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Production Planning and scheduling in the Footwear Industry

CARLOS ANDRÉ VAZ MOREIRA

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Candidate: Carlos André Vaz Moreira, No. 1161251, 1161251@isep.ipp.pt

Advisor: Ana Viana, agv@isep.ipp.pt

Co-Advisor: João Pedro Pedroso, jpp@fc.up.pt

Departamento de Engenharia Mecânica
Instituto Superior de Engenharia do Porto
Rua Dr. António Bernardino de Almeida, 431, 4200–072 Porto

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Abstract

In recent years, the Portuguese footwear industry has changed drastically. What used to be a low-cost mass production industry has changed to adapt to the needs of retail chains dealing with small orders and personalized footwear. These changes increase the demand for flexible and fast production lines, able to deliver orders of any size.

This thesis deals with production planning for the injection line of a company producing safety shoes. In this study, a new method for the lot-sizing is proposed to balance the production over the following weeks, minimizing the production costs, stocks and backlog requirements. This is complemented with a short-term planning (sequencing) algorithm for dealing with operational requirements.

In order to solve these problems, a hierarchical method is used to exchange data between the midterm lot-sizing problem and the scheduling a heuristic, providing feasible solutions to both.

Results obtained show that the company can significantly benefit from this new planning method.

Keywords: Lot-Sizing, Scheduling, Production Planning, Footwear Industry.

Resumo

Nos últimos anos, a indústria de calçado portuguesa tem mudado drasticamente. O que costumava ser uma indústria de produção em massa de baixo custo mudou de modo a adaptar-se a cadeias retalhistas que lidam com pequenas encomendas e calçado personalizado. Estas mudanças aumentam a procura de linhas de produção flexíveis e rápidas, capazes de entregar encomendas de qualquer dimensão.

Esta tese trata do planeamento da produção para a linha de injecção de uma empresa que fabrica calçado de segurança. Neste estudo é proposto um novo método de planeamento a médio/longo prazo para balancear a produção ao longo das semanas seguintes, minimizando os custos de produção, stocks e requisitos de atraso. Isto é complementado com um algoritmo de planeamento (sequenciamento) a curto prazo para lidar com os requisitos operacionais.

A resolução dos dois problemas recorre a um algoritmo que realiza a troca de dados entre o problema de dimensionamento de lotes a médio prazo e o sequenciamento da produção, de modo a encontrar uma solução viável para ambos.

Os resultados obtidos mostram que a empresa pode beneficiar significativamente com este novo método de planeamento.

Palavras-Chave: Lot-Sizing, Sequenciamento, Planeamento da produção, Industria do calçado.

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Chapter 1

Introduction

1.1 Project Background

1.1.1 Portuguese Footwear Industry

Nowadays, the Portuguese footwear industry assumes a role of international relevance. In terms of exports, it is essential to note that in 2018 it exceeded 1900 million euros, with an increase of 47,3% in only 10 years where and 95% of the footwear produced was exported, illustrating the strong international reputation of the product. Internally the industry keeps on growing. The number of companies has grown 4,9% and there are 4000 more employees in this industry, representing 12% of the jobs in the northern region of the country (APPICAPS, 2019).

In order to understand the success of the footwear industry, it is necessary to know its recent history, going back to the causes and decisions that led it to the current moment. In the 1990s, the Portuguese footwear industry had a policy of mass production, where most of the products were sold at low cost to large international companies. This policy was due to large multinationals producing in Portuguese territory, which had facilities prepared for mass production. The liberalization of international trade allowed these companies to move to Asian countries where labor costs were lower.

The new competitive context resulting from the appearance of Asian producers led to a strategy shift. Since the big brands had left the country, the industry was now composed of small retailers that could not compete with the price of the Asian producers. The new strategy focused on flexibility and fast processing of small orders and quality, adding value to the product. The creation of private labels, concern with design, internationalization, and commercial promotion led to the consolidation of the international success of the industry.

As we can see from the statistical results presented, the strategy followed was a success, making the Portuguese footwear industry one of the most expensive in the world. One of the pillars of the industry's success was its technological innovation. The importance of this area was recognized widely, being one of the three major strategic initiatives of the footwear cluster for the future and innovation. The improvement of processes to improve the flexibility and productivity of the sector is one of the focused strategies, which is the area where this thesis fits in.

Innovation in the sector is only possible with technological solutions, many of which result from the partnership between the footwear cluster and INESC TEC. This partnership has brought advances in technological development and innovation in the sector, and it is relevant to describe some of its contributions to the area.

1.1.2 INESC TEC and the Footwear Industry

INESC TEC - Institute for Systems Engineering and Computers, Technology and Science is a laboratory that originated at INESC's Porto branch, created in May 1985.

Currently, INESC TEC has 13 R&D centers and is affiliated with the University of Porto,the Polytechnic Institute of Porto and the University of Minho.

INESC TEC is an institution created to link the academic world and the world of Industry and Services and public administration in the scope of Information Technology, Telecommunications, and Electronics. The desire to create scientific and technological knowledge and apply it in the industry has made INESC TEC one of the most prominent institutions, with strategic partnerships in various sectors.

As mentioned in the previous sub-chapter, one of INESC TEC's partnerships is with the footwear industry, with whom it has been working since 1996. In that same year, LOGICSTORE, an automatic storage and distribution system for sewing threads, was developed at Kyaia Group's Paredes de Coura site ("Footwear Industry", 2020).

Another project between INESC TEC and Kyaia Group was the "High-Speed Shoe Factory". This project was aimed to design, develop and implement a new type of shoe factory oriented for single pair production. This new production model can respond in 24 hours to small orders made online without stock, restocking products in stores, and fast production of samples and tests of new products ("High-Speed Shoe Factory", 2016).

Besides the "High-Speed Shoe Factory", other projects in the scope of improving production flexibility and speed implemented at Kyaia are the "One Step Production

Process" and the "Modular multi-ring system for flexible supply of workstation". The first integrates a single system with all production processes from cutting to assembly. The second concerns an innovative logistics system with two rings - one outside ring that interacts with the machines and operators, and an inner ring that allows bypassing, leading each shoe to visit only the posts where operations will be performed (“Modular multi-ring system for flexible supply of workstation”, 2012).

The implementation of RFID systems was also studied and developed by INESC-TEC in the ShoeID project. The obtained solutions optimize processes and help to avoid losses in the logistics chain, incorporating RFID technology in the initial footwear production cycle (“Projeto ShoeID do INESC”, 2011).

A task of the Greenshoes 4.0 project, is to develop algorithms to solve a scheduling problem in shoe injection machines. In (Sadeghi et al., 2021) an integer optimization model was developed with the objectives of minimizing both changeovers and stocks. The initial model underwent a few simplifications, acceptable from a strategic and technological point of view, due to the impossibility of reaching admissible solutions. The simplified version does not take the changeovers into account directly, instead, it divides the week in two (cycles) and mould changeovers can only happen between these cycles. This version provided an optimal solution for the scheduling of a rotary injection machine for 38 weeks. Despite providing an optimal solution for the problem, the authors think these simplifications could be avoided by using an approximate method.

1.2 Research Questions

The relevance of this dissertation is based on the improvement of the functioning of AMF’s productive system, namely the manufacturing of footwear through direct soling. The footwear injection zone is a relatively new project in the company. Still, it is already one of the company’s main focuses due to the high cost-effectiveness and innovative characteristics that it offers. AMF aims to develop methods that allow the injection system to be used at its maximum capacity, ensuring that the product quality and customer satisfaction are within the values that differentiate the company. To provide guidance throughout the dissertation, the following research questions were defined and will be addressed throughout the different phases of the project:

RQ1: What kind of difficulties can be encountered while planning an efficient production system in a reality with high variability of models and quantities?

RQ2: Which are the existing methods to address the difficulties identified in RQ1 within a footwear company inserted in the current context?

To address the research questions, the following general objective was defined: To develop a long-term planning system and improve efficiency and performance of the footwear production system through the direct soling technique at AMF Safety Shoes. To achieve the general objective, the following specific objectives were established:

- To conduct a theoretical investigation that sets the framework for the different domains and pillars related to strategic and operational planning and a literature review on the methods previously used in the industry to solve and integrate these problems.
- To carry out an in-depth study of the current processes and techniques applied in AMF and analyze the constraints and capabilities of the injection machine currently used by the company.
- To develop planning methods adjusted to the productive system and the strategic needs of the company.
- To prototype a solution for the strategic planning and improve the operational planning of AMF's production system.

1.3 Methodology

The methodology used in this project is called Action-Research. This methodology has the advantage of involving the researcher and all parties involved in the project. Figure 1.1 presents the 5 fundamental steps: Diagnostics, action planning, action implementation, evaluation and discussion of results and specification of learning (O'Brien, 1998).

The constant involvement makes this methodology most appropriate given the purpose of the project. This implies collaboration between INESC TEC, the student researcher, and the company where the project takes place.

In the first phase of this methodology, a visit was made to AMF's facilities, where all the company's sectors were presented, including the injection area. During the entire project, meetings were held with the company's planning, production and IT managers whenever additional information was required. The factory visit and the weekly sessions allowed for a detailed description of the company's current state, identifying problems and opportunities for improvement.

After the problems were identified, the "new" planning system was idealized. The notable highlights of this phase are the specification of two planning phases and the use of heuristics and optimization to reach a reliable solution.

After planning the actions and reviewing the methods for implementing them, we moved on to the implementation phase. At this point, tests were performed and their results were collected.

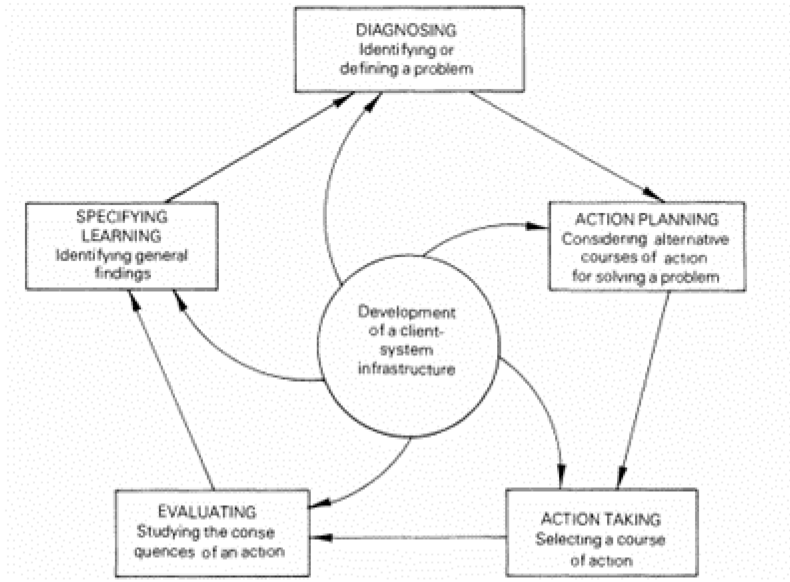

Figure 1.1: Action-Research Methodology Cycle from (Susman and Evered, 1978).

After collecting the results, the next step was to analyze and discuss the results, by comparison with the initial situation, in order to understand if the results obtained met the expectations and needs of the company.

Finally, the last phase consists of the Learning Specification, where the project's conclusions, the proposed improvements and future work were presented.

1.4 Thesis Structure

The present dissertation is organized into six chapters, structured according to how the work was planned and conducted. The project background, research questions, objectives, and the methodology adopted are presented in chapter 1.

In Chapter 2 the case study characteristics, the work to be performed and its objectives are described in more detail.

Chapter 3 is dedicated to the performed theoretical framework and literature review on relevant themes addressed by the project.

Subsequently, Chapter 4 presents the methods and tools used to solve the problems previously identified.

Chapter 5 contains the results of the application of both the mathematical model and the heuristics developed, described in Chapter 4.

Finally, Chapter 6 presents the project's main conclusions, final considerations, limitations, and future research recommendations to complement the present study.

Chapter 2

Case Study

The following thesis is developed at AMF Safety Shoes, a Portuguese company specializing in technical and safety shoes, and INESC TEC in the scope of the Greenshoes 4.0 project. Greenshoes 4.0 is a project that consists of several tasks. The task on which this thesis will focus is the implementation of a new method of production planning and sequencing on a footwear injection machine. The production of shoes using the direct injection method leads to the need to optimize the use of the injection machine, making an efficient planning system crucial to the smooth functioning of the production line.

Since the studied problem is real, it is necessary to obtain in-depth knowledge about its characteristics. First, because the production of shoes with direct injection is relatively new and innovative, there are not many academic articles that focus on this problem. And, second, because only with a complete understanding of the production system and the company can we elaborate a planning method that meets all the requirements and fits the company.

To understand the project's scope, in this chapter, a brief presentation of the company where the project was developed will be given,including a description of the current production process, the current planning method, and the problems encountered in using it. Finally, a basic structure and objectives of the new production planning and sequencing method to be developed will be defined.

2.1 AMF Safety Shoes

Albano Fernandes founded AMF Safety Shoes in 1999. They only produced for other companies/brands and conducted local, small-scale business in the early stages. However, over time, they were able to internationalize the company, which is currently multidisciplinar and innovative, according to its owner.

One of the branches of the AMF company, ToWorkFor, was created in 2016. This branch was created to find solutions for the labor market, producing resistant footwear with a modern and appealing design. The production of high-quality shoes led the company to achieve the status of the best safety shoe company in Portugal.

In 13 years, AMF showed a sharp rise in sales from 0.9 million in 2005 to 14 million euros in 2018. The same was valid for investment, which rose from 0.1 to 0.65 million euros. The number of employees has increased five times over this period, from 28 to 140.

The group's success is mainly due to the investment in technological innovation and research & development, especially in technology and innovation of materials.

Today, the company is proud to work directly with research teams and technology companies to remain at the forefront of its industry and offer its customers the best levels of comfort, safety, and ergonomics.

Figure 2.1: AMF plant in Guimarães.

2.2 Current Production System

AMF uses the Direct Injection method in the production of their shoes. They use injection machines to join the upper (upper part of the shoe) with the outsole (lower part of the shoe). This method allows for greater precision and uniformity in the shoe and provides a more waterproof, flexible, and lightweight shoe, conveying a greater sense of comfort. From an efficiency perspective, there are other benefits, such as reducing the workforce and time required to join the upper to the sole.

Figure 2.2: Example of a shoe produced in AMF.

In figure 2.2, we can see the main components in this production method. The upper is the part of the shoe that covers the wearer's foot. The insole is the part that is in contact with the wearer's foot. It is intended to give comfort to the shoe and works as an aesthetic element. The midsole is one of the injected components, its purpose is to join the sole to the upper, and it must be durable and resistant so that the pieces do not detach. Finally, the outsole is also an injected component and must be flexible and meet the safety requirements.

The use of this production method leads to a split in the production line. The first production line uses traditional methods for preparing the upper, and the second production line uses a rotating machine to inject the sole and midsole.

2.2.1 Assembly Line

Assembly begins with the arrival of the upper. The uppers arrive at the company via outsourcing. Before they are ready to be injected with soles and midsoles, they must undergo several assembly line processes.

The assembly of the uppers takes place on production line M3, which has 11 employees and a line leader. As this is the most crucial source of supply for the injection line, the planning of the assembly line is based on the planning of the injection machine.

The raw material warehouse supplies materials that, based on production orders, separate the materials for two different types of carts. The first type of carts is tree-shaped and contain the uppers (see figure 2.3), and the second type has several shelves for the insoles and other needed materials.

Figure 2.3: Finished uppers carts.

The assembly line comprises 10 PTs (Workstations), where each PT feeds the next PT, and the Work in Progress (WIP) is moved between them by a conveyor. The first five workstations are presented in figure 2.4.

In the first PT, the worker checks which article is next in the production order and supplies the conveyor with the respective uppers, toecaps, and insoles. In addition, he also registers in the company's ERP the pairs that come into production throughout the shift and the consumption of raw materials.

Then, in the second PT, the worker inserts the upper into a rotating machine to shape the stiffener to its desired format, hardening the shoe's base. After the operation, he puts the pair of uppers back on the conveyor.

The third PT is used to join the insole to the uppers by stitching. Usually, there are two strobel machines for this operation, one working the right foot and the other the left foot.

In the fourth PT, a mould is inserted in the uppers to prepare them for the remaining assembly process. Two workers usually occupy this post.

The goal of the fifth PT is to place the metal or composite toe cap on the moulded vamp. The fixation is ensured through a pressing machine.

In the sixth PT, the worker places the vamp in the centering machine, where the device will close the upper over the toecap, completely sealing the front of the shoe.

In the seventh PT, the upper's bottom is roughened, ensuring the elimination of excess material and uniformity with the help of a carding machine.

The main task of the eighth PT is the placement of a steel insole to ensure resistance to perforations. The insole is previously prepared with glue, is placed in the upper, and then placed in a press that guarantees its fixation.

The ninth PT marks the end of the assembly process, where an operator removes the mould from the upper and places it back on the conveyor.

Finally, on the tenth PT, quality control of the upper is performed. If any nonconformity is detected, the upper is placed back on the conveyor to be repaired. If it is in conformity, the operator places the upper on a cart that will later be transported to the injection line.

2.2.2 Injection Line

The injection process is carried out on a rotary machine with 24 stations, usually operated by two employees. Figure 2.5 presents the device used by AMF, manufactured by one of its partners, Desma.

Injection carts supply the injection line. These carts consist of twenty-four racks with a capacity of ten pairs of uppers each. These carts correspond precisely to the stations of the injection machine. That is, each cart is loaded according to the next ten machine cycles. The carts are placed near the buffer zone of the injection machine, where one of the workers is located (near position 4 represented in figure 2.7).

Besides the uppers, the machine is supplied with polyurethane (PU), the material used to inject the sole and the midsole.

During machine rotation, a sequence of operations takes place at each station to complete the injection cycle. Figure 2.7 provides a layout of the injection machine.

In the first position is injector 1. This injector is responsible for injecting the sole.

Figure 2.4: AMF´s assembly line.

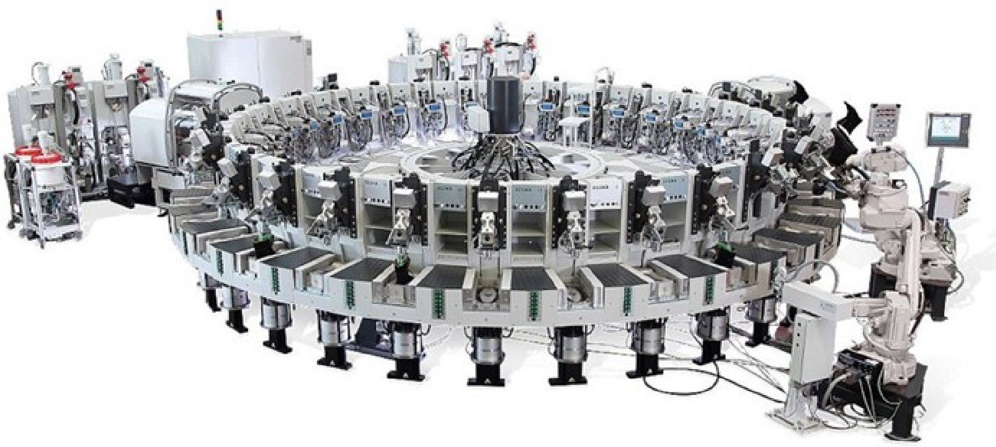

Figure 2.5: Injection rotating machine by Desma.

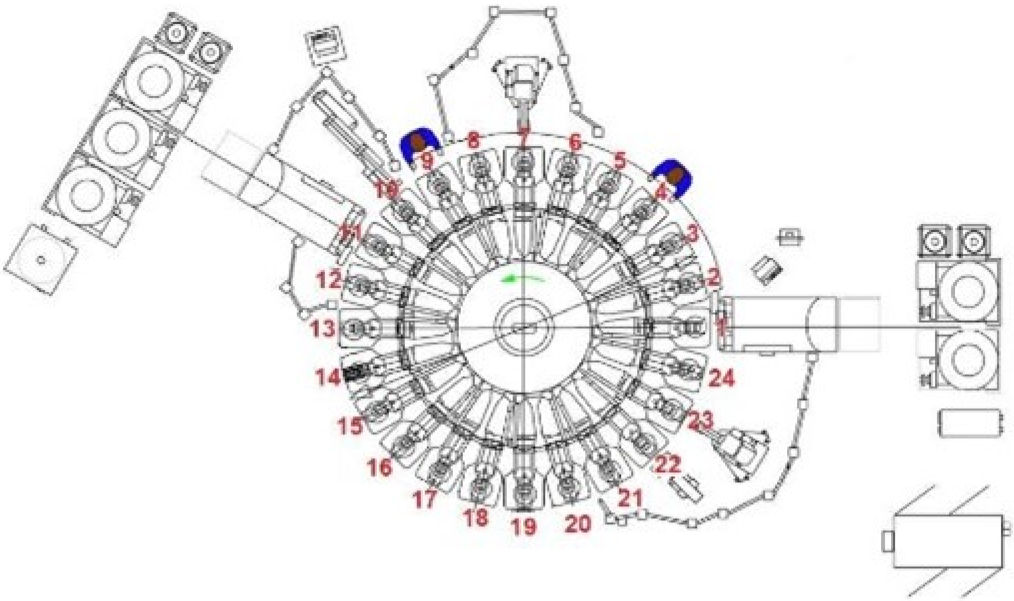

Figure 2.6: Layout of the injection machine.

In the fourth position, an operator is responsible for taking off the shoe previously injected from its place and putting on a new upper (ready to be injected). The operator who works in the 4th position is the machine manager and is responsible for recording all the interventions performed during his shift, from quality control to maintenance and mold adjustments.

In the seventh position, a carding robot cards the uppers according to the defined program.

The ninth position is occupied by another worker, who checks the injection channels' neatness and the conformity of the injected sole. If the shoe's outsole is rubber or thermoplastic polyurethane (TPU), the operator places it in the mold.

In the tenth position, the glue is reactivated on the outsole. In the 11th, the injection of the midsole is done by Injector 2.

Between the twelfth and twenty-first positions, the machine rotation has no specific operations. The associated rotation time of the machine also represents the curing time of the injected PU.

In the twenty-second position, a robot removes the PU residues in the injection channel of the mold, leaving it clean and prepared for the next injection.

Finally, in the twenty-third position, a robot applies a release agent into the mold in the form of a spray, ensuring that the injected PU does not adhere to the mold during the injection process.

At the end of this cycle, the product obtained is the pair of shoes with all the main components joined. However, some operations are still to be done for the shoe to be considered a final product. Processes such as inserting applications and laces, packaging, and identifying the packaging are carried out later on the finishing line.

2.3 Current Planning Method

The injection planning is carried out according to two principles: Efficiency of the injection molding machine and customer service. To achieve high machine efficiency and to be able to apply the planning to the day-to-day operations of the company, variables such as mold type, color, outsole type, and which uppers are available for injection are taken into account. Since this is a real production system, numerous restrictions and exceptional cases regarding injection sequences will be presented later in this chapter.

Figure 2.7: Current Planning Method Diagram.

In general, injection planning is supported by a simulator developed internally by AMF. The existing production orders are inserted into the simulator,as well as the availability of molds, their changeover times, and the availability of the injection molding machine.

The simulation process follows a set of user-defined rules that can be divided into:

1. Sorting rules;
2. Selection rules;
3. Mould exchange rules.

Sorting rules are used to sort the list of production orders (POs) chosen for the simulation. The user can choose whether to sort by priorities or by the order in which the POs are selected in the program.

Both the selection rules and the mould change rules are used to choose the most suitable PO according to the constraints of the injection machine. These rules are to select a PO with:

1. Same color;
2. Compatible color;
3. Incompatible color;

4. Same reference;
5. Same production order;
6. Split production order.

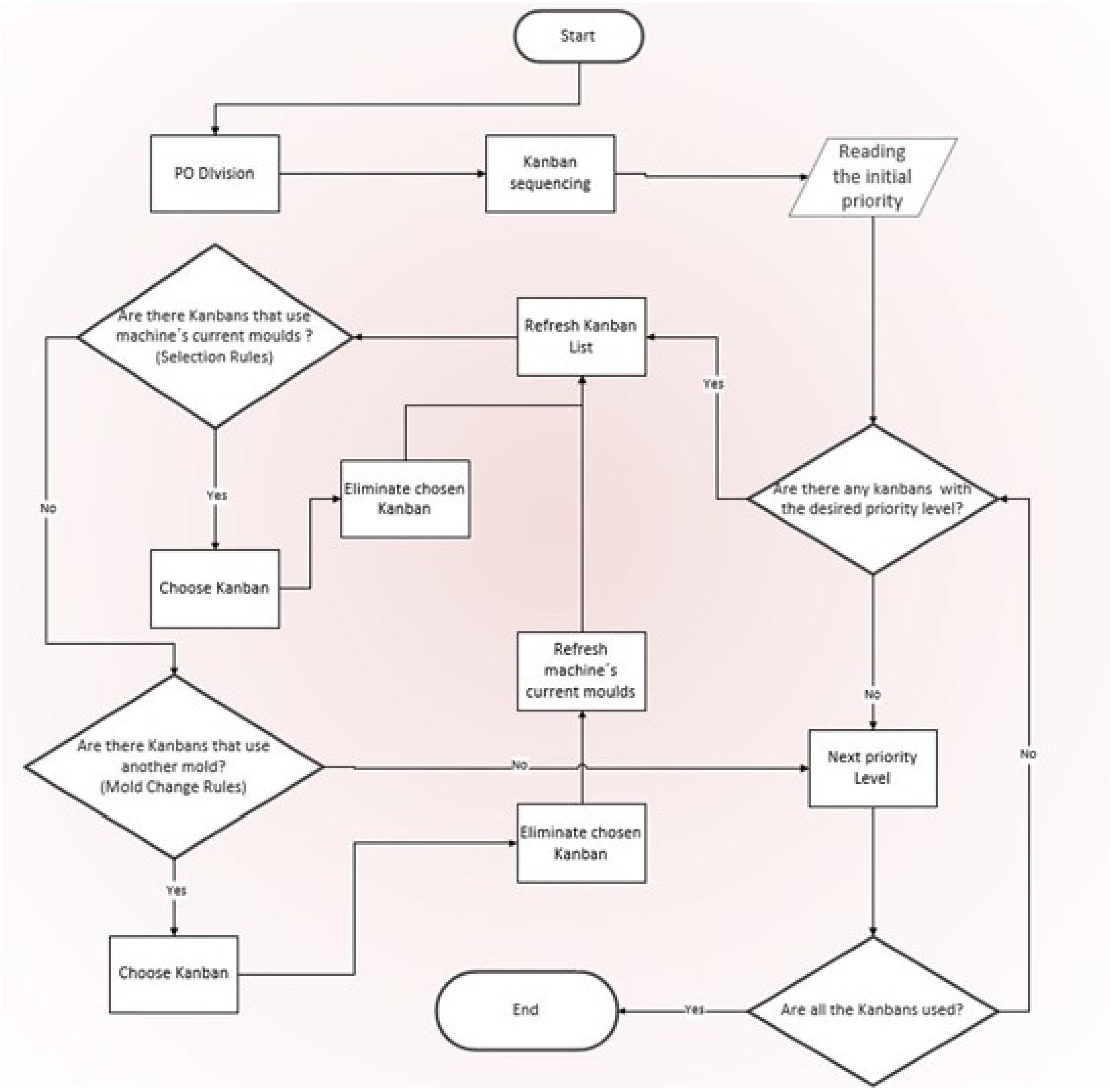

Figure 2.8: Current Planning Method Diagram.

Figure 2.8 shows that the algorithm starts by reading the chosen POs and dividing them into kanbans by size. Next, it organizes the kanbans according to the sorting rules and reads what the initial priority is. The company uses the name "kanbans" to define a divided PO, and it has no use as a production kanban.

After knowing what the first priority is, it checks if there are kanbans with that same priority and if so, it updates the list of available kanbans and sees if there are any kanbans that use the moulds currently in the machine. If yes, it chooses a kanban according to the selection rules, updates the list, and goes back to the same cycle. If not, it will check if there are kanbans that use another mold within the chosen priority. If there are, a kanban will be selected according to the mold change rules; this kanban is deleted from the list, the mold on the machine at that station is updated and returns to the initial cycle. If not, it means that there are no more kanbans in that priority order, so the simulation process moves to the next priority level.

After moving to the next priority level, it checks if there are still kanbans left to be sequenced; if yes, it goes back to doing the whole cycle again; if not, the cycle ends.

The simulator's output will be the injection sequence for each size per article, indicating which mould changes are necessary and when they should be performed. It is a common practice to perform several simulations where the selection and mould exchange rules are varied. The simulation that better suits the needs of the company at that particular moment is validated and selected by the production planner before starting the injection cart supply operation.

2.4 System Constraints

Having learnt in detail the production system, we realized that there are some aspects to consider to create a production plan that is feasible for the actual production system. There are three types of constraints, divided into machine constraints, mould constraints, and injection colors constraints.

2.4.1 Machine Constraints

The injection moulding machine consists of 24 stations, whereas only 12 stations are considered for simplification reasons since shoes are produced in pairs.

The *transition time* is the time taken between the rotation of two consecutive posts, and the *cycle time* is the time for one complete rotation of the machine, i.e., it is 24 times the *transition time*.

The *transition time* varies depending on which moulds are in the machine. Currently, the *transition times* are 18 and 20 seconds, depending on the mold this means that sometimes there are moulds with different *transition times* simultaneously in the machine; in such cases the considered *transition time* is always the longest.

The machine is not fully automatic and requires workers, which makes the availability of the machine limited by the workers' schedule.

The machine works with positions not occupied by molds, but it only injects when there is a mold associated with a position.

2.4.2 Mould Constraints

There are six types of moulds: Fusion, Michelin, Magnum, CLS, Infinity, and Sika. In addition to types, moulds are also distinguished by size.

Usually, the mold name is associated with the model name, i.e., the Magnum model uses Magnum moulds, but there are some exceptions.

The Elite model uses the Michelin moulds from the number below (e.g., the mould used to produce the Elite 38 model is Michelin 37). The Fusion model can use the Michelin mould in size 44.

When it comes to changing moulds, *fixed* and *variable times* are defined. The *fixed time* is the time accounted for stopping and starting the machine between mould changes, it is two minutes. The *variable time* refers to the time it takes to remove and place a new mould on a position, it is eight minutes.

2.4.3 Injection Color Constraints

As already mentioned, the machine has two injectors, one for the outsole and one for the midsole.

There are no color restrictions between sole and midsole injections.

The outsole can be injected or not injected, and when it is not injected, it has to be placed in the injection area to join with the upper.

Figure 2.9: Color code.

There are three possible scenarios when it comes to the machine's procedure in the injection process. *Incompatibility* means that the machine cannot make the change between the required colors. *Compatibility with purging*, that is, the injection color can be changed, but it is necessary to clean the injector, which will lead to material waste. *Compatibility without purging* arises when there is no color change between injections. Figure 2.9 presents the color code used to describe the scenarios

Figure 2.10: Compatibility matrix for the midsoles.

In midsoles, it is not possible to make White-Other Color and Other Color-White exchanges (see figure 2.10). The whole machine has to be reprogrammed to inject white midsoles, which has a high set-up time. When injecting a midsole in white, the following midsoles should also be white.

There is no incompatibility between injecting outsoles as we can see in figure 2.11.

Outsole Compatibility Matrix

	Black	Light-Grey
Black		
Light-Grey		

Figure 2.11: Compatibility matrix for the outsoles.

2.5 Proposed Solutions

The analysis and description of the production and planning processes used by AMF made us realize that some issues can be solved.

The current planning method does not consider the delivery dates of each OP and uses the user's experience and judgment as to which OP´s will be sequenced. A planning method that takes a global perspective of the planning horizon, i.e., making all OP´s available for planning, can lead to higher quality solutions due to the higher level of information used. By considering the delivery dates, it is no longer necessary to bond each OP with a sequence and priority since the company´s goal is to deliver the products on time.

There are other issues regarding the utilization of the simulator. The arrival of an unexpected order will lead to a complete reformulation of the production plan defined previously, slowing down the production processes. The creation of several instances manually can also pose a problem. The simulations are created based on rules, and the rules are changed by the planning engineer, who can be biased and miss some good simulations.

Still, the simulator presents several advantages. The results given are of great operational detail and mimic the machine´s restrictions and capacities.

After reviewing the characteristics of the factory and the behavior of the factory's production process, it is possible to define the overall outlines of the new solution.

The strategy defined is to divide the planning process into two parts: strategic planning and operational planning (see figure 2.12).

Strategic planning can be considered as a lot-sizing problem. In the first stage, planning would be done considering the entire time horizon. The results should be a simplified production plan to identify the need for stocks or delays in deliveries and the orders produced each week.

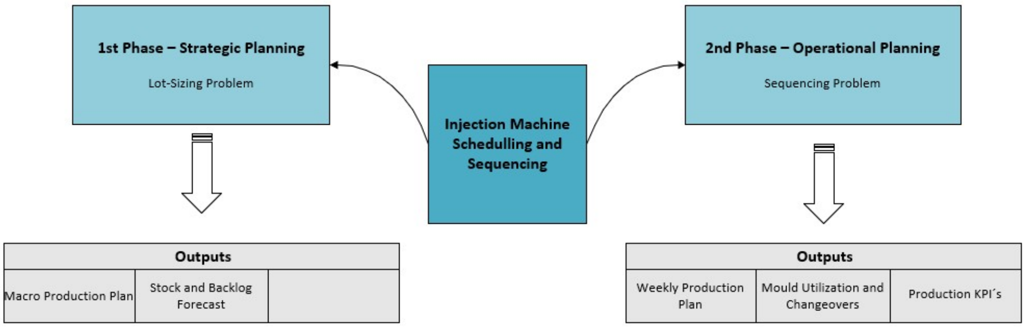

Figure 2.12: Proposed planning solution.

The operational planning would consider the results obtained in the first phase and, like the simulator currently used by AMF, would present a production plan with the production sequences and mould change needs; the production plan is obtained through exact models or heuristics.

Chapter 3

Relevant Literature

The main goal of production planning is to develop a plan based on forecasted demands or client orders that include the products to be manufactured and the available resources for a specific planning horizon. The plan should provide the company with information about what products will be produced in the defined periods from a macro perspective. For the operational level, the planning department delivers a production schedule detailed by minute, hour, or day and shows which product needs to be produced, in which machine, and its sequence (Jans and Degraeve, 2007).

The planning horizons for production planning models are typically divided into three categories: long-term, medium-term, or short-term planning (see Figure 3.1). Long-term planning is generally focused on long-term strategic decisions such as equipment and product choices. Medium and short-term planning involve making decisions on material flow, production lot-sizing, and production scheduling to optimize the production line's overall performance.

In this study, we consider two decision levels: one related to the lot sizing problem (upper level) and another to the scheduling problem (lower level). According to (Alves et al., 2021), the upper-level problem takes into account disaggregated demand and medium-term planning, and the goals are to meet the demand while satisfying the production systems constraints. The lower-level planning is a short-term planning, usually weeks or days, and deals with detailed information.

The thesis is focused on solving lot sizing and scheduling in an injection system in the footwear manufacturing industry. There are few studies in this area; however,

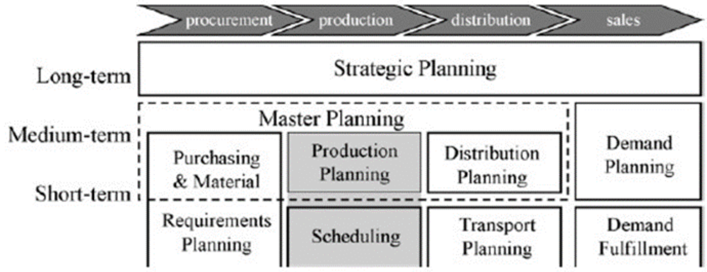

Figure 3.1: Planning horizons and the main tasks and goals from (Maravelias and Sung, 2009)

there are many publications regarding lot sizing and scheduling problems, and there are many proposed ways to solve these problems. In the following sections we present some of the relevant literature for Lot-Sizing problems, Simultaneous Lot Sizing and Scheduling problems and the techniques used to integrate both problems.

3.1 Lot Sizing

According to (Drexl and Kimms, 1997), the research on lot sizing started with the classical economic order quantity model (EOQ). This model considers a single-level production process with no capacity constraints, making it a single-item problem. Since these assumptions make the model very restrictive, other models were developed to bridge the gaps in the EOQ. These models are the Economic lot scheduling problem (ELSP) and the Wagner-Within problem (WW).

In the ELSP capacity restrictions are considered. Since most items typically share scarce resources, the ELSP is a single-level, multi-item problem. The WW problem assumes a finite planning horizon with dynamic demands. However, capacity limits are not considered, making it a single-item problem.

The next generation of models combines capacitated and dynamic approaches.

In (Jans and Degraeve, 2008) lot-sizing models were classified as the single item uncapacitated lot-sizing problem, the capacitated multi-item lot-sizing problem (CLSP), the continuous set up lot-sizing model (CSLP), and the discrete lot sizing and scheduling problem (DLSP). The single item uncapacitated lot-sizing problem is the simplest form of a lot-sizing problem. There are three key aspects to consider in each period: the production level, the set-up decision, and the available inventory and there are costs associated with each one of the variables. The objective is to minimize the total cost of production, set-up, and inventory. The same fundamental trade-off between set-ups and inventory is also found in the EOQ formula. The problem can be modelled as follows (Jans and Degraeve, 2007):

$$\min \quad \sum_{t=1}^{m}(vc_t x_t + sc_t y_t + hc_t s_t) \tag{3.1a}$$

$$\text{s.t.} \quad s_{t-1} + x_t = d_t + s_t \qquad \forall t \in \mathcal{T} \tag{3.1b}$$

$$x_t \leq \sum_{k=t}^{m} d_k \times y_t \qquad \forall t \in \mathcal{T} \tag{3.1c}$$

$$x_t, s_t \geq 0; y_t \in \{0,1\} \qquad \forall t \in \mathcal{T} \tag{3.1d}$$

In this model x_t represents the production variable for period t, y_t is the set-up variable and s_t the stocks variable. The costs associated with these decision variables are: vc_t, sc_t and hc_t , respectively. T is the set of all time periods. The objective function (3.1a) minimizes the total cost of production, set up and inventory. Constrains (3.1b) balances the demand and constraints (3.1c) express the fact that final inventory is not allowed, meaning that production is limited by the given demand.

Since companies do not have unlimited capacity and make more than one product, realistic models must take this into account. How these elements are modeled depends on the choice of the time periods and production mode.

Large Bucket vs Small Bucket Models

In a large bucket model, several items can be produced in the same period in the same machine; on the contrary, in small bucket models, a machine can only produce one type of product per period.

The CLSP is a large bucket model. In this model, several different items can be produced in each time period, and there is a limited production capacity available in each period. The main difference between this model and the single item uncapacitated lot-sizing problem is the addition of the capacity constraints and an extra index to identify the item. The objective is the same as in the previous model: minimize production, inventory, and start-up costs.

The CSLP is a small bucket problem. It uses a new decision variable that signals start ups if the machine needs to be set up for an item that was not set up in the previous period. Being a small bucket problem, it also has a constraint imposing that at most one type of a product can be produced in each time period.

Finally, the DLSP is a small bucket problem with an all-or-nothing approach to production. The model proposed by (Fleischmann, 1990) has a similar structure to the CSLP except that the capacity constraints become an equality, since if there is any production in a period it must be at total capacity.

There are many extensions of lot-sizing models, usually divided into four topics: set-up, production, inventory, and demand. For a detailed analysis of those models the reader is addressed to (Jans and Degraeve, 2008).

3.2 Lot-Sizing and Scheduling

Lot-sizing and scheduling problems have been topics of research in academia and a matter of concern for many companies over the years. Companies often have limited production capacities and demand for individual products is associated with time periods that are hard to predict. Furthermore, minimizing stocks at the end of each period is crucial to companies, as well as delivering the products on the defined dates. Set-ups are also a big part of the scheduling/lot-sizing problem since they can represent a relevant part of the time spent.

In order to be efficient and avoid waste, resources have to be meticulously managed in the company, and tackling the lot-sizing and scheduling problem should be a priority for the production and logistics departments—the main goal is to find the trade-off between the holding and set-up costs, under a set of constraints. This sub-chapter aims to introduce several types of lot-sizing and scheduling problems using the integrated approach while presenting their evolution and applications to real world problems.

In (Guimarães et al., 2014) a classification framework is proposed to classify the different modeling techniques used for lot-sizing and scheduling problems, as shown in figure 3.2.

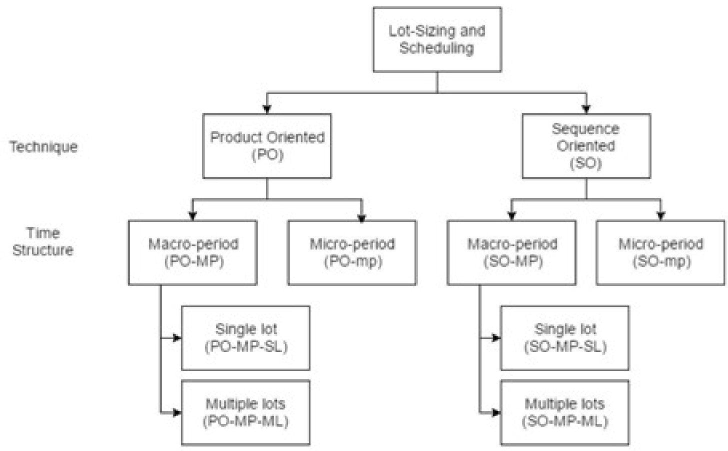

Figure 3.2: Classification framework from (Guimarães et al., 2014)

The techniques can be product oriented (PO) or sequence oriented (SO). When using a PO technique, the sequences are explicitly defined by the mixed integer programming model (MIP), in SO formulations the MIP model prescribes, for each period, a sequence from a pre-determined set of possible sequences.

The time structure can be based on macro-periods models (MP) or on micro-periods models (mP). In MP models, multiple set-ups are allowed on each period while on mP models only a single set-up per period is available.

This framework further classifies the models into single lot (SL) or multiple lot (ML). This classification is based on the number of productions lots of each product that is allowed to start within a time period.

The authors in (Copil et al., 2017) state that lot-sizing and scheduling models can be divided in five types. The general lot sizing and scheduling problem (GLSP) is the generic version of this type of models, and it is used to describe the remaining, which are: the capacitated lot-sizing problem (CLSP), the proportional lot sizing and scheduling problem (PLSP), the continuous set-up lot sizing problem (CSLP) and the discrete lot-sizing and scheduling problem (DLSP). The DLSP, CSLP and PLSP are small bucket models. The CLSP is a large-bucket model that determines lot sizes but not the sequence of the lots. According to (Suerie, 2005) the GLSP and the CLSD are hybrid models, since they combine macro periods and an approach to sequence the lots.

(Fleischmann and Meyr, 1997) also distinguish between the GLSP with loss of set-up state (GLSPLS) and the GLSP with conservation of set-up state (GLSPCS). In the first, set up state is not conserved in idle periods. In the GLSPCS no additional set-up is necessary after a idle period if the same product is produced again.

3.3 General Lot-Sizing and Scheduling Formulation

As stated before, all the basic formulations derive from the GLSP. To better explain how the derivations occur, we will first present the model proposed by (Meyr, 1999).

The proposed model considers several products k and a fictitious dummy product $k = 0$. For each physical product and each macro period, an associated demand d_{kt} has to be fulfilled. The coefficient a_k gives us the time taken to produce product k. Changeovers from product i to product k causes sequence-dependent setup costs sc_{ik}. sc_{i0} indicates the shutdown costs. Standby costs are indicated by pc_k and occur when a setup state for product k is preserved. A start up from the neutral state costs sc_{0k}. The model aims to minimize the total costs.

Micro periods s are used to model the sequence of products within the macro periods. In a micro period, either a product is produced, or the setup state is altered. Each macro period consists of a predefined sequence of micro periods. The length of each macro period t is given by the capacity C_t of the production resource. The length of micro periods results from multiplying the production quantities of product k in micro-period s q_{ks} by the production times a_k plus the setup times. W_{ks} define the setup state of the production resource for product k in micro-period s .Z_{iks} define changeovers from product i to product k within micro periods, and setups cause sequence-dependant setup times indicated by st_{ik}. Finally, variables l_{kt} denote the inventory of product k in macro period t.

The model's indices, parameters, and variables are in tables 3.1, 3.2 and 3.3, respectively. The model formulation is presented below.

i, k	Product index, i, k=0, 1, ..., K, where 0 is the neutral state
s	Micro period index, s=1, 2, ..., S
t	Macro period index, t=1, 2, ..., T
S_t	Set of micro periods s within a macro period t

Table 3.1: Indices table.

sc_{ik}	Setup cost for a changeover from product i to product k
hc_k	Holding costs for product $k > 0$ (per unit and macro period)
pc_k	Standby costs for preserving the setup state of product k on the production resource
a_k	Production time per unit of product k
st_{ik}	Setup time per unit of product k
C_t	Capacity of the production resource in a macro period t
l_{k0}	Initial inventory of product $k > 0$ at the beginning of the planning horizon
d_{kt}	Demand of product k in macro period t
W_{k0}	Indicates that the production resource is set up for product k at the beginning of planning horizon
q_k^{min}	Minimal production quantity of product $k > 0$; minimal time for neutral state $k = 0$

Table 3.2: Parameters table.

$q_{ks} \geq 0$	Production quantity of physical product $k > 0$ in micro period s; time spent in neutral state if $k = 0$
$qq_{ks} \geq 0$	Duration for which the setup state of product k is preserved on the production resource in micro period s
$l_{kt} \geq 0$	Inventory of product $k > 0$ at the end of macro period t
$W_{ks} \in 0, 1$	Set up state variable; $W_{ks} = 1$ indicates that the production resource is set up for product k in micro period s

Table 3.3: Decision variable table.

$$\min \quad \sum_{s=1}^{S}\sum_{i=0}^{K}\sum_{k=0}^{K} sc_{ik} * z_{iks} + \sum_{k=1}^{K}\sum_{t=1}^{T} hc_k \times i_{kt} + \sum_{k=0}^{K}\sum_{s=1}^{S} pc_k \times qq_{ks} \tag{3.2a}$$

$$\text{s.t.} \quad \sum_{k=0}^{K}\sum_{s\in s_t}(a_k \times q_{ks} + qq_{ks} + \sum_{i=0}^{K}\sum_{k=0}^{K}\sum_{s\in s_t} st_{ik} \times z_{iks} = c_t \qquad \forall t \tag{3.2b}$$

$$l_{kt} = l_{k,t-1} + \sum_{s\in S_t} q_{ks} - d_{kt} \qquad \forall t, k > 0 \tag{3.2c}$$

$$\sum_{k=0}^{K} W_{ks} = 1 \qquad \forall s \tag{3.2d}$$

$$a_k \times q_{ks} + qqks \leq C_t \times W_{ks} \qquad \forall k, t, s \in S_t \tag{3.2e}$$

$$z_i ks \geq W_{i,s-1} + W_{ks} - 1 \qquad \forall i, k, s \tag{3.2f}$$

$$q_{ks} \geq q_k^{min}(W_{ks} - W_{k,s-1}) \qquad \forall k, s \tag{3.2g}$$

The objective function (3.2a) calculates the total cost, that consist of set up and holding costs, plus costs for preserving set-up states. Constraints (3.2b) guarantee that the production does not exceed the capacity in any macro period. Constraints (3.2c) assure that the inventory at the end of period t is equal to the inventory at the end of the previous period $(t-1)$ plus the produced quantity minus the demand of that period. Constraints (3.2d) ensure that in each micro period a resource is set-up for only one product. Constraints (3.2e) guarantee that if one of the continuous variables q_{ks} or qq_{ks} is greater than zero, W_{ks} is set to one.

Constraints (3.2f) signal the changeovers. Binary changeover variables Z_{iks} can be relaxed. In an optimal solution, these decision variables only take values of zero or one. This is because of the combination of the objective function (3.2a) with constraints (3.2f). Constraints (3.2g) are used to determine minimum lot sizes q_k^{min}. Minimum lot sizes may be needed due to technical limitations of the production process and may also be necessary if triangle inequalities $(sc_{ik} + sc_{kj} \leq sc_{ij})$ are violated.

3.4 General Lot-Sizing and Scheduling Derivations

As previously mentioned, all the models mentioned in chapter 3.1 can be represented as derivations of the General Lot Sizing and Scheduling model. Figure 3.3 shows the relation between the models. It is possible to see that all models derive from GLSP since they are specializations of the latter. However, it is important to realize that the lower the level at which the model is, the more specialized it is, reflecting fewer real applications. On the other hand, specializations can serve as a basis for solutions to specific problems.

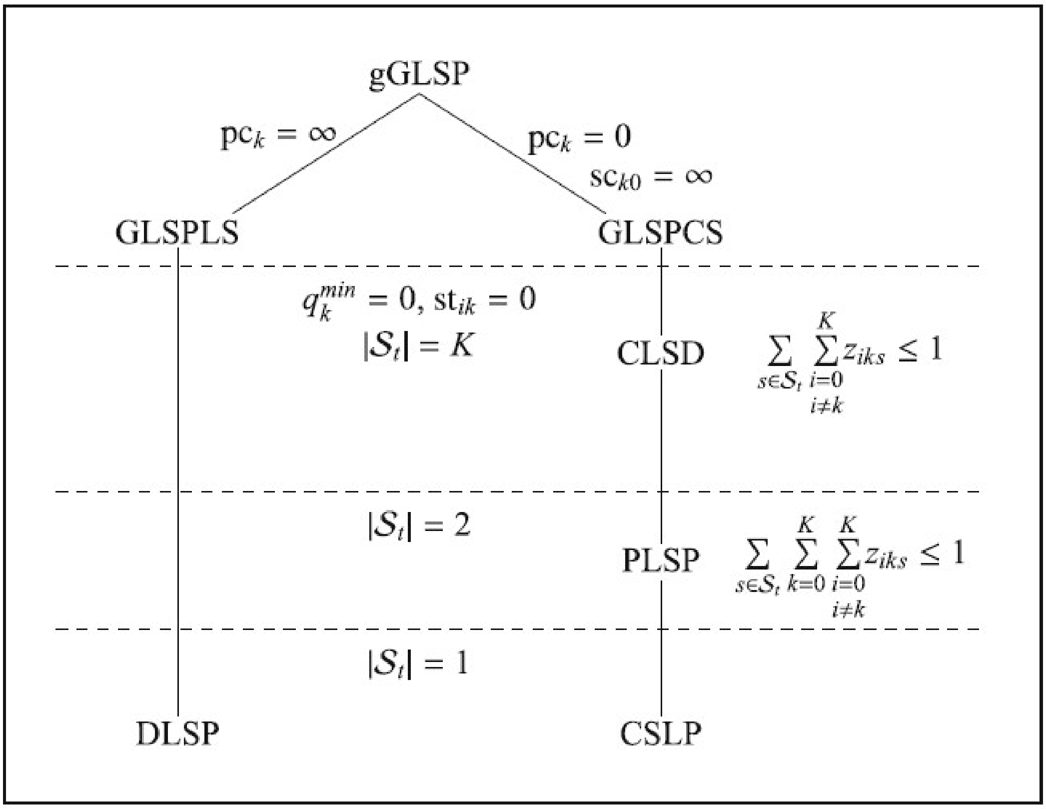

Figure 3.3: Relation between models from Meyr, 1999

(Fleischmann, 1990) starts by distinguishing the GLSP with loss of set up state (GLSPLS) and the GLSP with conservation of setup state (GLSPCS).

The Capacitated Lot-Sizing Problem (CLSD) allows the conservation of the set up state, but limits the number of lots per macro period to K, meaning that the number of micro periods per macro period is equal to the number of products ($S_t = K$). The CLSD does not minimize production quantities and set up times, adding $q_k^{min} = 0$ and $st_{ik} = 0$. It only allows each product to be setup once per macro period, by considering constraints (3.3a).

$$\sum_{s \in S_t} \sum_{i=0, i \neq k}^{I} Z_{iks} \leq 1 \qquad \forall t, k > 0 \tag{3.3a}$$

The Proportional Lot sizing and Scheduling Problem (PLSP) allows at most one single changeover per period, while the setup state can be conserved. Two different products can be produced in a single period. This will require $S_t = 2$ and adding the constraints (3.4a) to restrict the total number of changeovers per macro period.

$$\sum_{s \in S_t} \sum_{k=0}^{K} \sum_{i=0, i \neq k}^{I} Z_{iks} \leq 1 \qquad \forall t \tag{3.4a}$$

The Continuous Setup Lotsizing Problem (CSLP) is similar to the PLSP since at most one single changeover per period is possible and it allows the conservation of the setup state. The only difference between these two is that in the CSLP only one product can be produced per period.

The Discrete Lot sizing and Scheduling (DLSP) problem is different from all the others because of its *all-or-nothing* assumption. In each period, there is only the option to produce during the complete duration of the period or to not produce at all. Since this model is very specific, usually the periods are very short, making it a small bucket model.

3.5 Lot-Sizing and Scheduling Problem Applications in the Footwear Industry

One may know that the production system of each industry has its own characteristics, including the operational restrictions, the implementation of production processes, and the unique feature of facilities. Constraints reflecting such characteristics must be considered to ensure the production plan/schedule feasibility obtained from the mathematical model. We found some applications of mathematical models tackling the lot sizing or scheduling problems for the footwear industry and describe them below.

Multi-Mould Injection Machine Sequencing and Scheduling (MMIMSS) was first addressed in 2009. In the scenario studied, sequencing and scheduling solutions were developed for a rotating injection machine with two injectors considering changeover times and aiming to minimize make-span (Boctor et al., 2009).

The authors in (Huang et al., 2012) used genetic algorithms to solve the same problem and minimize the make-span considering constraints and set-up times.

The work in (Lopes et al., 2017) uses integer programming to solve the problem of one machine, one model, N orders, with the same intended delivery date and distinct quantities per size and the objective is to minimize the makespan.

The work in (Sadeghi et al., 2021) proposes a mathematical model for the long-term scheduling of an injection machine; the aim is to avoid delays. The proposed problem was to schedule the production of multiple models in a set of machines for 38 weeks. The high complexity of the real instance made it impossible to solve optimally in the required time. The instance was successfully solved after not considering set-up times directly without influencing the quality of the obtained solution .

We verify that all these studies focus on the minimization of makespan and indirectly on the minimization of set-ups, and that they do not consider constraints fundamental to the solution's use in a real environment such as: compatibility between models, sharing of moulds, the possibility of delays in orders, among others.

3.6 Lot-Sizing and Scheduling Integration

As previously mentioned this work focuses on solving upper-level and lower-level planning decisions. There are many production planning problems connecting lot-sizing and scheduling since handling them separately can lead to infeasible solutions and sub-optimal solutions.

According to (Dauzère-Péres and Lasserre, 1994) both problems are NP-hard even when considered individually. Therefore, solving the integrated problem for large instances is not efficient.

Figure 3.4 decomposes the problem into a lot-sizing problem and a detailed scheduling problem. The results of the lot-sizing problems are used as input for the scheduling problem. The method is *hierarchical* when the flow of information is only from the master problem to the slave problem. The *integrated* method is when lot-sizing and scheduling problems are solved simultaneously in a single mathematical model. If there exists a feedback loop between models, then the method is *iterative*.

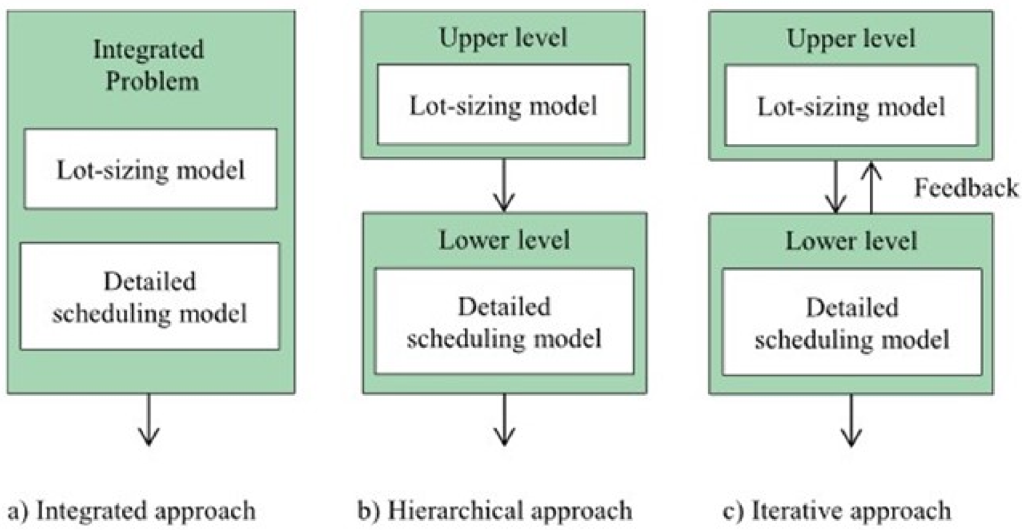

Figure 3.4: Approaches for solving production lot-sizing and scheduling problems from (Maravelias and Sung, 2009)

Integrated Approach

The integrated approach is a solid alternative to solve both problems jointly. However this can lead to many decision variables and consequently deal with only small instances of a problem (Wolosewicz et al., 2015). This approach is usually more complicated, but it eliminates the possibility for connection errors between the levels since it incorporates all the constraints into a single formulation (Dauzère-Péres and Lasserre, 1994).

For integrated lot-sizing and scheduling applications in different industrial scenarios, the reader is referred to (Toledo et al., 2015) and (Y. Lee and Lee, 2020).

Hierarchical Approach

According to (McKay et al., 1995), the master problem provides a set of high-level decisions such as production targets and selection of tasks that are then fed as input to the lower level scheduling problem. The goal is to obtain the complete scheduling solution in two steps. Hierarchical decomposition can also be used within a rolling horizon framework. This methodology uses detailed scheduling models for the first periods, and aggregate models are used for the later periods. In the first periods the production targets are exact and thus directly implemented, while the following periods are updated as the horizon rolls. (Sand and Engell, 2004) discuss hierarchical approaches that employ rolling horizon methods to address problems under uncertainty.

Iterative Approach

Without detailed resource and production cost constraints, the main problem's production goals or task unit assignments will likely be infeasible or suboptimal. In an iterative approach, instead of trying to find feasible solutions that are in the neighborhood of these decisions, iterative methods try to close the feedback loop from the scheduling sub-problems to the main problem. The objective is to find the true high-level optimal decisions. This can be achieved by adding integer cuts that exclude previously found solutions that provide multiple solutions of the main problem that will be evaluated by the scheduling problem (Maravelias and Sung, 2009).

Iterative methods are very promising. However, at the moment, their applications are very formulation-specific. For applications of iterative methods in the industry, the reader is referred to (Dogan and Grossmann, 2006) and (Stefansson et al., 2006).

3.7 Scheduling Heuristics

The single machine scheduling problem is an essential problem in machine scheduling models since it either allows to solve the single machine models or gives an initial solution to the decomposition of big problems into sub-problems.

(Pinedo, 2014) mentions that dispatch rules have been an area of active research for several decades and that a large number of different rules have been studied in the literature. These are important when trying to find a good solution concerning a single objective, like the minimization of makespan, maximization of delay or of total termination time.

In the SPT (Shortest Processing Time) dispatch rule, tasks are ordered according to their production time, from smaller to greatest, first processing the task with the shortest duration and so on. In contrast, the LPT (Largest Processing Time) rule first elaborates on the most time-consuming job.

(Sipper and Bulfin, 1998) mentions that a direct heuristic algorithm forces the problem to be one of two machines and use Johnson's algorithm. The distinct approaches to transform the m-machine problem into a two-machine problem produce different programs, so it is possible to choose the best one among all. Campbell, Dudek and Smith proposed a conversion approach, the CDS heuristic.

In the General SB (Shifting Bottleneck) routine, machines are sequenced one by one, successively, taking each time the machine identified as a bottleneck among machines not yet sequenced. Previously established sequences are re-optimized locally whenever a new machine is sequenced (Costa et al., 2014). The neighborhood search routine applies to the flow shop and job shop machines environment, with the objective of minimizing the makespan or the total weighted delay. Local search is a procedure that does not guarantee an optimal solution, usually trying to find a better program than the current one in the neighborhood.

Chapter 4

Implementation: Mathematical Model and Heuristics

The objective of the project is the development of a planning tool. The tool takes into consideration the optimization of the production system based on operational requirements such as the production of small quantities, number of injection positions per machine, multi-material injection, model compatibility, setups and changeovers. In the following sections the mathematical models and algorithms used to reach the final result will be presented.

4.1 Lot Sizing

The lot-sizing models presented in the following sections are aimed to solve the medium and long-term planning problem of a footwear injection machine.

In this section an overview of the mathematical model and its characteristics are presented. The development process was done in partnership with the company´s planning managers, taking multiple steps to create a model that would solve the medium and long term planning problems of a footwear injection machine.

The main goal of this model is to provide a more comprehensive view of the planning horizon to the machine planner and create solutions that meet the requirements of the production system while minimizing production and backlog costs.

The analysis of the production system done in chapter 2 gave us important information regarding the injection machine, that translates into assumptions and makes it possible to develop a mathematical formulation to the presented problem.

Assumptions

- All raw materials needed are received at the beginning of the planning horizon.
- The injection machine is fully functional and works 14 hours a day, 7 days a week.
- When changing from one product to another, set-up time and costs may exist.
- Each item has one assigned mould for being produced.
- Injection and set-up times are provided by the company.
- The machine may work with positions without assigned moulds.
- Holding inventory is allowed.
- The planning horizon is divided into periods, each period is one week.
- Weekly demand is known at the beginning of the planning horizon.

4.1.1 Multi-Item Lot Sizing Problem

This first model that was developed was a Multi-Item Lot-Sizing problem based on a model proposed by Pochet and Wolsey, 2006. In the typical multi-item lot-sizing problem, there are m items, n periods, demands for item i in period t, individual production limits, production costs, storage costs, fixed costs, machine production rates, set-up times, and machine capacity. A backlogging variable and cost were also included. This allows the items to be delivered later than the defined date.
The notation needed is provided in tables 4.1,4.2 and 4.3:

I	set of types and sizes of shoes
O	set of production orders
W	set of weeks in the planning horizon
M	set of injection moulds

Table 4.1: Sets table.

d_{iot}	$i \in I, o \in O, t \in W$	Demand of Item i and Order o in Week t (pairs)
p_i	$i \in I$	Fixed production cost of Item i
h_i	$i \in I$	Fixed storage cost of Item i
w_i	$i \in I$	Fixed backlogging cost of Item i
a_i	$i \in I$	Time to produce Item i (seconds)
b_m	$m \in M$	Time to set-up Mould m (seconds)
$U_{m,i}$	$m \in M, i \in I$	Utilization of Mould m to produce Item i
B_t	$t \in W$	Total utilization time for the machine in Week t (seconds)
MT		Effective utilization time for each Mould m (seconds)

Table 4.2: Parameters table.

x_{iot}	$i \in I, o \in O, t \in W$	Quantity of Item i in Order o produced in Week t
s_{iot}	$i \in I, o \in O, t \in W$	Quantity of Item i in Order o in stock in Week t
r_{iot}	$i \in I, o \in O, t \in W$	Quantity of Item i in Order o backlogged in Week t
y_{mt}	$m \in M, t \in W$	Activation/Set-Up of Mould m in Week t

Table 4.3: Decision variables table.

$$\text{min} \quad \sum_{i\in I}\sum_{o\in O}\sum_{t\in W}(x_{iot} \times p_i + s_{iot} \times h_i + br_{iot} \times w_i) \tag{4.1a}$$

$$\text{s.t.} \quad x_{iot} + s_{iot-1} + r_{iot} = d_{iot} + r_{iot-1} + s_{iot} \qquad \forall i \in I, o \in O, t \in W \tag{4.1b}$$

$$\sum_{o\in O} x_{iot} \times a_i \leq \sum_{(m,i')\in MI:i'=i} (MT \times y_{mt} \times U_{mi'}) \qquad \forall i \in I, t \in W \tag{4.1c}$$

$$\sum_{i\in I,o\in O} (x_{iot} \times a_i) + \sum_{m\in M} (y_{mt} \times b_i) \leq B_t \qquad \forall t \in T \tag{4.1d}$$

$$x_{iot} \geq 0 \qquad \forall i \in I, o \in O, t \in W \tag{4.1e}$$

$$s_{iot} \geq 0 \qquad \forall i \in I, o \in O, t \in W \tag{4.1f}$$

$$r_{iot} \geq 0 \qquad \forall i \in I, o \in O, t \in W \tag{4.1g}$$

The objective function (4.1a) focuses on minimizing production costs, inventories and delays. Constraints (4.1b) are the product conservation constraints. Constraints (4.1c) ensure that the mould set-up that the item uses has been done. It also limits the production capacity of the mould. Constraints (4.1d) is the machine capacity constraint, linking the production of different items. Constraints (4.1e), (4.1f) and (4.1g) are the non negativity constraints.

After presenting the first solution to the planning managers, it became apparent that the model was oversimplifying the company's reality. The industry in which AMF operates has high volatility in customer orders and in the delivery of materials by suppliers. As stated before, footwear companies are highly reliant on suppliers to meet their delivery deadlines. A delay in the arrival of raw material can lead to restructuring the entire planning, which translates into high costs if this re-planning is not done efficiently. To adapt the model to this reality, it is necessary to consider the availability of raw materials.

The other factor to take into account is the productivity of the machine. The company has the ability to hold stocks at low cost and therefore focuses on getting as many orders as possible. One of the planning goals is to reduce the number of weeks it takes to produce all the selected production orders. If we add information in the objective function, to make the production plan as short as possible week-wise, the most likely result would be filling the machine with orders, offering little flexibility if new orders come in. Therefore, for keeping the plan more realistic, it was considered that around 20% of the machine capacity should be available after the next two weeks, such is achieved by setting the limit of the machine to 80%

of its total capacity from week 3 of the planning onward. These percentages were proposed by the company and validated after several tests. This planning method allows the machine to be used at full capacity in the two weeks immediately ahead, where usually no changes occur, and in the following weeks, there is the ability to change or add orders that arise within short notice.

Figures 4.1 and 4.2 show us the difference between having the full capacity for all weeks in the planning horizon and having capacity restrictions after the second week. It is possible to observe that in the first scenario it would take less weeks to finish the production, but it would also make it impossible to react to any sort of issue or to new unexpected orders.

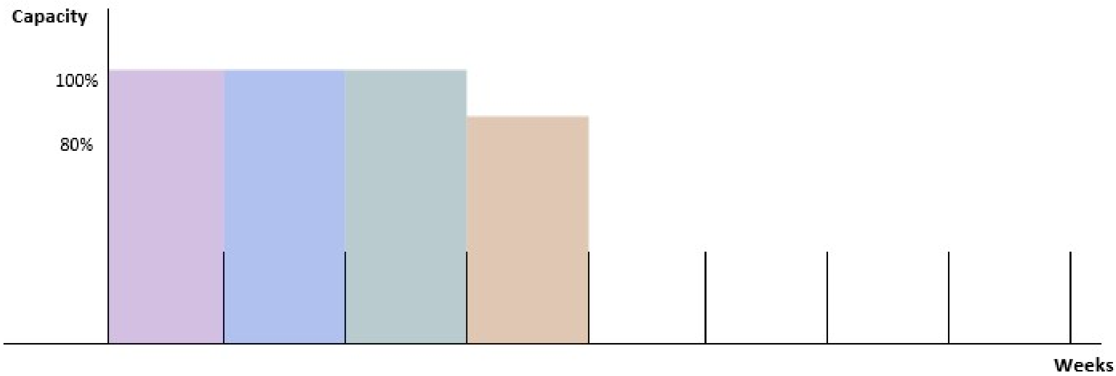

Figure 4.1: Lot Sizing with 100% availability in all weeks

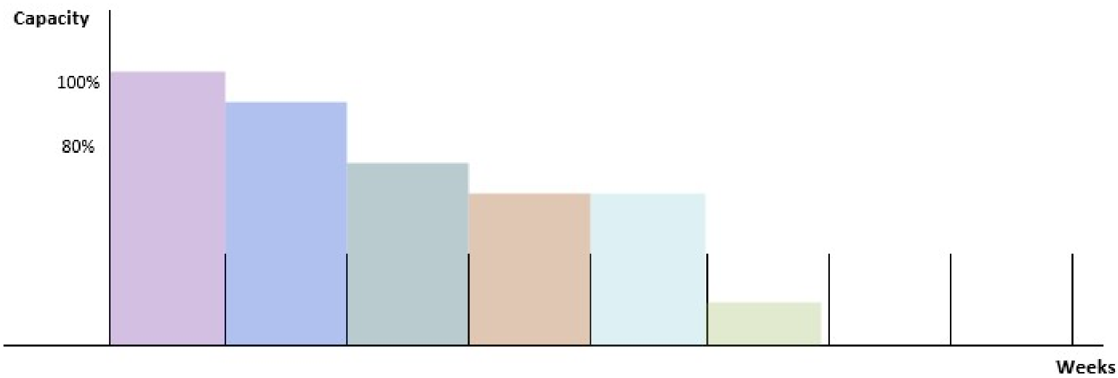

Figure 4.2: Lot Sizing with 80% availability for all but the first two weeks

4.1.2 AMF's Lot Sizing Problem

After the conclusions reached in the previous section, some modifications to the existing model were implemented to meet the company's requirements.

The model adaptation required five new parameters and three decision variables. In addition, existing constraints were revised and a new one was added. These additions are represented in tables 4.4 and 4.5.

G_{iot}	$i \in I, o \in O, t \in W$	Raw material of Item i and Order o arriving in Week t
EB_t	$t \in W$	Extra machine time in Week t
MTE		Extra time per mould
α		Price of activating the extra time in a week
β		Price of using a week to produce

Table 4.4: New parameters table.

e_t	$t \in W$	Activation of extra time on Week t
ms_t	$t \in W$	Activation of production in Week t
rm_{iot}	$i \in I, o \in O, t \in W$	Availability of raw material for Item i in Order o in Week t

Table 4.5: New decision variables table.

New Objective Function and Constraints

$$\min \quad \sum_{i\in I}\sum_{o\in O}\sum_{t\in W}(s_{iot}\times h_i + r_{iot}\times w_i) + \sum_{t\in W}(e_t\times\alpha + ms_t\times\beta\times t) \tag{4.2a}$$

$$\text{s.t.} \quad ms_t\times x_{iot} + s_{iot-1} + r_{iot} = d_{iot} + r_{iot-1} + s_{iot}$$

$$\forall i\in I, o\in O, t\in W \tag{4.2b}$$

$$\sum_{o\in O} x_{iot}\times a_i \leq \sum_{(m,i')\in MI:i'=i}((MT + e_t\times MTE)\times y_{mt}\times U_{mi'})$$

$$\forall i\in I, t\in W \tag{4.2c}$$

$$\sum_{i\in I,o\in O}(x_{iot}\times a_i) + \sum_{m\in M}(y_{mt}\times b_i) \leq B_t + EB_t\times e_t$$

$$\forall t\in W \tag{4.2d}$$

$$G_{iot-1} + rm_{iot-1} - x_{iot} = rm_{iot}$$

$$\forall i\in I, o\in O, t\in W \tag{4.2e}$$

$$rm_{iot}\geq 0$$

$$\forall i\in I, o\in O, t\in W \tag{4.2f}$$

$$x_{iot}\geq 0$$

$$\forall i\in I, o\in O, t\in W \tag{4.2g}$$

$$s_{iot}\geq 0$$

$$\forall i\in I, o\in O, t\in W \tag{4.2h}$$

$$r_{iot}\geq 0$$

$$\forall i\in I, o\in O, t\in W \tag{4.2i}$$

In this model three main changes have been made. The first change is the addition of a parameter MTE (Machine Time Extra). As previously defined, starting from week 3 onwards there is a standard time for production (80% of total capacity) and an extra time (the remaining 20%). This extra capacity may or may not be used depending on the production needed each week. The use of the *Machine Time Extra* has associated costs.

The second change is the need for raw material for an order to be available. The parameter G_{iot} defines the amount of raw material of item i and order o that arrives in week t. The item and order can only start being produced in week $t+1$.

Finally, the objective function was adapted to the new reality. As mentioned before, the goal is to produce the largest number of pairs in the smallest number of weeks possible. For the model to minimize the number of weeks used, it is necessary to give a cost to the use of each week. The objective function now takes into account the week utilization variable and the overtime utilization variable.

The objective function (4.2a) continues to minimize costs, in this case, given by the sum of the costs of delays and stocks, costs of using extra time, and costs of using the machine in each week. The parameters α and β where defined during the test sessions and can be changed by the planning manager.

In constraints (4.2b) the binary variable of machine activation in the week was added. In constraints (4.2c) and (4.2d) the possibilities of activation of overtime were added. In such cases that triggers the increase of the total production capacity and the capacity per mold.

Constraints (4.2e) are used for the conservation of raw materials. Constraints (4.2f) are the non-negativity constraint for the new raw material availability variable.

After several test sessions with members of the company, we understood that the model was adapted to AMF´s reality and allowed for the flexibility needed in a real production system. Despite the success in adapting the model, there was another requirement made by the company. As mentioned before, the company can negotiate with its customers to deliver orders earlier than planned. However, the delivery windows vary from customer to customer and from order to order. Therefore, the model must take this information into account to present the best medium/long-term planning solution.

4.1.3 AMF´s Lot Sizing Problem with Time-Windows

It was recognized that the delivery date could be either fixed or not, depending on the client. The planning team identified some customers whose delivery dates are flexible and allow both early and late deliveries without cost or any consequence to the company. To solve this problem, the previous model was adapted not to have a single delivery week but a time window in which no stock or delay costs would be charged. This reconstruction was based in a model proposed by (C.-Y. Lee et al., 2001).

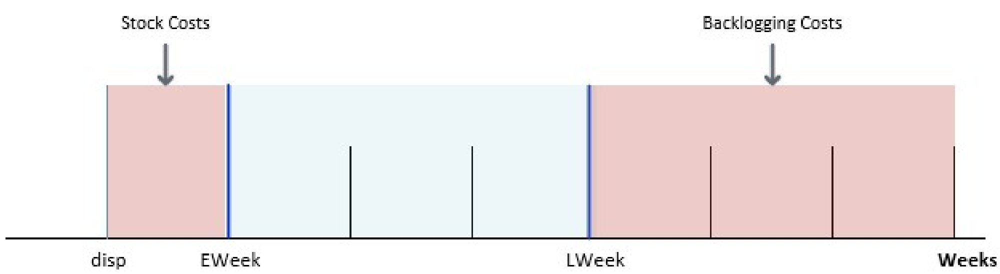

Figure 4.3: Lot Sizing with Time-Windows

Figure 4.3 exemplifies the impact in the objective of adding these time-windows. If it is determined that an order has a time window of 3 weeks to be delivered (span between *EWeek* and *LWeek*) it means that the production and delivery of the order can be done within this time window without any additional costs occurring.

However, stock and backlogging costs still exist, if the delivery is made between the moment when the raw material is available (*disp*) and the *EWeek* it is necessary to have stocks, when the delivery is made after the *LWeek* period, costs for the delays will also be attributed. Tables 4.6 and 4.7 represent the new parameters and decision variables.

d_{io}	$i \in I, o \in O$	Raw material of Item i and Order o (previously with defined week t)
$EWeek_{io}$	$i \in I, o \in O$	Earliest possibly week to deliver item i in order o
$LWeek_{io}$	$i \in I, o \in O$	Latest possibly week to deliver item i in order o

Table 4.6: New parameters table.

e_t	$t \in W$	Activation of extra time on Week t
ms_t	$t \in W$	Activation of production in Week t
TD_{iot}	$i \in I, o \in O, t \in W$	Demand for Item i in Order o in Week t

Table 4.7: New decision variables table.

New Objective Function and Constraints

$$\min \quad \sum_{i \in I, o \in O, t \in W} (r_{iot} \times w_i + s_{iot} \times h_i) + \sum_{t \in W} e_t \times \alpha \tag{4.3a}$$

$$\text{s.t.} \quad ms_t \times x_{iot} + (s_{iot-1} - r_{iot-1}) - TD_{iot} = -r_{iot} + s_{iot} \qquad \forall i \in I, o \in O, t \in W \tag{4.3b}$$

$$\sum_{o \in O} x_{iot} \times a_i \leq \sum_{(m,i') \in MI : i'=i} ((MT + e_t \times MTE) \times y_{mt} \times U_{mi'})$$

$$\forall i \in I, t \in W \tag{4.3c}$$

$$\sum_{i \in I, o \in O} (x_{iot} \times a_i) + \sum_{m \in M} (y_{mt} \times b_i) \leq B_t + EB_t \times e_t$$

$$\forall t \in W \tag{4.3d}$$

$$G_{iot-1} + rm_{iot-1} - x_{iot} = rm_{iot}$$

$$\forall i \in I, o \in O, t \in W \tag{4.3e}$$

$$TD_{iot} = 0$$

$$\forall i \in I, o \in O, t \in 1...EWeek[i,o] - 1 \tag{4.3f}$$

$$TD_{iot} = 0$$

$$\forall i \in I, o \in O, t \in LWeek[i,o] + 1...last(Weeks) \tag{4.3g}$$

$$TD_{iot} \geq 0$$

$$\forall i \in I, o \in O, t \in EWeek[i,o]...LWeek[i,o] \tag{4.3h}$$

$$\sum_{t \in EWeek[i,o]...LWeek[i,o]} TD_{iot} = dio$$

$$\forall i \in I, o \in O \tag{4.3i}$$

$$x_{iot} \geq 0$$

$$\forall i \in I, o \in O, t \in W \tag{4.3j}$$

$$s_{iot} \geq 0$$

$$\forall i \in I, o \in O, t \in W \tag{4.3k}$$

$$r_{iot} \geq 0$$

$$\forall i \in I, o \in O, t \in W \tag{4.3l}$$

$$rm_{iot} \geq 0$$

$$\forall i \in I, o \in O, t \in W \tag{4.3m}$$

Adding the parameters $EWeek$ and $LWeek$ allows us to define the time windows to deliver the product. This leads to a change in the objective function (4.3a). Now, instead of minimizing the weeks needed to fulfill the production, we now minimize the costs with stocks and backlogs.

Constraints (4.3b) are in charge of the product conservation. They were adapted in order to work with the new model. Constraints (4.3c), (4.3d) and (4.3e) are the same as in model (4.2a - 4.2g) and are the capacity constraints and the conservation of raw material. Constraints (4.3f), (4.3g) and (4.3h) have the role of defining in which weeks an order can be delivered or demanded, based on the customer's specifications. Constraints (4.3i) define that the quantity ordered by the customer must be fully distributed between the weeks that are between the time windows. Finally, constraints (4.3j), (4.3k), (4.3l) and (4.3m) are the non-negativity constraints.

This model was interesting and could lead to results very much aligned with the company´s aims. However, it requires prior in-depth knowledge of the customer´s needs and capabilities. The large amount of time required to obtain this information slows down the planning process making it too long. Due to this limitation, the model used in to validate the solution in the next section is the *AMF's Lot Sizing Problem*.

4.2 Lot-Sizing and Scheduling Integration

In Chapter 3 we saw that both the lot-sizing and the scheduling problem are considered NP-hard, even if they are solved individually.

It is necessary to pay attention to the parameterization of the master problem and the data transfer between the two problems in order to avoid errors.

To facilitate the transfer of data between problems, the AMPL API was used. AMPL API is an interface that allows access to the features of the AMPL interpreter from within a programming language. All model generation and solver interaction are handled directly by AMPL, leading to excellent stability and speed while the library acts as an intermediary. Figure 4.4 shows the architecture of the API.

Using this method we can obtain the solution and variable values directly through python. In the next section we will understand why this facilitates the data collection to perform the sequencing for the next week.

4.3 Scheduling Algorithm

Following the resolution of the lot-sizing problem, it is necessary to perform the sequencing of the injection molding machine. Since we are dealing with a real problem with a large dimension, it is impossible to reach an optimal solution in efficient time using integer programming, as was done for the first part of the planning. Integer

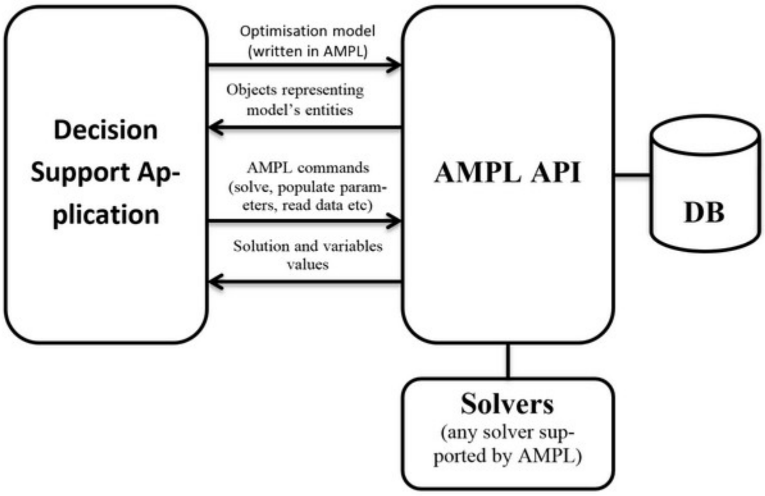

Figure 4.4: Architecture schema of AMPLAPI

programming models were briefly tested, as well as constraint programming, but it was impossible to get feasible results for any test cases. Furthermore, it was also clear from the project developed by (Sadeghi et al., 2021), that it is necessary to heavily simplify the problem to obtain solutions for rotary injection machine scheduling. Thus, it was necessary to define an approach that would obtain a good solution in a short time-period.

In chapter 3, we saw that the company already uses a sequencing algorithm called *simulador* to obtain solutions in short time. According to the planners, the results obtained are acceptable. Still, sometimes it is necessary to do several simulations manually, with different rules and priorities, until a solution under the company's objectives is reached. Such a method can take a long time and is reliant on the planner's knowledge and experience.

After discussions with the company, it was defined that a similar heuristic would be developed, with fewer hardcoded rules to generate more solutions and find one that minimizes the makespan of the set of chosen orders. A variation of the *Longest Processing Time* (LPT) rule with a random component to select the best solutions among the ones obtained is used. In the following sections, the algorithm's behavior will be discussed in more detail.

4.3.1 Reading Data

Since Python is an object-oriented language, it was logical to create classes to represent the production system.

To facilitate the manipulation of the data, the moulds, models and orders classes were created. In the molds class we find all the information related to the molds. Its ID, the family of molds (MouldType) to which they belong, the size, the quantity and the equivalent molds are all attributes of this class. The models class contains all the models produced by the company. The attributes associated are the ID, the reference and the size, the injection colors of the sole and insole, the transition time and the imprint. Lastly, the orders class is intended to identify the quantity and models to be produced. Its attributes are the ID, the reference (model to make), the size and the quantity to produce.

The orders to be sequenced can be read in two ways: Through an excel file or the result of the optimization model for the lot-sizing problem.

The first option was used in the initial stages of the algorithm development since it is more practical to select the production orders to be sequenced in an excel file and quickly obtain the sequencing result.

The second option is directed to the use by the company. After executing the strategic planning for, for example, six weeks, we will know the models and quantities to be produced. This information is automatically provided to the sequencing algorithm, and in addition to the strategic planning for the next six weeks, the operational planning for the next week is also generated.

4.3.2 Mould Initialization and Changeover

After reading the data, the injection machine needs to be initialized. The class "Machine" was also created with attributes representing the current position, the total number of positions, the sole and insole injection colors, and the rotation time between positions of the machine. Some functions essential to the machine's operation which will be used in the following sections, are also created.

This function allows defining the mould in the injection machine.

A list *lpt_order* is created to help implement the LPT rule. This list is ordered by quantity. The initialization of the molds follows this rule, and the molds placed in the machine in an initial phase correspond to the production orders with the highest quantity.

In figure 4.5 we can see the flowchart that represents the operation of the mould initialization. The algorithm starts by reading the first order in the lpt_order list. Then it checks if the colors of the insole of the chosen order are compatible with the machine colors and if the molds compatible with that order are available. If yes, the mould is added to a comp_moulds list; if no, the following order is chosen, which goes through the same process. Once there are N molds in the comp_mould list, one is randomly chosen and initialized at the current position. If there are no more orders in the lpt_order list, the algorithm goes to the random selection phase, even if there are not N moulds in the comp_mould list. This process is repeated for all positions.

This process is only performed once before the sequencing begins. There is a possibility that the mould can be changed during the sequencing process. In this

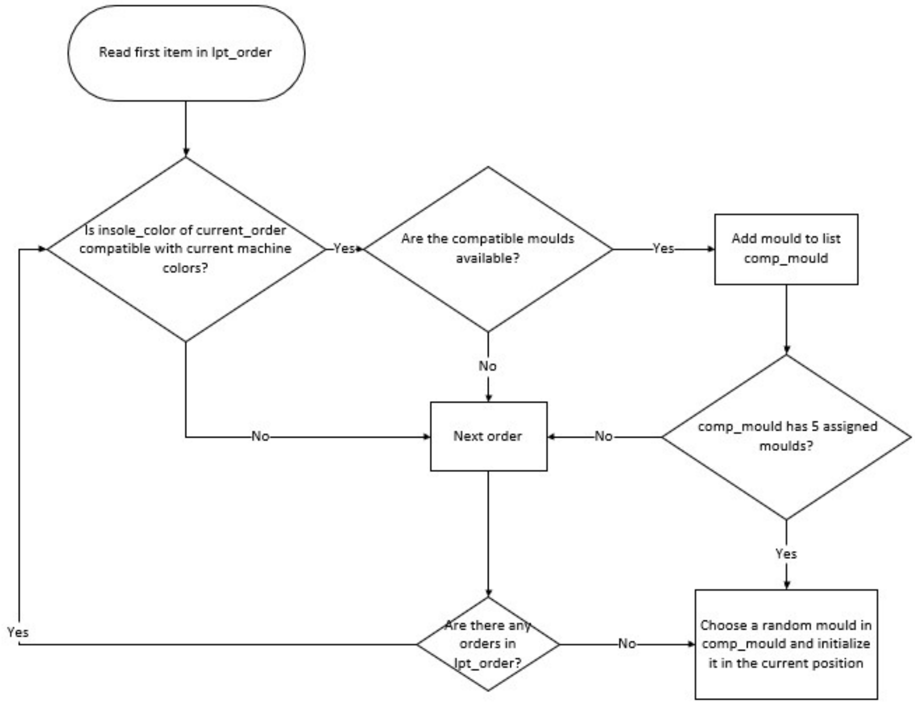

Figure 4.5: Mould initialization and changeover fluxogram

case, a function whose operation is similar to the one described in figure 4.5 will be called. The only difference is verifying the remaining quantity in each order. If the quantity is zero, the order is discarded since it is already produced.

4.3.3 Order Sequencing

After reading all the necessary data, the algorithm moves on to the sequencing phase. This phase aims to select orders that satisfy the machine rules and, at the same time, reduce the number of mould and color changes of the injectors since the changeover times are high.

As we can see in Figure 4.6 ,the script starts by calculating the total quantity of pairs to be produced (*total_qty*) and uses a while loop to ensure that all pairs of shoes are sequenced on the injection machine.

After concluding that the total quantity of pairs is greater than 0, it will see if the order injected at the current position and in the previous lap has not yet been completely produced. If not, it will select this exact order, *inject* it and move on to the next position. The *inject* operation subtracts one pair from the order that has been injected. Checking this first condition will make the sequencing easier to read since when an order is selected for a specific position, it will be assigned there until it is entirely produced.

If the order selected in the previous turn has already been fully produced, the *lpt_order* list starts iterating in search of a new compatible order. Initially, it checks to see if the mold at the current position is compatible with the selected order. If it is not, the algorithm selects the following order. If it is, it will define whether the current order is considered perfect or not. A perfect order is defined as follows: the chosen order has to have the same *rotation time*, same *injection color* for the insole and has to use the same mould.

Suppose that the current order is considered a perfect order, it is immediately selected for injection, starting the cycle again for the next position. If the order is not perfect, it must be checked to see if it is compatible with the injection colors. If so, it will be saved in the *comp_orders* list and later used. If it is incompatible, it is discarded and moves on to the following order, repeating the process. The procedure is repeated until the *comp_orders* list has N orders assigned or no more iterations to be performed in the *lpt_orders* list. If *comp_orders* is not zero, it will go through the same procedure as if it had N orders. If there are no orders assigned, it means that no order has a matching mold or insole injection color. This means that the mould and injection color must be changed.

Changes in moulds and injection color can only be made every ten laps. If the current lap is not a multiple of ten, the machine will rotate to the next position and perform the whole process again. If the lap is a multiple of ten, the mold change is made. After the mold change, it is checked if it is possible to change the color of the insole injector. This change is done if there are only two or less different insole colors in the orders that remain available, thus starting a new cycle. If there are more than two different insole colors, the machine rotates and starts a new cycle with a new mold in the previous position.

The order selection process is complex because it is a rotating machine, and there are many constraints regarding colors and rotation times. This algorithm uses fewer rules than the one currently used in the company, creating more sequencing possibilities and achieving better results, as we will see in chapter 5. The algorithm is run several times to take advantage of the randomness used, and the best solutions are saved and presented to the user.

4.3.4 Report

In this section the results of the sequencing algorithm are presented. As already mentioned, the company has a sequencing algorithm developed internally and integrated in its ERP. Given this, one of the requirements was that the presentation of the solution obtained by the new sequencing was similar to the one currently used by the company.

In figure 4.7 we can see the results presented through an excel file that displays which model and size will be produced in each lap and position of the machine. The

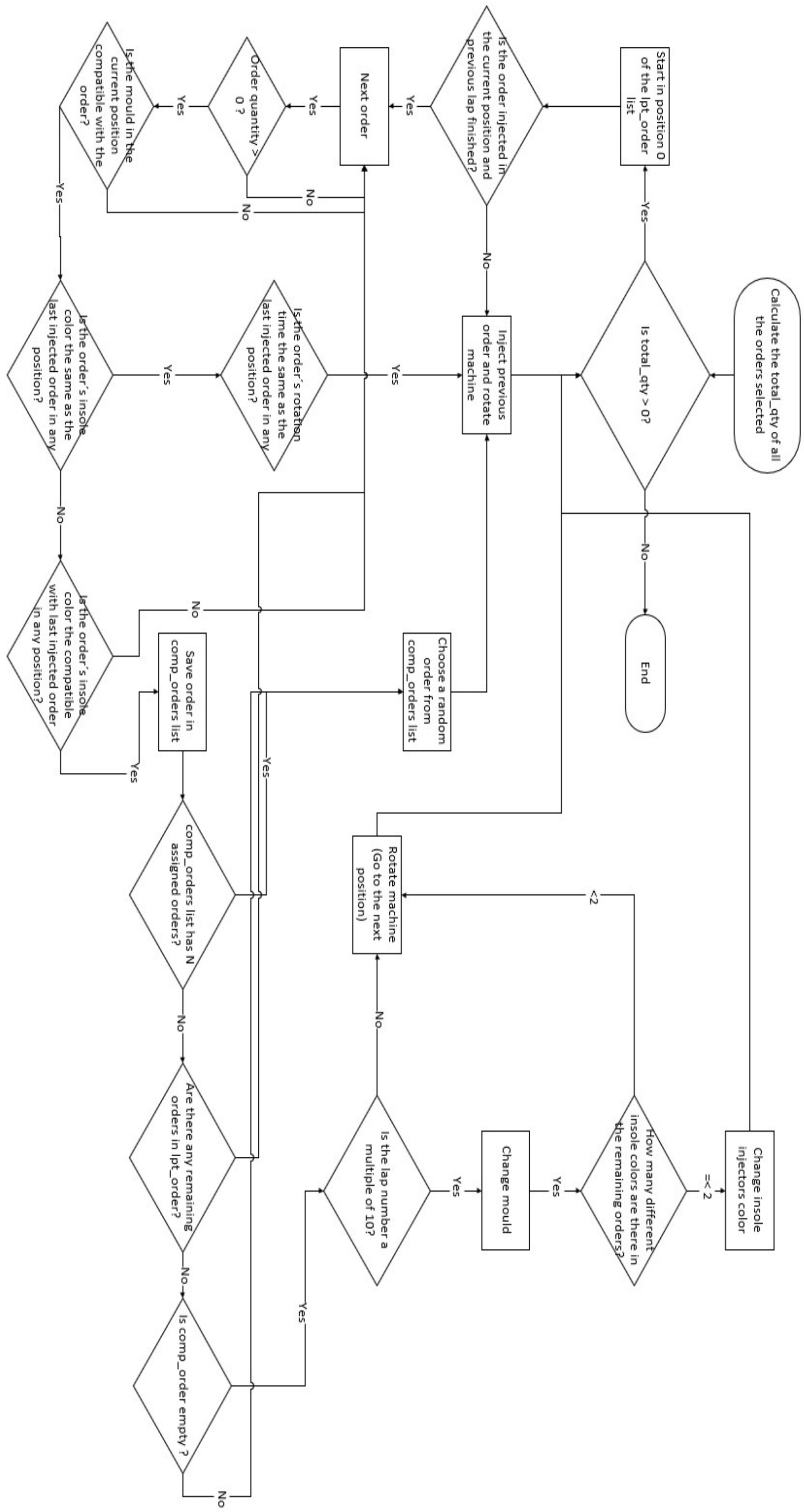

Figure 4.6: Order sequencing fluxogram

mould changeover is also indicated, stating the position and lap in which it must be made (Presented between Lap 30 and Lap 31). In addition to the production and mould changeover, some manufacturing data that allows users to define which production plan to use, is also displayed. This information is presented in figure 4.8 and is composed of the total number of laps, the stops for changing moulds and the number of moulds used, the time stopped and under production and the total number of pairs produced.

Lap No	Laps	Pos 1	Pos 2	Pos 3	Pos 4	Pos 5	Pos 6	Pos 7	Pos 8	Pos 9	Pos 10	Pos 11	Pos 12
											FSN 39		
1		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
2		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
3		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
4		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
5		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
6		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
7		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
8		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
9		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
10		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
11		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
12		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
13		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
14		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
15		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
16		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
17		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
18		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
19		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
20		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
21		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
22		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
23		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
24		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
25		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 39	6A15.20-SB 40	6A15.20-SB 43
26		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41		6A15.20-SB 40	6A15.20-SB 43
27		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41		6A15.20-SB 40	6A15.20-SB 43
28		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41		6A15.20-SB 40	6A15.20-SB 43
29		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41		6A15.20-SB 40	6A15.20-SB 43
30		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41		6A15.20-SB 40	6A15.20-SB 43
											FSN 37		
31		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 37	6A15.20-SB 40	6A15.20-SB 43
32		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 37	6A15.20-SB 40	6A15.20-SB 43
33		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 37	6A15.20-SB 40	6A15.20-SB 43
34		6A15.20-SB 42	6A03.10-S3 42	6A03.10-S3 43	6A15.20-SB 42	6A15.20-SB 44	6A15.20-SB 44	6A15.20-SB 43	6A15.20-SB 45	6A15.20-SB 41	6A15.20-SB 37	6A15.20-SB 40	6A15.20-SB 43

Figure 4.7: Sequencing data

Total Laps	270
Total Stops	11
Mould Changeovers	32
Time Stopped	5,333333333
Time Working	35,86666667
Total Pairs	2010

Figure 4.8: Manufacturing data

Chapter 5

Computational Results

This chapter presents the results obtained by the optimization model developed for long-term planning, implemented in AMPL, and the scheduling algorithm implemented in Python. Although the developed software presents solutions for both problems together, the results will be presented in different sections to represent better the work developed.

It is essential to mention that the test instances for both problems were created with different dimensions and characteristics, allowing us to analyze the performance of the methods used. These instances were created together with the IT and planning department of AMF to guarantee that the data provided is in accordance with the reality of the case study and replicate the problems faced by the company.

In section 5.1 the results obtained by using the mathematical model developed for long-term planning are presented. The results will be shown in the form of capacity utilization graphs of the injection machine. Later the planning methods are compared. The results of the sequencing algorithm are shown in section 5.2, through tables indicating the most critical performance indicators and compared with the results presently obtained by the AMF simulator.

The results presented were obtained using an HP Pavillion computer, with 8 GB RAM and Intel Core i7-8565U CPU (1.80GHz 1.99 GHz).

5.1 Long/Medium-Term Planning (Lot-Sizing)

As mentioned in chapter 4, developing a mathematical model for AMF was an iterative process, where the company was present in the design and requirements definition of the model. This led to several models being created. To demonstrate how they perform, we present a few instances that represent the company's reality and problems.

In an initial phase, the orders being planned are chosen and uploaded to an Excel file. After running several macros, this Excel file (Data_Feeder) provides the necessary data for solving the problem using the AMPL IDE. The results are then obtained through another Excel file and presented using PowerBI (see Figure 5.1).

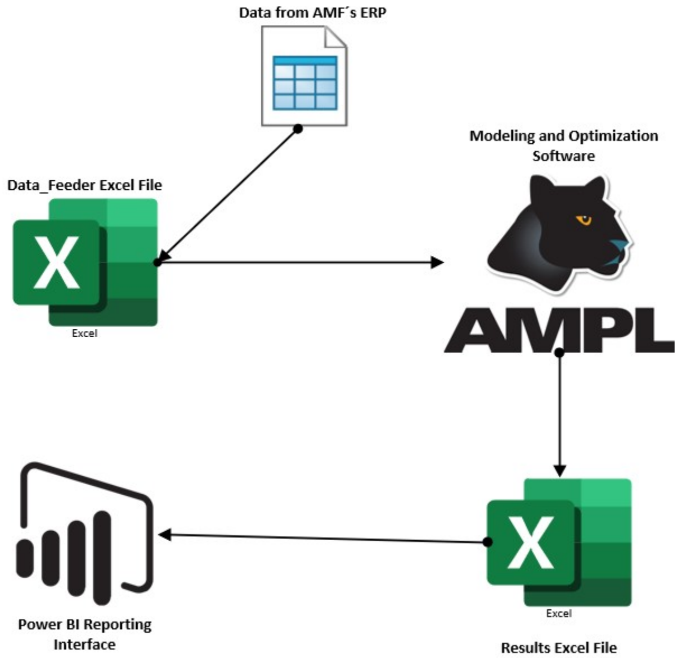

Figure 5.1: Solution Diagram

Since the company had no long/medium-term planning method, these initial results cannot be compared with its current state as it is non-existent. As such, two instances with two variations were created to demonstrate the potential of the mathematical model developed (table 5.1).

Instance 1

The 1 - AMF instance it is represented the real orders between September 10 and October 29.

Table 5.1: Lot-Sizing Instance List

Instance ID	Nº of Weeks Used	Production	Stock	Delays
1 - AMF	7	32241 pairs	19758 pairs	0 pairs
1 - Traditional	7	32241 pairs	1613 pairs	753 pairs
2 - AMF	4	22277 pairs	9393 pairs	175 pairs
2 - AMF + New Order	4	23777 pairs	8851 pairs	175 pairs

In figure 5.2 we can see how the demand is distributed during these seven weeks. These capacity graphs have two threshold lines: the one in red represents the machine´s total capacity and the green 80% of the total capacity, value defined in chapter 4. In the first week the workload is very low, which is not ideal since the goal is to keep the machine as full as possible for the first 2 weeks. The only week when demand is higher than capacity is week 5, with about 9500 pairs of shoes. One can see that the current situation does not represent a problem for the company and would be easy to plan without relying on large stocks or backlogging.

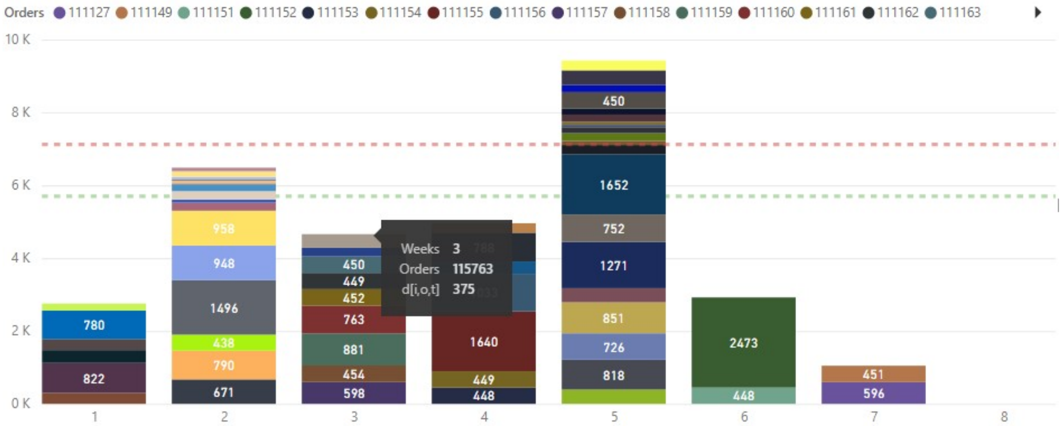

Figure 5.2: Demand in instance 1 - AMF and 1 - Traditional.

In this first instance, we will compare the results obtained by the mathematical model adapted to the needs of MFA with a traditional Lot-Sizing model where the objective function is composed of stock and backlog costs only. Figure 5.3 shows the weekly distribution of production for September and October. As we can see, weeks 1 and 2 are very close to the capacity limit, represented by the red line. The following weeks are close to the optimal capacity, around 80% of the total capacity, represented by the green line. This scheduling allows the company to maximize the capacity of its resources while still being able to respond to new orders that may arise in the following weeks. It is also possible to verify that all demand is met in 6 weeks, where the sixth week is half of the total capacity.

This straightforward graph gives the planning department the ability to think six weeks ahead and realize that they can look for new orders or add any orders that are

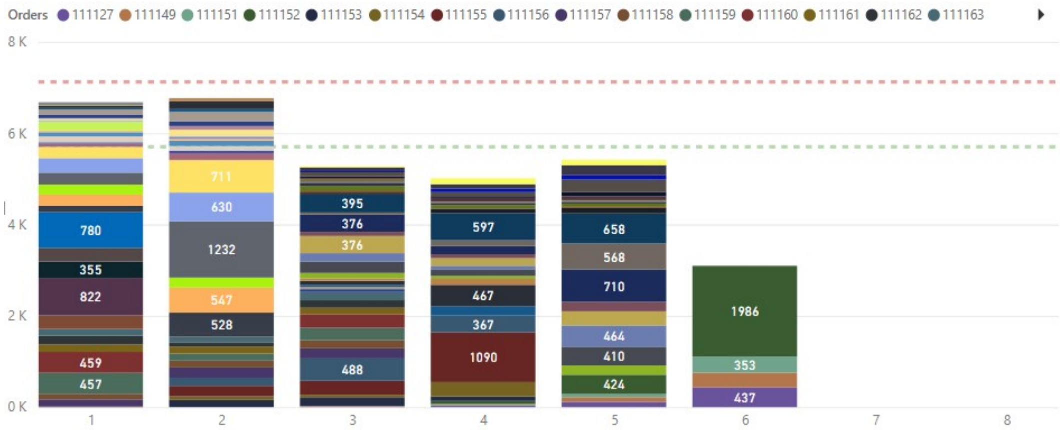

Figure 5.3: Results of AMF´s Lot-Sizing model in instance 1.

forecasted to come in. Using PowerBI it is possible to access much more information, such as stock levels and backlogs, mold usage, and the orders and quantities to be produced each week.

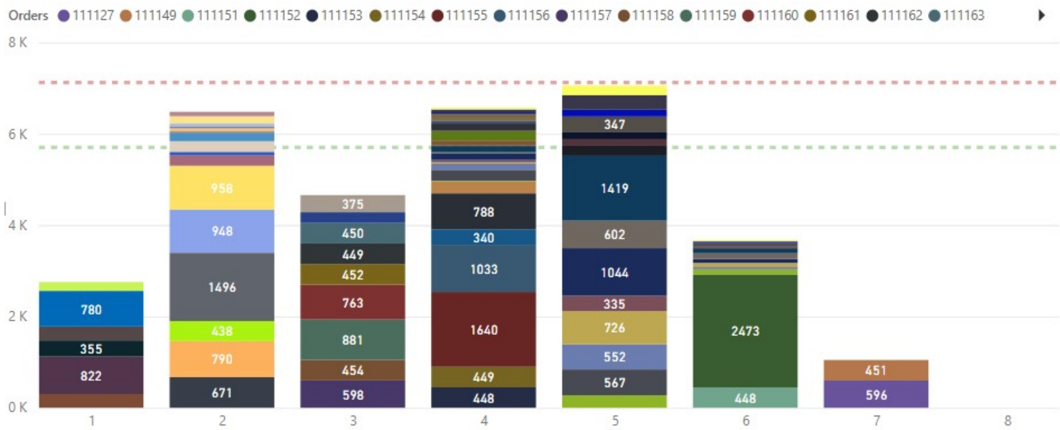

Figure 5.4: Results of a traditional Lot-Sizing model in instance 1.

Figure 5.4 represents the results obtained by a more traditional just-in-time (JIT) planning style. In this case, it is possible to see from the demand graph that there is no need to deliver orders late since it is only in week 5 that the demand is greater than capacity, and this is easily solved by producing to stock in week 4.

This approach to planning can be helpful in some companies; however, in this case study such long-term planning can lead to some problems. The first is low production in the first weeks when the company aims to maintain machine utilization levels around 100%. The other problem is that in weeks 4 and 5 there is no possibility of accepting new orders, which is negative for the company given the volatility of the industry and the importance that MFA gives to the customer relationship.

With the analysis of the first instance, it is possible to understand why the proposed approach was accepted. Although there is some production for stock every week, the company manages to support it in a costless way. The existence of stocks promotes the highest capacity utilization of the production system without neglecting the flexibility required in today's production systems.

Instance 2

After understanding how the model behaves with real instances, let's now analyze how the model behaves when there is a need to incorporate an unplanned order. To mimic such scenarios, fewer OP's with larger quantities will be used to make it easier to see them in the graphics.

Figure 5.5 presents the demand of instance 2. The combined demand for weeks 1 and 2 is 7185 pairs, above the total capacity of the machine (7120 pairs). Week 3 has demand well above the full machine capacity, which could pose a problem for that week if unexpected orders arise. However, it is expected that the solution provided will deliver the orders on the scheduled dates.

Figure 5.5: Demand in instance 2.

Like in the previous instance, the machine utilization in weeks 1 and 2 is close to 100%, and in week 3, where demand is very high, it is possible to keep 20% of the capacity idle for a potential order. This is possible by producing part of the orders with delivery in week 3 in weeks 1 and 2 (see Figure 5.6).

Even without using any planning tool, we realize that it is possible to accept an order for week 3 as long as it does not exceed the total capacity of the machine. For example, it is possible to accept a new order of about 1500 pairs (without considering the use of molds, which could make the solution unfeasible).

Figure 5.7 shows the solution if this new order is added to the mathematical model. It is assumed that due to the order coming in unexpectedly, the raw materials are only available in week 2. The solution shows the most efficient way to produce this new order, represented in red.

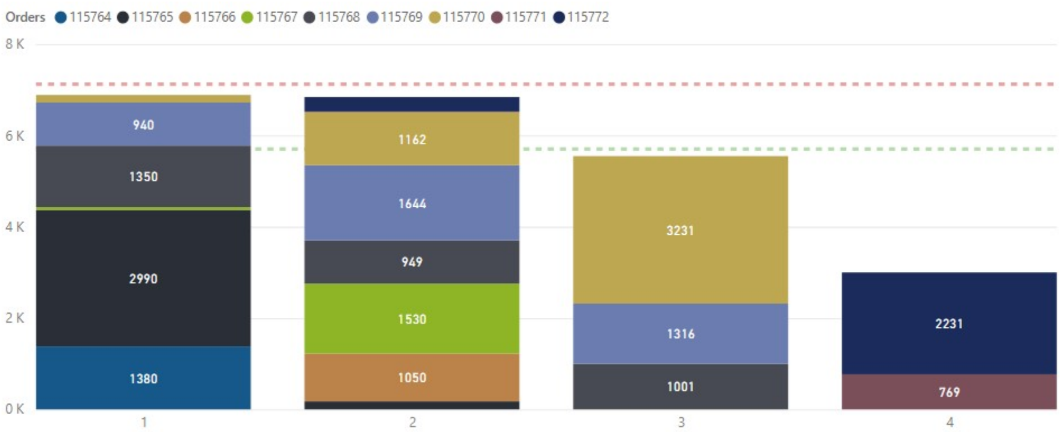

Figure 5.6: Results of AMF´s Lot-Sizing model in instance 2.

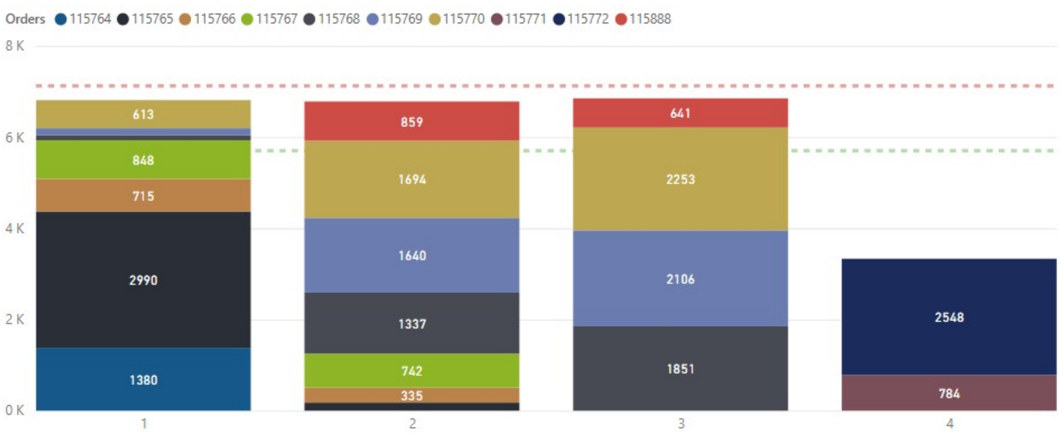

Figure 5.7: Results of AMF´s Lot-Sizing model with an added order in instance 2.

Looking to figure 5.5 may be counter intuitive for the planning department to accept new orders if their delivery date is in week 3 since there is already a significant overload in that week. Looking at both figure 5.6 and figure 5.7, we see that it is possible to meet demand without significant delays while keeping machine utilization at acceptable levels.

Summary

There are many advantages to using this tool, the most important one being the ability to have a macro plan for the coming weeks or months with the items to be manufactured. This way, it is possible to have a general overview of the moulds, the injection material, and the raw material (uppers) needed. The Lot-Sizing model also supports the supply chain department since most of the uppers are obtained through subcontracting services and have long lead times. It is also a valuable tool to define preventive maintenance since it is possible to identify the weeks with less workload.

Overall, the use of this tool is appreciated by the company and should be implemented in the company's ERP in the near future.

5.2 Short-Term Planning (Scheduling)

In this section the results obtained by the sequencing algorithm that was developed will be presented and compared with the results obtained by the company's existing tool, the *simulator*.

As for medium-long term planning, the test problems created for operational planning vary in size and characteristics so that it is possible to evaluate the performance depending on the type of problem.

The size of the test problems used is shown in table 5.2.

Table 5.2: Scheduling Instance List

Instance ID	Number of Models	Total Pairs
1	4	16002 pairs
2	13	13360 pairs
3	9	7923 pairs
4	6	5696 pairs
5	4	9895 pairs

Table 5.3 represents the results obtained via the *simulator*. The *simulator* was run several times for each problem, with different rules selected by the planner, and the best iteration was chosen. During the project, it was realized that one of the limiting factors of this tool were the rules selected. These decisions are made according to the user´s experience, which can lead to situations where the best combination

of rules was not tested.

Table 5.3: *simulator* Results

ID	Laps	Stops	Change overs	Time Working(h)	Time Stopped(h)	Use %
1	1490	18	19	192,93	3,11	89,5%
2	1985	13	15	262,5	2,57	56,1%
3	888	5	5	104,91	0,82	72,4%
4	592	21	36	78,93	6,13	77,5%
5	1090	9	9	139,54	3,12	75,6%

The results obtained using the sequencing algorithm are shown in table 5.4. As mentioned before, the algorithm proposed in this thesis has far less hard-coded rules and uses a random choice of orders (within a previous selection) to find different solutions. The algorithm is run 500 times for each instance, and the best iteration is chosen based on the total time to fulfill the production of all orders. It takes less than 5 minutes to come up with the solution, which is important for this particular case because, in this way, you can make quick changes if something unexpected comes up.

Table 5.4: Sequencing Algorithm Results

ID	Laps	Stops	Change overs	Time Working(h)	Time Stopped(h)	Use %
1	1420	13	15	190,39	2,5	88,5%
2	1335	11	15	177,87	2,5	80,3%
3	837	4	4	103,68	0,67	75,1%
4	552	20	33	73,47	5,5	86,7%
5	1090	4	4	130,8	0,67	77,2%

Comparing the results of the two methods, we can see that the new sequencing algorithm presents better overall solutions.

In terms of stops and mould changes, it is possible to verify that the new algorithm presents fewer mould changes (less 2,6) and needs fewer stops (less 2,8) to perform them, meaning that it changes more moulds per stop than the previous planning method. This leads to a decrease in the time the machine is not producing.

There are two scenarios to consider, regarding the production time and required turns when comparing the two sequencing methods. When there are few models, the algorithms solutions are not very different. When the number of models is more significant, the problem's difficulty increases, and greater benefit can be seen in using the new algorithm. The example is instance 2, time spent to produce the defined production orders is 32% less. The average reduction in the results obtained by the algorithm are 40,25 less laps and a reduction of 5,45 hours, when we are not considering Instance 2.

As far as the percentage of machine utilization is concerned, there are improvements (increase of 7,34%), but do not reach the levels aimed by the company. The average machine utilization in the tests performed is 81,56% with the new planning method. The company's goal is for these values to be around 90%.

This problem derives from the non-uniformity in the order sizes. It is known that the central sizes of shoes (40-43) are in much higher demand than the others. This leads to the need of using many laps to produce these sizes and what typically happens is that the last 10% of laps have only one or two positions working. A small study will be made in the next section to understand if the number of moulds would influence the machine utilization percentage.

Mould Utilization Analysis

This brief analysis aims to understand if the increase of moulds in the central sizes benefits the company regarding the machine utilization and the number of laps needed to conclude the production. After comparing the results obtained by the simulator and the new production algorithm, it was possible to verify similarities in the production plans obtained by both. In the last laps, the machine always works with only a couple of positions, making the machine utilization very low and increasing the time required to finish the plan. In table 5.5 we can see that in the last 10% of laps, the machine utilization is very low compared to the normal utilization rate. It is possible to see that there is a considerable decay in the utilization of the machine in the final stages of planning. This is because, at the end of the plans, there is a small set of sizes (typically size 40 to 43) that have not yet been produced, for which there is only one mold available, thus leading the machine to do several laps with almost no positions making shoes.

Table 5.5: Machine Utilization Comparison

ID	Use %	Use % in the last 10% of laps
1	88,5%	20,6%
2	80,3%	15,3%
3	75,1%	24,8%

Instances 1, 2, and 3 will be tested by adding either one or two more moulds of each type for the sizes between 40 and 43 (see tables 5.6 and 5.7). In Instance 1 we see that in both cases, there is an increase in the number of laps needed to complete the production plan without bringing benefits in terms of machine utilization. In contrast, instance 2 presents significant improvements when using a larger amount of moulds. In the two tests performed, the machine utilization is higher than 90%, and there is also a substantial improvement in machine utilization in the last laps. In the last instance, there is a slight improvement in the first test (using one more mould for each type). However, when increasing the number of moulds (using two more moulds for each type), we see that the utilization and the number of laps are worse than the standard plan.

Table 5.6: Sequencing Results with +1 Moulds

ID	Laps	Use %	Use % in the last 10% of laps
1	1505	88%	20,16%
2	1170	94,3%	69,8%
3	814	81,4%	23,9%

Table 5.7: Sequencing Results with +2 Moulds

ID	Laps	Use %	Use % in the last 10% of laps
1	1581	85,9%	29,16%
2	1187	93,2%	50,4%
3	934	70,6%	8,3%

The obtained results are inconclusive and due to the small sample used, it is impossible to draw conclusions that would allow us to confidently claim that the increase in moulds would enable the company to reach the targeted utilization levels. Besides that, we believe that a cost-opportunity study should be done to better support the decision of investing in more moulds.

Summary

The new sequencing algorithm consistently achieves better results than the current solution. In the simulations performed above, we verified that there is an opportunity for improvement in all instances. Whether it is in the efficient use of the stops, machine utilization, or the time required to produce the selected orders, the new algorithm outperforms the *simulator*.

The use of the algorithm in combination with the solution presented in chapter 5.1, allows AMF to make detailed weekly production plans. Such plans are developed to eliminate the need to assign priorities and manually choose the proper rules so that there are no delays in deliveries, facilitating the planning team's tasks.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

The main objective of this project was to create a new planning method for a complex production system in a real footwear factory. The results of the chosen approach were demonstrated and compared with the results obtained by the existing method in the company.

A mathematical optimization model for the real problem was first created and programmed in AMPL. The analysis of the results confirmed that the model corresponds to the case study as described, being capable of solving real problems accurately and presenting solutions that enable a new vision of the company's long and medium-term planning.

To tackle operational planning, an algorithm was developed, which considers all the constraints of the injection machine and presents a new way to perform the sequencing of production orders.

Finally, to use the two planning methods together, an algorithm was developed in Python that allows using the strategic planning results to carry out the operational planning.

The analysis of the results obtained led to the conclusion that the developed sequencing algorithm generates better solutions than the *simulator* currently used by the company, regarding the production makespan, the number of mould changeovers and machine stops, and also the machine utilization.

It is essential to mention that the analysis of the results also allowed the identification of some improvement opportunities in the company, such as the machine utilization in the last 10% of laps.

Thus, in conclusion, it can be stated that the proposed objectives for this dissertation project were successfully met.

6.2 Future Work

In this dissertation it is assumed that all production orders selected for planning were client confirmed orders. However, AMF already has a basic forecasting system that defines production orders to be produced for stock. One of the company's goals is to improve this forecasting system and the relation between forecasting and the planning system. It is anticipated that if production to stock is used to complement the production plan, one can increase machine utilization rates and decrease the number of laps where there are less than three occupied positions.

Machine utilization levels are one of the factors to be improved. Hence, it is necessary to make a more in-depth analysis of the mould quantities and evaluate if the lack of moulds limits the utilization of the machine.

Finally, implementing this new planning method in the company's ERP is the next step in this project, since currently, the use of this tool is done through excel files and an API.

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Appendix A

Internal Tool

A.1 Lot-Sizing Excel Template

In this section, you can find the excel template developed to assist in the data selection and treatment that will then be used by the optimization method and will give a solution to the Lot-Sizing problem.

Orders	Weeks	Items	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	Gas Week
114501	1	6A11.00-O2	0	0	10	20	40	60	100	230	200	130	0	0	10	0	0	0	0	0
111180	2	6C12.20-O2	0	0	0	0	0	30	70	130	192	64	104	16	0	0	0	0	0	0
114199	2	6C12.00-O2	0	10	10	20	30	40	60	150	144	88	40	8	0	0	0	0	0	0
111168	3	6B11.20-O2	0	0	10	20	30	20	60	128	144	96	64	24	8	0	0	0	0	0
111169	3	6C11.20-O2	0	0	10	50	30	60	100	150	80	64	24	16	16	0	0	0	0	0
111167	4	6C11.00-O2	0	0	10	20	20	30	60	150	144	96	56	16	0	0	0	0	0	0
111164	5	6A11.00-O2	0	10	20	20	30	50	90	180	170	120	80	20	10	0	0	0	0	0
111166	5	6C12.00-O2	0	0	10	20	20	40	80	130	144	88	48	16	8	0	0	0	0	0
111162	9	6B11.20-O2	0	0	10	20	20	40	70	136	144	96	48	16	0	0	0	0	0	0
111163	9	6C12.20-O2	0	10	10	20	10	40	60	140	128	96	64	24	0	0	0	0	0	0
111161	10	6C11.00-O2	0	10	10	20	20	40	80	120	136	88	56	16	8	0	0	0	0	0
111157	11	6A11.00-O2	0	0	0	30	40	50	90	180	200	120	60	30	0	0	0	0	0	0
111158	11	6C12.20-O2	0	0	10	20	20	40	80	140	144	88	48	16	0	0	0	0	0	0
111159	11	6A49.50-S3	0	10	20	30	30	100	150	300	250	150	100	30	10	0	0	0	0	0
111160	11	6B49.55-S3	0	0	10	20	50	100	150	200	200	150	100	40	0	0	0	0	0	0
111153	12	6B11.20-O2	0	0	10	10	30	40	70	136	136	80	56	24	8	0	0	0	0	0
111154	12	6C11.40-O2	0	0	10	20	20	50	60	120	152	96	56	16	0	0	0	0	0	0
111155	12	6A49.51-S1P	0	10	30	40	50	200	400	500	500	300	100	50	10	0	0	0	0	0
111156	12	6B50.51-S3	0	0	0	10	20	150	200	300	400	150	100	50	0	0	0	0	0	0
111151	14	6B11.20-O2	0	10	10	10	20	40	70	144	136	88	48	16	8	0	0	0	0	0
111152	14	6B49.50-S3	0	0	20	50	150	400	500	800	600	400	250	100	30	0	0	0	0	0
111127	15	6A11.00-O2	0	10	20	20	30	50	90	170	170	120	70	30	20	0	0	0	0	0
111149	15	6C11.00-O2	0	10	10	10	30	40	60	140	128	88	56	24	8	0	0	0	0	0
111126	16	6C11.20-O2	0	0	10	10	20	40	80	130	144	88	56	16	8	0	0	0	0	0
111124	18	6A11.00-O2	0	0	10	20	30	60	100	180	180	120	70	20	10	0	0	0	0	0
111125	18	6C11.00-O2	0	0	10	20	20	40	70	120	160	88	48	16	8	0	0	0	0	0
111122	19	6B11.20-O2	0	0	10	20	20	40	70	120	136	96	56	24	8	0	0	0	0	0
111123	19	6C11.20-O2	0	0	10	20	30	30	60	130	136	104	48	24	8	0	0	0	0	0
111121	20	6C11.40-O2	0	10	10	20	20	40	60	140	128	96	56	16	8	0	0	0	0	0

Items Unicos
6C11.40-O2
6B11.20-O2
6C11.20-O2
6A11.00-O2
6C11.00-O2
6B49.50-S3
6A49.51-S1P
6B50.51-S3
6C12.20-O2
6A49.50-S3
6B49.55-S3
6C12.00-O2

Cost p/ Unit Backlog	Cost for Extra Time
Costb	Costet
2	750

Converter Dados

Gerar Instancia

Gravar

Figure A.1: Lot-Sizing Data Template

A.2 Scheduling Excel Template

In this section, you can find the excel template used to manually select orders to use in the sequencing algorithm. This is an alternative to the integrated method and can be used to quickly test the results for the addition or deletion of some production orders.

Order	Ref	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
122702	6A51.90-S3		5	0	0	40	105	175	210	150	90	50	15	10			
122725	6B45.20-S3		0	0	5	25	45	75	150	195	150	125	70	30			
122728	6A51.90-S3		10	10	10	40	95	150	180	140	80	40	15	10			
122730	6A49.11-S1P		5	10	20	45	110	160	205	180	110	55	25	10			
122779	6B45.20-S3		0	0	5	30	50	95	175	220	165	140	80	30			
122780	6B84.20-S3		5	5	10	35	65	100	150	170	120	65	45	25			
122784	6A49.11-S1P		5	10	25	55	115	175	215	180	115	65	25	10			
123517	6A51.90-S3		0	0	0	15	140	225	250	160	65	15	0	0			
124587	6B51.90-S3		0	20	60	79	140	180	180	140	0	39	0	0			

Get Data

Backup

Figure A.2: Scheduling Data Template