Flow shop scheduling of multi phase plywood production with parallel machines

Samuli Mäkinen

School of Science

Thesis submitted for examination for the degree of Master of Science in Technology. The document can be stored and made available to the public on the open internet pages of Aalto University.

Espoo 29.12.2019

Supervisor

Prof. Antti Punkka

Advisors

Dr Anssi Käki

MSc Heikki Kujala

Aalto University
School of Science

Aalto University
School of Science

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi
Abstract of the master's thesis

Author Samuli Mäkinen

Title Flow shop scheduling of multi phase plywood production with parallel machines

Degree programme Mathematics and Operations Research

Major Systems and Operations Research **Code of major** SCI3055

Supervisor Prof. Antti Punkka

Advisors Dr Anssi Käki, MSc Heikki Kujala

Date 29.12.2019 **Number of pages** 51+4 **Language** English

Abstract

Plywood production scheduling is a difficult and time consuming task as multiple orders, different machines and material usage have to be simultaneously taken into account. The problem is particularly very difficult on resources that have sequence dependent setup times like on bonding and coating machines. Those two are also the resources that dictate the schedules on other machines and therefore they are usually scheduled first.

In this Thesis, a mixed integer linear program is formulated for solving the scheduling problem of bonding and coating machines. The purpose of the model is to make a good schedule in terms of setup times, selected operations and waiting time in an intermediate storage. The model has to be solved fast enough to be useful in a daily work of production planners. In the Thesis, different approaches to make the scheduling faster are introduced and studied in terms of a solution time and a goodness of the solution using two example cases. Later a real-world implementation of the scheduling model that is solved using a commercial optimization solver is introduced and its usefulness is evaluated based on end users feedback. The results from the example cases and user interviews show that the model is able to produce useful schedules and make the daily planning work of the production planners easier.

Even though scheduling has recently been widely studied in the literature, production scheduling in plywood industry has received very little attention. However, in related industries such as paper production, there are multiple studies in different problem setups. This thesis tries to reduce this gap in the literature by presenting a mixed integer linear programming based approach to solve the plywood scheduling problem.

Keywords Optimization, MILP, Scheduling

Aalto University
School of Science

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi
Diplomityön tiivistelmä

Tekijä Samuli Mäkinen

Työn nimi Flow shop skedulointi vanerituotannossa rinnakkaisilla tuotantoasemilla

Koulutusohjelma Matematiikka ja Systeemitieteet

Pääaine Systeemi- ja operaatiotutkimus **Pääaineen koodi** SCI3055

Työn valvoja Prof. Antti Punkka

Työn ohjaaja TkT Anssi Käki, MSc Heikki Kujala

Päivämäärä 29.12.2019 **Sivumäärä** 51+4 **Kieli** Englanti

Tiivistelmä

Vanerituotannon aikataulutus on haastava ja aikaa vievä tehtävä johtuen työstövaiheista eri laitteilla, materiaalien käytöstä ja suuresta määrästä tilauksia, jotka kaikki tulee ottaa samanaikaisesti huomioon. Tehtävä on vaikea erityisesti laitteilla, joissa on järjestyksestä riippuva vaihtoaika, kuten ladonta- ja pinnoituslaitteilla. Nämä kaksi laitetta ohjaavat aikataulutuksen myös muilla laitteilla ja siksi aikataulu niillä suunnitellaan yleensä ensin.

Tässä työssä formuloidaan lineaarinen sekalukuoptimointimalli aikataulutusongelman ratkaisemiseksi ladonta- ja pinnoituslaitteilla. Mallin tavoitteina on luoda hyvä aikataulutus vaihtoaikojen, valittujen operaatioiden ja välivarastossa kuluvan odotusajan suhteen. Mallin tulee luoda tuotantoaikataulu niin nopeasti, että se on hyödyllinen tuotannonsuunnittelijoiden päivittäisessä työssä. Tässä työssä esitellään myös erilaisia lähestymistapoja nopeuttaa aikataulutuksen ratkaisemista, joita tutkitaan kahden esimerkkitapauksen kautta aiktaulutuksen laadun ja ratkaisunopeuden suhteen. Myöhemmin työssä esitellään käytännön toteutus aikataulutusmallista, joka ratkaistaan käyttäen kaupallista optimointiohjelmistoa. Toteutuksen hyödyllisyyttä arvioidaan loppukäyttäjiltä kerätyn palautteen perusteella. Esimerkkitapausten tulosten ja loppukäyttäjien kommenttien perusteella voidaan sanoa, että malli pystyy tuottamaan hyödyllisiä aikatauluehdotuksia ja helpottamaan päivittäistä tuotannonsuunnittelijoiden aikataulutustyötä.

Vaikka skedulointia on viime aikoina tutkittu laajasti kirjallisuudessa, tuotannon aikataulutus vaneriteollisuudessa ei ole juurikaan saanut huomiota. Esimerkiksi eri teollisuuden aloilla, kuten paperiteollisuudessa, skedulointia on tutkittu laajasti erilaisista asetelmista. Tämä työ pyrkii täydentämään kirjallisuutta esittelemällä lineaarisen sekalukuoptimointiin pohjautuvan ratkaisun vaneriaikataulutusongelman ratkaisemiseksi.

Avainsanat Optimointi, MILP, Skedulointi

Contents

Abstract 3

Abstract (in Finnish) 4

Contents 5

1 Introduction 7
1.1 Background 7
1.2 Objective and scope 8
1.3 Structure of the thesis 8

2 Background 10
2.1 Plywood production 10
2.1.1 Plywood production process 10
2.1.2 Plywood production planning at UPM 11
2.2 Scheduling in literature 12
2.2.1 Scheduling in manufacturing 12
2.2.2 Single and parallel machine models 13
2.2.3 Shop scheduling 14
2.2.4 Scheduling with setup costs 15
2.2.5 Scheduling in industry 17
2.2.6 Rolling horizon 19

3 Optimization model 21
3.1 Problem description 21
3.2 Problem formulation 23
3.2.1 Decision variables and parameters 23
3.2.2 Constraints 26
3.2.3 Objective function 32
3.2.4 Selection of multipliers in objective function 33

4 Solving approaches 34
4.1 Model splitting 35
4.2 Rolling horizon 37
4.3 Feasible solution finding 38
4.4 Early stopping 38

5 Results 40
5.1 Example case: Effect of model splitting and early stopping 40
5.2 Example case: Effect of rolling horizon, feasible solution finding and early stopping at bonding optimization 42
5.3 Real world implementation and feedback from end users 44

6 Conclusions 47

A Gurobi log of coating model with real-world data **52**

B Setup times between bonding and coating operations in first example case **54**

C Results from the first example case using different models **55**

1 Introduction

1.1 Background

UPM is a Finnish forest company that consists of six business areas: UPM Specialty Papers, UPM Raflatac, UPM Communication Papers, UPM Energy, UPM Plywood and UPM Biorefining. UPM employs globally around 19000 employees and has a turnover of 10 billion euros. In total 2400 of the employees work in the Plywood business area. The case company has a capacity to produce yearly over million cubic meters of birch and spruce plywood and veneers. The production is done in 9 mills of which 7 are located in Finland. The mills have different production capabilities and therefore also different product mixes.

The case mill in this thesis is UPM Plywood's Joensuu mill, which is specialized in highly processed products as they have special coating and machining capabilities. The mill has an annual capacity of 55 000 m^3 and it produces only birch plywood. Large share of the products from the Joensuu mill are used in the transportation industry or as an insulation components in LNG transportation ships.

Plywood production process has multiple phases and in the Joensuu mill there are multiple parallel lines for most of the phases. Therefore, many orders can be handled simultaneously and raw material availability has to be taken into account on all work stations. Orders can vary by the materials used, dimensions of the product, size of the order and by machining and coating made at the end of production chain which all add some complexity to the scheduling of the plywood production. Different orders may also require different setups at the production stations.

If consecutive orders at each production station are very similar, the setup time and costs shall be minimized. But often it is not optimal to produce only similar types of products. This is due to the raw material of the plywood; Veneers, which are glued together to form a plywood, are peeled from logs and there is quite a good estimate of the grade distribution of the obtained veneers. For each plywood there are pre-determined grade requirements given by the client. Therefore, all grades might not be used by the same distribution as veneers are obtained from the logs. This leads to problems with an intermediate veneer storage. Usually this storage is relatively small and, for example, balancing the use of surface and intermediate veneers by having an optimal average thickness of a product mix is critical for the efficiency of the mill.

The plywood production is scheduled by production planners. Because of the complexity of the process, the scheduling takes a lot of their work time and may still lead to a schedule that could be improved. Also the price of the raw material drives factories to minimize their intermediate storages in order to minimize the need to dispose veneers e.g. by burning them in energy production. Currently there is a software to help the production planners to make the schedule and ease the planning process. It also has very rough heuristics that can be used to schedule different operations. However, the base of the schedule must still be completely made by the production planners and the end result is solely dependent on the knowledge of the planner. Even though scheduling problems are widely studied and there are many existing approaches for different problems in the literature, prior to this Thesis there have not been any approaches to improve and ease this scheduling process by adding an optimization feature to the current planning software. In the literature, this type of plywood production scheduling can be categorized as a flow shop scheduling problem which is assigning jobs to resources at specific times.

1.2 Objective and scope

This thesis develops an optimization model for creating a base of the schedule for plywood production. The model should include bonding and coating phases of the plywood production process. They were chosen because they are the work phases that are planned first and dictate the schedule for other work phases. The other work phases have some limitations and they are taken into account as constraints of the model.

The solution of the model is imported into an existing planning software of UPM Plywood and the solution can be assessed by a production planner there. Based on the result, the planner can either accept or reject the schedule proposal given by the optimization model. A feasible solution should be produced quickly because creating a production plan for upcoming week is just one of the weekly tasks of the production planners. Also in case that the solution is not accepted or if there are any changes in the production, the planner might want to run the optimization model again. Thus the optimization model should be fast enough to solve to be useful for the planners.

Flow shop scheduling models are usually formulated as a Mixed Integer Linear Programs (MILP). Because of the integer variables, it is not possible to find the solution using only traditional fast linear optimization algorithms like Simplex. Therefore, large models of this kind are usually computationally challenging and some model relaxations have to be made in order to find the solution quickly.

The scope of this thesis is limited to cover only the production scheduling problem of the Joensuu plywood mill. This Thesis does not cover what kind of orders should be assigned for the factory in order to make a good schedule but only solving an optimal schedule for some existing order backlog.

1.3 Structure of the thesis

The remaining of the Thesis is structured as follows. Background of plywood production and a literature survey on production optimization with focus on flow shop scheduling and other scheduling approaches in related industries is given in Chapter 2. The scheduling problem description and mathematical formulation for the Joensuu mill are presented in Chapter 3. The discussion on solving of the initial model is given in Chapter 4 which also presents modifications to the initial model in order to meet performance requirements. Results from two small example cases and a discussion on the experiences of production planners using the model are given in Chapter 5. Finally, in Chapter 6 discussion on the feasibility of the model and on the issues that could be addressed in the future conclude the Thesis.

2 Background

2.1 Plywood production

2.1.1 Plywood production process

Plywood production consists of three major phases that each include many operations. These phases are veneer manufacturing, plywood manufacturing and further processing. Some mills only perform one or two of these phases, for example, UPM Kalso mill manufactures only veneers. Different phases and operations are visualized in Figure 1.

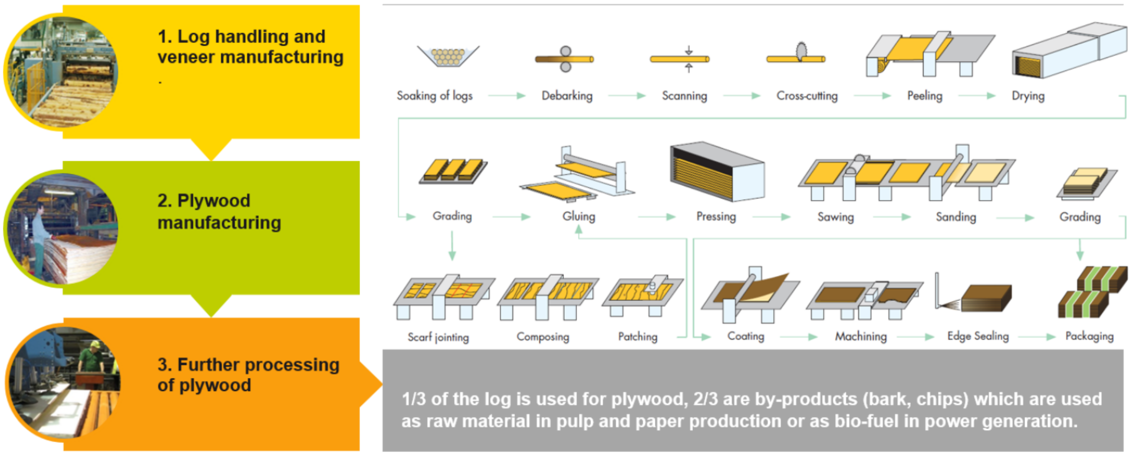


Figure 1: Plywood production phases (adapted from *Wood-based panels industry* (Akkanen et al. 2018))

In the veneer manufacturing phase logs are processed into veneers. The logs are first soaked in a conditioning pool, debarked, scanned and cut into blocks of appropriate length (Akkanen et al. 2018). The lengths vary by the factory but usually there are one to four lengths that are used based on the capabilities and product mix of the mill. Next the blocks are peeled with veneer lathe into a long mat that is clipped to dried before veneer grading (Akkanen et al. 2018). In the veneer grading the veneers are classified in different surface and intermediate veneer qualities. Some of the veneers are further processed before they can be used in plywood manufacturing phase.

Plywood manufacturing phase starts with gluing veneers at lay-up station. The veneers with correct quality and dimensions are placed for the veneer feeders. If the length of the veneers stay the same and the width decreases only a little or stays the same, some veneers from previous order may be used in the next order and setup time will be smaller than on average. Otherwise all veneers have to be changed which usually takes several minutes. Also some settings may have to be changed if the dimensions of the product are different from the previous order. Glue is applied on at least every second veneer of each plywood and the type of glue may differ between consecutive orders. Changing the type of glue causes a long setup time and therefore at least in Joensuu mill it is done at most twice a week and only at one lay-up station. Thickness and material of the veneers may also differ but Joensuu mill uses only 1.5 mm thick birch veneers. After gluing, the plywoods are pre pressed and hot pressed followed by sawing to match the dimensions of the end product. In the end after sanding the plywoods are ready for grading or further processing.

Some plywoods are further processed before grading and packaging. The last phase includes coating and machining operations. In coating a Phenol film or other overlay material can be pressed to one or both sides of the plywood (Akkanen et al. 2018). Some coating machines can use multiple different overlay materials but changing the material may take a long time, even one whole working shift at some mills. The difficulty of setup depends on the type of coating material change. If the material type stays the same but length of the veneer or coating pattern changes, the setup requires changing only few material rolls to the machine which can be done in minutes. In case that the type of material changes the setup usually takes much longer. For example, in Joensuu mill depending on the change, the setup may take time from few minutes up to three hours. In machining operation plywoods are machined into different shapes and machining may include, for example, bevels and grooves (Akkanen et al. 2018). At UPM Joensuu mill some time has to be reserved for testing with LNG veneers. Due to high quality requirements of veneers that go into LNG ships, quality tests must be performed before packaging and shipping the final product.

2.1.2 Plywood production planning at UPM

Production planning in plywood mills is done by production planners. The planning can be divided into rough-cut and fine planning. In rough-cut planning orders are accepted to the mill in the way that weekly capacity is not exceeded on any production phase. Also veneer balance should be taken into account during rough planning. If the order backlog consists of only very thin plywoods, surface veneers would most likely run out and the veneer storage would be filled up with intermediate veneers. This creates a bottleneck in the veneer manufacturing phase and the total output of the factory would decrease.

In fine planning the accepted order backlog is divided to operations which are scheduled for different machines. Because most of the orders differ in materials, dimensions and shipping dates, each order requires own operation to be scheduled on each machine. The most relevant setups happen in cluing and coating phases and therefore the planning usually starts from those two. When cluing is scheduled, the material need is known at every hour and the veneer manufacturing can be planned to match this. In the planning of coating operations the intermediate storage can be used to obtain a schedule where setup times are minimized. This is important because making coating for one order can take less time than changing the overlay material and settings at the coating machine. As in rough-cut planning, also in fine planning the veneer balance should be taken in account by distributing the consumption of surface veneers evenly during each week.

There may be limitations on different machines. For example, some orders can be glued only on certain cluing machines due to dimensions of the product or gluing material. The size of the orders may differ a lot which adds more complexity at least in fine planning. Smallest orders only include less than 50 plywoods whereas the largest ones may take the production capacity of the whole mill for a week. The largest orders are usually divided into sub orders and distributed evenly during multiple weeks especially if the end product is very thin or thick to avoid problems with unbalanced veneer consumption. In Joensuu mill the weekly amount of LNG products has to be taken in account in production schedules due to quality tests. The weekly production of LNG veneers may not exceed the testing capacity.

2.2 Scheduling in literature

There are multiple papers in the literature that cover production scheduling from very different problem settings and approaches. In this section we try to focus on modeling of production scheduling on industries that have similar problem setup as plywood production. This is done by starting with basic concepts followed by studying approaches to scheduling with setup costs in Section 2.2.4 and scheduling in industries that have some similarities in production panning to plywood industry in Section 2.2.5. In the end we briefly study literature on the use of rolling horizon approach to reduce the complexity of scheduling problems.

2.2.1 Scheduling in manufacturing

In manufacturing and service industries scheduling has an important role in daily decision making of, for example, production, transportation and information processing (Pinedo 2009). The scheduling is done by allocating different resources to activities in order to optimize the objectives of the company. The resources can be, for example, different machines, employees of the company or trains in transportation scheduling. These resources are allocated to activities like stages in construction project or operations in a workshop (Pinedo 2009). Different activities usually have due dates, earliest possible starting times and some activities may be prioritized. The company may have one or multiple objectives for the schedule. The objectives can be, for example, minimizing the total time to complete all activities, minimizing the number of activities completed after due date or minimizing the cost to complete all the activities (Pinedo 2009).

The scientific analysis of scheduling started in the fifties with simple problems and since the literature has advanced to address more complex problems with multiple objectives and constraints and a large number of scientific publications have been made of the topic (Gupta and Kyparisis 1987). The scheduling problems are usually modeled as linear programs (LP) or mixed integer linear programs (MILP) but there are also other formulations such as nonlinear programs (Pinedo 2009). For example, Barros and Weintraub (1982) described that LP and MILP models are the only techniques that are largely used in forest planning. As many of the scheduling problems are NP-hard, multiple heuristic methods and dispatching rules have been developed to find a feasible solution that is close enough to the optimum. For example, Panwalkar et al. (1993) presented a heuristic for minimizing the mean tardiness for the single machine sequencing problem and Manson et al. (2002) proposed a modified shifting bottleneck heuristic for minimizing total weighted tardiness in complex job shops developed especially for scheduling in a semiconductor wafer fabrication facility. However, these methods usually fit to solve specific type of problem and dispatching rules such as "Earliest due date first", "Minimum slack" or "The shortest setup time first" fail to perform efficiently with more complex objectives (Pinedo 2009).

In manufacturing the resources are often referred as machines and tasks that are completed in those machines as jobs. A job may consist of a single or multiple operations done on multiple machines (Pinedo 2009). Manufacturing scheduling can be divided to different classes of models. They include, for example, Project scheduling, Machine scheduling and Shop scheduling, Lot scheduling and scheduling in supply chains (Pinedo 2009). The plywood production problem can be classified as Machine scheduling and Shop scheduling. This class of models include single and parallel machine models and shop scheduling models.

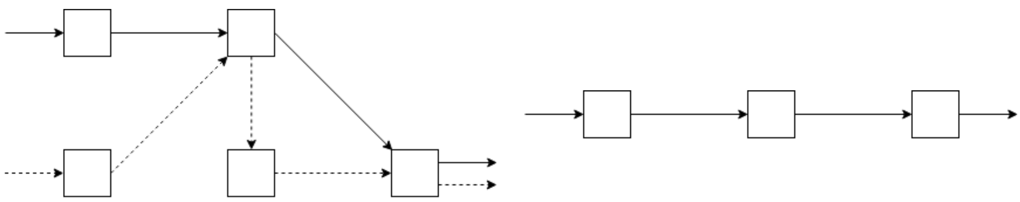
2.2.2 Single and parallel machine models

Single machine models are useful even in multi-stage environment if there is a single bottleneck in the system. With single bottleneck the schedule in the bottleneck resource usually defines the schedules on other resources in the system. In this case the schedule should be made by solving the problem with bottleneck resource first and other operations afterwards (Pinedo 2009). Single machine models have been studied as two types of problems that slightly differ in their formulation. The first one belongs to lot scheduling as in it the problem is to find the optimal batch sizes when a number of products are to be manufactured on a given machine (Gupta and Kyparisis 1987). In this type of problem the objective is to minimize costs caused by setups and inventory, for example, in paper mills. In the second type of problems a number of jobs with given lot sizes are sequenced on the machine (Gupta and Kyparisis 1987). Here the typical objectives are e.g. total tardiness, mean completion time and number of tardy jobs. The objective may also have multiple criteria like, for example, Sen and Gupta (1983) proposed in their approach to minimize a linear combination of flow times and maximum tardiness of a given number of jobs on a single machine.

Parallel machine models are also useful in multi-stage production environments as they are generalization of single machine models. Here instead of single machine being the bottleneck, a stage with multiple machines in parallel is the bottleneck. The machines may be identical or they can have different capabilities. This means that in some cases one or some of the machines might only be able to process some of the jobs whereas other parallel machines can process the others. There can also be differences in operating speed or quality of work between the parallel machines (Pinedo 2009). Only few of the efficient algorithms of single machine problem can be used in parallel machine problem and most of the results for parallel problem assume that the machines are identical (Graves 1981). One of early approaches to solve the problem with non identical parallel machines was one proposed by Horn (1973) who showed that sequencing operations in a parallel-machine environment can be formulated as an assignment problem.

2.2.3 Shop scheduling

In shop scheduling the jobs consist of one or more operations that have to be processed on different machines (Brucker and Knust 2012). The operations of the same job cannot be processed at the same time and a machine can process only one operation at a time. The most general formulation with chain precedences is called job shop scheduling (Brucker and Knust 2012). In that each job may be processed one or multiple times on each of the machines depending on the problem. If all of the jobs go through same machines in the same order, the job shop scheduling problem is called a flow shop scheduling (Pinedo 2009). The difference between the two can be seen in figures 2a and 2b.



(a) Job shop

(b) Flow shop

Figure 2: In job shop scheduling jobs may have different routes whereas in flow shop scheduling all jobs have the same route

In flow shops the sequence may vary on different machines or it can be locked in which case the problem is referred as permutation flow-shop problem (Brucker and Knust 2012). In case that there are multiple machines in parallel at each or some of the stages, the environment is called a flexible flow shop. Some formulations of flexible flow shop models allow a job to bypass a stage in case that the job does not need processing on there (Pinedo 2009). An example schedule for a flow shop problem with three machines $M = \{1, 2, 3\}$ and four jobs $N = \{1, 2, 3, 4\}$ with an operation O_{ij} $i \in M, j \in N$ on each of the machines is presented in Figure 3. As seen from the figure, all of the jobs start from machine 1 and the operation on next machine is not started before the previous operation of the job is completed.

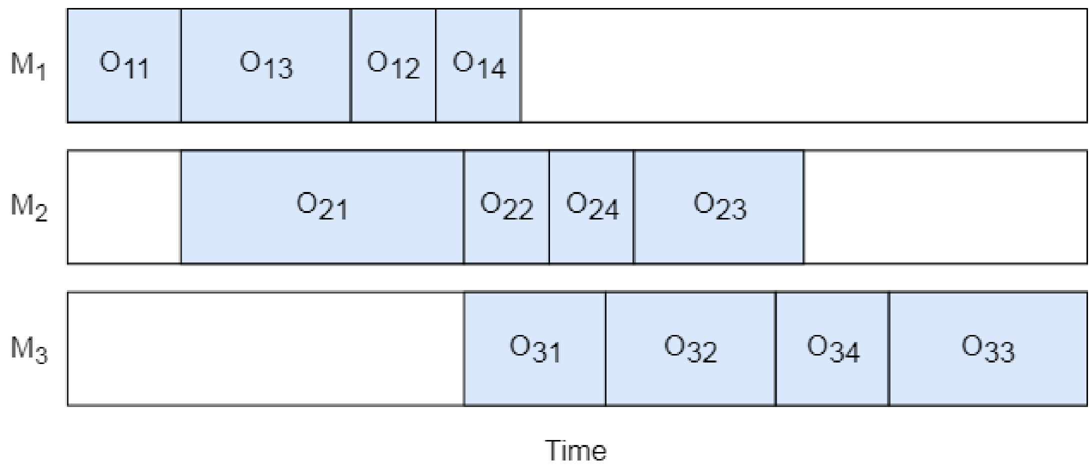


Figure 3: Example production schedule for flow shop problem with three machines and four jobs

Due to complexity of job shop scheduling problems many have studied different approaches to solve these problems. Balas et al. (2008) approached a job shop scheduling problem with setup times, deadlines and precedence constraints by using Shifting Bottleneck Procedure where they treated the single machine scheduling problems that arise in the process as Traveling Salesman Problems with time windows. Mousakhani (2013) compared a MILP model of flexible job shop problems with sequence dependent setup times to minimise total tardiness with three available models which either suffered from non-linearity or was ineffective due to its large complexity size. He also approached large-sized problems with metaheuristic based on iterated local search that showed good results compared to algorithms like tabu search and variable neighbourhood search. Osman (1989) proposed a simulated annealing heuristic to obtain an approximate solution for a permutation flow-shop scheduling problem. He compared simulated annealing with known constructive heuristics and with descent methods. He showed that simulated annealing produces often a better solution than the descent methods he used and stated that descent methods are erratic without a good starting solution.

2.2.4 Scheduling with setup costs

Interest in scheduling with setup costs or times began in the mid sixties and since in the early 2000s on average more than 40 paper have been published yearly (Allaverdi et al. 2008). In many industries production schedule is planned in a way that setup times and costs are minimized. Setup times are significant, for example, in textile industry where the time to change fabric on a machine depends on the type of current and next fabric type and in label sticker manufacturing where the machine that glues the surface material and liner together requires a sequence-dependent setup time when the job changes from one class to another (Allaverdi et al. 2008). Scheduling with setup times can also be applied in mass services such as batching in courts as

Simons and Russel (2002) presented in their case study.

As stated before, lately there has been a lot of research on scheduling with setup costs. Pan et al. (2001) provided a heuristic for NP-hard single-machine scheduling problem with due dates and class setups. The heuristic finds an approximate schedule that minimizes the maximum lateness on a set of jobs. In their paper they address the problem of balancing between long production runs of same product that may make others tardy and large amount of setups that would cause the production efficiency to decrease. Rabadi et al. (2004) approached single machine scheduling problem using a branch-and-bound algorithm. They studied minimizing of the total amount of earliness and tardiness with common due date for all operations. They also stated that the problem becomes NP-hard when sequence-dependent setup times are included. To reach optimal solution they used, a branch-and-bound algorithm and showed that problem with up to 25 jobs can be solved in a reasonable time.

Three stage heuristic to parallel machine scheduling with sequence-dependent family set-up times was proposed by Eom et al. (2002). The heuristic was based on dividing jobs in small job-sets, grouping by the due date within applicable families using apparent tardiness cost with set-up rule and scheduling families using tabu search. In the end jobs are allocated to machines using a threshold value and a look-ahead parameter. However, Eom et al. only considered identical machine case. A more recent approach for both single and parallel machine scheduling with sequence-dependent setup times and costs was proposed by James and Almada-Lobo (2011). They combined metaheuristics and mixed integer programming to find solutions to scheduling and lotsizing problems and compared their approach to other MIP-based heuristics in the literature and to a state-of-the-art commercial solver.

Branch and bound algorithm is also used in flow shop scheduling problems as Ríos-Mercado and Bard (1999a) applied it on permutation flow shops with sequence-dependent setup times. They also proposed heuristic for minimizing the makespan of the flow shop scheduling problem with sequence-dependent setup times (Ríos-Mercado and Bard (1999b)). The heuristic uses a cost function that penalizes for both large setup times and bad fitness of schedule to transform an instance of the problem into a traveling salesman problem. Liu and Chang (2000) addressed a scheduling problem of flexible flow shops with Sequence-Dependent Setup Effects. They started with formulating the problem as an MIP problem and presented a Lagrangian relaxation-based approach with search heuristic to solve that. The approach produced near-optimum solutions in about 6 minutes of CPU time to daily scheduling of a realistic integrated circuit testing facility of 30 machines. Moghaddas and Houshmand (2008) stated that many researchers do not take setup times into consideration or they model it as part of processing time. They developed a MILP model for a job shop scheduling problem with sequence dependent setup times with a good performance to find feasible solutions in a reasonable computation time. However, the performance of finding optimal solutions was weak and the model was unable to find the optimum in larger problems. Hence, they developed a heuristics based on priority rules considering random generated setup times. Because of inability to find the optimal solutions with large problems in reasonable computational time, they proposed three lower bounds, which could be implemented to evaluate different heuristics and metaheuristics in large problems.

2.2.5 Scheduling in industry

Scheduling decisions may vary a lot between different industries. Here we study a few approaches proposed in the literature to solve scheduling problems in industries where production scheduling involves similar problems as plywood production scheduling.

Scheduling decisions in paper production can divided to order allocation, run formation and sequencing, trimming and load planning according to Keskinocak et al. (2002) who introduced scheduling solutions for the paper industry. Due to similarity to plywood production scheduling problem, the most interesting part of paper production scheduling is the run formation and sequencing which includes forming and sequencing of batches of similar type of paper on paper machines. This part can be modeled as single or parallel machine scheduling problem where raw material such as pulp with product specific recipe is turned into paper reels at paper machine. Keskinocak et al. (2002) proposed an agent-based decision support framework for the whole scheduling process that they implemented in several paper mills in North America. They introduced a separate model for order sequencing at paper machines which is based on Single-Dispatch algorithm. The idea of the algorithm is to select a job from the set of remaining jobs and schedule it as the next job on that machine.

Santos and Almada-Lobo (2012) approached problem of integrated pulp and paper mills planning and scheduling where the problem is to synchronize the material flow moving through the pulp and paper mills while minimizing operation costs. They also have to take significant sequence-dependent setups in paper type changeovers into account while sequencing at paper machine. This is done by adding parameters for paper lost in a changeover from one grammage to another and similarly parameters for time lost in a changeover between different grammages, i.e. these parameters describe setup times and setup costs. The parameters were used in constraints to model the pulp consumption and quantity of paper produced at each sub-period. The whole process was modeled as a stochastic mixed integer program. Santos and Almada-Lobo proposed local search heuristic that is based on the stochastic MIP formulation to obtain a feasible solution.

In packaging industry plants that produce multiple different types of paper bags the machine environment can be described as a flexible flow shop. Those environments include, for example, presses, sewing lines, pinch tuber and bottomer and self opening sacks machines. Adler et al. (1993) approached the packaging industry scheduling problem where different jobs have priorities and shipping dates. Also the processing times of the jobs and setups are known in advance. They proposed a five step algorithm that schedules the jobs at different stages of production. The first step is bottleneck identification which tells from which machine to start the scheduling. The scheduler or production planner usually knows the machine and if not, some procedure to determine that may be used. Second and third step include computation of time windows for jobs at bottleneck resource and machine capacity computations at the bottleneck stage. In these steps due dates, processing times and setup times are taken in account when calculating earliest and latest start times for operations at bottleneck resource and loads for different machines. Fourth step in the algorithm includes scheduling at the bottleneck resource. They used ACT rule by Salvendy (1992) to do the scheduling. After that in the fifth step the scheduling is made on other machines. Adler et al. (1993) state that the bottleneck stage usually determines the sequence on other stages but there might be some minor swaps that reduce the setup time. They also state that with this algorithm incorporated into the current production scheduling system, the production planners are able to do better schedules in the two case factories.

Lin and Liao (2003) performed a case study on scheduling problem taken from a label sticker manufacturing company. In label sticker manufacturing the production system is a two-stage hybrid flow shop with sequence-dependent setup times at first stage and dedicated machines at the second. The machine on the first stage is called calender and it is used to glue liner and surface material together. The second stage includes two different types of cutting machines that will be used to process different types of end products. The objective for the problem approached by Lin and Liao is to schedule one day's mix of label stickers in a way that the weighted maximal tardiness is minimized. They introduce a setup matrix that tells how long does it take to change from one class of product to another. Depending on the previous product, the change takes time from 6 up to 50 minutes. Because the problem is NP-hard, Lin and Liao approached the problem by developing a heuristic. The proposed a scheduling rule including three elements; Determine production schedule at first production stage, dispatch the jobs in queue at second stage and develop and improve the schedules. For these elements they used, for example, sequencing methods such as longest processing time first (LPT) and first in first out (FIFO), Approximate Algorithm 1 proposed by Gupta and Darrow (1986) and procedure that includes tabu search method.

Even though production scheduling is essential part of plywood production due to complexity of the production and material handling, the literature on the subject is very limited in mathematical modeling point of view. One of the few papers discussing scheduling in plywood manufacturing is one written by Kotak (1975). He applied linear programming in production planning by balancing available raw materials against product mix desired by sales division. This approach resembles more rough-cut planning at UPM where orders are divided to different mills in a way that raw material usage is steady.

2.2.6 Rolling horizon

Difficulty of mixed integer linear programs grows considerably when more integer variables are added to the problem. Especially with long time-horizons the scheduling problems may become almost impossible to solve even with state of the art optimization solvers. To address this problem multiple heuristics have been presented as described in previous sections of literature survey. One approach to solve these computationally heavy problems is to limit the number of integer variables by performing the scheduling in parts of shorter time horizon. This approach is called rolling horizon.

There are multiple ways to perform rolling horizon in a scheduling problem. The problem may be solved forward or backward and with overlapping or non overlapping time intervals. With overlapping intervals a part of solution from previous interval passed as initial guess for solver in the next one. Graphical representation of rolling horizon with five overlapping intervals is given in Figure 4. As seen from the figure, each of the sub problems has now 73% shorter time horizon than the original problem which means that also the number of integer variables is smaller and the problem is computationally a lot easier.

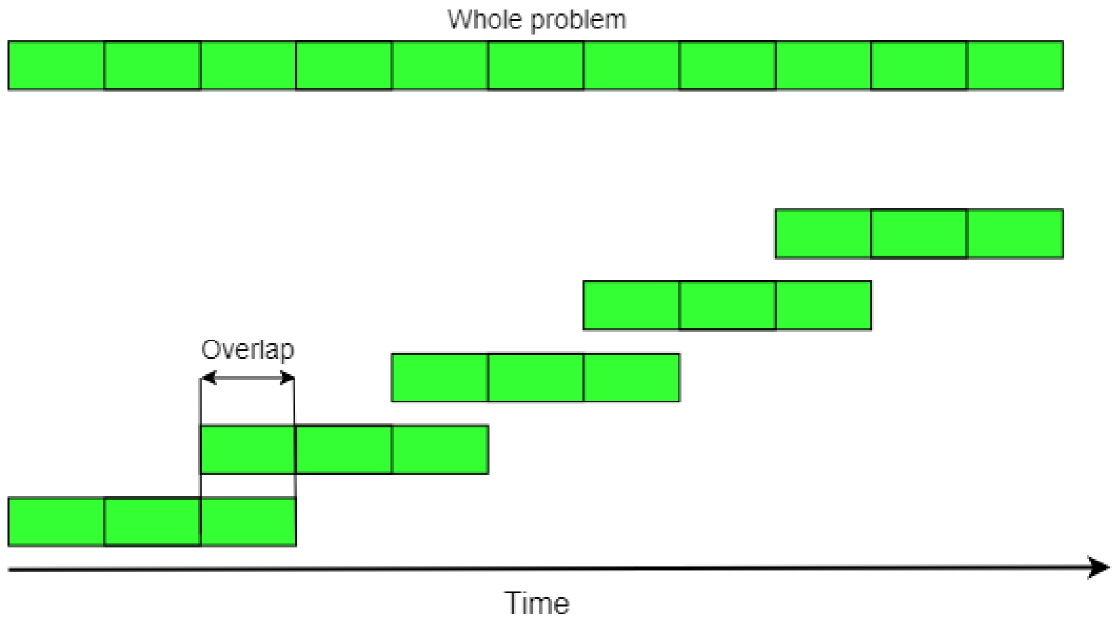


Figure 4: Rolling horizon with overlapping intervals

However, rolling horizon scheduling rarely leads to a globally optimal solution. Dimitriadis et al. (1997) presented the three rolling horizon algorithms and compared their speed and solution to global optimum in medium term scheduling of multipurpose plants. All of the rolling horizon algorithms provided good approximations for the problem with significant reduction in computational time. Also with limited number of maximum branch and bound nodes, all approaches were able to give a better solution for the scheduling problem. The best performing rolling horizon approach was forward rolling horizon algorithm. There are also other approaches to solve scheduling problems using rolling horizon. Beraldi et al. (2008) approached a parallel machine lot-sizing and scheduling problem with sequence-dependent set-up costs using rolling horizon and fix-and-relax heuristics. They showed that with lower bounds provided by a truncated branch-and-bound, the gap between the best heuristic solution and the lower bound never exceeds 3% in their problem setup. Ovacik and Uzsoy (1995) used rolling horizon procedures for dynamic parallel machine scheduling problem with sequence-dependent setup times. They stated that their computational experiments showed that rolling horizon heuristics significantly outperform dispatching rules combined with local search methods, both on average and in the worst case.

3 Optimization model

3.1 Problem description

The plywood scheduling problem involves scheduling of bonding and coating operations with a time horizon of one week in a way that 1. setup times are minimized, 2. all jobs are made in time, 3. the raw material usage is balanced, 4. plywoods are not in intermediate storage before coating for too long and 5. jobs that have more urgent due date are prioritized. The fifth objective is due to large number of jobs available which means that some of the jobs will not be included in the schedule of next week. Therefore, if too many of the jobs with long due dates are used and not the ones that are more urgent, making a feasible schedule in the following weeks might be very difficult. This also helps at the end of production chain because the end products will not have to be stored for a long period of time before the transportation.

In the case mill there are three parallel bonding machines and one coating machine. All of the plywoods are not coated which means that those jobs only contain bonding operation. Also it is possible that some of the jobs contain only coating operation, for example, in case that the plywoods come from other UPM factory for coating and machining. Bonding operation must always be done before coating and there must be 24 hour time buffer between the operations due to other production phases between those two and cooling of the plywoods before the coating. The latest end times for the jobs are given and they usually are determined by the shipping time and time reserved for machining and packaging. There is also earliest start time for jobs that include only coating operation due to arrival time of the plywood to the mill. Also the schedule may not include too many jobs with LNG plywood due to limited LNG testing capacity in the mill. The setup in the case mill can be seen from Figure 5. As seen from the figure, some jobs require only bonding operation and some only coating operation.

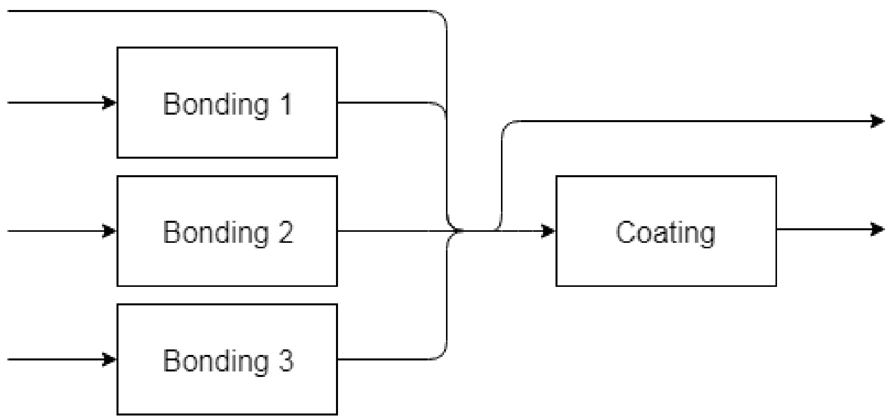


Figure 5: Problem setup in the case mill

The bonding machines have different capabilities which means that some of the orders cannot be bonded on certain machine or machines. Also some of the bonding operations must be processed at the beginning of the week due availability of certain type of glue. Only one operation can be handled at a time on a machine and there setup time between operations depends on the dimensions and type of current and previous product. The next operation must start right after the previous one i.e. on each of the bonding machines there is always production or setup with an assumption that the there is enough raw material available all the time. Also on the coating machine only one operation can be handled simultaneously and there is a setup time between different operations with product dependent length. There may be idle time on the coating machine in case that there is no operation to process or it is more optimal to wait for some operation to be ready for processing and coat that before making a large setup. A waiting time is not that critical on coating machine because it is rarely the bottleneck resource of the mill and the operators can be temporarily moved to other tasks. However, the intermediate storage before coating should be minimized and therefore the solutions with some of the plywoods staying there for too long are penalized.

To summarize, when scheduling operations at bonding and coating machines at case mill, the following constraints must be satisfied:

C1 Each job has at most one operation scheduled in bonding and coating phases.

C2 Operation can be performed only on bonding machines that have capability to handle the operation

C3 Each machine can perform only one operation at a time.

C4 The veneer consumption of surface and intermediate veneers must be within given limits.

C5 Total number of LNG veneers produced must be below weekly testing capacity in bonding.

C6 At bonding the start time of the next operation is end time of the previous operation plus setup time.

C7 At coating the start time of the next operation is greater than start time of previous operation plus setup time.

C8 If job includes only coating operation, the operation cannot be started before earliest start time.

C9 The last operation of a job must be done before latest end time of the job.

C10 If job includes both bonding and coating operation, the coating operation cannot be started before 24 hours have passed from end of bonding operation.

C11 Some of the operations on bonding machines must be done at the beginning of the week due to raw material availability.

3.2 Problem formulation

The first approach to model the problem was to model machines with binary variables of hourly time slots in a way that to complete n hour long operation, n time slots should be assigned to that operation. This leads to computationally too heavy a problem as, for example, when scheduling for one week with 50 jobs, there would be 168*50 = 8400 binary variables for each machine. A more promising approach involves operation slots for each machine. In this formulation we have binary decision variables for each machine that tells whether an operation is assigned to be nth operation processed on that machine. However, by doing this we had to introduce a new variable to track ending times of each operation in order to make sure the operations are done in time. Also this second approach did not allow to make operation in smaller parts, but in the end it did not matter as the larger jobs are already split to sub jobs in the input data by production planners. In this section we introduce this second formulation that was made to model the problem as flexible flow shop with parallel machines at first stage and single machine at second.

3.2.1 Decision variables and parameters

In the plywood scheduling problems there is set of jobs J, set of bonding machines B and set of coating machines C which in this case is just one machine. We also have n_B operation slots for each of the bonding machines and n_C slots for the coating machine. Decision variables X_{jbn} are binary variables that describe whether bonding operation of job $j \in J$ is scheduled on machine $b \in B$ at operation slot $n, n \in \{1, 2, , ..., n_B\}$. For coating, we have similar decision variables Y_{jcn} where the difference is that operations are scheduled on coating machines $c \in C$ with operation slots $n, n \in \{1, 2, ..., n_C\}$. Because there is only one coating machine in the case factory, we can express the latter decision variables as Y_{jn}.

In the formulation we have also other variables to model the material usage, track the start times of operations and to model the setups. For material usage we have two kind of variables. P_{nl} tells how much premium quality veneers is used until the end of operation slot n for product length $l \in L$ at all of the bonding machines. A_{nl} describes the material usage in a way that if the average thickness of the plywoods until end of operation slot n is optimal for product length of $l \in L$, the value of A_{nl} is 0. Each of the operations have pre-calculated values that describe the deviation from optimal thickness scaled with the size of the operation in a way that negative values point to thickness lower than the optimal and positive to higher. At the case factory there are two possible lengths l for the product at bonding phase which are 1300 mm and 1600 mm, i.e. $L = \{1300, 1600\}$.

R^B_{bn} and R^C_n describe the end time of the operation in operation slot n at bonding machine b and start time of the coating machine. We also have end times for each of the bonding and start times for the coating. Variables S^B_{jbn} and S^C_{jn} include the end times of bonding and start times of coating operations of job $j \in J$ if it is done at operation slot n at coating machine or bonding machine b. The setup time at bonding machine b that happens before operation slot n is given as binary variable T^B_{bnt} where value equals to 1 if setup time t of possible setup times Tr^B occurs at given time. Similar setup times for coating machine are described by variables T^C_{nt}. These setup related variables are included to be able to penalize different setups based on their lengths.

In addition to variables, index sets and constants discussed here, there are few others that are needed for the formulation including, for example, matrix of set up times from operation i to j, $i, j \in J$ and matrix of operation lengths of processing job j at machine b. All the parameters and index sets used in the formulation of the model are given in Table 1. The decision variables and auxiliary variables for modeling are given in Table 2.

Table 1: Parameters and index sets used in the formulation of plywood scheduling problem

J	Set of jobs
B	Set of bonding machines
L	Set of product lengths
J^C	Set of jobs that have only coating operation
J^B	Set of jobs that have only bonding operation
J^{B_b}	Set of jobs that can be bonded on bonding machine $b \in B$
J^{LNG}	Set of jobs that are LNG orders
J^{TL}	Set of jobs that have to be included in schedule due to strict time limit
J^U	Set of jobs that are most urgent but do not have to be included
$J^{B_b^0}$	Set of jobs that have to be bonded at the beginning of the week at machine $b \in B$
j_b^0	Job of latest planned operation on bonding machine $b \in B$
j_C^0	Job of latest planned operation on the coating machine
ET^{B_b}	End time of latest planned operation on bonding machine $b \in B$
ET^C	End time of latest planned operation on the coating machine
SL_b	First operation slot to be scheduled on bonding machine $b \in B$
n_B	Number of operation slots at each machine in bonding
n_C	Number of operation slots at coating
N	Set of operation slots when material usage constraints are inspected
Tr^B	Set of possible setup times at bonding
Tr^C	Set of possible setup times at coating
ST_{ij}^B	Setup time at bonding machine between operations of jobs $i \in J$ and $j \in J$
ST_{ij}^C	Setup time at coating machine between operations of jobs $i \in J$ and $j \in J$
Pu_{jl}	Premium veneer usage with length $l \in L$ of job $j \in J$
Pul_l	Hourly average premium veneer usage limit for length $l \in L$
Av_{jl}	Thickness related variable for job $j \in J$ and veneer length of $l \in L$
Au_l	Upper limit for thickness related parameters for length $l \in L$
Al_l	Lower limit for thickness related parameters for length $l \in L$
O_{bj}^B	Operation length of bonding operation of job $j \in J$ at bonding machine $b \in B$
O_j^C	Operation length of coating operation of job $j \in J$
E_j	Latest end time for last operation of job $j \in J$
S_j	Earliest start time for coating operation of job $j \in J^C$
U_j	Amount of plywoods at job $j \in J$
W	LNG testing capacity in number of plywoods
M	A large suitably chosen value

Table 2: Decision and auxiliary variables used in the formulation of plywood scheduling problem

X_{jbn}	A binary decision variable for job $j \in J$ at bonding machine $b \in B$ at operation slot $n \in \{1, 2, , ..., n_B\}$
Y_{jn}	A binary decision variable for job $j \in J$ at operation slot $n \in \{1, 2, , ..., n_C\}$
R^B_{bn}	End time of operation slot $n \in \{1, 2, , ..., n_B\}$ on bonding machine $b \in B$
R^C_n	A decision variable for start time of operation slot $n \in \{1, 2, , ..., n_C\}$ on the coating machine
P_{nl}	Amount of premium quality veneers of length $l \in L$ used until the end of operation slot $n \in \{1, 2, , ..., n_B\}$
A_{nl}	Sum of thickness parameters of bonded operations of length $l \in L$ until the end of operation slot $n \in \{1, 2, , ..., n_B\}$
S^B_{jbn}	End time of bonding operation of job $j \in J$ if it is done at machine $b \in B$ at operation slot $n \in \{1, 2, , ..., n_B\}$
S^C_{jn}	Start time of coating operation of job $j \in J$ if it is done at operation slot $n \in \{1, 2, , ..., n_C\}$
T^B_{bnt}	A binary variable whether setup of length $t \in Tr^B$ happens at bonding machine $b \in B$ before operation slot $n \in \{1, 2, , ..., n_B\}$
T^C_{nt}	A binary variable whether setup of length $t \in Tr^C$ happens at the coating machine before operation slot $n \in \{1, 2, , ..., n_C\}$
ET_j	Extra hours that plywoods of job $j \in J$ stay in intermediate storage

3.2.2 Constraints

The modeling starts with adding common constraints for the model. As stated in **C1**, each job must have at most one operation scheduled in bonding and coating phases. This can be formulated as:

$$\sum_{b \in B} \sum_{n=1}^{n_B} X_{jbn} \leq 1, \qquad \forall j \in J$$

$$\sum_{n=1}^{n_C} Y_{jn} \leq 1, \qquad \forall j \in J$$

We also know that some orders cannot be bonded on certain machines as stated in Constraint **C2**. Also some jobs do not require coating operation. This leads to following constraints:

$$\sum_{b \in B} \sum_{n=1}^{n_B} X_{jbn} = 0, \qquad \forall j \in J \setminus J^{B_b}$$

$$\sum_{n=1}^{n_C} Y_{jn} = 0, \qquad \forall j \in J^B$$

In some situations, we might not want to perform equally many operations on all of the bonding machines. This may be due to differences in end times of latest already planned operations on different bonding machines or due to differences in average lengths of operations that can be done at different machines. For example, if latest planned operation ends at bonding machine 1 on Monday and at machine 2 on Friday, we should not schedule as many operations on both of the machines. For this pre-calculated constants SL_b were introduced in Table 1 that describes which is the first operation slot to be scheduled on bonding machine b. Combining this with Constraint **C3** that requires each machine to perform only one operation at time we get following formulation:

$$\sum_{j \in J^{B_b}} X_{jbn} = 1, \qquad \forall b \in B, \forall n \in \{SL_b, SL_b + 1, ..., n_B\}$$

$$\sum_{j \in J} X_{jbn} = 0, \qquad \forall b \in B, \forall n < SL_b, n \in \mathbb{N}$$

At coating machine the number of operations to schedule should already be chosen suitably and the starting slot index is not needed there. Constraint **C3** can be formulated for coating as:

$$\sum_{j \in J \setminus J^B} Y_{jn} = 1, \qquad \forall n \in \{1, 2, ..., n_C\}$$

In the formulation we use latest previously planned operation as first operation in the next weeks schedule.

$$X_{jbn} = 1, \qquad \forall b \in B, j = j_b^0, n = SL_b$$

$$Y_{j1} = 1, \qquad j = j_C^0$$

To model setup related constraints we need values ST_{ij}^B and ST_{ij}^C which describe setup times between operation of jobs i and j at bonding and coating machines. All the setup times are instances of values in possible setup times TR^B and TR^C. The setups happening between operation slots in bonding can be presented as follows:

$$T_{bnt}^B = 0, \qquad \forall t \in Tr^B, \forall b \in B, \forall n \leq SL_b, n \in \mathbb{N} \tag{3.1}$$

$$\sum_{t \in TR^B} T_{bnt}^B = 1, \qquad \forall b \in B, \forall n > SL_b, n \in \mathbb{N} \tag{3.2}$$

$$T_{bnt}^B \geq -1 + X_{jbn-1} + \sum_{i \in J | ST_{ij}^B = t} X_{ibn}, \qquad \forall j \in J, \forall b \in B, \forall n > SL_b, n \in \mathbb{N}, \forall t \in TR^B \tag{3.3}$$

Equations (3.1) and (3.2) ensure that there are not any setups before first scheduled operation and there is always a setup between the operations. Equation (3.3) forces binary variable T^B_{bnt} to be one if the setup time between operations at machine b in slots $n-1$ and n is t. Similar constraints for coating setup times are given below:

$$T^C_{1t} = 0, \qquad \forall t \in Tr^C$$

$$\sum_{t \in TR^C} T^C_{nt} = 1, \qquad \forall n \in \{2, 3, ..., n_C\}$$

$$T^C_{nt} \geq -1 + Y_{jn-1} + \sum_{i \in J | ST^C_{ij} = t} Y_{in}, \qquad \forall j \in J, \forall n \in \{2, 3, ..., n_C\}, \forall t \in TR^C$$

The material usage constraints can be divided to thickness related and premium veneer related constraints. As Constraint **C4** suggests, for both there are limits that can not be violated. Amount of premium veneer used after operation slot n is formulated as:

$$P_{1l} = 0, \qquad \forall l \in L$$

$$P_{nl} = P_{n-1l} + \sum_{b \in B} \sum_{j \in J} X_{jbn} Pu_{jl}, \qquad \forall l \in L, \forall n \in \{2, 3, ..., n_B\}$$

Similar constraints can be formulated for average thickness related values:

$$A_{1l} = 0, \qquad \forall l \in L$$

$$A_{nl} = A_{(n-1)l} + \sum_{b \in B} \sum_{j \in J} X_{jbn} Av_{jl}, \qquad \forall l \in L, \forall n \in \{2, 3, ..., n_B\}$$

In both Pu_{jl} and Av_{jl} values for job j are 0 if the length of the product is not l. Also all values for already scheduled operations that are used as first operations in the formulation, are set to 0 as they should be scheduled in a way that satisfies Constraint **C4**. The limits for both P_{nl} and A_{nl} are checked few times during the week after operation slots N. For example, we might want to make sure that material usage is steady in intervals of approximately two days because unstable material usage can be compensated with leeway in veneer storage for periods shorter than that.

$$\sum_{b \in B} (R^B_{bn} - ET^{B_b}) Pul_l - P_{nl} \geq 0, \qquad \forall n \in N, \forall l \in L \tag{3.4}$$

$$A_{nl} \leq Au_l, \qquad \forall n \in N, \forall l \in L \tag{3.5}$$

$$A_{nl} \geq Al_l, \qquad \forall n \in N, \forall l \in L \tag{3.6}$$

With Equation (3.4) we check that the hourly material usage is below Pul_l for length $l \in L$ in intervals given by N. Equations (3.5) and (3.6) make sure that in those same intervals average thickness related parameter is within given limits.

Constraint **C5** says that amount of LNG veneers produced should be limited to LNG testing capacity W. This can be formulated as follows:

$$\sum_{b\in B}\sum_{j\in J^{LNG}}\sum_{n\in\{1,2,\ldots,n_B\}} X_{jbn}U_j \leq W$$

End times of bonding and start times of coating operations and operation slots are modeled with variables R^B_{bn}, R^C_n, S^B_{jbn} and S^C_{jn}. R^B_{bn} and R^C_n describe end and start times on operation slots at bonding and coating machines. The start time of first operation is given as end time of latest planned operation at the machine. Those operations are included as first operation on each machine.

$$\begin{aligned}
R^B_{bn} &= 0, \qquad \forall b \in B, \forall n < SL_b, n \in \mathbb{N}\\
R^B_{bn} &= ET^{B_b}, \qquad \forall b \in B, n = SL_b\\
R^C_1 &= ET^C\\
R^C_2 &\geq ET^C + \sum_{t\in Tr^C} tT^C_{2t}
\end{aligned}$$

End times for next bonding and start times for next coating operations are calculated as constraints **C6** and **C7** suggest:

$$R^B_{bn} = R^B_{bn-1} + \sum_{j\in J^{B_b}} X_{jbn}O^B_{jb} + \sum_{t\in Tr^B} tT^B_{bnt}, \qquad \forall b \in B, SL_b < n \leq n_B, n \in \mathbb{N}$$

$$R^C_n \geq R^C_{n-1} + \sum_{j\in J\backslash J^B} Y_{jn-1}O^C_j + \sum_{t\in Tr^C} tT^C_{nt}, \qquad \forall n \in \{3, 4, ..., n_C\}$$

Start times of coating and end times of bonding operations of job $j \in J$ can be calculated using start times given by operation slot times R^B_{bn} and R^C_n. This leads to quadratic constraints because in order to get the time of operation $j \in J$ at some machine, we need to multiply decision variable X_{jbn} or Y_{jn} with corresponding operation end or start time R^B_{bn} or R^C_n. Therefore the constraint is linearized using following procedure proposed by Rubin (2010) in his blog post:

In case that we have two variables x and y and we have to calculate their product $z = xy$, we have a quadratic problem. If one of the variables, lets say x, is binary, the product can be linearized by introducing upper bound U and lower bound L for value of y. Next the following constraints are added:

$$\begin{aligned}
z &\leq Ux\\
z &\geq Lx\\
z &\leq y - L(1-x)\\
z &\geq y - U(1-x)
\end{aligned} \tag{3.7}$$

If $x = 0$, the first two constraints of equations (3.7) force z to be equal to 0. The two last say that $y - U \leq z \leq y - L$, where $z = 0$ satisfies the inequalities. In case that $x = 1$, the first two constraints say that $L \leq z \leq U$ which is satisfied by $z = y$ and the last two constraints become $y \leq z \leq y$ which forces z to be equal to y.

We follow this procedure by adding the following constraints to get end times for bonding operations in (3.8) and for start times for coating operations in (3.9). Here upper bound U is M and lower bound L is 0.

$$\begin{aligned}
S^B_{jbn} &\leq MX_{jbn}, && \forall j \in J, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \\
S^B_{jbn} &\geq 0, && \forall j \in J, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \\
S^B_{jbn} &\leq R^B_{bn}, && \forall j \in J, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \\
S^B_{jbn} &\geq R^B_{bn} - M(1 - X_{jbn}), && \forall j \in J, \forall b \in B, \forall n \in \{1, 2, ..., n_B\}
\end{aligned} \tag{3.8}$$

$$\begin{aligned}
S^C_{jn} &\leq MY_{jn}, && \forall j \in J, \forall n \in \{1, 2, ..., n_C\} \\
S^C_{jn} &\geq 0, && \forall j \in J, \forall n \in \{1, 2, ..., n_C\} \\
S^C_{jn} &\leq R^C_n, && \forall j \in J, \forall n \in \{1, 2, ..., n_C\} \\
S^C_{jn} &\geq R^C_n - M(1 - Y_{jn}), && \forall j \in J, \forall n \in \{1, 2, ..., n_C\}
\end{aligned} \tag{3.9}$$

If a job includes only coating operation, it cannot be started until earliest start time S_j as stated in Constraint **C8**. This can be formulated using the start time variables S^C_{jn}.

$$\sum_{n=1}^{n_C} S^C_{jn} \geq S_j \sum_{n=1}^{n_C} Y_{jn}, \qquad \forall j \in J^C \tag{3.10}$$

This constraint makes sure that if the operation is scheduled, it will be done after the earliest start time. We also know that the last operation of job must be done before latest end time of the job as stated in Constraint **C9**. This cannot be formulated in a way that for all of the operations there is a strict constraint for being started before the latest start time of the job, because all operations will not be scheduled as there are more operations available than are needed to fill the schedule of the following week. Therefore we introduce predetermined set of operations that have to be scheduled due to strict time limit. This means that those operations have to be done before end of the week that is being scheduled or during small buffer after that. This set of jobs is denoted as J^{TL} and based on which operations are required for the job, one of the following constraints must hold:

$$\sum_{b \in B} \sum_{n=1}^{n_B} X_{jbn} = 1, \qquad \forall j \in J^B \cap J^{TL}$$

$$\sum_{n=1}^{n_C} Y_{jn} = 1, \qquad \forall j \in J^{TL} \setminus J^B$$

For all other jobs $j \in J \setminus J^{TL}$ we can assume that Constraint **C9** holds or they can be scheduled during following weeks as otherwise they would have been included into

J^{TL}. For jobs $j \in J^{TL}$ Constraint **C9** can be formulated as:

$$\sum_{b \in B} \sum_{n=1}^{n_B} S^B_{jbn} \leq E_j, \qquad \forall j \in J^B \cap J^{TL} \tag{3.11}$$

$$\sum_{n=1}^{n_C} S^C_{jn} + O^C_j \leq E_j, \qquad \forall j \in J^{TL} \setminus J^B$$

Large number of the jobs have both bonding and coating operations. For those we have to make sure that the bonding operation is done at least 24 hours before the coating operation starts as told in Constraint **C10**. To do this we have to ensure that if a job has both coating and bonding operation to be scheduled, the coating operation cannot be done if the corresponding bonding operation is not done during the scheduling interval.

$$\sum_{n=1}^{n_C} Y_{jn} \leq \sum_{b \in B} \sum_{n=1}^{n_B} X_{jbn}, \qquad \forall j \in J \setminus (J^C \cup J^B)$$

After this the 24 hour constraint can be presented as follows:

$$\sum_{n=1}^{n_C} S^C_{jn} \geq \left(\sum_{b \in B} \sum_{n=1}^{n_B} S^B_{jbn} + 24 \right) \sum_{n=1}^{n_C} Y_{jn}, \qquad \forall j \in J \setminus (J^B \cup J^C) \tag{3.12}$$

Here also multiplication of binary and continuous variable is required and therefore we use first two and fourth constraints of equations (3.7) to model Equation (3.12) as linear constraints. The third constraint is left out due to inequality.

$$\begin{aligned} \sum_{n=1}^{n_C} S^C_{jn} &\leq M \sum_{n=1}^{n_C} Y_{jn}, && \forall j \in J \setminus (J^B \cup J^C) \\ \sum_{n=1}^{n_C} S^C_{jn} &\geq 0, && \forall j \in J \setminus (J^B \cup J^C) \\ \sum_{n=1}^{n_C} S^C_{jn} &\geq \left(\sum_{b \in B} \sum_{n=1}^{n_B} S^B_{jbn} + 24 \right) - M(1 - \sum_{n=1}^{n_C} Y_{jn}), && \forall j \in J \setminus (J^B \cup J^C) \end{aligned} \tag{3.13}$$

There are some bonding operations that we know have to be done at the beginning of the week at bonding machine 3, due to material requirements. This is also stated in Constraint **C11**.This can be formulated as:

$$\sum_{n=SL_b+1}^{SL_b+|J^{B_b}|+1} X_{jbn} = 1, \qquad \forall b \in B, \forall j \in J^{B_b}$$

3.2.3 Objective function

The most important thing in a good schedule is small setup times between operations. Therefore minimization of setup times at both bonding and coating phases is included in objective function. We also want to favor operations of most urgent jobs into next week's schedule to avoid too tight schedule on the following week. Third thing that we want to include in the objective function is minimization of waiting time in veneer storage before coating operation. This is done by allowing plywoods to be less than 24 hours in this storage and the time extra time they stay there is penalized. To do this we introduce new variable ET_j that tells how many extra hours plywood of job $j \in J$ has been in this intermediate storage. The values of ET_j are calculated by:

$$\begin{aligned} ET_j &= 0, \qquad \forall j \in J^B \\ ET_j &\geq 0, \qquad \forall j \in J \setminus J^B \end{aligned} \tag{3.14}$$

$$ET_j \geq \sum_{n=1}^{n_C} S_{jn} - S_j - 24, \qquad \forall j \in J^C \tag{3.15}$$

$$ET_j \geq M(1 - \sum_{n=1}^{n_C} Y_{jn}) - S_j - 24, \qquad \forall j \in J^C \tag{3.16}$$

$$ET_j \geq \sum_{n=1}^{n_C} S_{jn} - \sum_{b \in B} \sum_{n=1}^{n_B} S^B_{jbn} - 48, \qquad \forall j \in J \setminus (J^C \cup J^B) \tag{3.17}$$

$$ET_j \geq M(1 - \sum_{n=1}^{n_C} Y_{jn}) - M(1 - \sum_{b \in B} \sum_{n=1}^{n_B} X_{jbn}) - \sum_{b \in B} \sum_{n=1}^{n_B} S^B_{jbn} - 48, \qquad \forall j \in J \setminus (J^C \cup J^B) \tag{3.18}$$

Equations (3.16) and (3.18) make sure that if some coating operations are not included even if they can be started, the ones that can be started earlier will get larger penalty. 48 hours in equations (3.17) and (3.18) is due to 24 hour reserved for other operations between bonding and coating and for cooling of the plywoods.

Now using setup related variables T^B_{bnt} and T^C_{nt}, set of jobs that are most urgent out of all operations J^U and extra time of plywoods in intermediate storage ET_j we can formulate the objective function that is minimized:

$$\delta_1 \sum_{b \in B} \sum_{n=1}^{n_B} \sum_{t \in TR^B} T^B_{bnt} + \delta_2 \sum_{n=1}^{n_C} \sum_{t \in TR^C} T^C_{nt} - \delta_3 \sum_{b \in B} \sum_{n=1}^{n_B} \sum_{j \in J^U} X_{jbn} - \delta_4 \sum_{n=1}^{n_C} \sum_{j \in J^U} Y_{jn} + \delta_5 \sum_{j \in J^U} ET_j \tag{3.19}$$

Here multipliers $\{\delta_1, ..., \delta_5\}$ are chosen based on discussions with production planners about relative importance of different objectives in scheduling. The process of choosing these multipliers is explained more deeply in next Section 3.2.4. In the objective function (3.19) the first and the second term are the sums of all setup times during the optimization period. The next two terms calculate the amount of urgent operations included in the schedule. Because the objective is minimized, these terms are subtracted as we want to include as many urgent operations as possible and avoid making schedule full of operations that could be done, for example, three weeks from now. The last term calculates the total extra time of plywoods in the intermediate storage.

3.2.4 Selection of multipliers in objective function

There are multiple different methods to select multipliers for different elements in the objective function such as ordinal weighting methods and trade off weighting method (Keeney and Raiffa 1976). In this case it was natural to use trade off weighting as production planners have a good understanding what makes a good production schedule and which attributes are more important than others. The weighting was done together with the planners by comparing, for example, how much more setup time we have to save in coating part if we have 1 hour more setups in bonding. Later based on initial results, the weights can be adjusted if we clearly see that some attributes are emphasized too much in the resulting schedule.

One weakness of the objective function (3.19) is that in theory the last term that sums the extra time plywoods stay in the intermediate storage might steer the model to favor schedules that use more jobs which have only bonding operation than would be necessary. However, in practice this was not noticed to be a problem as the weight for waiting time is much smaller than for setup time and urgent operations in bonding. Furthermore, the separated model described later in Section 4.1 that is created to solve the schedule faster does not face the same possible problem as the bonding part is solved separately from coating part and the wait time does not affect there on the operations selected to the schedule. There the term for wait time only makes sure that there is no needless gaps in the coating schedule and operations will be done in a way that the plywoods do not stay for too long in the intermediate storage.

4 Solving approaches

The formulation described in Section 3.2 was implemented using Python Interface for state of the art optimization solver Gurobi. The solver was unable to find optimum or even feasible solutions for larger models with over 100 available jobs and thousands of binary variables in a reasonable time. We also tried other formulations including modeling with hourly time periods and modeling with estimate of average setup time included in operation times and giving penalty based on which operations were consecutive in a machine. The latter one would leave out the requirement for binary variable for setups happening between operation slots. However, these attempts did not improve the performance of the model and therefore were not further investigated.

Because production planners might want to see schedule proposal multiple times during a week or they might choose to rerun the model after some modifications to the input data, the model has to give good enough a solution during the same day or, even better, in a few minutes. Therefore, the original model was not suitable for the application and we should either use some heuristic method or alter the model to reduce the computation time in a way that the result would still be close enough to the optimum. Due to the special requirements, for example, average thickness and material limitations, there were no heuristic method found in the literature that would be fully suitable for the plywood scheduling problem and at the same time be simple enough to implement in a reasonable time.

We chose to address the problem by using different approaches to reduce the computational time required to solve the MILP model. Before meeting the computational time requirement, multiple different approaches had to be combined including some found during the literature survey and some discovered in the model testing. The different approaches used were splitting model into two parts, using rolling horizon approach, finding feasible solution first in separate model and early stopping as also shown in Figure 6. Two first approaches are based on reducing the size of the model and the last two are methods to reduce redundant computation time. The approaches and their effect on the modeling are presented more in detail in the sections given in the figure.

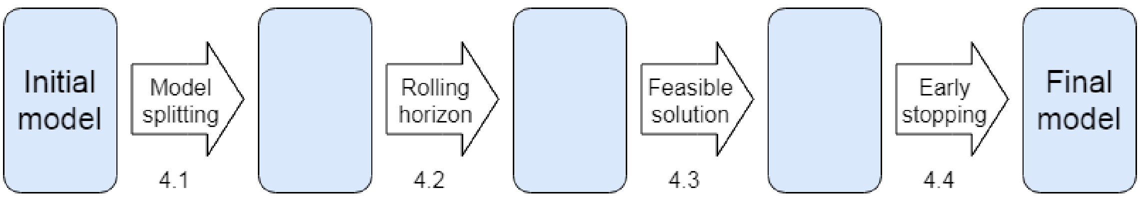


Figure 6: Path of using different approaches in order to meet the computation time requirement

4.1 Model splitting

Solving the production phases in separate models is common in different heuristic methods and solving approaches of scheduling problems as seen, for example, in multiple papers investigated in the literature survey (Manson et al. (2002), Balas et al. (2008), Keskinocak et al. (2002), Adler et al. (1993), Lin and Liao (2003)). Many of the approaches start with determining the bottleneck resource that will be scheduled first. In the case mill the bottleneck resource is bonding and therefore minimizing the setup times there results to higher throughput of the mill. Minimizing the setups at the coating machine only reduce the working time required to perform the setups and therefore the bonding phase is selected to be scheduled first. The possible disadvantage of this approach is that when we are not taking schedule of the coating machine into account while making the bonding schedule, there might be operations that have to stay more time in the intermediate storage or more time consuming setups have to be made compared to scheduling that is done in a single model.

To address the problem of extra time consuming setups at coating machine, we calculate the new end times for all the bonding operations E_j^B in a way that some extra time is reserved to make the coating. By doing this, in case that coating of different grade is currently in production, there will be enough time to coat more operations of that grade before making the material change. The latest end times of bonding operations of jobs that have no coating operation stay the same.

The advantage of solving production phases separately is that the number of constraints and variables in the model is considerably reduced. In bonding only the constraints that include bonding related variables have to be taken in account. Also constraints (3.13) for coating starting 24 hours after the bonding end time can be left out from the formulation as earliest start times for coating operations can be calculated after the bonding schedule is done. The end times of bonding operations S_{jbn}^B are now only needed for operations with strict time limit of being ready in less than one week plus some small time buffer. This is due to completion times of different bonding operations can be calculated from end times of operation slots R_{bn}^B after the scheduling is done and end time constraints of bonding operations are not needed for other operations as we only make the schedule for one week at a time. Therefore Constraint (3.11) for end times of bonding operations can be reformulated as:

$$\sum_{b \in B} \sum_{n=1}^{n_B} S_{jbn}^B \leq E_j^B, \qquad \forall j \in (J \setminus J^C) \cap J^{TL}$$

As the end times of bonding operations S_{jbn}^B are now only included for operations with strict time limit, the constraint linearization has to be done only for those:

$$\begin{aligned} S^B_{jbn} &\leq MX_{jbn}, && \forall j \in (J \setminus J^C) \cap J^{TL}, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \\ S^B_{jbn} &\geq 0, && \forall j \in (J \setminus J^C) \cap J^{TL}, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \\ S^B_{jbn} &\leq R^B_{bn}, && \forall j \in (J \setminus J^C) \cap J^{TL}, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \\ S^B_{jbn} &\geq R^B_{bn} - M(1 - X_{jbn}), && \forall j \in (J \setminus J^C) \cap J^{TL}, \forall b \in B, \forall n \in \{1, 2, ..., n_B\} \end{aligned}$$

The objective function for bonding optimization can now be formulated as:

$$\delta_1 \sum_{b \in B} \sum_{n=1}^{n_B} \sum_{t \in TR^B} T^B_{bnt} - \delta_3 \sum_{b \in B} \sum_{n=1}^{n_B} \sum_{j \in J^U} X_{jbn}$$

Because the complexity of the model is now considerably reduced, in case that the steady material usage is a problem and extra focus is needed for that, we can introduce new variables that tell us how much the average thickness deviates from ideal situation to positive direction A^+_{nl} and negative direction A^-_{nl} where $n \in N$ and $l \in L$. The values for these variables are calculated as:

$$A^+_{nl} \geq 0 \qquad \forall l \in L, \forall n \in N$$

$$A^-_{nl} \geq 0 \qquad \forall l \in L, \forall n \in N$$

$$A_{nl} = A^+_{nl} - A^-_{nl}, \qquad \forall l \in L, \forall n \in N$$

Now using these variables with suitably chosen multipliers δ_6 and δ_7 we can take the material usage in account in the objective function. The multipliers are different for different directions as when deviating to direction of less than ideal average thickness the impact to quality of the schedule is usually larger.

$$\delta_1 \sum_{b \in B} \sum_{n=1}^{n_B} \sum_{t \in TR^B} T^B_{bnt} - \delta_3 \sum_{b \in B} \sum_{n=1}^{n_B} \sum_{j \in J^U} X_{jbn} + \delta_6 \sum_{l \in L} \sum_{n \in N} A^+_{nl} + \delta_7 \sum_{l \in L} \sum_{n \in N} A^-_{nl} \tag{4.1}$$

For coating model we still need to use all the variables S^B_{jn} as the starting time of any operation has to be larger than earliest start times given by constants S_j. We also add starting times for operations that were made in bonding to S_j by adding 24 hours to the ending time of bonding operation of the job. Now the start time Constraint (3.10) can be included for all operations $j \in J \setminus J^B$ and Constraints (3.13) for 24 hour difference between bonding and coating operations can be left out from the coating scheduling model. Because we have no bonding operations in the coating model, we can exclude the jobs that include bonding operation but were not scheduled in the bonding phase from the model. By doing this when modeling the time that plywoods of job $j \in J$ stays in the intermediate storage before coating, we can leave out constraints of three equations (3.14), (3.17) and (3.18). This is due to we have no jobs that do not have coating operation available and the jobs where bonding operation was scheduled in bonding phase can now be modeled as jobs with no bonding operation with earliest possible start time S_j available.

The objective function for coating optimization includes the coating related elements of the original objective function:

$$\delta_2 \sum_{n=1}^{n_C} \sum_{t \in TR^C} T_{nt}^C - \delta_4 \sum_{n=1}^{n_C} \sum_{j \in J^U} Y_{jn} + \delta_5 \sum_{j \in J^U} ET_j$$

4.2 Rolling horizon

Rolling horizon is another good approach to reduce the dimensionality of the scheduling model. As in model splitting, there are disadvantages in this approach because resulting schedule may not be global optimum. However, there are good results of using rolling horizon in the literature, for example, as stated in literature survey Beraldi et al. (2008) used rolling horizon with heuristics in a scheduling problem and the gap between lower bound and the solution never exceeded 3% in their problem setup.

Even with separated models for bonding and coating, especially the bonding phase can still be computationally very challenging if the average size of the operations is very small. This leads to situation with over hundred operations to be scheduled which cannot be done with good enough solution due to strict time requirement. To address the problem we can apply rolling horizon method to bonding scheduling and also to coating if necessary.

The key idea of rolling horizon approach we used is described below:

1. Determine number of operation slots to schedule in a way that the model can be efficiently solved and approximated end time at each machine is at maximum one week from the beginning of optimization. Set values for first operation slot to schedule SL_b if starting times at different machines deviate.

2. Calculate approximated end time based on number of operations to schedule and based on that select operations that have to be included to schedule due to time limit, which is the set J^{TL}.

3. Solve the resulting MILP problem. If the whole week is scheduled after this, we can stop and save the results.

4. If the whole week is not yet scheduled, save the operations that are started before some percentage, e.g. 80%, of the time horizon of the model calculated in part 2. The operations that are started after that will be given as initial solution for the first operations in the next part.

5. Repeat from step 1.

This procedure results to more models to be solved but each of those is considerably smaller and computationally a lot easier to solve than the original one. Therefore the computation time required to solve the whole scheduling problem is smaller. At step 2 usually some small time buffer have to be used when selecting the jobs that have to be included to ensure the feasibility of next subsequent model.

4.3 Feasible solution finding

While testing the performance of initial model, we noticed that finding the first feasible solution can take a very long time and after that the optimization solver quickly finds improvements to the first solution. To reduce this computation time to find the first feasible solution a new model is created that has very simple or no objective function and terminates right after the first solution is found.

For example, in bonding optimization this means that variables and constraints for deviation in average thickness to positive and negative direction can be left out from the formulation as they do not affect to the feasibility of the solution but are only calculated for the objective function. Also when the objective function does not include multiple sums of different variables, the computation required at each step of the iteration is smaller and e.g. root relaxation calculation and other steps the solver performs are done faster.

After the feasible solution is found, it will be passed as an initial solution for the actual model. Now the solver can start right away from a feasible solution which has been found a lot faster than would with the actual model and start improving the solution.

4.4 Early stopping

Another thing that was found to take a lot of time for the optimization solver during the scheduling is proving optimality. For example, in hindsight a coating model with over 900 binary variables took less than 10 seconds to find good enough solution, less than 70 seconds to find a solution that is very close to optimum and the optimum in precision of ten thousandth was found after 470 seconds. However, the solver was able to prove that the solution is actually the optimum after 106000 seconds of finding it which is more than 29 hours. The log from Gurobi solver of this case can be seen in Appendix A.

Also others have noticed this same phenomenon. As described in the literature survey Moghaddas and Houshmand (2008) developed a MILP model for job shop scheduling problem and they were able to find feasible solutions in a reasonable time but especially with larger problems finding the optimum was very difficult. They limited the computation time to 3600 seconds but did not specify how close to optimum they got compared to heuristic algorithm.

Because we are not interested in proving the global optimum but we want a feasible and good enough solution fast for production planners to work with, we chose to also apply early stopping in the scheduling. This can be done, for example, in three ways given below:

1. Stop when some pre-determined amount of time has passed.
2. Stop when solver has not been able to improve the solution in some pre-determined amount of time.
3. Stop when the current solution is close enough to the lower bound found by the solver.
4. Stop when predetermined objective value has been reached that can be based on previous optimizations or some heuristic solution

When combining feasible solution finding in separate model and early stopping, we are able to increase the number of operation slots to schedule at each step in rolling horizon without increasing the solving time. This leads to less rolling horizon steps to be performed which in the end could mean a solution that is closer to global optimum with less computation time.

5 Results

In this chapter, the performance of the scheduling formulation and different solving approaches introduced in Chapter 4 are studied through two example cases in sections 5.1 and 5.2. After that Section 5.3 discusses the performance of implemented real world application with comments from end users of the application. The examples presented in this chapter are small compared to real world problem as computation time required to solve a large problems with the initial model is too big. Also visualization of the results is easier with smaller problems. The first example case is used to investigate the effect of model splitting to both computation time and solution optimality. We also discuss the effect of early stopping in the original and separate models. In the second example case scheduling only bonding phase is investigated. This is done by studying the effect of rolling horizon approach and the computation time saved when using separate feasible solution finding model proposed in Section 4.3. As a reference, Earliest due date first dispatching rule, which is basically scheduling operation by their latest end times, is used in both example cases. The rule of course results to worse schedules than production planners would make but it gives us some value to benchmark the results of the MILP models. Redeeming quality of this dispatching rule is that the resulting schedule is usually feasible in terms of latest end times.

5.1 Example case: Effect of model splitting and early stopping

The first example problem we consider is to schedule 15 bonding and 15 coating operations with only one bonding and coating machine. There are a total of 27 jobs of which 21 include a bonding operation and 21 include a coating operation. The first operation is used as the starting operation in bonding machine i.e. it is the latest operation that is already scheduled with end time of 0. Operation 27 is the first operation at coating machine with end time of 40. All operations in this case have same length of 10 hours. Table 3 presents detailed information about the jobs.

Job	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
Operations	B	B	B	B	B	B	BC	BC	BC	BC	BC	BC	BC	BC	BC	BC	BC	BC	BC	BC	BC	C	C	C	C	C	C
End time	200	70	239	247	450	350	150	250	245	452	455	110	245	250	375	280	115	245	256	355	450	80	241	255	275	280	200
Start time	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	57	45	101	110	0
Thickness	1	0	-1	-2	2	1	0	-1	-2	2	1	0	-1	-2	2	1	0	-1	-2	2	1	0	0	0	0	0	0
Premium	0	0	0	100	0	0	0	0	125	200	0	0	0	0	0	0	0	125	0	0	0	0	0	0	0	0	0

Table 3: Details of the jobs in the first example case

The operations row in the table tells which operations the job includes. B represents bonding operation, C coating operation and BC both operations. End time row describes the latest end time of the last operation in hours from the beginning. As seen from the end times, jobs 2, 7, 12, 17 and 22 have to be done during the next 150 hours of bonding and coating. Therefore those operations are included in set of jobs with strict time limit J^{TL}. Urgent jobs J^U that should but does not have to be included in the schedule are jobs 3, 4, 8, 9, 13, 14, 18, 19, 23 and 24. In case that the job does not have bonding operation, start time row tells when the coating operation can be started. Thickness row describes value of thickness related parameter Av_j and premium row describes the number of premium veneers used in the bonding operation. In the example case thickness related value and premium veneer usage is checked 3 times, after fifth, tenth and last scheduled bonding operation. The maximum average hourly usage of premium veneers is 3 and the sum of thickness values has to be between -3 and 6. The setup times between bonding and coating operations used in this example case can be seen from Appendix B in tables B1 and B2.

In this problem setup weight multipliers of objective function were chosen in a way that bonding setups are weighted more than coating setups due to time lost in bonding phase may result to lower overall production of the mill. Values of the multipliers in objective function are: $\delta_1 = 10$, $\delta_2 = 1$, $\delta_3 = 0.4$, $\delta_4 = 0.4$ and $\delta_5 = 0.01$.

The problem was solved using three different methods. First method was using the original model described in Chapter 3. Next we solved the problem using separated models where the bonding phase is solved first in own model and coating phase after that based on the result of the first model. The last method used is widely known dispatching rule "Earliest due date first". The rule is used to solve the bonding model and after that the coating operations are scheduled based on earliest possible start times given in Table 3 and obtained by adding 24 hours to end times of already scheduled bonding operations which is required in Constraint **C10** of the model.

Using these three methods we get the results in Table 4. As expected, the original model results to best objective value but it takes most computation time to find the optimum. In this case we stopped the calculation after 100 000 seconds and the latest improvement was found after 40 000 seconds of computation time. However there was still a 36,7 % gap between best bound that solver had proved and current solution, which means that there may exist a solution with better value for objective function.

Table 4: Solution times and value of the objective function using different models

	Solution time	Objective value
Original model	>100 000s	$\leq$ 17.098
Separate models	44.16s	17.942
Dispatching rule	<1s	59.799
Original model with time limit	100s	22.098

By doing the model separation, the solver was able to give optimal solutions in separate models in 24.33 and 19.83 seconds which in total is under 45 seconds. This is a clear improvement in solution time compared to the original model but the value of the objective function is slightly worse. However, in practice the difference of less than 0.9 in objective value means less than 1 more easy ten minute setup in bonding phase or less than 1 hour more setups in coating phase.

As seen from the objective values in the result table, both of the models clearly outperform dispatching rule which results to very high objective function value of almost 58. This is even more than the first feasible solution found after 8 seconds using original model which had an objective function value of 53. Therefore, the dispatching rule should not be used in this case even though the computation time of it is very small compared to optimization models.

Because solving original model to optimum is clearly not wise as it takes more than a day to solve the problem, we compared the original model with early stopping to separate models. We chose to give 100 seconds of computation time for the solver so that it would be in same magnitude as computation time of separate models. As seen from the result table, in 100 seconds the original model performed worse than separate models. Actually, when the different factors in the objective function are separated, separate models lead to better schedule in all of the factors. Still, the solution was very good compared to dispatching rule. The original model required 1762 seconds of computation time to reach better solution than separate models, which is almost 40 times the required computation time. If we used early stopping rule for separate models, e.g. stop when the solution is not improved in 5 seconds, we would have reached objective value of 18.109 in less than 15 seconds. This solution is very close to one solved to optimum and we would have been able to save more than 60% in computation time.

The schedules given by Original model with 100 seconds time limit, separate models and dispatching rule are given in Appendix C where in tables C1 and C2 we can see the operations selected to the schedule and the setup times between the operations.

5.2 Example case: Effect of rolling horizon, feasible solution finding and early stopping at bonding optimization

The second example case is a problem of creating a bonding schedule with two parallel bonding machines. The schedule should include 30 bonding operations on each machine. There is total of 80 operations available with processing time of 5 hours. All of the operations cannot be performed on both of the machines as 20 of them can only be done on the first machine and 20 on the second. As in first example case also in this there are average thickness related values and premium veneer usage related values given for each operation. The detailed values and setup times used are not highlighted here due to large problem size.

This problem differs from the bonding optimization of the first example case by having the objective function that includes also deviation from optimal average thickness which is seen in Equation (4.1) in Chapter 4.1. Here we want to penalize more for deviating down from optimal average thickness as it may lead to bottleneck in veneer production. Therefore the multipliers for those were chosen to be $\delta_6 = 0.2$

and $\delta_7 = 0.4$. Other bonding related multipliers in objective function were same as in the first example case.

Here we compared again three different methods to solve the scheduling problem. First we started with bonding model that is separated from original optimization model described in Chapter 4.1. Here based on results of the first example case and knowing that the real world application has to produce schedules quickly, we chose to use early stopping. For simplicity we used early stopping with strict time limits of 50, 100 and 200 seconds. Also the effect of finding feasible solution first in separate model was investigated as the problem size is now a lot larger than in the first example case. Next the same model was solved in two rolling horizon periods where in the first one 20 next operations for each machine are solved and 15 first of those are saved. In the next period remaining 15 operations are scheduled for each of the machines. The time limited and urgent order sets are modified in the first sub-problem to match the approximated end time, which in this case is easy to estimate as the operation lengths are constant. The computation time is limited to half of the single model computation time for each of the rolling horizon periods for solution to be comparable with the first method. Lastly we used modified Earliest due date first dispatching rule to get a benchmark schedule. The rule with two machines is very simple and is now working in following way:

1. Choose operation with earliest due date that can be bonded on first machine and is not yet used. Save the selected operation and do the same on the second machine.
2. If there is less than 60 operations scheduled go back to step 1

The objective function values with total computation times of 50, 100 and 200 seconds are seen in Figure 7 for single model and rolling horizon approach. As seen from the figure, using rolling horizon the solver is able to find very good solution quickly compared to single model approach. By increasing the available computation time, the objective value of rolling horizon approach only decreses by 0.4 from 20.4 to 20.0. Solving the whole period in a single model should result to better objective function value at the optimum, but 200 seconds was not enough to bypass the solution of rolling horizon approach. Value of the objective function for single model was 68.4 at 50 seconds, 27.6 at 100 seconds and 20 at 200 seconds. The objective function value with solution of Earliest due date first dispatching rule is 142.0. Compared to that both of the optimization models result to very good schedules even with less computation time available.

Even though based on Figure 7 rolling horizon seems to perform better than single model, when increasing the available computation time enough, single model should result to better solution. However, the time required for that depends on the problem size. In practice we have noticed that finding even one feasible solution with very difficult models may take several minutes but in very small models we should not use rolling horizon approach as single model can take more operations in account at the same time. Also if there are lot of time limited orders and there is not much

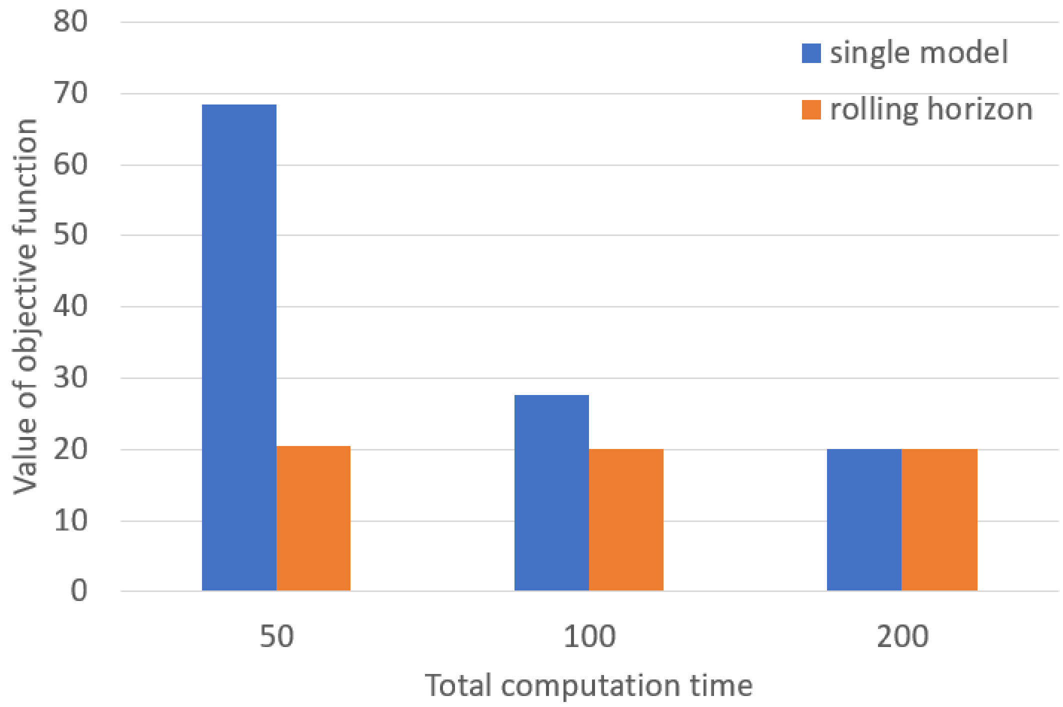


Figure 7: Values of objective function using rolling horizon and single model with total computation time of 50, 100 and 200 seconds

flexibility in the schedule, finding the first feasible solution can take a long time. Because of this we also investigated how much can we save time when using separate model to find feasible solution. In this case the amount of time saved is not much as the first solution is found in 4.36 seconds with single model. Using separate model with simpler objective function and without constraints related to objective function, the solver is able to find feasible schedule in 3.81 seconds which is only 13% less. However, in practice we have noticed that it is useful to always use separate model for finding feasible solutions as again with very temporally tight order backlog we can save a lot of time and with easier problems it does not increase the total computation time required.

5.3 Real world implementation and feedback from end users

The optimization model was implemented as a plugin to existing planning software of UPM Plywood. The objective of the plugin is to give an initial schedule for production planners to work with in a way that the schedule proposal is given quickly enough for the plugin to be useful in daily planning work. At the same time the proposed schedule should be good enough so that production planners can accept it as a schedule to follow in production without any or with very few modifications to implement.

Because of the time requirement we knew that finding the global optimum is not possible and the real world implementation had to use different solving approaches described in Chapter 4 to reach good enough a schedule quickly. Different methods used were selected by pre analyzing the orders e.g. the number of rolling horizon periods depends on the estimated number of operations to schedule and the number of operations that need strict time limit in the model. The actual optimization models are solved on separate computing server that has more computational power than the computer on which the examples in this paper are calculated. In this way we usually need less computation time to reach a good solution and at the same time the production server is not loaded by optimization solver. Current production version of scheduling plugin is able to produce the schedule proposal in less than 15 minutes.

Based on discussions[1] with end users, the scheduling tool was well received at the case mill. The most important benefit of the tool is that it frees up work time of the planners as it basically performs one of the important tasks in fine planning. The end users mentioned that when they are making the weekly schedule, they take into account the same factors that are used by the optimization model in objective function and constraints e.g. average thickness and changes in product dimensions that affect the setups times. Also the weekly schedule may be done faster with help of the tool than only by hand.

Other important benefit of the model is the minimization of mistakes in the schedule. When the scheduling tool makes a proposal and production planner reviews it, there are basically two agents who have reviewed the order backlog. This is more than currently as now the production planner is alone responsible that the current plan is good and all the orders will be produced in time.

The end users were also pleased with the simple user interface and to the use logic of the tool. They liked that the result of the model is not directly set as production plan but can be reviewed before accepting or rejecting and the accepted plan can be further developed by the user in an interface that they are already familiar with. The interface was kept very simple e.g. starting optimization required only to select the machines to include in optimization model.

This far the end users have been happy with the schedules proposed by the tool. However, the tool has been in use at Joensuu mill only for a short period of time and therefore the end users could not say for sure that current version of the tool is producing good enough schedules reliably.

In the discussions, the end users also found a few weaknesses of the tool and areas of development. Firstly if the schedule proposal is modified by the planner at multiple parts of the schedule, it might be very difficult say that the average thickness and the setups are still optimal during the whole week. Also in case of modifying the order of bonding operations, the coating part should be simultaneously taken in account.

[1] Most of discussions happened with Petri Jormanainen who is a production planner at Joensuu mill

Therefore, expert knowledge is still needed even with help of the scheduling tool. The end users also stated that current model might not work in temporally very tight situations such as after strikes. In those situations they may not be able to produce all orders in time and optimization model could not find any feasible solutions. Then the scheduling problem should be formulated in a way that the lateness of orders is minimized and at the same time the material usage is as close to the optimal as possible to keep the production efficient.

6 Conclusions

The primary objective of this thesis was to develop a optimization that creates a base of the schedule for plywood production i.e. schedules bonding and coating phase operations for the following week. A MILP formulation for the problem was very computationally heavy and thus did not satisfy secondary objective that was to make the optimization model fast enough to be useful for the planners. To address this we introduced four different approaches that were used to reduce the computation time required. Using all of these four approaches we were able to make a formulation that produces a good initial schedule for planners in less than 15 minutes even with larger and more difficult order backlogs.

As seen from results of example cases in Chapter 5, compared to well known dispatching rule, optimization models performed very well and thus optimization should produce better schedules for selected machines than very rough heuristics that are currently available in existing planning software. The benefit can most easily be seen from Appendix C as the total time required to produce the operations was few hour less on both bonding and coating machine using a schedule given by the optimization models. Also, we noticed that in difficult problems the solver is able to find better solutions more quickly with separated models and rolling horizon approach. However, using, for example, too many rolling horizon periods might lead to models that will not result to global optimum as they cannot take the whole scheduling period in account. Therefore, the script that creates the models should carefully select the amount of orders to schedule in each rolling horizon period. This problem could also be addressed by introducing a term that assesses the goodness of remaining operations into objective function but it was not implemented as it would have made the model even more complex than it is now.

Based on feedback from the end users, we can clearly see that the scheduling tool is very useful and creates a value for UPM Plywood by reducing the amount of work time required to create a schedule and by decreasing the probability of mistakes when production planner is creating the schedule. Therefore, we can be confident that the end users will be using the tool in the future when they are creating production schedules and so we also get more data on performance of the model. However, if the results are excellent for long period of time, we must beware of planners trusting the results too much and not reviewing them well enough. This is because the model is always a simplification of a reality and it cannot take every variable into account.

There is still a lot to improve and monitor in the current model that is implemented in a production environment. Firstly, selection of suitable early stopping strategy turned out to be very difficult task. As seen for example in Appendix A, the gap between best bound found and current value of the objective function is still very high when the optimum is found. Therefore, using gap based stopping criteria was not suitable for the problem especially when there was high number of orders that required strict time limit as in worst case this could cause a lot of unwanted computation time. In the end we chose to use the time based approaches mentioned in Section 4.4.

The second problem that could be addressed was already mentioned in Section 3.2.4 about the possible problems of choosing too many operations of jobs with no coating operation due to objective function in original model. This does not affect the current solution in production environment as there the model is separated into two parts but this might reduce the value of the conclusions we can make from the first example case.

In case of very unequally sized orders we may have problems with the average thickness and premium veneer usage related constraints. This is because the constraints are placed after certain pre determined operation slots instead of exact times e.g. after every two days of production. Thus, we cannot, for example, check the premium veneer usage every two days of production but it is checked e.g. every 10 operations on each of the bonding machines. Now in case that only large operations are set to other machine and small ones for another, in a worst case the resulting schedule may be unoptimal in terms of material usage. However, for simplicity we chose this formulation as otherwise we would have had to model how much of each operation is done before certain time limits. This would have led to a much more complex model that does not meet the computation time requirements.

Lastly, there is still very little data available about the goodness of the schedules proposed by optimization model because the plugin has been in production only for a while. For example, weights of the objective function and suitability of some constraints could be further studied. When we get more data from the production use of the model, we could for example investigate which schedules are accepted and which are rejected by the production planners and also study what kind of modifications are made to accepted schedule proposals of the model.

This kind of optimization model could also be implemented on other mills of UPM Plywood. Actually we implemented very similar models on two other mills simultaneously with Joensuu mill model. All the mills have special capabilities which leads to different objectives and constraints for the schedules. Therefore, the optimization model presented here might not be suitable in all mills and at least some investigation must be made before applying it to other mills. However, for the two other mills where the optimization model was also implemented, the model had many of the same elements than the model presented in this paper and the modeling took considerably less time. Also in the future the scheduling model could be expanded to contain other production phases that have sequence dependent setup times and are not scheduled in order that is solely dependent on bonding and coating phase. An example of these phases are production phases of Maxi-sized veneers in Savonlinna mill which are somewhat different compared to production phases of ordinary veneer products.

References

L. Adler, N. Fraiman, E. Kobacker, M. Pinedo, J. C. Plotnicoff, and T. P. Wu. BPSS: A Scheduling Support System for the Packaging Industry. *Operations Research*, 41(4):641–648, 1993.

I. Akkanen, T. Jannes, M. Kekki, T. Kiiski, V. Kortelainen, S. Lind-Kohvakka, K. Liski, T. Mäkinen, H. Pajuoja, J. Rainio, T. Räsänen, I. Silvennoinen, I. Tarvakkainen, P. Torniainen, T. Tynkkynen, and R. Varis. *Wood-based panels industry*. Suomen Sahateollisuusmiesten Yhdistys ry and Suomen Puuteollisuusinsinöörien Yhdistys ry, 2018.

A. Allaverdi, C. T. Ng, T. C. E. Cheng, and M. Y. Kovalyov. A Survey of Scheduling Problems with Setup Times or Costs. *European Journal of Operational Research*, 187(3):985–1032, 2008.

E. Balas, N. Simonett, and A. Vazacopoulos. Job shop scheduling with setup times, deadlines and precedence constraints. *Journal of Scheduling*, 11(4):253—262, 2008.

O. Barros and A. Weintraub. Planning for a Vertically Integrated Forest Industry. *Operation Research*, 30(6):1168–1182, 1982.

P. Beraldi, G. Ghiani, A. Grieco, and E. Guerriero. Rolling-horizon and fix-and-relax heuristics for the parallel machine lot-sizing and scheduling problem with sequence-dependent set-up costs. *Computers & Operations Research*, 35(11):3644–3656, 2008.

P. Brucker and S. Knust. *Complex Scheduling Second Edition*. Springer Berlin, 2012.

A. D. Dimitriadis, N. Shah, and C. C. Pantelides. RTN-based Rolling Horizon Algorithms for Medium Term Scheduling of Multipurpose Plants. *Computers & Chemical Engngineering*, 21:1061–1066, 1997.

D. H. Eom, H. J. Shin, I. H. Kwun, J. K. Shim, and S. S. Kim. Scheduling jobs on parallel machines with sequence-dependent family set-up times. *International Journal of Advanced Manufacturing Technology*, 19(12):926—-932, 2002.

S. C. Graves. A Review of Production Scheduling. *Operation Research*, 29(4): 646–675, 1981.

J. N. D. Gupta and W. P. Darrow. The two-machine sequence dependent flowshop scheduling problem. *European Journal of Operational Research*, 24(3):439–446, 1986.

S. K. Gupta and J. Kyparisis. Single Machine Scheduling Research. *Omega*, 15(3): 207–227, 1987.

Gurobi. Gurobi optimization solver. URL https://www.gurobi.com/.

W. A. Horn. Minimizing Average Flow Time with Parallel Machines. *Operation Research*, 21(3):846–847, 1973.

R. J. W. James and B. Almada-Lobo. Single and parallel machine capacitated lotsizing and scheduling: New iterative MIP-based neighborhood search heuristics. *Computers & Operations Research*, 38(12):1816–1825, 2011.

R. L. Keeney and H. Raiffa. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs.* Whiley New York, 1976.

P. Keskinocak, F. Wu, R. Goodwin, S. Murthy, R. Akkiraju, S. Kumaran, and A. Derebail. Scheduling Solutions for the Paper Industry. *Operations Research*, 50(2):249–259, 2002.

D. B. Kotak. Application of Linear Programming to Plywood Manufacture. *INFORMS Journal on Applied Analytics*, 7(1):56–68, 1975.

H. T. Lin and C. J. Liao. A case study in a two-stage hybrid flow shop with setup time and dedicated machines. *International Journal of Production Economics*, 82 (2):133–143, 2003.

C. Y. Liu and S. C. Chang. Scheduling flexible flow shops with sequence-dependent setup effects. *IEEE Transactions on Robotics and Automation*, 16(4):408–419, 2000.

S. J. Manson, J. W. Fowler, and W. M. Carlyle. A modified shifting bottleneck heuristic for minimizing total weighted tardiness in complex job shops. *Journal of Scheduling*, 3(6), 2002.

R. Moghaddas and M. Houshmand. Job-Shop Scheduling Problem With Sequence Dependent Setup Times. *Proceedings of the International MultiConference of Engineers and Computer Scientists 2008 Vol II, IMECS*, 2008.

M. Mousakhani. Sequence-dependent setup time flexible job shop scheduling problem to minimise total tardiness. *International Journal of Production Research*, 51(12): 3476—-3487, 2013.

I. Osman. Simulated Annealing for Permutation Flow-Shop Scheduling. *Omega*, 17 (6):551–557, 1989.

I. M. Ovacik and R. Uzsoy. Rolling horizon procedures for dynamic parallel machine scheduling with sequence-dependent setup times. *International Journal of Production Research*, 33(11):3173–3192, 1995.

J. C. H. Pan, J. S. Chen, and H. L. Cheng. A heuristic approach for single-machine scheduling with due dates and class setup. *Computers & Operations Research*, 28 (11):1111–1130, 2001.

S. S. Panwalkar, M. L. Smith, and C. P. Koulamas. A heuristic for the single machine tardiness problem. *European Journal of Operational Research*, 70:304–310, 1993.

M. L. Pinedo. *Planning and Scheduling in Manufacturing and Services.* Springer New York, 2009.

G. Rabadi, M. Mollaghasemi, and G. C. Anagnostopoulos. A branch-and-bound algorithm for the early/tardy machine scheduling problem with a common due-date and sequence-dependent setup time. *Computers & Operations Research*, 31(10): 1727—-1751, 2004.

P. A. Rubin. Or in an ob world: Binary variables and quadratic terms, 2010. URL https://orinanobworld.blogspot.com/2010/10/binary-variables-and-quadratic-terms.html.

R. Z. Ríos-Mercado and J. F. Bard. A branch-and-bound algorithm for permutation flow shops with sequence-dependent setup times. *IIE Transactions*, 31(8):721—-731, 1999a.

R. Z. Ríos-Mercado and J. F. Bard. An Enhanced TSP-Based Heuristic for Makespan Minimization in a Flow Shop with Setup Times. *Journal of Heuristics*, 5(1):53–70, 1999b.

G. Salvendy. *Handbook of Industrial Engineering, Dispatching. Chapter 83.* Whiley New York, 1992.

M. O. Santos and B. Almada-Lobo. Integrated pulp and paper mill planning and scheduling. *Computers & Industrial Engineering*, 63(1):1–12, 2012.

T. Sen and S. K. Gupta. A Branch-and-Bound Procedure to Solve a Bicriterion Scheduling Problem. *IIE Transactions*, 15:84–88, 1983.

J. V. Simons and G. R. Russel. A case study of batching in a mass service operation. *Journal of Operations Management*, 20(5):577–592, 2002.

A Gurobi log of coating model with real-world data

The computation is made on laptop with Intel Core i5-4300U 1.9GHZ CPU and 4GB of RAM.

```
Optimize a model with 15745 rows, 1848 columns and 49056 nonzeros
Variable types: 696 continuous, 1152 integer (1152 binary)
Coefficient statistics:
  Matrix range     [1e+00, 3e+02]
  Objective range  [3e-02, 7e-01]
  Bounds range     [1e+00, 1e+00]
  RHS range        [2e-01, 3e+02]
Presolve removed 4651 rows and 316 columns
Presolve time: 0.35s
Presolved: 11094 rows, 1532 columns, 70648 nonzeros
Variable types: 549 continuous, 983 integer (962 binary)
Presolved: 1532 rows, 12626 columns, 72180 nonzeros


Root relaxation: objective 1.419049e+00, 1348 iterations, 0.14 seconds

    Nodes    |    Current Node    |     Objective Bounds      |     Work
 Expl Unexpl |  Obj  Depth IntInf | Incumbent    BestBd   Gap | It/Node Time

     0     0    1.41905    0   85          -    1.41905      -      -    0s
H    0     0                       8.1514363    1.41905  82.6%     -    0s
     0     0    1.60992    0   84    8.15144    1.60992  80.2%     -    0s
...
     0     2    2.04562    0  139    8.13144    2.04562  74.8%     -    4s
     9    10    2.25480    5  115    8.13144    2.08482  74.4%  84.0    5s
H   29    30                       7.8914363    2.08482  73.6%  80.9    5s
H  115   101                       7.7114363    2.09798  72.8%  75.3    7s
H  145   119                       7.2914363    2.09798  71.2%  79.6    8s
   321   234    3.08615   13  102    7.29144    2.17184  70.2%  75.6   10s
...
   963   613    3.35690   24  120    7.29144    2.47936  66.0%  82.2   60s
H  979   588                       7.2414363    2.47936  65.8%  83.9   61s
H 1010   578                       7.0414363    2.47936  64.8%  83.6   63s
  1047   593    6.27187   25  108    7.04144    2.56729  63.5%  86.1   65s
H 1111   595                       6.9414363    2.57428  62.9%  87.5   68s
  1146   601    3.01968   21  118    6.94144    2.57593  62.9%  88.7   70s
...
 13531  9179    4.39913   41  129    6.92144    3.13386  54.7%   122  465s
```

```
 13739  9306    5.90516   27  120    6.92144    3.13844  54.7%   122  472s
H13754  9280                       6.8214363    3.13844  54.0%   122  472s
 13813  9306    4.34729   37  109    6.82144    3.13907  54.0%   122  478s
 14004  9446    5.75852   24  106    6.82144    3.14736  53.9%   123  484s
...
 132801 70914     cutoff   85          6.82144    4.37227  35.9%   292 10004s
 133001 71029    5.86582   81  145    6.82144    4.37340  35.9%   292 10019s
H133131 71127                       6.8214346    4.37340  35.9%   292 10019s
 133257 71202    4.98629   41  158    6.82143    4.37431  35.9%   292 10036s
 133446 71324    5.48322   67  178    6.82143    4.37498  35.9%   292 10052s
 133598 71385    5.82554   63  167    6.82143    4.37541  35.9%   293 10067s
...
 1327852   730     cutoff   84          6.82143    6.78248  0.57%   352 115515s
 1328026   574     cutoff   45          6.82143    6.78943  0.47%   351 115533s
 1328173   446     cutoff   40          6.82143    6.79453  0.39%   351 115535s

Cutting planes:
  Gomory: 16
  Cover: 795
  Implied bound: 144
  Projected implied bound: 23
  MIR: 630
  Flow cover: 1227
  Inf proof: 2
  Zero half: 192

Explored 1328677 nodes (466793385 simplex iterations) in 115539.69 seconds
Thread count was 4 (of 4 available processors)

Solution count 10: 6.82143 6.82144 6.82144 ... 7.04144

Optimal solution found (tolerance 1.00e-04)
Best objective 6.821436285168e+00, best bound 6.821434558264e+00, gap 0.0000%
```

B Setup times between bonding and coating operations in first example case

Job	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	0	0	0	0	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
2	0	0	0	0	0	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
3	0	0	0	0	0	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
4	0	0	0	0	0	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
5	0	0	0	0	0	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
6	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
7	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
8	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
9	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
10	0,2	0,2	0,2	0,2	0,2	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2
11	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,4
12	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,4
13	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,4
14	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,4
15	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,4	0,4	0,4	0,4	0,4	0,4
16	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,2
17	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,2
18	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,2
19	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,2
20	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0	0	0	0	0	0,2
21	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,4	0,4	0,4	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0

Table B1: Setup times between bonding operations of the jobs in the first example case

Job	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
7	0	0	0,3	0,3	0,3	0,3	1	1	1	1	3	3	3	3	3	3	3	3	1	1	1
8	0	0	0,3	0,3	0,3	0,3	1	1	1	1	3	3	3	3	3	3	3	3	1	1	1
9	0,3	0,3	0	0	0,3	0,3	1	1	1	1	3	3	3	3	3	3	3	3	1	1	1
10	0,3	0,3	0	0	0,3	0,3	1	1	1	1	3	3	3	3	3	3	3	3	1	1	1
11	0,3	0,3	0,3	0,3	0	0	1	1	1	1	3	3	3	3	3	3	3	3	1	1	1
12	0,3	0,3	0,3	0,3	0	0	1	1	1	1	3	3	3	3	3	3	3	3	1	1	1
13	1	1	1	1	1	1	0	0	0,3	0,3	0,3	0,3	3	3	3	3	3	3	1	1	1
14	1	1	1	1	1	1	0	0	0,3	0,3	0,3	0,3	3	3	3	3	3	3	1	1	1
15	1	1	1	1	1	1	0,3	0,3	0	0	0,3	0,3	3	3	3	3	3	3	1	1	1
16	1	1	1	1	1	1	0,3	0,3	0	0	0,3	0,3	3	3	3	3	3	3	1	1	1
17	3	3	3	3	3	3	0,3	0,3	0,3	0,3	0	0	1	1	1	1	1	1	3	3	3
18	3	3	3	3	3	3	0,3	0,3	0,3	0,3	0	0	1	1	1	1	1	1	3	3	3
19	3	3	3	3	3	3	3	3	3	3	1	1	0	0	0,3	0,3	0,3	0,3	3	3	3
20	3	3	3	3	3	3	3	3	3	3	1	1	0	0	0,3	0,3	0,3	0,3	3	3	3
21	3	3	3	3	3	3	3	3	3	3	1	1	0,3	0,3	0	0	0,3	0,3	3	3	3
22	3	3	3	3	3	3	3	3	3	3	1	1	0,3	0,3	0	0	0,3	0,3	3	3	3
23	3	3	3	3	3	3	3	3	3	3	1	1	0,3	0,3	0,3	0,3	0	0	3	3	3
24	3	3	3	3	3	3	3	3	3	3	1	1	0,3	0,3	0,3	0,3	0	0	3	3	3
25	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	0	0	0,3
26	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	0	0	0,3
27	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	0,3	0,3	0

Table B2: Setup times between coating operations of the jobs in the first example case

C Results from the first example case using different models

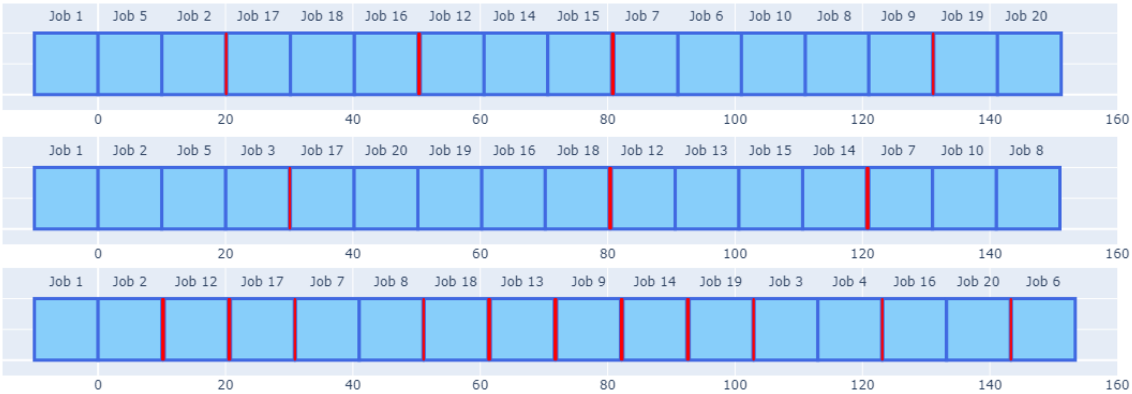


Table C1: Bonding schedule using original model with 100 seconds time limit up, separate models in the middle and dispatching rule at the bottom. Red colour represents setup time

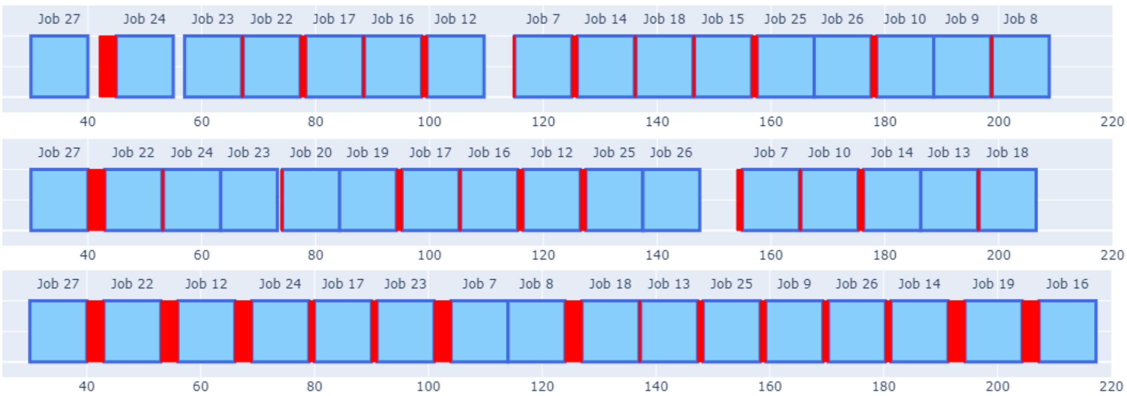


Table C2: Coating schedule using original model with 100 seconds time limit up, separate models in the middle and dispatching rule at the bottom. Red colour represents setup time