instance, according to the study presented in [38], in 2002, there were only 7% of sawmills operating efficiently in British Columbia, Canada. Similarly, a study conducted in [39] states that only around 30% of sawmills in Norway were operating efficiently from 1974 to 1991. More recently, a number of sawmills have invested in innovative production technologies relying on automated sawing systems to increase their productivity. However, they often focus on improving some limited

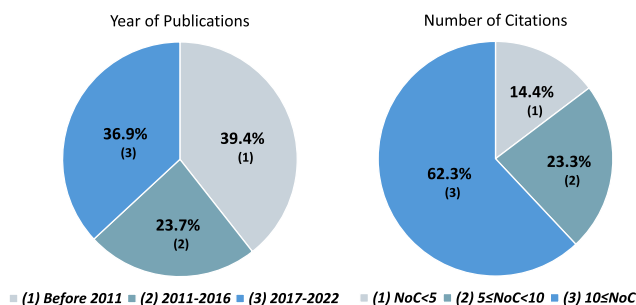


FIGURE 3. Statistical distribution of reviewed papers in terms of year of publications (a) and number of citations (b).

aspects such as economic profits obtained by new sawmilling machinery [4], [9], [10]. However, for a highly efficient operation of the whole production process, various factors need to be considered in order to meet increasingly complicated market demands using limited and variable raw material resources [37]. In fact, the prime step towards the renovation of traditional production

infrastructures into advanced automation systems through digitalization of production processes and developing corresponding automated decision support systems is to recognize potential benefits that such renovation can bring to sawmills and the entire forest supply chain [11]. Furthermore, for a successful implementation of an automated decision-making system for wood processing, various challenges such as financial limitations, technical requirements of machinery, market demands, and the presence of uncertainty should be tackled [40]. Such challenges may increase the size and the complexity of the decision-making problem significantly. Besides, recognizing opportunities and challenges of process automation and identifying which opportunities to pursue are key steps for sawmills for a better estimation of their return on investment for achieving a sustainable manufacturing [12]. By investigating the selected literature, in this section, we aim at answering the following research questions: *Q1* What potential opportunities can be identified as a result of implementing automated decision-making systems in the wood production process?, *Q2* What are the challenges to be addressed for seizing these opportunities? We investigate *Q1* in Section II-A while discussing *Q2* in Section II-B.

### A. IDENTIFYING OPPORTUNITIES OF AUTOMATED DECISION-MAKING IN WOOD PROCESSING

In this study, we refer to *opportunities* as the ability to turn investment costs incurred in the use of automated systems and employing automated decision-making approaches into benefits for wood processing companies [41]. We identify three main views of opportunities in the selected papers including: (Ao1) *economic profits*, (Ao2) *technical achievements*, and (Ao3) *environmental incentives and penalty avoidance*. Figure 4 shows the classification of the different types of opportunities and possible actions to obtain them according to the selected papers reviewed. It is worthwhile noting that automating decisions in manufacturing environments by

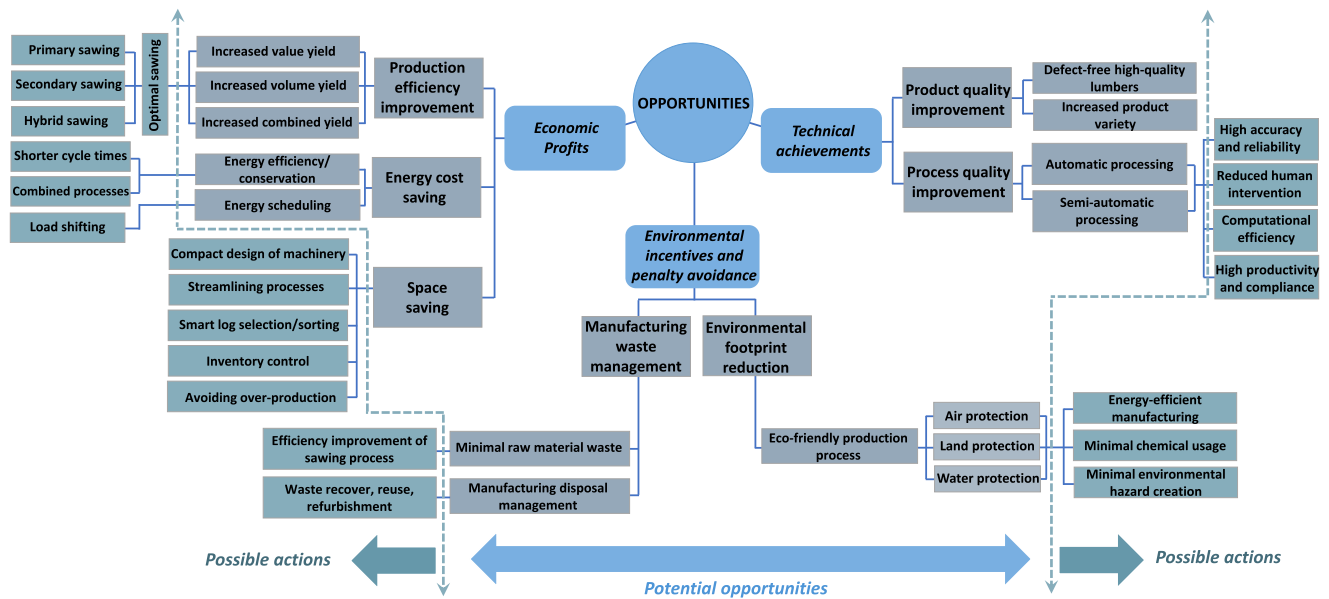


FIGURE 4. An overview on the state-of-the-art opportunities of automated decision-making in wood processing systems.

implementing automated machines and smart controls often allows sawmills to seize multiple opportunities across different categories with a single strategic investment, considering that a variety of the decision areas are interlinked [12]. In fact, an efficient decision-making strategy can result in obtaining overlapping benefits from different categories (see the Venn diagram presented in Fig. 5). For this reason, sawmills are encouraged to identify their potential development directions in order to maximize their profitability from all economic, technical, and environmental standpoints [11]. For instance, when a sawmill invests on an optimal energy management system, it enjoys benefits from both reduced energy costs which belongs to the economic profits as well as lower carbon emissions regarding the environmental benefits. By increasing the awareness of sawmill planners regarding such potential benefits, they are encouraged to open up various opportunities through carrying out sufficient primary investigations before any investment in production renovations. As a result, they can be able to ensure a more efficient decision-making system over the whole production process. The aim of this section is to provide researchers and stakeholders with insight into these opportunities through an in-depth literature review. The classification of related literature to each group of opportunities is presented in Fig. 6.

1) ECONOMIC PROFITS

The process of turning logs into lumbers as the main product of wood processing has traditionally a very low conversion efficiency of about 35% [42]. This is while up to 80% of total production costs are attributed to the cost of logs, making it the most important cost factor of production planning in sawmills [18], [43]. On the other hand, as fuel and

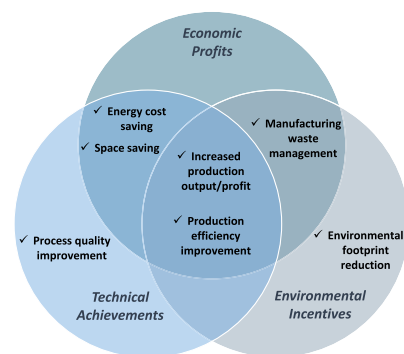


FIGURE 5. Venn diagram showing the overlaps between main groups of opportunities towards a profitable and sustainable wood manufacturing industry.

electricity prices increase, sawmills face increased operational costs [16]. These rising expenses, accompanied by other costs such as the need of more spaces for new production lines, facilities, storage, and parking lots when sawmills' business grows, cause sawmills to be financially challenged. The analysis of novel decision-making approaches that can contribute to a reduction of cost from different perspectives is therefore at the forefront of relevant studies [12].

The selected studies exploring the economic profits of optimal decision-making processes can be generally divided into three groups: *production efficiency improvement* [16], [18], [19], [20], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], *energy cost savings* [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], and *space savings* [53], [56], [82], [83], [84], [85], [86], [87].

### *a: PRODUCTION EFFICIENCY IMPROVEMENT*

First and foremost, over the past few decades, there has been a constant effort to discover economic profits by improving production efficiency of sawmills through maximizing their output product yields (i.e., the amounts of final lumber volumes or values) through the use of automated and computerized systems [16]. The earliest studies in the 1960s started with examining the effect of some sawing factors such as saw-line placement and kerf width on lumber yield improvement to increase economic profitability [44], [45]. These studies mostly focused on developing alternative sawing strategies relying on simple computer simulation models or mathematical programming for production output and profit improvements. For instance, an interesting effort in [45] examines several sawing methods on a unique log to investigate lumber yield improvement for reducing production cost.

Later, along the same line, studies such as [46] considered more sawing factors including the orientation of the first opening face in each log to evaluate their effects on the final volume or value yields and consequently, corresponding cost savings achieved. Despite providing sawmill managers with insights into the relationship between various sawing factors and economic value added due to process improvement, most of these approaches were difficult to implement and their produced data were not easily understandable by machine operators.

In response to the need for an efficient, feasible, fast, and flexible method to model log sawing, researchers thereafter developed a number of general and more user-friendly computerized models to simulate the log sawing process, including the Best Opening Face (BOF) simulator which is a computer simulation model for recovering lumbers with different dimensions from small and straight logs [46], [47]. Although some of these simulation models are interesting and relatively practical, they have significant limitations and a large percentage of the logs is still wasted [16].

As a step towards developing more advanced models to automate the decision-making process at sawing level while focusing on economic profitability, studies such as [48] and [50] considered more realistic models assuming that logs may have non-ideal characteristics such as truncated conical shapes and surface defects, i.e., knots, splits, decay, holes, etc. Accordingly, they introduced computer simulations with increased model accuracy to maximize yields and consequently, to gain more economic profits. A group of researchers, for instance the authors of [51] and [52], developed a graphic log sawing simulator as an analytical tool for automated log sawing. In their experiments, logs are modeled as cylinders or truncated cones. Using a programming model, the intersection of the log and cutter representations was calculated with the aim of maximizing logs' recovery yields.

Several research works consistently report that the production yield strongly depends on the method chosen for the log recovery [10]. On this basis, some studies such as [16], [20], [53], [54], [55], and [56] classify the output product yields

of wood processing according to the increase of either logs' *volume recovery* or *value recovery (grade recovery)*. Whereas the focus of the former is on increasing the mean cubic recovery of lumber volume from a gross log volume processed, the latter aims at maximizing the value of the lumber products by incorporating quality [56]. It is imperative to consider log shapes when the focus is on increasing the volume recovery, and defects when the aim is to enhance value recovery of the logs [53]. While a sole focus on volume-optimized solutions can be mostly found in older research, recent studies tend to consider the value of final products and producing lumbers with higher quality grades to increase economic profits and to avoid over-production of unnecessary products [57].

Recently, with the aim of maximizing profitability, also combinations have been explored by researchers. For example, the possibility of improving final profits by using a combination of volume and value recovery methods [53], [55], [58] were studied.

More specifically, the work in [53] presents a hybrid volume-value recovery method by integrating different phases of the sawing process, namely a primary sawing phase during which logs are cut into flitches, and a secondary sawing phase in which flitches are cut into final lumbers. Their method maximizes the product volume in the primary sawing phase and the product value in the secondary sawing phase. The authors report that the hybrid sawing method can establish a compromise between the volume recovery and the value recovery, resulting in significant lower overall losses and costs.

Instead, the authors in [57] and [58] present a hybrid volume-value recovery method which is capable of considering customer demands dynamically to match customer orders of lumbers with different volumes and grades with a given supply of logs.

Whereas quality-based value-optimized solutions are more explored recently than volume-optimized solutions, they typically require a thorough knowledge of log's internal defects [57]. In practical implementations, this requires a scanning system based on computerized tomography (CT) or magnetic resonance imaging (MRI) technologies [18]. However, as many sawmills act as independent small and medium-sized enterprises, it can be extremely expensive for them to afford the costs of these advanced scanners. Thus, economic alternatives should be explored to allow smaller production companies taking advantage of economic opportunities.

One of these solutions is to continue focusing on sawing methods based on external scanning, while implementing novel optimal control strategies. For instance, by incorporating online control strategies that consider the dynamics of the system in an online manner, even without having knowledge of the logs' internal defects, methods are capable of observing the condition of the log after each cut, and depending upon its health, can decide about the next cut [19]. Another solution is to separate the sawing phases, so that there is no internal scanning performed in the primary sawing phase, but instead defect detection is performed in the secondary sawing phase

Economic profits	Technical achievements	Environmental incentives and penalty avoidance
<b>Production efficiency improvement</b> [16], [18], [19], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [20], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70]	<b>Process quality improvement</b> [2], [4], [11], [16], [17], [37], [54], [57], [74], [83], [91], [92]	<b>Environmental footprint reduction</b> [99], [100], [101], [102], [103]
<b>Energy cost saving</b> [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81]	<b>Product quality improvement</b> [10], [16], [17], [19], [53], [57], [58], [93], [94], [95], [96]	<b>Manufacturing waste management</b> [84], [98],[99], [101], [102], [104], [105]
<b>Space saving</b> [53], [56], [82], [83], [84], [85], [86], [87]		

**FIGURE 6.** Assignment of related literature to each group of opportunities.

by simpler scanning systems [53], [88]. Nevertheless, each of these methods has its own limitations in terms of control complexity, computation time, and the need for appropriate sawing equipment. So far, existing studies do not provide comprehensive and effective solutions to address these issues. Filling these gaps requires further research.

*b: ENERGY COST SAVINGS*

Further economic opportunities can be opened up via more efficient decision strategies that have potential to change the sawmills’ energy usage. In fact, the wood processing industry is an energy-intensive sector which has a promising potential to achieve energy savings by implementing energy management programs [71], [72]. In general, electricity is the most commonly used energy source in sawmills (e.g., for sawing, lighting, saw sharpening, maintenance activities), however, there are also uses of natural gas, wood waste, and even fuel oil and diesel (e.g., for the drying process) [73]. In the past, since the energy cost accounted for only a small portion of the total production cost of sawmills, the energy management was not seen as a top priority in this sector. However, due to the significant increase in the cost of energy in recent years, energy management programs have attracted greater attention [71].

In the context of energy management, there are basically two strategies to seize the relevant economic opportunities (i.e., energy cost minimization), namely *energy efficiency/conservation* and *energy scheduling*. The energy efficiency/conservation refers to those technological/behavioral developments to “reduce” overall energy usage [89].

The primary goal of applying an energy efficiency/conservation program to sawmills is to reduce the energy consumption of the production process [71]. A number of studies examine applications of energy efficiency/conservation programs to sawmills’ operation in terms of cost saving and profitability enhancement [71], [73], [74], [75]. In this regard, the set of actions can involve the use of energy-efficient

motors, compact design of multi-level sawings, the use of efficient lighting systems, shutting off unnecessary loads such as idling motors, the use of air-drying before kiln-drying to save energy in the lumber drying process, and insulating kiln surfaces [75]. Although developing these methods and upgrading traditional facilities to more energy-efficient ones can be an effective solution to increase the economic efficiency of sawmills, the costs associated with such renovations typically also require significant investments. Furthermore, as sawmills expand their production lines while their business grows, their energy consumption inevitably increases and, as a result, they may need to pay higher tariffs due to their higher energy consumption during “peak-demand periods”. Therefore, relying solely on energy efficiency/conservation programs cannot fully prevent imposing excessive energy costs. It is therefore necessary to develop complementary solutions that can ensure the cost-effective use of existing facilities in relation to the energy consumption.

To this end, researchers are recently looking at designing and implementing smart energy scheduling programs for sawmills’ production processes [76], [77], [78], [79]. The energy scheduling refers to the “shift” of energy usage from normal consumption periods to off-peak-demand periods in response to variations in energy prices [89]. The major focus of the relevant studies is on establishing the automatic operation of some high-consuming production phases (such as the drying process in batch kilns) to be done during off-peak hours (i.e., mainly during night or early morning) [76], [77], and the use of renewable energy sources and energy storage devices to support their internal energy required [78], [79]. The future perspective of energy scheduling implementation in sawmills seems promising due to the growth of open electricity markets, the expansion of smart energy tariff rates, and interesting incentives offered by utilities to industrial manufacturers for shifting their energy usage patterns and the use of renewable energy sources. However, the design of the corresponding automated systems and efficient decision-making and control mechanisms are very challenging, as the system should be efficient and secure, and should preserve the production level and lead time despite the change in the normal operating hours of the sawmill.

Aside from the application of energy efficiency/conservation and energy scheduling programs, modern sawmills, which produce large quantities of biomass based on unsawn logs and wood residues, have the opportunity not only to use their biomass for internal use, but also to sell their surplus on the energy market [77], [80]. As a result of exploiting these opportunities, sawmills not only can gain economic benefits, but can also become an active player on the energy market. More research on this aspect is needed to mature the topic.

*c: SPACE SAVINGS*

Finally, another class of opportunities that automated decision-making strategies can provide to the sawmill operation planning is the possibility to optimize the floor space and storage utilization [82]. Since floor space is usually a limited



resource for companies, it is important to use the minimum amount of space possible to accomplish a given production task. Indeed, relocating or expanding a manufacturing facility requires significant effort and cost. In a case where products demand increases and consequently, the need for a higher production capacity becomes essential, the problem of lack of space can become a serious challenge for sawmills [83]. Although this topic has been less focused on in related studies so far, rising land prices, limitations on the company's physical expansion, and the high cost of relocating and structural changes of the company make it an important aspect for ongoing studies.

Recently, some researchers are addressing this issue by offering alternative solutions which permit enormous savings in terms of costs such as a more compact design of machinery [53], streamlining equipment and processes [84], smart log selection and sorting [85], inventory control [86], [87], and smart manufacturing for avoiding over-production [56].

## 2) TECHNICAL ACHIEVEMENTS

Sawmills are typically characterized by continuous production processes that run at all times with very large quantities of material continuously flowing through the process [11], [22]. It is therefore essential for every company to technically improve the operation of production processes – from log scanning to sawing, trimming and drying phases – in order to effectively use the company's equipment and to increase its productivity and efficiency, as well as its final product quality and diversity [11]. In this regard, automating decisions in manufacturing environments by implementing automated machines, manufacturing lines, and robot-supported systems with smart controls can greatly assist sawmills to handle technical challenges in their production processes [90]. We identified two main categories where smart systematic decisions in using semi-automated or fully-automated production systems can benefit sawmills, namely *process quality improvement* and *product quality improvement*.

### a: PROCESS QUALITY IMPROVEMENT

A large number of steps in the production process of traditional sawmills relies heavily on manual decisions made by human operators [16]. Technical decisions in sawmills mainly include the control of debarking machines, the measurement and sorting of logs, the control of positioning of logs in the sawing line, the selection of sawing patterns, the control of parameters for drying batches, the final sorting of sawn lumbers, the selection of final product sorting, and the use of measured information in later production phases [83]. In the case of missing expertise, fatigue, or carelessness of operators, these experience-based decisions can result in poor performance or malfunctioning of the system and equipment. The most common issues are machine failures, process losses, low production speed, low lumber yields and increased energy losses [16], [54].

Hence, rather than relying on human intervention, the adoption of smart autonomous and computerized systems for the process improvement of sawmills can lead to a more efficient wood product industry, as it can offer sawmills considerable technical advantages such as higher accuracy and reliability of measurements, control, and cutting [11], higher production and energy efficiency during sawing and drying phases [74], [91], [92], faster production processes [4], [37], and higher productivity and compliance [17], [57]. This process improvement usually centers around some critical steps: (a) an efficient selection and design of automated equipment such as robot-assisted sawing systems, scanning devices, automatic positioning systems for the log face, and conveyor belts, (b) monitoring the state of the process steadily, (c) the coordination between different stages of the process, and (d) continuous process quality measurement by analyzing input and output data [2], [11].

### b: PRODUCT QUALITY IMPROVEMENT

Technical achievements can also be assessed from the perspective of customer needs and product quality. Having in mind the competitive wood product market, significant attention has recently been directed to this aspect in order to increase customer satisfactions [57], [58], [93]. Considering that the wood processing is practically a destructive and, therefore, irreversible process, the focus of many studies is on the use of advanced scanning and detection systems for obtaining more accurate external and internal log characteristics for a quality-based sawing, [94], sawing machines with flexible sawing pattern to achieve the highest-grade products from logs [10], [16], [17], [53], and production of lumbers with different dimensions and irregular shapes (not just the cubic lumbers) to satisfy a wider range of customers from different dependent industries [19], [95], [96]. All these potential technical values can be attributed to the use of automated decision-making processes supported by advanced manufacturing technologies.

## 3) ENVIRONMENTAL INCENTIVES AND PENALTY AVOIDANCE

The forestry sector accounts for up to 17% of the world's total greenhouse gas emissions [97]. Throughout the supply chain of wood industry, the wood production process may cause different types of environmental impacts from harvesting to disposal [98]. Deforestation caused by removing trees, greenhouse gas emissions during the production process, wood wastage, toxic chemicals used in manufacturing, and industrial waste disposal pollution are a number of the known environmental impacts sourced by the wood production process [99].

Due to the fact that wood production is directly tied to forest resources, and the wood processing involves various stages of using industrial machinery and drying kilns that are energy-intensive and polluting, sawmills are usually subject to special government regulations and supervisions [99], [100].

To date, regulations have been enacted by governments to limit industrial producers' environmental impacts [100]. More than 40 countries around the world implement mandatory legal controls and measures to prevent industries from negatively affecting the environment. They carry out this process either by *incentivizing* companies using environmental subsidies and tax deduction/exemption or by *penalizing* companies that violate environmental laws using monetary fines [101], [102]. As an example, the Mississippi's Department of Environment Quality imposed a \$2.5 million fine on a wood product manufacturer after breaking environmental regulations, which is the largest known penalty against such a facility in an industry.

On the other hand, sawmills can create significant environmental opportunities by adopting measures and innovations to increase their "*eco-efficiency*" [103]. In fact, advanced technologies and process changes which reduce resource use and environmental impacts through process improvements allow sawmills to avoid being fined, to receive subsidies, and to greatly contribute to the environmental sustainability [102]. In general, the use of automated decision-making systems and smart machines throughout the production process of sawmills can provide them with many promising environmental opportunities, which can be generally grouped into *environmental footprint reduction* and *manufacturing waste management*.

#### a: ENVIRONMENTAL FOOTPRINT REDUCTION

The environmental footprint reduction encompasses all the measures taken to limit a company's emission impacts on land, air, and water qualities. Environmental hazard reduction, eco-friendly chemicals usage, eco-friendly production process (the use of efficient and energy/performance optimized processing strategies) should all be parts of these measures [101]. In this regards, energy-efficient processing and kiln drying systems (leading to a lower degree of unwanted carbon dioxide emission), the use of less toxic and more environmentally friendly lumber preservatives, the development of renewable energy resources for sawmills' internal energy uses, and the implementation of energy management programs (e.g., energy scheduling) can significantly reduce the total amount of sawmills' produced greenhouse gases [103].

#### b: MANUFACTURING WASTE MANAGEMENT

Efficient decision processes targeting manufacturing waste minimization including raw materials and industrial waste disposals can be another critical action towards a cleaner production [104]. On the one hand, the use of improved and new processing and control machinery instead of outdated equipment can minimize raw material wastes by improving *sawing efficiency* [101]. On the other hand, reusing, recycling, or refurbishing manufacturing wastes rather than disposing them can reduce the burden of transportation to landfills, the amount of toxic waste created from disposal of synthetic materials, and the requirement for new waste disposal sites [102]. As a result, these actions can make a significant

contribution to the reduction of greenhouse emissions produced by sawmills and to the elimination of environmental pollution [98].

Nevertheless, in most cases, obtaining potential environmental benefits is not viewed as an independent objective from economic and technical profits, as actions taken within those categories can significantly affect environmental achievements [105]. Hence, environmental objectives are rarely studied independently when relating to the design of automated decision-making at the sawmill level. Rather, they are often viewed as an element of sawmill operation optimization, alongside economic and technical objectives [84]. Still, relevant research studies report that even in that case, this dependant consideration of environmental objectives has a significant impact on improving environmentally-friendly sawmill production [98], [99], [105].

However, in the future, governments may need to provide more attractive incentive policies to persuade sawmills to devote special space to environmental opportunities and to improve their environmental sustainability. Besides, as some of the main barriers for a rapid development of eco-friendly production activities in sawmills are a lack of knowledge on the existing environmental incentives and insufficient infrastructure and budget for running industrial waste and energy management programs. Presenting a range of informative and attractive financing mechanisms by governments (such as grants, loans and government-sponsored initiatives) can support the realization of environmental policies.

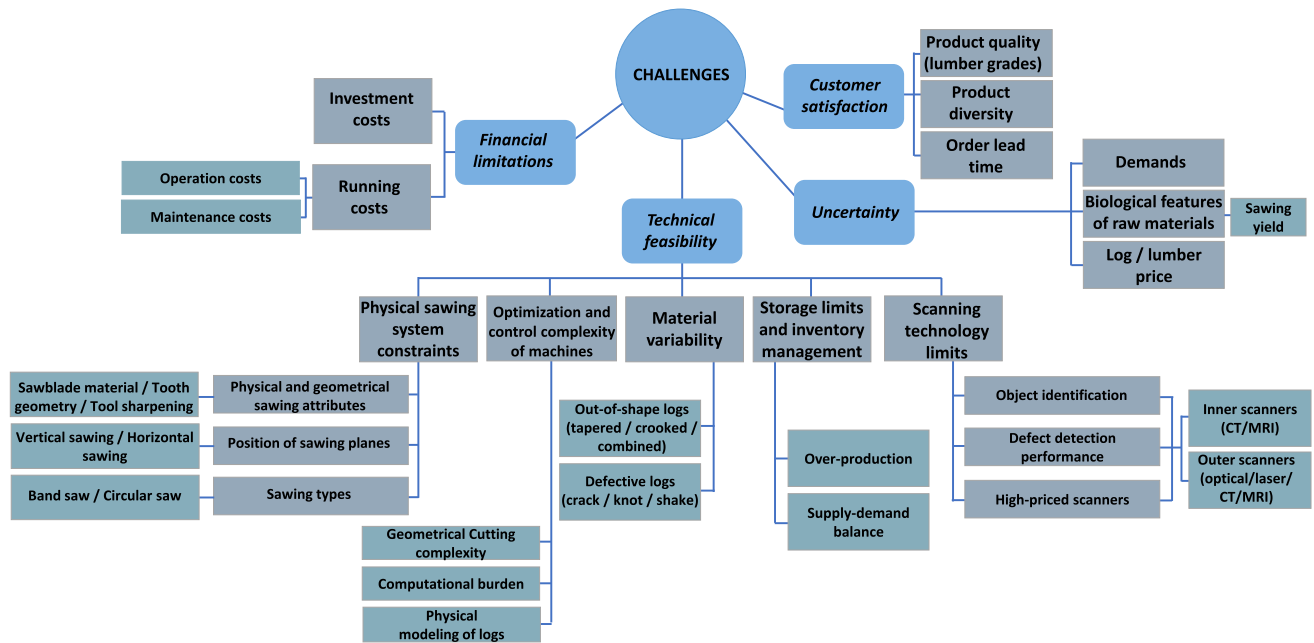
## B. CHALLENGES OF AUTOMATED DECISION-MAKING

In this study, we refer to *challenges* as difficulties, limitations, constraints, and feasibility issues related to the development of smart systems and the use of automated decision-making approaches for the wood production process in sawmills [41].

Despite of the potential of automation to simplify and optimize decision-making processes in wood production systems and, therefore, to open up new opportunities for improving companies' profitability and competitiveness, many companies are still reluctant to start such automation deployment due to their concerns about the associated challenges [15]. Based on our study of selected papers, we generally recognize four major categories of challenges for the smart automation of sawmills' production processes, namely (Ac1) *financial limitations*, (Ac2) *technical feasibility*, (Ac3) *customer satisfaction*, and (Ac4) *uncertainty*, see Fig. 7. Literature assignment to each group of challenges is presented in Fig. 8.

### 1) FINANCIAL LIMITATIONS

The decision to invest in automated manufacturing, and the operation and maintenance of its corresponding smart technologies can be very costly for a sawmill as they require a large capital investment [106]. The cost of outlining, building, and installing a fully automated wood processing system may range from thousands to millions of Euros depending on the automation level and type [12]. Hence, automated



**FIGURE 7.** An overview on the state-of-the-art challenges of automated decision-making in wood processing systems.

solutions for the production process of a sawmill may primarily be hindered by companies' financial limitations [86]. In fact, a sawmill should take into account both initial *investment costs* for upgrading their machinery and equipment, and *running costs* that incorporate *operation* and *maintenance* expenses.

#### a: INVESTMENT COSTS

A substantial amount of initial investment costs is typically attributed to the purchase of new equipment, machinery, and facilities, such as modern industrial robots (e.g. automated cutting, sawing, and trimming machines), advanced scanning systems (e.g., CT and MRI scanners), smart sensors, new information and communication systems, and computer processing and image analysis systems [20], [106]. Nevertheless, raising enough funds to purchase such equipment can be a significant challenge, especially for small and medium-sized businesses which are critical suppliers for meeting local demands [16].

Equipping a sawmill with advanced scanners allows for a non-destructive method of wood quality analysis and grading based on detailed information on log's quality and internal features prior to processing. This technology has been regarded a hot topic, culminating in a revolutionary innovation for increasing wood processing efficiency and quality [18], [107], [108].

For many sawmills, however, acquiring such internal scanners are unaffordable due to their high costs. Still, the development of these new technologies can hugely affect the competitive wood market environment in favor of a limited number of powerful companies which can afford to invest in such expensive technologies.

Few studies have examined how traditional companies can survive in competitive market environments and address financial challenges under the implications of changing technological conditions [2], [16]. Scholars report that it is very essential for sawmills to base dynamic and optimal investment decisions on a reasonable investment calculation. The calculations of this sort are often unique to corporate finance and are dependent on a number of company and even country-specific factors [2]. To assess the financial challenges and the effects of technological upgrades on a production process, the economic output in terms of the investment amount, the net present value, and the payback period should be estimated using efficient *simulation models* in a pre-investigation phase [2], [10], [11], [43], [94]. For a company with a limited budget, this step can reveal the fastest way to recover the investment and the most cost-effective upgrade. An interesting example of such an assessment is provided in [2], where a simulation model is developed for various scenarios to evaluate the profitability and the rate of investment recovery regarding the use of a CT scanner in the production process of a sawmill.

On the whole, the topic of developing more creative methods that can increase production efficiency with a company's limited capital and resources is not well established, and thus, should be prioritised in future studies. For example, an innovative alternative to the expensive CT/MRI scanning-based models can be the development of dynamic, online methods that optimize production tasks by updating the log data after each cut only by the use of cheaper optic scanners [17], [85], [88]. Another promising solution is to focus on building *semi-automated* processes based on human-robot interaction, which may require some human

interventions at certain points. From a financial perspective, semi-automated systems can be a better fit for medium and small sawmills to meet their production goals with low-risk investments [90], [96].

#### *b: RUNNING COSTS*

Another group of financial challenges is attributed to the costs of operating and maintaining automation equipment [85]. Automated tools usually require more maintenance services than those for traditional ones. Many studies focus on developing new decision-making approaches by automating production lines without taking into account the associated running costs. In practice, estimating running costs is a more challenging task than the one for investment costs, since it involves many technical considerations and knowledge that may not be within the scope of a sawmill technician's expertise [106]. In most cases, third-party company's technicians handle repairs and inspections of installed automated systems. An occurrence of any problem, even small, can sometimes cause a disruption in the operation of the entire production system of a sawmill, causing delays in the orders delivery process and resulting economic losses [56].

In addition, some findings in the relevant literature further demonstrate that since most automated machines and equipment are powered by electricity, changes in energy rates can directly impact the final price of the products [84]. Keeping track of these costs requires updating the revenue projections and calculations over time, which is a complex process that demands a greater amount of knowledge and investigations.

## 2) TECHNICAL FEASIBILITY

Following the decision to invest and the consideration of financial concerns, the next category of challenges to be evaluated in the process of automating and smartening wood production are technical feasibility issues in the design and implementation of automation systems and flexible machines. In general, sawmills receive orders from customers based on required dimensions, volume, species, and grade of lumbers [32]. To satisfy these customer requirements, a sawmill decision-maker needs to choose the type of logs to process, determine the sawing procedures to be applied, manage raw material and product inventories, and schedule production in a cost-effective and punctual manner [28]. In order to automate such tasks in a smart production environment, a large number of technical challenges need to be addressed, of which the most critical ones prioritized by the literature are *physical sawing system constraints*, *optimization and control complexity of automated machines*, *material variability*, *scanning technology limits*, and *storage limits and inventory management*.

#### *a: PHYSICAL SAWING SYSTEM CONSTRAINTS*

First of all, the core of a wood production system is the wood sawing machine. Hence, the most essential phase in automating a sawmill's operation process is the design of an efficient, fast, and flexible sawing system [11].

However, optimal planning and high-performance operation of a sawing machine for obtaining an effective utilization of resources, minimum wood loss and maximum productivity are very challenging to sawmills due to the presence of different technical and operational constraints [25], [31], [32]. The design of sawing systems is mainly concerned with the development of software and hardware technologies to optimize and control sawing operations [13]. During recent decades, the literature presented innovative ideas towards stating and solving sawing optimization and control problems while meeting a variety of sawing feasibility constraints [17], [109]. A group of technical challenges is with regard to physical and geometrical sawing features (e.g., sawblade material, tooth geometry and tool sharpening) [82], [83], [101] the position of sawing planes (e.g., vertical or horizontal sawing) [17], [95], [96], and sawing types (e.g., band saw or circular saw) [101], [110]. These features are primarily considered and customized according to the sawmills' requirements, including the dimensions and types of final products as well as the characteristics and species of raw materials [7]. In most cases, constrained problems can easily incorporate such physical limitations and features.

#### *b: OPTIMIZATION AND CONTROL COMPLEXITY OF AUTOMATED MACHINES*

The automation of wood processing systems entails more complex technical considerations. In fact, the problem of cutting different pieces from stock materials in order to maximize volumes or values of the pieces is referred in literature as the cutting stock problem [111]. The problem of sawing a log and cutting it into predefined pieces with the aim of maximizing the output yields is a variant of the cutting stock problem, which is referred as the sawing problem.

There are several factors affecting the difficulty of solving the specific sawing problem, including geometric complexity associated with cutting rectangular pieces from circular surfaces [109], [112]. In this case, the circular geometry of the patterns can impose non-linearities to the sawing optimization problem [32], [112]. Hence, an increase in the number of orders and the duration of the planning period may lead to a significant increase in the complexity of the problem and the computational effort involved [7], [16], [56], [64], [65].

#### *c: MATERIAL VARIABILITY*

A further complexity that deserves special attention arises from material variability, which needs to be reflected in the physical modeling of a log. Indeed, a log can have a variety of cross-sectional areas because of differences in diameter throughout the trunk [110]. However, in the existing literature, a log is usually treated as a regular cylinder whose diameter equals the minimum diameter of the real log [7], [16]. Logs, moreover, are seldom cylindrical, and instead are irregular and of random form, neither straight nor round. As a result, the optimal solution generated by such methods is no longer valid once any part of the log deviates from the



Financial limitations	Technical feasibility	Uncertainty
Investment costs	Physical sawing system constraints	Biological features of raw materials
[2], [10], [11], [16], [17], [18], [20], [43], [85], [88], [90], [94], [96], [106], [107], [108]	[7], [11], [13], [17], [25], [31], [32], [82], [83], [95], [96], [101], [109], [110]	[7], [8], [15], [87], [120]
Running costs	Optimization and control complexity of machines	Demands
[56], [84], [85], [106]	[7], [16], [32], [56], [64], [65], [109], [111], [112]	
Customer satisfaction	Material variability	[15], [41], [121], [122]
Product quality	[7], [16], [95], [110], [113], [114]	Log / lumber price
[32], [50], [82], [106], [118], [119]	Scanning technology limits	
Product diversity	[9], [16], [17], [19], [28], [34], [85], [87], [115], [116], [107], [108], [112], [114]	[86], [123]
Order lead time	Storage limits and inventory management	
[5], [14], [41]	[5], [8], [15], [28], [31], [34], [85], [117]	

FIGURE 8. Assignment of related literature to each group of challenges.

cylindrical definition [95]. Hence, this sort of assumptions is inaccurate and can waste a large amount of the potential yield as the sawing process creates low-price by-products or sawdust. In addition, in order to improve sawmill productivity, log quality assessment and defect detection are of major importance prior to sawing process as the price of final lumbers is influenced not only by their dimensions but also directly by their quality of the wood [113], [114].

d: SCANNING TECHNOLOGY

Typically, the sawing patterns are either generated manually or with the support of scanners. In the former, by selecting a subset of manually generated patterns, the number of logs of each type can be determined. Alternatively, the latter uses scanner technology to provide a three-dimensional view of the log within a software tool that supports the operator to find optimal sawing patterns in a shorter amount of time [112].

The performance of the scanning process, and consequently the accuracy of log modeling and optimization, is a hotly debated topic in related studies, as it can distinguish log feature variations according to their shape and dimensions, as well as their internal and external quality levels for running a superior grading task [107], [108]. In fact, a proper scanning is a proven method of capturing one of the biggest obstacles to an efficient sawmill design, namely *material variability* [9], [85], [87]. The detection of *out-of-shape logs* using three-dimensional outer scanning (e.g., optical/laser, CT, and MRI scanners) and *defective logs* using inner scanning (e.g., CT and MRI scanners) allows the optimization tools to flexibly adapt the problem constraints and feasible solution spaces to the realistic model, thereby increasing sawing yields significantly [19], [28], [115]. In addition, extracting logs' features enable the sawmill decision-maker to select which log mix should be sawn to fulfill the yield targets [17], [85].

To this end, however, the issues associated with the accuracy of object identification [116], defect detection performances [16], and the significant price of inner scanners [115] should be adequately addressed.

Improving sawing efficiency through advanced scanning systems and enhanced sawing strategies can prevent overproduction and large wastes and can allow sawmills for smart production in accordance with customer orders (i.e., matching demand points with supply points) [34], which consequently reduces the challenges for managing raw materials and final products storage facilities [114].

e: STORAGE LIMITS AND INVENTORY MANAGEMENT

Sawmills also face challenges related to material and product inventories, so that the inventory management of sawmills is currently a subject of a large set of research works [5], [28], [31], [34], [85]. In this context, the sawmill's inventory management is often carried out related to the capacity considerations appearing in the sawing optimization problem as problem constraints, such as the maximum production capacity of a sawmill (in terms of machinery and physical constraints) [15], [117], the maximum amount of logs that can be purchased per month [8], initial inventory and monthly log inventory capacity [85], logs and lumbers transportation capacity [34], [117], and market capacity [28], which are all expressed in terms of the limits and capabilities of machines and limits in adequate company's infrastructure [8]. In short, towards more flexible operations with a better control of raw materials and finished products, technical challenges are by far the most popular topics of discussion in research works within the scope, and probably, this trend will continue in the future due to the extreme importance of processing speed and response accuracy in future advanced automated wood processing systems.

3) CUSTOMER SATISFACTION

As the wood industry is facing a competitive market, a key concern of sawmills for their processing renovation is to keep, and even to strengthen, their customer-centric environment in terms of *product quality* [32], [50], [82], [106], [118], [119], *product diversity* [9], [40], [41], [83], and *order lead times* [5], [14], [41]. In fact, for an automated sawmill, having a trade-off between maintaining a high level of services and being efficient with respect to the company's financial targets is very essential [9]. Hence, customer satisfaction is often regarded as a hard constraint in sawmill planning due to the risk of consequent losses of market share [5], [9].

It is well discussed in the literature that understanding competition markets and identifying customer values creation through the use of intelligent and automated systems is a prerequisite for sawmills to automate their production processes while preserving their profit margins [41]. In this regard, moving towards automating wood production and processing systems may initially raise concerns for sawmill managers about changing traditional routine manufacturing in connection with the demand fulfilment. A sawmill may hesitate

about automating its production process given the limits in the possibility of manipulation in the automated processes, manufacturing speed limitations, insufficient training experience on the system operation, unknown long-term performance of the automated system in producing high-quality products, and possible hardware and software failures or interruptions that may cause delivery delays. Due to that, the sawmill managers need to be adequately convinced that implementing an advanced intelligent production system can ensure efficiency, security and reliability of production planning and positively impact customer satisfaction while increasing flexibility of production and final product characteristics, thereby facilitating product customization and responding to dynamic customer demands. Hence, the company's competitive profits can be considerably enhanced.

The majority of wood producers, in the past, focused on producing lumbers with a limited number of predetermined dimensions [40]. Therefore, customers mostly had to choose and register their orders according to the available options. Nowadays, however, many customers prefer customizing their orders [41]. It is estimated that as few as 10% of wood producers can offer wood products with a high degree of customization [106]. In the traditional production system, supplying customized orders to increase a company's competitive manufacturing advantage requires extra human resources with expertise to accomplish such tasks. In contrast, even though the production of customized products with desired dimensions is still a challenge for automatic sawing machines, recent research is moving rapidly towards improving the flexibility and efficiency of cutting systems, so as to produce wood products of arbitrary sizes and grades to satisfy customer special orders with no need for expertise of human resources.

#### 4) UNCERTAINTY

Wood product manufacturers commonly face the challenge of making decisions on the basis of unreliable or incomplete information, leading to a large amount of uncertainty in the decision-making model [85]. In the case of assuming simplified deterministic models for the wood production planning, ignoring uncertainty can result in non-optimal sawing, unnecessarily high inventories of products with inferior quality and lower prices, and consequently, obtaining low yields [120]. Thus, the consideration of uncertainty is essential to ensure that the decisions based on the results of the model are feasible and near-optimal with respect to the actual data [9]. While a significant number of decisions in wood processing are affected by uncertainties, the most critical uncertain factors are *product demands*, *biological features of raw materials* - which affects sawing yields-, as well as *the prices of logs and lumbers* [8], [85], [87].

At one hand, scholars argue that more detailed and accurate information can contribute to more efficient production and marketing performance [24]. On the other hand, flexibility and agility in manufacturing are vital for managing different sources of uncertainties [41]. Nevertheless, for sawmills

to become agile, advanced processes and technologies should be established to detect and respond to unexpected variations [85].

A number of research has been conducted on how to deal with the uncertainty in the wood production management. Most of these studies focus on the random characteristics of raw materials which are classified based on some log's attributes such as diameter class, species, length, taper, and defects [7], [8], [15], [87], [120]. The main reason for imposing this uncertainty is that logs, required to plan the next sawing patterns, are not always available to be scanned in sawmills before planning, or advanced scanning systems are unavailable [87]. A group of studies further address another common sources of uncertainty involved in predicting final demands [15], [41], [121], [122], as well as variability in the price of logs and lumbers in wood markets [86], [123].

To deal with multiple types of uncertainties, research studies primarily use probabilistic tools to accommodate uncertainty into various sawing model scenarios, product demands, and logs and lumbers prices to provide a level of robustness against changes, making a profitable plan in dynamical, disturbance-prone wood production systems [8], [15], [41], [87], [120], [121], [122], [123], [124], [125].

Despite the importance of existing modeling methods in wood production planning within uncertain environments, developing efficient algorithms that are able to deal with the large number of possible scenarios under uncertainty and the associated computational burdens are usually difficult in practice [120]. In addition, most of available approaches require knowledge of the distribution of the uncertain data, which is generally unknown or difficult to obtain. Thus, despite the availability of theoretical methods, there have been very few practical applications of stochastic approaches dealing with uncertainty. Moreover, in general, there is still a lack of efforts that provide a comprehensive practical evaluation and demonstration of these approaches and their assessment in terms of robustness and computational testing through real-world implementations.

#### C. A GENERAL MATHEMATICAL MODEL FOR SUPPORTING EFFICIENT PRODUCTION IN SAWMILLS

In order to provide readers with insight into how the discussed topics can be connected to a corresponding mathematical model, we formulate a general optimization problem in which introduced opportunities are considered as problem objectives and introduced challenges are considered as problem constraints:

$$\begin{aligned} & \max_{\mathbf{x}} (f_{ep}(\mathbf{x}), f_{ia}(\mathbf{x}), f_{ei}(\mathbf{x})) \\ & \text{subject to } \mathbf{x} \in \mathcal{X} \end{aligned} \quad (1)$$

where  $\mathbf{x}$  is the vector of decision variables,  $\mathcal{X}$  is the constraint set (or feasible set), and  $f_{ep}(\mathbf{x})$ ,  $f_{ia}(\mathbf{x})$ , and  $f_{ei}(\mathbf{x})$  are the objective functions related to the economic profits (e.g., value or volume of finished products), technical achievements (e.g., grade/diversity of products), and environmental

incentives/penalty avoidance (e.g., carbon emission reduction in production process and transportation), respectively.

To accommodate the constraints and the decision variables domains, the constraint set  $\mathcal{X}$  can be defined as the following functional form:

$$\begin{aligned} \mathcal{X} = \{x \in \mathbb{R}^n \mid & \mathbf{g}_{fl}(x) \leq \mathbf{b}_{fl}, \mathbf{h}_{fl}(x) = \mathbf{c}_{fl}, \mathbf{g}_{tf}(x) \leq \mathbf{b}_{tf}, \\ & \mathbf{h}_{tf}(x) = \mathbf{c}_{tf}, \mathbf{g}_{cs}(x) \leq \mathbf{b}_{cs}, \mathbf{h}_{cs}(x) = \mathbf{c}_{cs}, \\ & \mathbf{g}_u(x) \leq \mathbf{b}_u, \mathbf{h}_u(x) = \mathbf{c}_u, \mathbf{x}_{lb} \leq \mathbf{x} \leq \mathbf{x}_{ub}\} \end{aligned} \quad (2)$$

where  $n$  is the number of decision variables,  $\mathbf{g}_{fl}$ ,  $\mathbf{g}_{tf}$ ,  $\mathbf{g}_{cs}$ ,  $\mathbf{g}_u$ , and  $\mathbf{h}_{fl}$ ,  $\mathbf{h}_{tf}$ ,  $\mathbf{h}_{cs}$ , and  $\mathbf{h}_u$  respectively define sets of inequality and equality constraints related to the financial limitations (e.g., capital budget limit), technical feasibility (e.g., geometrical constraints related to the sawing problem, storage limits, etc.), customer satisfaction (e.g., lead time satisfaction), and uncertainty (e.g., demand and price variations). Additionally,  $\mathbf{b}_{fl}$ ,  $\mathbf{b}_{tf}$ ,  $\mathbf{b}_{fl}$ ,  $\mathbf{b}_u$ , and  $\mathbf{c}_{fl}$ ,  $\mathbf{c}_{tf}$ ,  $\mathbf{c}_{fl}$ , and  $\mathbf{c}_u$  are respectively the corresponding vectors of inequality and equality constraints' parameters. Two vectors  $\mathbf{x}_{lb}$  and  $\mathbf{x}_{ub}$  represent lower and upper bounds of decision variables, respectively.

Ideally, many economic, technical, and environmental profitability aspects should be maximized while respecting various groups of constraints. However, a comprehensive modelling and formulation of the sawmill profit maximization problem can turn into a very large and complicated problem that is challenging to solve. Therefore, many studies focus only on a limited set of objectives and constraints (e.g., only increased value yields of log sawing considering geometrical constraints - see the use case discussed in Section IV-A). The problem of sawmill operation optimization can be approached in a variety of ways depending on scales and types of the problem, such as linearity or non-linearity, and numbers and types of decision variables and constraints. The following section provides an overview of the literature on the relevant methodological aspect.

### III. METHODOLOGIES

Despite of rapid advances in information and communication technologies that have provided an unprecedented opportunity to change the paradigm of decision-making processes in the forest industry and more specifically, in the wood processing step, the realization of dynamic, automated decision-making systems requires careful design and testing of advanced control and optimization techniques [22].

In fact, there are several interrelated steps to turn raw materials into finished goods and delivering them to costumers or distribution centers, in which a variety of decisions should be made for optimizing economic, technical, and environmental performances of the production process [4]. Over these steps, different constraints regarding financial, technical, customer-oriented, and uncertainty aspects should be taken into account and results need to be calculated within a short period of time [2].

To achieve efficient production, sawmill decision makers need to properly 1) model decision-making processes

and 2) use appropriate decision-making strategies. In fact, the behavior of each physical system and decision support process such as those discussed in Section II should be firstly described using mathematical concepts and equations to examine how changes within the framework may affect results. Once corresponding mathematical models are obtained, in the second step, a variety of analytical and computational techniques can be applied for optimization, analysis, and synthesis purposes. The typical activities associated with modeling decision-making processes and applying decision-making strategies include optimal bucking of harvested logs, machinery design, equipment locations, cutting, trimming, and drying of logs, and logistics for transporting finished products to customers or distribution centers [6], [25]. Thus far, a large number of approaches have been proposed and developed in the literature to support decision makers. Most of these approaches are based on stating and solving constrained optimization problems.

Among all operational decision-making steps in a sawmill, the most critical and discussed problem is the way of selecting and cutting logs with varying qualities and sizes into a set of predefined shapes, so as to achieve the highest product yields and the least losses, while meeting a group of constraints such as technical limitations of automation systems, customer demands, environmental obligations, and order lead times [17]. This problem can be seen as the problem of cutting stock materials into smaller pieces with a view to maximize yields and minimize waste, which is well known in the literature as *cutting stock problem* (for more detail, see the interesting review presented in [126]). In the wood industry, this problem is characterized by cutting certain lumbers from stock circular logs, which is commonly termed *sawing problem* [109]. In fact, the sawing problem can be viewed as a variant of multi-dimensional, rectangular (in most cases), and multiple-size cutting stock problem [112].

Apart from the sawing problem, log bucking as a pre-processing decision before sawing [56], [88], optimal decisions of wood processing after sawing such as trimming and drying operation planning [77], [78], [80], [91], [92], [118], [119], upgraded machinery design for having a fast and compact process [43], [95], and transport decisions including routing and scheduling [8], [13], [34], [117] have been among highly-explored topics of decision-making optimization in sawmills.

This section seeks to provide a guideline for researchers and manufacturers for a better understanding of how the opportunities described in the previous section can be achieved through applying intelligent optimization and control techniques, and how the associated roadblock can be tackled efficiently. For this purpose, this section brings together findings of essential literature focusing on the methodological point of view. By investigating the selected papers (see Table 2), we aim at answering the following research questions: *Q1) What innovative decision-making approaches can be applied to the wood production process to ensure the optimal performance of a sawmill, and thereby*

improve its profitability?, and Q2) How can the complexities associated with designing an automated decision-making system in the wood production process be addressed? To answer these questions, we present a general overview of the most popular topics of research in the field, classified into: algebraic model-based mathematical programming, search algorithms, and artificial intelligence approaches.

### A. MODEL-BASED MATHEMATICAL PROGRAMMING

In order to formulate decision-making problems in sawmills, a vast majority of existing studies relies on algebraic mathematical models to provide a precise solution to the corresponding constrained optimization problem.

In the following, we discuss some of the highly-explored mathematical models available in the literature for modeling and formulating decision-making processes to support smart production in sawmills.

#### 1) LINEAR PROGRAMMING (LP) MODELS

LP has been among the most prominent methods for modeling decision-making processes in sawmills including sawing optimization problems [59]. The earliest optimal sawing solutions proposed in the literature are typically based on LP algorithms [60], [61]. For example, LP applications are primarily developed in [60] to select optimal log sawing policies for wood waste minimization. A simple LP model is later extended in [61] to maximize possible lumber volume yields considering a number of logs in different size groups. Next, other studies such as [37] and [109] establish linear models for the sawing problem, while taking into account more realistic considerations and a wider range of technical and operational constraints related to sawing features and feasibility issues. As a more comprehensive study, the work in [109] minimizes the total number of logs cut while considering the constraints of demand satisfaction, the dimensional features of the logs, log stock capacity, and the decision variables' domains.

Decision optimization goals throughout different steps of a sawmill are also modeled as multi-objective optimization problems with linear objective functions and linear constraints, which can be solved by LP algorithms. A promising related example is presented in [37], where the authors formulate a multi-objective optimization problem dealing with five objectives for the sawmill planning, namely minimizing the total cost of production, maximizing the net income from selling the ordered products and extra by-products, minimizing waste wood regarding sawing recovery factors, minimizing the number of logs needed to satisfy order demands, and last but not least, minimizing the time needed to complete the production task.

Furthermore, in some cases, LP is used to solve the sawing problem in combination with other decision-making problems, in particular bucking decision optimization [56], transport decisions and post-sawing decisions optimization [13], [117] in a supply chain context. The study in [56] developed an LP model in combination with an iterative algorithm to

generate the optimal bucking of tree length stems and sawing pattern. In [117], a linear objective function is established for a sawmill operation optimization problem which takes into account production, transport, drying, and inventory costs. An agent-based sawmill operation planning is instead proposed in [13] which relies on linear system models and linear objective functions. Wherein, LP is developed for optimal sawing, drying and grading considering various production, feasibility, inventory, and demand constraints.

An interesting review paper on the applications of LP to the optimization of automated wood production processes is provided in [59] where a special focus is given to the economic profits, i.e., the minimization of expected production cost through optimal sawing strategies.

Modeling sawmill decision systems using linear methods can provide accurate optimal solutions in a tractable manner, particularly when dealing with problems of smaller sizes and with fewer product orders and diversities, so that they can be solved by commercial math programming solvers in a reasonable time. However, in real sawmill production systems, linearity is often an unrealistic assumption. In fact, an LP model assumes a linear relationship between problem input and output, production and cost, production and total revenue, and problem technical and feasibility constraints, which is rarely the case in practical implementations.

Moreover, due to the nature of sawing problems that commonly require the introduction of integer variables (due to the combinatorial optimization properties of sawing problems [127]), the use of linear functions with continuous variables or linear approximations may lead to inaccurate results which are far from optimal. This can result in sub-optimal lumber production where the potential value of logs is wasted [17].

#### 2) MIXED-INTEGER LINEAR PROGRAMMING (MILP) MODELS

As the main objective of a wood production plan, the raw material optimization can be mathematically regarded as a combinatorial optimization problem on the basis of choosing the best solution among a discrete set of feasible solutions [18], [127]. Therefore, MILP approaches are generally better suited to such problem structure compared to LP approaches. For this reason, model-based MILP approaches are another popular class of techniques employed in the literature for obtaining optimal decisions of wood sawing [4].

An interesting example is presented in [43], where a MILP model is developed for an optimal sawing problem by introducing integer decision variables related to the possible sawing patterns that the model can choose from, and the number of finished products with predefined dimensions. The authors use this MILP model in combination with a simulation tool to maximize the volume recovery of the sawing process and to increase the sawmill's profit. However, in the proposed model, quality aspects such as defects are not considered, which simplifies the problem significantly.

Instead, a MILP model is formulated in [5] to determine optimal production planning in a sawmill by incorporating



all the cutting patterns possible for different log diameters, given by an exhaustive generation algorithm. In this case, a large number of decision variables are simultaneously calculated, including daily logs procurement, suppliers selection, quantity of processed logs, cutting pattern assignment, log and lumber inventories, and operation times. In [4], the same authors state the optimal daily production planning of sawmills as the problem of packing a set of rectangles into the circle surface, while applying an MILP algorithm to solve it and to achieve the maximum sawmill profit.

The application of multi-objective optimization problems in the form of integer programming is also studied in some related papers. For instance, multiple objectives for supporting decisions in the daily production planning of a sawmill are pursued in [31], addressing sawmill profit maximization, raw material loss minimization, inventory control, and demand satisfaction as objectives, where the overall problem is stated using an MILP formulation.

Another group of research works emphasizes post-processing stages of lumber production such as lumber drying operation planning, with the goal of enhancing energy efficiency and maintaining the quality of finished products [92], [118]. A successful processing of these steps requires the fulfillment of different operational conditions while multiple decisions must be made to accomplish these tasks. In order to facilitate the relationship among these decisions, MILP formulations are extended in [118] and [92] for the simultaneous optimization of drying operations, including the scheduling of kilns and filling them with packages of lumbers.

In general, solving such complex integer programming problems in large-scale systems, in particular combinatorial problems with many decision variables using conventional exact algorithms can be computationally challenging, rendering the approach inefficient in practical implementations [128]. Although LP and MILP models are widely used to formulate decision optimization problems in planning for the wood processing – which necessitate both objective and constraint functions to be linear with continuous or integer variables – finding their solution using exact algorithms with exponential computational complexity are rarely applicable in real world scenarios. On the other hand, studies such as the one in [129] find that the relationship between sawing yields and lumber quality is not linear in most of the cases. In fact, the majority of scenarios examined by this study does not prove to have a linear relationship between sawing yield and lumber quality. Therefore, the authors argue that linear models may not provide true minimum cost solutions for sawing problems with realistic constraints such as lumber grade requirements, and the industry may be sometimes ill-advised to rely on those models.

### 3) NONLINEAR PROGRAMMING (NLP) MODELS

Mathematically, a more realistic modeling of decision support systems in sawmills for the complex conversion process

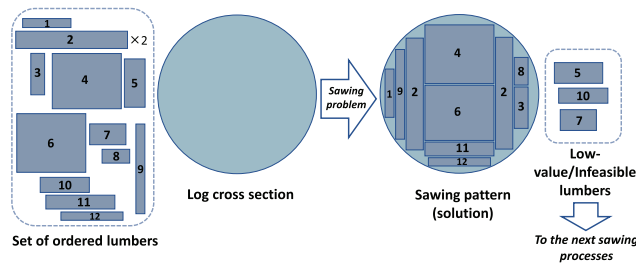
of logs into finished lumbers gives rise to optimization problems in nonlinear forms. Apart from the nonlinear nature of optimization models in a wood production system, such as the relationship between yields and lumber grades [129] and the cost of energy bought from open electricity markets [130], the most distinguished non-linearity in the system is with regard to the geometric complexity of the sawing problem [109]. This non-linearity is associated with the problem of packing a subset of rectangles (or other irregular shapes) into a circular surface as a convex region (see the example presented in Fig. 9) while minimizing the remaining volume, or maximizing the volume used/product values [109], [112]. Solving this problem is challenging primarily due to the computational complexity in satisfying feasibility constraints [7].

The non-linearity in the sawing optimization problem is addressed in the literature through several approaches. For instance, a mixed-integer NLP model for the sawing optimization problem is developed in [7], which however, is only solvable for very small-scale problems. A value-based cant sawing optimization problem with nonlinear constraints is instead studied in [109] which is later reduced to a set partitioning problem to simplify the original optimization problem.

Some other nonlinear modeling of the sawing optimization problem are detailed in [9] and [21], however, they are then converted into simpler forms of linear programming through approximation strategies.

Another type of operational planning problem, described in [78], [79], and [80] deals with optimizing the energy consumption of lumber drying systems, where thermal models of the kiln system are represented in nonlinear forms. In [80], by modeling total heat demands in batch kilns during the drying scheme, increasing energy efficiency of the sawmill along with obtaining high quality lumbers after drying process are intended. Wood types, lumber dimensions and kiln types are taken into account. In the studies presented in [78] and [79], optimization of the sawmill drying process for different wood species using solar kiln with thermal storage is extensively discussed.

In general, exact mathematical algorithms can only find the solution of NLP problems in very small-scale scenarios, or alternately, such problems need to be converted into linear forms. Even in small-scale systems with low number of variables, commercial solvers are rarely able to provide a tractable solution to such problems in an efficient way [1]. For example, in the case study presented in [7], where only nine rectangles are involved as required lumber sizes, the software takes more than one hour to calculate the optimal solution. This stays in contrast to decision optimization models in real wood production systems that need to calculate a large number of decision variables during a short period of time. These issues are driving researchers towards developing more computationally efficient algorithms which provide reasonable near-optimal solutions in shorter computation times, such as dynamic programming (DP) or approximation algorithms [62].



**FIGURE 9.** A sample sawing problem for obtaining optimal feasible sawing pattern solution by extracting a set of ordered lumbers from a circular log cross section.

#### 4) DYNAMIC PROGRAMMING (DP) APPROACHES

Having considered the computational complexity of calculating a large number of continuous and integer decision variables based on different mathematical optimization models, the concept of DP is essentially suitable for solving such combinatorial problems using recursive programming [88]. In fact, DP provides an alternative strategy for solving large-scale and complex manufacturing problems that can be discretized and sequenced [131]. By the use of this approach in wood production planning, the original sawing problem can be divided into simpler sub-problems, and the solutions obtained for each sub-problem are used to achieve an optimal solution for the original sawing problem [17]. By saving the solutions of overlapping smaller sub-problems, a DP algorithm can significantly reduce computation times by avoiding re-computation due to the use of prior saved solutions. As DP is able to solve linear or nonlinear problems with discrete or continuous variables, it has been successfully applied to a variety of sawmill decision planning problems.

An early application of DP for addressing a wood processing problem is presented in [49], where a DP algorithm is developed to determine the optimal one-dimensional cross-cutting pattern of a log into shorter logs.

Later on, capabilities of DP algorithms for dealing with various types of optimization problems in a tractable manner allowed them to be applied to different sawing types, such as live sawing (i.e., a log is cut into flitches using sawing planes that are parallel to each other), cant sawing (i.e., a log is cut into three portions along the initial sawing orientation), and grade sawing (i.e., a log is cut into four portions at the small end for a given sawing orientation, where two parallel portions have the same series of parallel cuts which are orthogonal to the cuts of two other portions), see Fig. 10. An example of a DP application for the optimization of live sawing and cant sawing with two-dimensional perspectives is considered in [63] to maximize volume lumber yield from cylindrical logs. This model for the first time provides the possibility of considering a variety of board thicknesses with a guarantee of optimal volume yield, showing that DP can be an efficient method to solve sawing problems with larger scales and higher number of decision variables in a reasonable time. However, in [63], the sole focus is on maximizing cross-section area while no quality aspect and value yields

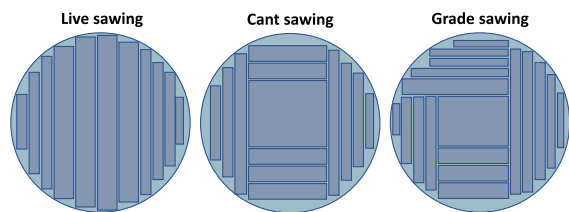
are considered. Following this work, an extended DP model for optimal sawing of logs is detailed in [64] by performing a parametric analysis to find all optimal sawing patterns as a function of log diameter. Such early applications of DP in sawing operations are still in use today. However, these methods are now commonly combined with more advanced technologies, such as advanced scanning and image processing systems, to address quality-based grade sawing with added values [1].

Whereas mentioned studies do not address the presence of defects in logs, another group of studies applies DP algorithms to more complex sawing problems having a better understanding of the log's inner and outer characteristics, thereby allowing consideration of the finished product quality. A primary related effort is made in [20] focusing on the application of DP to quality-based sawing strategies, which accounts for the impacts of defects in finished products values. By using a defect scanner and an image-processing system, this study extends the log's model to a three-dimensional model with cross-section and length optimization for various grades. The flexibility and computational efficiency features of DP is further utilized in [88] for dealing with a combined problem of optimal log bucking and sawing as a coordinated production system taking into account lumbers' quality. The sawing optimization is modelled as the well-known standard knapsack problem with integer variables, which is then solved by a DP algorithm.

A wider class of quality factors such as partial wane allowance in lumbers is studied in [95], where the sawing problem is formulated as a set packing problem with the objective of maximizing total products' value. Some interesting results through a comparison between the DP approach and a heuristic algorithm is presented in [95], showing that DP can find solutions with a higher quality than the one of the heuristic approach, while the former has a lower solution speed as expected.

Among more recent works, DP is frequently used for optimizing log grade sawing according to the positions and shapes of internal log defects, which can be scanned or predicted [1], [16], [40], [53], [58]. A substantial increase in lumbers' value are observed in the results presented in [53] when DP is used for a grade sawing problem defined as two nested longest path problem. This promising work combines primary sawing and secondary sawing processes by a two-stage sawing strategy. By first determining the optimal pattern for cutting a slab into boards through an inner optimization problem, and then calculating the optimal pattern for cutting a log into slabs by a master problem, the method eliminates the need for expensive internal scanning capabilities. This feature can be very interesting for companies with limited budgets.

A comprehensive study on mathematical models and problem formulations of the sawing optimization problem with a variety of sawing types is conducted in [17] based on DP algorithms, which laid the foundation for a large group of later studies (for instance, the works in [16], [32], [56], and [65]). The study in [17], and following that, the studies in [16],



**FIGURE 10.** Three major sawing patterns in wood processing.

[32], [56], and [65] extend DP methodologies to the most commonly used primary sawing strategies in real sawmills, i.e., live sawing, cant sawing, and grade sawing (see Fig. 10), such that the value of the lumber products obtained from the log is maximized in all cases. Moreover, the computation complexity for finding optimal solutions of each sawing type is discussed. The work in [17] interestingly reports that the execution times of the DP algorithms for determining optimal sawing strategy, as well as the methods for defect recognition and modeling, and automated lumber grading are not yet suited to real-time applications in a real sawmill. The authors contend, however, that by taking advantage of parallel computing at different stages of the automated decision-making process, the execution times could be improved significantly. Nevertheless, due to the fact that DP algorithms use stored sub-solutions to be faster in computation, they require a large deal of memories to store the result of each sub-problem without ensuring that the stored values will be utilized. Consequently, their use in large-scale sawmills could still be expensive and challenging, particularly if parallel computing is intended. Hence, if memory is scarce, the implementation of DP for wood processing optimization may become infeasible.

## B. SEARCH ALGORITHMS

Although a significant number of existing approaches for addressing decision-making problems in sawmills are formed using model-based mathematical programming methods which are deterministic, recent studies are increasingly moving towards faster alternative methods due to concerns regarding the complexity of more advanced production systems and memory limitations. These methods mainly rely on search algorithms. Search algorithms generally reduce the accuracy of problem solutions in order to increase problem-solving speed, however, they typically return solutions that are close to optimal, which is usually sufficient for obtaining a satisfactory yield in most industrial applications [132]. In situations where problem-solving speed is a critical requirement, search algorithms can consequently be very useful. It is precisely the situation that can arise in optimizing the decision-making performance of a sawmill, especially if the scale of the problem is large (e.g., the problem contains various continuous and integer decision variables, the presence of uncertainty, significant variety of orders, and a cluster of logs to be optimally cut instead of a single log) [122]. Moreover, a majority of mentioned deterministic model-based methods

assumes that all input data for the decision-making optimization problem are accurately known in advance. However, this assumption is rarely valid in real-world scenarios. Ignoring input uncertainty often leads to poor estimates of the system performance [8]. To cope with this challenge, search algorithms usually track and characterize stochastic behaviors of the random input parameters to provide a realistic decision-making in uncertain manufacturing environments [122]. Hence, relevant approaches based on search algorithms are largely applied to the production optimization in manufacturing, including wood production systems.

The following is a discussion of some of the widely-explored search algorithms for supporting smart optimal production processes in sawmills.

### 1) STOCHASTIC APPROACHES

A great deal of attention has been paid to stochastic approaches in recent years as a result of their extensive theoretical and practical applications in industrial manufacturing. In particular, stochastic optimization is the process of optimizing the value of a mathematical or statistical function when some parameters are subject to randomness [133]. It can generally handle systems with a high degree of nonlinearity, dimensionality, and uncertainty in parameters, so that classical deterministic model-based methods cannot address them efficiently [87].

Stochastic approaches are especially relevant when different sources of uncertainty are present in the input data of decision-making processes (such as demand, raw material and product prices, and raw material quality). Although there are some deterministic robust approaches for accommodating uncertainty in sawmill production system models [9], [24] (where solutions are robust if input data varies slightly within predefined ranges), most relevant research uses stochastic algorithms where uncertain coefficients are represented by random variables with a probability distribution. For instance, the stochastic characteristics of logs are taken into account in a group of studies using multi-stage stochastic programming [8], [15], [87], [120]. To develop production scenarios based on log attributes such as length and diameter, studies in [124] and [125] use discrete-event simulations. Another application of stochastic optimization is developed in [15] for addressing multi-period, multi-product production planning under uncertainty in the products' demands and the quality of raw materials. The authors describe demand uncertainty as a dynamic stochastic data process, while raw material quality uncertainty is defined as scenarios with stationary probabilities. Using a sawmill production planning scenario as a case study, the authors demonstrate that the stochastic approach can produce near-optimal results while being computationally efficient. The study in [120] takes into account non-homogeneous characteristics of logs by modeling random yields as scenarios with discrete probability distributions. A two-stage stochastic programming model is proposed to solve this sawmill operation optimization problem. In this example, by considering a moderate number of scenarios

among the huge number of possible scenarios for random yields, the authors obtained an acceptable optimality gap, less than 1% of the actual optimal value, within a short calculation time. In a different work, the study in [8] considers short-term uncertainty in the supply of raw materials, such as when harvesting is not in sync with demand or when logistics considerations and transportation schedules cause changes to harvesting. Hence, only an estimate can be made as to how many and what types of logs can be collected. This work then establishes an interesting coordination between different planning decisions in a sawmill using a two-stage stochastic optimization formulation with the aim of satisfying demands at the lowest possible cost. Logs and lumbers inventories, raw material purchase and production capacities, and number of working hours are further considered in this work.

Stochastic models are further used to address another common source of uncertainty involved in predicting final demands [15], [41], [121], [122]. In [122], a stochastic model with random yields and a monthly planning horizon is solved with accelerated scenario. The prices of raw materials, finished products, and energy can be considered as other important factors influenced by uncertainty, which are often modeled through stochastic approaches and scenario analyses [123].

Stochastic approaches are successfully employed to analyze technical efficiency of some real sawmills in [134], [135], and [136] using statistical analysis techniques. The works in [134] and [135] treat sawmills as a single output production system with lumbers as their sole product, while the study in [136] incorporates multiple-output nature of sawmills by considering both lumbers and wood chips as output products. These studies in [134], [135], and [136] report interesting analyses of technical inefficiencies in production processes of small and medium-scale sawmills, and stressing potential improvements in their performance by increasing capacity utilization and optimal use of raw materials, meeting governmental policies of forest resource conservation, and preventing environmental degradation and desertification.

Another use of stochastic approaches are developed in [91] and [119] for optimal sorting of lumbers into different moisture content groups before drying stage in kilns. Both studies argue that lumber sorting optimization in sawmills can reduce the drying time to a considerable extent and avoid lumbers' over-drying or under-drying which negatively affect lumbers grade recovery.

A comprehensive comparison between the performance of stochastic and deterministic production planning models in sawmills is presented in [66]. In this comparison, system performance is evaluated both with and without uncertainty considerations. Under different combinations of planning horizon, re-planning frequency, and average and variation of demand, the authors present a decision framework guiding managers to choose between deterministic and stochastic approaches considering backorder and inventory costs as key performance indicators.

Even though literature reports interesting applications of stochastic approaches in supporting sawmill decision-making processes within uncertain environments, a wide range of scenarios can be expected for process yields in these systems due to the variety of decisions during multiple processing stages [120]. This therefore leads to the important questions of how to handle random scenarios for real-world applications and how to efficiently estimate the probability distribution of different uncertain parameters while still preserving the obtained solutions reasonably close to optimal values. Despite the availability of theoretical methods, there have been very few practical applications of stochastic approaches dealing with uncertainty of wood production systems. Thus, research on these topics should be expanded through industrial validations in the future.

## 2) HEURISTIC AND METAHEURISTIC APPROACHES

Heuristic and metaheuristic approaches attempt to find reasonably fast solutions for optimization problems, however, without a clear indication at the outset on when they may succeed or fail, and without any guarantee if the solution returned is optimal [137]. Nevertheless, knowing some information on previous processes and ranking alternatives in search algorithms usually allow heuristics and metaheuristics to find "good" approximate solutions in an acceptable computing time without having to exhaustively search every possible solution [62]. Whereas heuristics are problem-dependent algorithms for specific given problems, metaheuristics do not require particular knowledge on specific problems to be solved, so that they can be considered as general problem-solving frameworks for a broad range of problems [138]. For real-world complex systems with numerous decision variables, a great deal of data, and nonlinear models, both heuristics and metaheuristics are very attractive for providing fast, feasible, near-optimal, and inexpensive (due to their low memory requirement) solutions [127]. Hence, the use of these approaches is very popular for supporting fast decisions in manufacturing planning.

In wood production industry, heuristics and metaheuristics are mainly used for addressing complex large-scale sawing problems wherein the use of exact methods or exhaustive search algorithms can be very time-consuming [7], [16].

Regarding heuristics, an interesting relevant effort is made in [122] on a realistic large-scale sawing problem. This study models the sawing problem as a multi-stage stochastic mixed-integer optimization problem with uncertainty in raw material quality and product demand. Solving this problem efficiently within a reasonable time frame is generally not possible for existing commercial solvers. Hence, the authors develop a heuristic approach to tackle this problem by considering a subset of scenarios at each iteration rather than considering all possible scenarios. Using a scenario selection rule and a scenario updating method, this work enhances the convergence rate of the algorithm and the quality of the



approximate solution for the sawing problem significantly. The study in [7] uses a heuristic approach to solve the sawing problem defined as packing of rectangles into a circular container. The proposed heuristic is based on two stages. First, it makes a list by sorting product orders as rectangular lumbers in terms of their width and height. Second, the established list is used to construct a feasible solution, adding rectangles constructively to the circular log until the list is empty, or until no further rectangles can be added. The authors argue that the heuristic method is favorable for large-scale sawing problems with reference to computation time and sawing recovery loss. This study, however, does not consider any product value recovery. An analysis of the results obtained from the implementation of a heuristic approach and a DP algorithm for sawing problems in [16] shows that heuristic approaches can more efficiently handle complex constraints in sawing problems, such as log grade sawing operations, in comparison to deterministic approaches. This work develops a heuristic approach for the sawing problem, and reports that this approach can determine opening face and near-optimal grade sawing patterns in a reasonable computing time while no significant difference is observed in obtained mean lumber values between heuristic and the DR approach. A further comparison and evaluation of the quality of solutions obtained from a heuristic and a deterministic mathematical model formulated as an MILP problem in scheduling and production planning of a real sawmill is provided in [128]. As compared to the study in [16], the study in [128] takes a broader perspective, taking into account not only raw material costs, but also inventory and backlog costs. Considering these three cost factors, the authors argue that the deterministic model outperforms the heuristic approach in terms of solution optimality and computational complexity, especially for high product demand close to the production capacity. However, this work does not report any evaluation on whether these results are valid for more complicated scenarios with many constraints, such as grade sawing.

In another group of studies, the use of metaheuristic approaches are investigated to address production planning problems in sawmills. An interesting attempt to solve a complex sawing problem with multiple objectives and a variety of realistic constraints is presented in [62]. This work considers different types of raw materials and final products. It aims to minimize excess production and raw material waste within an operative time constraint while meeting demand and preferably using stored raw materials in the warehouse. In this case, the optimization problem is formulated as a multi-objective MINLP problem for which an efficient exact solution method is not available. Hence, this problem is solved using the well-known scatter search metaheuristic. The method is evaluated through a realistic case study and is shown to be efficient in addressing the defined objectives and constraints within a required deadline. In [112], two different approaches with the integration of two metaheuristic algorithms are formed for maximizing the volume yield of

logs during the operational planning of a sawmill. According to the authors' report, even the worst average computation time was less than two minutes for this approach applied to different scenarios, which is fast enough for a computer tool to facilitate daily sawmill operations. In addition, metaheuristic approaches enhance the integration of traditionally isolated stages in sawmill operations. For example, in [43], a metaheuristic algorithm is used to combine the primary sawing and ripping stage of logs while minimizing the cost of production and satisfying demand.

A comparison between the performance of a heuristic approach and a metaheuristic approach in addressing a large-scale nonlinear sawing problem is presented in [7]. The metaheuristic approach, which is based on the well-known simulated annealing concept, employs a construction function to generate geometrically feasible solutions while searching within the space of feasible solutions to yield results for the packing of rectangles into containers of various shapes. The heuristic approach, on the other hand, sorts the product orders based on their dimensions, and accordingly, fits the rectangles constructively inside the circular container. According to this work, both methods provide complementary computational results. However, when dealing with smaller problems, the metaheuristic approach provides better results. For larger problems, both approaches are almost equally effective. There are, however, significant differences in computation time depending on the problem scale, namely, the metaheuristic approach requires a long computation time when addressing large-scale problems, which makes the heuristic approach more suitable in such cases. Instead, the study in [112] shows that the sawmill operation planning can be significantly improved by combining metaheuristics and heuristics when selecting logs and generating sawing patterns. Another combination of heuristics and metaheuristics is further developed in [81], which examines the problem of drying lumbers in conventional kilns under real-world conditions. Accordingly, the heuristic approach solves scheduling and loading problems by calculating lumber packages' positions, times, and kilns. The solution of the heuristic is further improved by a metaheuristic, thereby minimizing the overall tardiness of dried lumber packages by optimal scheduling and loading of dry kilns.

In summary, considering the large number of possible scenarios to be incorporated in different stages of sawmills' decision making processes, for example, generated sawing patterns in sawing problems, it is of utmost importance to further study the interesting features of heuristics and metaheuristics in tackling large-scale sawmill production optimization problems to reach efficient solutions within a reasonable time frame. However, due to the fact that such approaches cannot guarantee that the optimal solution will be found, and the time required for finding a good near-optimal solution can be lengthy in an unfortunate circumstance, further research should focus on developing efficient algorithms that remain reliable in terms of optimality and computational

efficiency while taking into account complex contributing factors in real-world industrial systems.

### C. ARTIFICIAL INTELLIGENCE APPROACHES

Recent years have witnessed a significant migration from conventional model-based mathematical programming and search algorithms towards artificial intelligence and in particular, learning-based approaches for decision and control targets in smart manufacturing systems [139]. This tendency stems from the need for intelligent solutions and near real-time decisions that can flexibly address the increasing complexity of modern manufacturing processes in dynamic and uncertain industrial environment [140]. In fact, intelligent learning algorithms can predict new output values by learning from historical data using data-driven models, and can make use of this strategy to improve systems performance [35].

In large-scale manufacturing systems, analyzing and managing a large amount of data generated by new technologies, such as internet-of-things and advanced metering infrastructures, can be very challenging. These challenges can be addressed by artificial intelligence technologies thanks to their ability for developing computer programs to perform a variety of tasks, and to simulate the intelligent way of problem solving [139].

Despite the fact that artificial intelligence approaches can be very useful for automating and semi-automating systems supporting decision-making in sawmills, the related literature regarding their use in the sawmill operation optimization seems relatively sparse compared to the other discussed approaches.

A short review on the application of artificial intelligence in the optimization of sawmill operation planning appears in [22]. However, the review mainly focuses on supply chain logistics and transportation. According to another literature review in [140], data analysis and learning-based approaches will be the core of Industry 4.0 applications for increasing the productivity of future smart sawmill production systems.

Most often, artificial intelligence technologies are used in conjunction with simulation tools in the relevant context. An example of this strategy is presented in [67], where the authors develop four machine learning algorithms to train the model of a sawmill simulator to simplify data computation of the sawing problem for converting logs into lumbers. The study in [68] focuses on generating metamodels for sawing simulation using machine learning algorithms. This work uses some problem-specific metrics and traditional machine learning metrics to evaluate the fitted metamodels which can compliment the sawing simulator. By incorporating machine learning within simulators, studies in [69] and [70] propose the use of neural network models to simplify and accelerate the simulation of sawmill operation planning problems. Based on the results presented by these studies, the proposed integration strategies can increase efficiency and reduce computational complexity of the decision-making simulations.

There have been significant recent explorations of using artificial intelligence in log quality evaluation and defect detection along with advanced scanning and image processing systems to achieve an efficient grade sawing. For example, the authors in [113] demonstrate that neural networks can automatically classify and locate wood surface knots faster, more accurately, and more reliably compared to conventional slow and expensive methods. Another similar study presented in [114] focuses on automated wood defect detection to optimize operation of sawmills and find effective log processing solutions. In this study, a machine learning technique is used to develop a high precision and fast method for detecting the types of defects in logs even with a very small amount of initial data from CT images. This allows improvement of existing software applications for scanning-based grade sawing.

To summarize, artificial intelligence approaches allow for intelligent analysis of data, enabling online decisions and predicting phenomena that are difficult to model with conventional approaches [139]. Hence, artificial intelligence algorithms can be used very effectively to manage complex systems with uncertainty and material variability, as they are widely used in manufacturing optimization under uncertain industrial conditions [35]. In spite of this, there have been no significant contributions in literature to the use of artificial intelligence approaches for tackling uncertainty in sawmill operation planning. Moreover, recent technological advancements on the Internet of Things (IoT), digital sensing, and big data analytics can enable wood production processes to employ advanced techniques already used in other smart manufacturing sectors, such as interactive data analysis based on data collection and real-time analysis to guide the subsequent data collection steps [141], dynamic feature extraction/selection-based algorithms to identify the most important features/operations in production data [142], and big data quality improvement by suppressing noisy features and managing issues related to data collection, data security, data transformation, and storage [143]. Nevertheless, in artificial intelligence and data analytics, it is imperative to practice and test on real systems, as well as to collect training data in sufficient quantities and of high quality. Although real-world implementation and data analysis are vital for validating complex problems with numerous variables and nonlinearities, yet only a limited number of practical sawmill decision support systems have been implemented through artificial intelligence approaches.

### IV. USE CASES

In this section, we discuss two use cases from literature to illustrate how to model and implement different decision-making processes in real sawmill production systems. These examples can help readers to gain a clearer understanding of how the optimization approaches and automation systems discussed relate to their modelling and applications. Each case is examined for its objectives, constraints, methodologies, and evaluation results.



sets and combinatorial properties of the problem enforce non-linearity and computational complexity. This work defines the sawing problem as arranging rectangles into a circular container in two dimensions (see Fig. 9). The study focuses on an *economic profit* objective (see the objective function defined in (3)) along with *technical feasibility* constraints (see the dimensional and geometric constraints defined in (4)-(11)). More precisely, the aim is to pack a subset of rectangular lumbers into a circular cross-section of a log while maximizing the total cutting yield. Given that  $\mathcal{N} \triangleq \{1, \dots, n, \dots, N\}$  is the set of lumbers where  $N$  is the total number of lumbers that can be selected, the  $N$ -dimensional vector  $\mathbf{p} \triangleq (p_1, \dots, p_i, \dots, p_N)^\top$  represents the selection of lumbers for consideration in the optimal sawing pattern. Then, the model is described by a MINLP as follows:

$$\max_{\mathbf{p}} \sum_{i=1}^N L_i W_i p_i \quad (3)$$

$$\text{subject to: } (v_{ix}^l, v_{iy}^l) = (c_{ix} - L_i/2, c_{iy} - W_i/2), \quad \forall i \in \mathcal{N} \quad (4)$$

$$(v_{ix}^r, v_{iy}^r) = (c_{ix} + L_i/2, c_{iy} - W_i/2), \quad \forall i \in \mathcal{N} \quad (5)$$

$$(v_{ix}^{ul}, v_{iy}^{ul}) = (c_{ix} - L_i/2, c_{iy} + W_i/2), \quad \forall i \in \mathcal{N} \quad (6)$$

$$(v_{ix}^{ur}, v_{iy}^{ur}) = (c_{ix} + L_i/2, c_{iy} + W_i/2), \quad \forall i \in \mathcal{N} \quad (7)$$

$$(v_{ix}^k - X_0)^2 + (v_{iy}^k - Y_0)^2 \leq R_0^2 p_i, \quad \forall i \in \mathcal{N}, \forall k \in \{ll, lr, ul, ur\} \quad (8)$$

$$\left\{ \begin{array}{l} (L_i/2 + L_j/2)p_i p_j - |c_{ix} - c_{jx}| \leq 0, \\ \quad \forall i, j \in \mathcal{N}, i \neq j \\ \text{or} \\ (W_i/2 + W_j/2)p_i p_j - |c_{iy} - c_{jy}| \leq 0, \\ \quad \forall i, j \in \mathcal{N}, i \neq j \end{array} \right. \quad (9)$$

$$p_i \in \{0, 1\}, \quad \forall i \in \mathcal{N} \quad (10)$$

$$X_0, Y_0 \geq R_0, \quad (11)$$

where  $L_i$  and  $W_i$  are respectively the length and the width of the  $i$ th rectangular lumber,  $R_0$  is the radius of the log's circular cross-section,  $(X_0, Y_0)$  are the coordinates of the center of the log's circular cross-section,  $(c_{ix}, c_{iy})$  are the coordinates of the gravity center of the  $i$ th rectangular lumber, and  $(v_{ix}^k, v_{iy}^k)$  for  $\forall k \in \{ll, lr, ul, ur\}$  is the index set of four vertices of the  $i$ th rectangular lumber. The formulation defines  $f_{ep}(\mathbf{p}) = \sum_{i=1}^N L_i W_i p_i$  as an economic objective function, while there are geometrical linear equality constraints (4)-(7) for the definition of vertices, and nonlinear inequality constraints (8) and (9) as technical feasibility constraints (see Section II-C). By introducing new binary variables ( $z_{ij}$ ) and a large positive number ( $M$ ), the conditional "or" constraint (9) can be converted into the following simpler equivalent constraints:

$$|c_{ix} - c_{jx}| + (L_i/2 + L_j/2)p_i p_j \leq M z_{ij},$$

$$\forall i, j \in \mathcal{N}, i \neq j, z_{ij} = 0, 1 \quad (12)$$

$$|c_{iy} - c_{jy}| + (W_i/2 + W_j/2)p_i p_j \leq M(1 - z_{ij}),$$

$$\forall i, j \in \mathcal{N}, i \neq j, z_{ij} = 0, 1 \quad (13)$$

The main computational difficulty of this problem arises from the satisfaction of the nonlinear constraints. To solve this optimization problem, three methods are presented and compared, one using *model-based mathematical programming* discussed in Section III-A (by a NLP model) and two using *search algorithms* discussed in Section III-B (a heuristic algorithm named ordering heuristic, and a metaheuristic algorithm called simulated annealing). The ordering heuristic method involves sorting lumber in decreasing order by dimension, and then, fitting rectangles constructively inside circular containers until the list is empty or there is no more room to pack the following rectangle. Instead, the simulated annealing is a useful metaheuristic for finding global optimum in an extensive search space with many local optima. A variety of lumber sets were used in this study to evaluate the performance of these three methods.

On the one hand, it was shown by the exact model that a yield of about 70% of the log area can be achieved in a reasonable time (471s) when there are only eight lumbers. However, when the number of lumbers is increased to nine, the method fails to find an optimal solution within the 3600s computational time limit. This shows the limitations of the exact nonlinear model in solving large-scale problems.

On the other hand, with problems where there is a greater number of lumbers, both the ordering heuristic and the simulated annealing algorithms provide solutions of similar quality with more than 90% of the total yields. As the problem size grows, however, the ordering heuristic outperforms simulated annealing in terms of computation time significantly. For example, when solving a problem with 200 lumbers and a log with a radius of 50 measuring units, the result obtained by the ordering heuristic shows a sawing yield of 96.23% in 3.20s computation time, which almost has the same sawing quality but is much faster than the result obtained by the simulated annealing with a sawing yield of 96.24% in 573.7s computation time.

## B. SAWMILL OPERATION OPTIMIZATION WITH INVENTORY/BACKORDER CONSIDERATION

A multi-product, multi-period production planning problem considering uncertainty in raw material quality and product demand is examined on a realistic scale prototype sawmill in [15].

This study examines *economic profit* objectives in terms of raw material costs as well as expected inventory and backorder costs (see the objective function defined in (14)). The problem includes *technical feasibility* constraints such as machine capacities (as in (16)) and storage limits and inventory balancing (as in (15) and (17)), as well as *customer satisfaction* constraints by defining different quality classes of raw materials in both objective (14) and constraint (15). Furthermore, the proposed model takes into account *uncertainty* in



demand and non-homogeneous characteristics of raw materials by defining a stochastic process and random variables with stationary probability distributions defined in (14) for uncertain parameters during the planning horizon.

The main objective is to reduce log consumption cost while considering inventory holding and backorder costs.

This problem is solved using *search algorithms* discussed in Section III-B by a multistage stochastic model. A dynamic stochastic process presented as a scenario tree is used to model the uncertain demand, while a static random variable with a stationary probability distribution is used to model the uncertain yield. The work considers the production plan, inventory, and backorder sizes as decision variables of the problem. The multi-stage stochastic programming problem is then formulated as:

$$\begin{aligned} \min \sum_{n \in \mathcal{T}} P(n) & \left( \sum_{t \in t_n} \sum_{c \in C} \sum_{a \in A} M_{ct} \phi_{ac} e_{at}(n) \right) \\ & + \sum_{n \in \mathcal{T}} P(n) \left( \sum_{i=1}^S P^i \left( \sum_{t \in t_n} \sum_{p \in P} (H_{pt} z_{pt}^i(n) + B_{pt} b_{pt}^i(n)) \right) \right) \end{aligned} \quad (14)$$

$$\text{subject to: } z_{ct}(n) = z_{ct-1}(m) + s_{ct} - \sum_{a \in A} \phi_{ac} e_{at}(n),$$

$$\begin{aligned} n \in \mathcal{T}, \quad t \in t_n, \quad c \in C, \\ m = \begin{cases} a(n), & t-1 \notin t_n \\ n, & t-1 \in t_n \end{cases} \end{aligned} \quad (15)$$

$$\sum_{a \in A} \delta_{ar} e_{at}(n) \leq Q_r, \quad n \in \mathcal{T}, \quad t \in t_n, \quad r \in R \quad (16)$$

$$\begin{aligned} z_{pt}^i(n) - b_{pt}^i(n) &= z_{pt-1}^i(m) - b_{pt-1}^i(m) \\ &+ \sum_{a \in A} \rho_{ap}^i e_{at}(n) - d_{pt}(n), \quad n \in \mathcal{T}, \quad t \in t_n, \\ p \in P, \quad i &= 1, \dots, S, \\ m &= \begin{cases} a(n), & t-1 \notin t_n \\ n, & t-1 \in t_n \end{cases} \end{aligned} \quad (17)$$

$$\begin{aligned} e_{at}(n) \geq 0, \quad z_{ct}(n) \geq 0, \quad z_{pt}^i(n) \geq 0, \quad b_{pt}^i(n) \geq 0, \\ n \in \mathcal{T}, \quad t \in t_n, \quad c \in C, \quad p \in P, \quad a \in A, \\ i = 1, \dots, S, \end{aligned} \quad (18)$$

where the decision variables  $e_a(n)$ ,  $z_p(n)$ ,  $z_c(n)$ , and  $b_p(n)$  represent the number of times each process  $a$  should be run, inventory size of product  $p$ , inventory size of raw material with the quality class  $c$ , and backorder size of product  $p$ , respectively. The indices  $S$ ,  $i$ ,  $(n, m)$ ,  $t$ ,  $p$ ,  $c$ ,  $a$ ,  $r$  respectively denote the total number of scenarios, scenario of the random yield, node of the scenario tree, time period, product, raw material class, production process, and machine. Set  $\mathcal{T}$  represents the scenario tree and  $d_p(n)$ ,  $P(n)$ ,  $P^i$ ,  $M_r$ , and  $\delta_a$  are the parameters related to demand of product  $p$ , probability of node  $n$ , and probability of scenario  $i$  for the random yield, the capacity of machine  $r$ , and the capacity consumption of machine  $r$  by process  $a$ , respectively.

In the objective function (14), the first term addresses the expected raw material costs for demand nodes, and the second term represents the expected inventory and backorder costs for demand nodes and yield scenarios within the planning horizon. In models (14)-(18), the decision variables including production plans (i.e.,  $e_a(n)$ ) and state variables of inventory and backorders (i.e.,  $z_p(n)$ ,  $z_c(n)$ , and  $b_p(n)$ ) are indexed both for nodes and for time periods.

It is assumed that at each stage of the demand scenario tree, the decision-maker is capable of adjusting the production plan  $e_a(n)$  to maximize the sawmill profitability. The presented numerical results indicate that the multi-stage stochastic model provides better solutions than other methods compared, including a deterministic model which neglects the uncertainty in processes yields and products demands. For instance, based on the results provided by the presented method, production costs and inventory/backorder costs are nearly 30% and 70% lower than those from a mean-value linear programming method. However, this method requires a significantly longer computation time than the other methods compared (almost 29% more than the time for mean-value linear programming method), so an improvement strategy in terms of computational complexity is necessary.

In summary, considering the importance of yields and demands variations on production plans, as well as customer orientation, which is a priority in sawmills that rely on export markets, obtaining production plans with a minimal inventory and backorder sizes can benefit sawmills significantly.

## V. DISCUSSIONS, CONCLUSION AND RECOMMENDATIONS

In this paper, we presented a comprehensive survey of existing studies on automated decision-making in wood processing systems. This review started from identifying how the automatization of production processes and development of automated decision support systems can bring potential benefits to sawmills and the forest supply chain as a whole. We then discussed the most-identified challenges and roadblocks ahead of this automatization. In the next step, we focused on methodological aspects of designing and implementing advanced control and optimization techniques for the realization of automated decision support systems throughout different steps of wood processing to achieve potential opportunities and tackle corresponding challenges, resulting in efficient production in sawmills.

Although we highlighted some specific outcomes and research directions within each subsection of Sections II and III, the following paragraph summarize some more general conclusions and insights that emerged from this review in terms of potential opportunities, challenges, and methodological aspects considering the current state and future research directions.

### A. CURRENT STATE

Considering the papers reviewed, the following can be summarized as the current state of progress in the research topic:

- Regarding potential *opportunities* identified as a result of implementing automated decision-making systems in the wood production process, three main aspects were recognized in the selected papers, namely economic profits, technical achievements, as well as environmental incentives and penalty avoidance. Among the total papers reviewed, 58% focus on economic profits, which is noticeably higher than papers discussing technical achievements and environmental incentives/penalty avoidance, which account for 27% and 15% of the total papers reviewed respectively. On the one hand, these results can demonstrate that economic factors are the primary motivation for the automation of manufacturing processes, as this aspect has also been the main objective of the earliest related works in this area dating back to the 60s. In this regard, a major emphasis of research has been on production efficiency improvement through improved output product yields (36% of all related papers), however, energy efficiency and space saving have also been other important research areas contributing to upgrading economic profits in sawmills through developing automated decision-making systems. On the other hand, these results can further reveal gaps in research for the other two aspects, in particular, environmental incentives and penalty avoidance. This is while legal controls and measures for preventing industries from negatively impacting the environment is increasing rapidly. In light of the direct use of forest resources in wood production, as well as the use of energy-intensive and polluting machinery and drying kilns, sawmills are increasingly regulated and supervised by governments. So far, however, environmental goals have seldom been examined as an independent objective at the sawmill level when it comes to designing automated decision-making strategies.
- As for *challenges* in the automation of sawmills' production processes, four major aspects were recognized in the literature, namely financial limitations, technical challenges, customer satisfaction, and uncertainty. Among them, technical challenges are by far the most popular topic, accounting for 54% of the total number of related papers reviewed. This popularity is due to the critical importance of processing speed and response accuracy in advanced automated wood processing systems for providing more flexible operations with a better control of raw materials and finished products. The next highly-explored challenge in the literature is dealing with financial limitations that include initial investment costs for upgrading machinery and equipment, as well as operating and maintenance costs. There are, however, other expected costs that have not been taken into account in most of the papers reviewed. For instance, a rise in energy rates can directly affect the final price of most automated machines and equipment powered by electricity. The process of tracking these costs requires updating revenue projections and calculations over time, which involves a deeper understanding and more investigation on the entire production process. In addition, although significant studies report that wood product manufacturers broadly face the challenge of making decisions on the basis of unreliable or incomplete information, it is surprising that only about 11% of papers reviewed address the challenge of uncertainty in production system parameters and decision-making models, when compared to technical challenges and financial limitations. Finally, there has been relatively little attention paid to the customer satisfaction aspect. As the wood industry faces a competitive market, sawmills are concerned about keeping and even strengthening their customer-centric environment as part of their processing renovation. Hence, it is necessary to ensure that sawmill operations planning can be automated while maintaining a high level of services with low order lead time and being efficient with respect to the company's financial targets.
- Regarding *methodologies* for facing various decisions over several interrelated steps to transform raw materials into finished goods and deliver them to customers or distribution centers, three major categories of methods were identified, namely model-based mathematical programming, search algorithms, and artificial intelligence. These methods are typically chosen according to types of decisions, problem sizes, and the level of solution speed and accuracy required. Although recent studies are increasingly focusing on fast search algorithms or artificial intelligence techniques due to concerns regarding the complexity of advanced production systems and memory limitations, deterministic model-based mathematical programming methods -with 62% of the total number of papers reviewed- still remain a prominent class of approaches for addressing decision-making problems in sawmills. On this line, dynamic programming (DP) is the most-widely used model-based mathematical programming method which has commonly applied to sawing and bucking operations optimization. The DP algorithms, however, require a large memory to store the results of each sub-problem due to the fact that they use stored sub-solutions in order to be faster in computation. Therefore, their use in large-scale sawmills could be costly and challenging, especially if parallel computing is intended. In the situation that can arise in optimizing the decision-making performance of a sawmill, especially if the scale of the problem is large, problem solving speed is a critical requirement. Many studies have concluded that stochastic, heuristic, and metaheuristic search algorithms can be very helpful in such situations, in particular when multiple complex objectives need to be tackled (see Table 2). Last but not least, artificial intelligence has been used in another class of approaches for analyzing data and enabling online decisions in sawmill operation planning. Nevertheless, artificial intelligence has so far been a

very small contributor to the wood processing automation, accounting for only 9% of all methods reviewed. Additionally, although artificial intelligence algorithms are often capable of managing complex systems with uncertainty and material variability, there have been no significant contributions to literature describing their application to uncertainty management in sawmill operation planning. On the other hand, a large number of studies and review papers discussed that for validating the effectiveness of the designed approaches for complex problems with numerous variables and nonlinearities, practice and testing on real systems, collecting sufficient quantities and high-quality data, and evaluating decision support system performance by real-world implementations are crucial. There are, however, only a few available practical implementation of approaches for sawmill decision support systems. In fact, despite the existence of some small-scale practical tests, the number of successful large-scale industry applications is still rare in the literature.

### B. FUTURE RESEARCH DIRECTIONS

There are still other important and challenging research topics which have not received much attention yet. The following are some of the future research directions briefly summarized:

- Even though there are a large number of relevant studies supporting automated decision-making in sawmills, most of them only focus on improving a sole aspect such as economic profits from improved sawing yields. Although sawing is a very important stage over wood processing, future studies should also incorporate other potential opportunities to increase overall sawmill profitability, in particular energy aspects and environmental-friendly production. Sawmills may be able to widely integrate energy-efficient pre-processing, processing, and kiln drying methods into automated decision-making systems to reduce energy consumption costs and degree of unwanted carbon dioxide emission, while developing the use of renewable energy resources for their internal energy uses. In fact, a well-designed decision planning can result in benefits overlapping from different categories of opportunities. The sawmill industry is therefore encouraged to identify its potential development paths to maximize its profitability on all levels, including the economic, technical, and environmental perspectives. However, seeking a greater number of opportunities requires a consideration of multiple objectives and corresponding constraints, which can lead to a significant increase in the size and complexity of the decision-making problems, requiring more advanced control and optimization strategies. A thorough examination of these aspects needs to be conducted in future research.
- As one of the most challenging aspects of wood processing, random characteristics of raw materials impose

significant uncertainty into the wood processing problem. Having more detailed and accurate information on logs' characteristics is essential for eliminating this uncertainty from the model and contributing to more efficient production performance and higher production yields. Hence, a timely topic for future research should be the development of advanced scanning systems (such as CT and MRI scanners), smart sensors, new information and communication systems, and computer processing and image analysis with specific application to wood processing systems.

- Although advanced scanning systems offer obvious advantages to sawing decisions, evaluating the potential productivity increase before investing in these high-cost technologies is necessary (economic evaluations of the purchase of scanners versus possible returned yields). In fact, as many sawmills operate as independent small and medium-sized businesses, moving towards advanced scanning systems can be challenging to them due to their high initial costs, long payback periods, and the need for significant modifications to current operations. To survive in the highly competitive wood marketplace under current turbulent economic conditions, more economic alternative solutions should be also explored to allow smaller production companies to take advantage of economic opportunities. An example of such methods is the use of online optimization and control approaches which can observe the condition of the log after each cut and dynamically update the sawing model without having knowledge of the logs' internal characteristics in advance. Another relevant alternative method could be to separate the sawing phases, so that there is no internal scanning at the primary sawing phase, and internal defect scanning is only applied to the secondary sawing phase by simpler scanning systems. Nevertheless, each of these methods may have its own limitations including control complexity, high computation time, and the need for appropriate sawing equipment. So far, existing studies do not provide comprehensive and effective solutions to address these issues. These gaps in research should therefore be filled by future studies.
- Whereas some decision-making problems such as transportation and routing optimization, and energy scheduling are frequently formulated by model-based mathematical programming in the form of continuous and integer linear programming problems, more complex problems such as quality-based grade sawing and kiln drying optimization with numerous decision variables, a great deal of data, and nonlinear models can be more efficiently addressed through search algorithms since the use of exact methods can be very time-consuming or even intractable. Nevertheless, when a multi-objective decision-making problem is intended across different stages of a sawmill in which different forms of objectives and constraints may exist, multi-stage approaches and the combined use of deterministic

and search algorithms may offer the most efficient solution quality and speed. There is still much to be learned about the ability of these methods to deal with large real-world challenges in the future.

- Since sawing optimization is the primary objective for improving sawmill operation planning, an emphasis should be placed on further improving physical modelling of logs and the sawing algorithms performance. The following are some future improvement directions that have not been sufficiently addressed so far: 1) enhancing logs' model accuracy by using more realistic cross-sections in three-dimensional log modelling such as elliptical instead of circular cross-sections, 2) developing length and taper sawing optimization throughout the trunk for various grades, 3) producing lumbers with different dimensions and irregular shapes (not just the cubic lumbers) to satisfy a wider range of customers from different dependent industries, and 4) extending efficient approaches for accommodating different sources of uncertainty such as various defect sizes and types, irregularity in log shapes, and variable products demand in the system modelling.

In summary, the presented review and discussion on the current state and the future directions of research can provide a foundation for researchers and practitioners to further explore the topic.

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**SEYED MOHSEN HOSSEINI** (Member, IEEE) received the Ph.D. degree in electrical and information engineering from the Polytechnic University of Bari, Bari, Italy, in 2021. From September 2019 to March 2020, he was a Visiting Ph.D. Student with the Department of Electrical and Electronic Engineering, The University of Manchester, Manchester, U.K. From 2021 to January 2022, he was a Research Fellow with the Decision and Control Laboratory, Polytechnic University of Bari. He is currently an Assistant Professor with the Faculty of Science and Technology, Free University of Bozen-Bolzano, Bolzano, Italy. His research interests include modeling, optimization, and control of complex automation systems, distributed, decentralized, and robust control algorithms.



**ANGELIKA PEER** (Member, IEEE) was born in Brunico, Italy. She received the Diploma Engineering degree in electrical engineering and information technology and the Doctor of Engineering degree from the Technical University of Munich, Germany, in 2004 and 2008, respectively. She has been a Full Professor at the Free University of Bozen-Bolzano, Italy, since November 2017. From 2014 to 2017, she was Full Professor at the Bristol Robotics Laboratory, University of the West of England, Bristol, U.K., and before that, she was a Senior Researcher and a Lecturer at the Institute of Automatic Control Engineering and a TUM-IAS Junior Fellow of the Institute of Advanced Studies, Technical University of Munich.

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