Eco-efficient production planning for the footwear industry

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Master's Dissertation

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Abstract

This dissertation deals with the development of a decision support tool for optimizing production planning on a rotary injection machine, specifically in the footwear industry, in the context of the BioShoes4All project. The main objective was to maximize production efficiency and minimize energy consumption, balancing these two goals to promote more eco-efficient and economically viable production practices.

The study began with a relevant theoretical background, exploring concepts of production planning, energy efficiency and optimization methodologies, with an emphasis on the construction of heuristics. The methodology involved a detailed characterization of the current production process, an analysis of the problem's objectives and the implementation of a heuristic multi-objective optimization model.

The tool developed uses a random search approach to identify an initial solution, followed by a neighborhood search to improve that solution, considering different combinations of weights assigned to the defined objectives: number of delayed orders, total delay and energy consumption per pair of shoes produced. Analysis of the results revealed that the proposed methodology is effective in finding compromise solutions that improve production efficiency while reducing energy consumption.

The study's conclusions point to success in meeting the defined objectives, while highlighting the limitations encountered, such as the limited availability of data and the time-consuming execution of the algorithms. Several opportunities for future work were also identified, including further analysis of the dependencies between the defined criteria and the exploration of alternative heuristic methods to further optimize the production process.

Resumo

Esta dissertação aborda o desenvolvimento de uma ferramenta de suporte à decisão para otimização do planeamento de produção numa máquina de injeção rotativa, especificamente na indústria do calçado, no contexto do projeto BioShoes4All. O principal objetivo foi maximizar a eficiência de produção e minimizar o consumo de energia, equilibrando estas duas metas para promover práticas de produção mais ecoeficientes e economicamente viáveis.

O estudo teve início com uma fundamentação teórica relevante, em que são explorados conceitos de planeamento de produção, eficiência energética e metodologias de otimização, com ênfase na construção de heurísticas. A metodologia envolveu a caracterização detalhada do processo de produção atual, análise dos objetivos do problema e a implementação de um modelo heurístico de otimização multiobjetivo.

Esta ferramenta desenvolvida utiliza uma abordagem de procura aleatória para identificar uma solução inicial, seguida de uma procura na vizinhança para melhorar essa solução, considerando diferentes combinações de pesos atribuídos aos objetivos definidos: número de ordens atrasadas, atraso total e consumo de energia por par de sapatos produzido. A análise dos resultados revelou que a metodologia proposta é eficaz em encontrar soluções de compromisso que melhoram a eficiência de produção enquanto reduzem o consumo de energia.

As conclusões do estudo apontam para o sucesso no cumprimento dos objetivos definidos, destacando as limitações encontradas, como a disponibilidade limitada de dados e o tempo de execução demorado dos algoritmos. Foram também identificadas várias oportunidades para trabalhos futuros, incluindo a análise mais aprofundada das dependências entre os critérios definidos e a exploração de métodos heurísticos alternativos para otimizar ainda mais o processo de produção.

Agradecimentos

Não faria sentido escrever esta dissertação sem antes agradecer a todas as pessoas que foram fundamentais para o meu desempenho académico.

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Depois, uma palavra à minha família. Primeiro, começando pelo meu pai que em toda a minha vida foi um pilar importante para o meu crescimento, sei que durante este meu percurso não me faltou nada e nunca faltará. Sou hoje um homem diferente 5 anos depois de ter entrado na faculdade e muito te devo a ti.

À minha mãe, por me ensinar a lutar pelos meus sonhos e por todo o carinho. Mãe é mãe e não há palavras suficientes para descrecver toda a gratidão que tenho por ti.

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"We ourselves feel that what we are doing is just a drop in ocean. But if that drop were not there,
I think the ocean would be less by that missing drop."

Mother Teresa

Contents

Acronyms and Symbols

KPI	Key Performance Indicator
PO	Production Order
PU	Polyurethane
RCL	Restricted List of Candidates
MOO	Multiple Objectives in Optimization
WSM	Weighted Sum Model

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Chapter 1

Introduction

This dissertation project was developed at Institute for Systems Engineering and Computers, Technology and Science (INESC TEC), an Institute for Systems Engineering and Computers, Technology and Science. It emerged within the context of an agreement between INESC TEC and AMF Safety Shoes, Tabuadelo, Guimarães, for the optimization planning of a rotating machine used for the production of shoes, while taking into account the importance of saving the consume of energy and increasing the production efficiency of that machine. To stand out and be able to maintain the prestige in a sector so competitive and technologically evolved as footwear is, AMF works together with INESC TEC in order to have a permanent focus on seeking out the latest news, trends and technologies.

1.1 Portuguese Footwear Industry

Portuguese industries are young, modern, and focused on the future. As a result, they are constantly evolving, combining tradition and technology. This development is due to the hard work of the current generation of Portuguese entrepreneurs aligned with their creativity on marketing strategies and interest on technological innovation (Portuguese Shoes [2024b]).

According to APPICAPS, in Portugal there are two main poles: one comprises the Municipalities of Felgueiras and Guimarães and the other includes the Municipalities of Santa Maria da Feira, Oliveira de Azeméis and São João da Madeira. It means around 80% of the firms are located in that cluster, which can be explained for being a positive location for exportations, with favorable infrastructure and good access to markets (Marques and Guedes [2015]).

Over the last decade, Portugal has been evolving in this sector as Portuguese brands have been gaining some strong position, by bringing innovative, irreverent and unique tone to the brands. In addition to the increasing of the quality of products, they are differentiating themselves with the exploration of market segments. From an old and dying industry, a revived sector has developed, with a new presence and new communication that keeps evolving and imposing itself more globally. Over the past two decades, the footwear industry has distinguished itself in global marketplaces and advanced along the value chain. The sector has transformed, adapting to demands faster and being more adaptable. In addition, the shoe business has improved its ability to create new products. One of the primary advantages of the Portuguese footwear business nowadays is its strong manufacturing reputation.

Portugal is expanding in almost all of the most important markets, including Germany (accounted for 21.6% of exports, which translates to 433.58 million euros), France (accounted for 11.93% of exports, which translates to 384.16 million euros), and the Netherlands (accounted for 9.58% of exports, which translates to 306.67 million euros), according to a more thorough examination of the evolution of exports. According to studies conducted last year, Portugal exported 76 million pairs of shoes in 2022, bringing in 2 009 million euros. Comparing these numbers to 2021, they showed a rise of 10.5% in volume and 20.2% in value. The growth in footwear exports was 13.8% over the previous year. In comparison to 2021, there was an increase of 8.7% in the average cost of a Portuguese shoe, which is now 26.40 euros (APICCAPS/INE [2022]).

With recent positive years, the Portuguese footwear industry is planning a significant investment of 140 million euros over the next three years. This initiative aims to establish Portugal as a global leader in sustainable footwear solutions, reinforcing the country's export capabilities through its strong, innovation-driven production base. This effort involves more than 100 entities, including universities, companies and research institutions, all collaborating to promote a decade of growth in international markets. Despite the strong export performance of the last decade, the industry has to adapt to remain competitive. This adaptation focuses on the integration of innovative materials, ecological products, digitalization and new business models, targeting markets where consumer choice is driven more by fashion and technological sophistication than by price alone. A key part of this strategy is the BioShoes4All project, which has been allocated 80 million euros and aims to revolutionize the industry through the development of new biomaterials, sustainable production practices and circular economy initiatives, positioning Portuguese footwear as a leader in sustainable innovation on the global scene (Portuguese Shoes [2024a]).

1.2 AMF Safety Shoes and BioShoes4All Project

AMF Safety Shoes was founded in 1999 by Albano Fernandes, who brought with him a wealth of experience in the footwear and sole sectors. The company started out as a small operation with just 20 employees and a daily output of 250 pairs of shoes. Over the years, through strategic innovation and partnerships, including collaboration with INESC TEC, AMF has grown to become an internationally recognized leader in the development, manufacture and marketing of high-quality technical footwear designed to protect feet. The company expanded its brand in 2005 with the creation of "2work4", later renamed "TOWORKFOR", which now has a global presence in more than 35 markets. Today, AMF employs more than 150 people and continues to differentiate itself through innovation and sustainable practices, positioning itself as a benchmark company in the highly competitive footwear industry (AMF Shoes [2023]). The Figure 1.1 presents the headquarters in Guimarães (Neves [2022]).

Figure 1.1: AMF Safety Shoes Headquarters

This dissertation is framed in the BioShoes4All project, in line with AMF's commitment to innovation and sustainability. This ambitious project is structured around five fundamental pillars: biomaterials, ecological footwear, circular economy, advanced production technologies and training and promotion. It involves a consortium of 69 partners, including companies from the leather, materials and technology sectors, as well as several universities and research bodies. The project aims to develop new bio-based materials and processes, create eco-designed footwear with a lower environmental footprint, improve circularity in production processes and introduce innovative technologies to digitize the footwear sector. This work focuses on optimizing eco-efficient production planning, integrating energy consumption profiles, ultimately contributing to more sustainable and profitable production processes. This project is further detailed in Chapter 2.

1.3 INESC TEC

INESC TEC is a private non-profit association with public utility status that focuses on advanced consulting and training, technology transfer, scientific research and development. INESC TEC is seen as an interface institute, as it brings together academia, companies, public administration and society, with the aim of creating value and immediate social relevance by aggregating knowledge and research results in technology transfer projects.

As a result of a restructuring process at INESC, which was created in May 1985, INESC Porto (initially, and then, INESC TEC) was formed in 1998. In the year it was founded, its founding members were INESC, the University of Porto and the Faculty of Engineering of the University of Porto; in 2006, the Faculty of Sciences of the University of Porto and the Polytechnic Institute of Porto. Currently, INESC TEC is present in three areas, Porto with six centers, Braga and Vila

Real, and has a total of 13 R&D centers, structured in four thematic clusters: Computer Science; Industrial and Systems Engineering; Intelligent Systems Networks; Energy.

INESC TEC began to contribute to the footwear sector in the 1990s by developing new equipment and automating and computerizing the systems that were already in place. The first footwear projects were initiated in 1992 with the intention of creating adaptable logistics systems. At Kyaia's Paredes de Coura facility, INESC TEC installed the LOGICSTORE, a highly inventive system for storage and automatic distribution to seam lines, in 1996. The needs of the footwear industry were naturally followed and supported by the expansion and diversification of INESC TEC's research fields. Thus, in addition to system simulations, production line optimization models, heuristics and algorithms were created to balance the manufacturing lines (AMF Shoes [2023]).

1.4 Objectives

The aim of this dissertation is to develop a decision support tool for planning the production of a rotating machine (DESMA Rotating Machine) in order to maximize production efficiency and minimize the machine's energy consumption. With this approach, it is hoped to improve the production process towards more environmentally friendly operations, while at the same time achieving a significant reduction in manufacturing costs.

In this context, this automatic machine is responsible for the direct injection of Polyurethane (PU), working as an adhesive to firmly connect the lower part of the shoe (outsole) and the upper part of the shoe. Therefore, the purpose of this project is to develop and design optimization strategies for eco-efficient production planning and scheduling. To increase machine performance, Key Performance Indicators were defined and analyzed. The energy consumption can reduce production costs and minimize environmental impact, and the production rate and cycles times might facilitate identifying areas for improvement and maximize resource utilization.

The study will encompasses an examination of various parameters, to ensure a comprehensive understanding of the dynamic connection between production efficiency, energy consumption, and environmental impact. Through the development of a decision support tool, the aim is to explore multiple scenarios, each characterized by unique sets of rules and criteria. Thus, the goal is to discover optimal strategies that improve machine utilization while minimizing energy consumption.

1.5 Methodology

The thesis project consists of four main phases. In the initial phase, a literature review was conducted to understand the current state of production planning, energy efficiency in manufacturing, and related optimization methodologies.

Then, the description and characterization of the problem were held. It required not only gathering production data, but also understand the overall production process, including machine features, operating rules and critical constraints to precisely define the problem scope. By incorporating insights from the current practice at the company, the analysis went deeper into identifying potential areas for improvement within the manufacturing process.

In the third phase, optimization strategies were designed and developed in order to minimize energy consumption and maximize production efficiency, which would promote environmental sustainability and cost-effectiveness. The strategies were developed with the use of various tools and techniques, including Python for algorithm development, SQL database program for managing and querying production data, and Excel for diverse data sets analysis.

Finally, after applying the model, results and conclusions were derived from the gathered information. This phase involved analyzing the outcomes of the optimization strategies to assess their impact on production efficiency and energy consumption, providing a comprehensive understanding of the improvements achieved.

1.6 Dissertation Structure

This dissertation is divided into six chapters. The first chapter introduces the project, explaining the objectives and methodology applied throughout.

The second chapter presents a detailed case study as a foundation for this project's research, exploring the processes involved and the injection molding process. It also describes the features of the system.

The third chapter provides a theoretical background that supports the development of the solutions presented later in the dissertation.

Chapter four describes the methodology adopted in this project, explaining the approach proposed in order to achieve the defined objectives.

The fifth chapter presents the computational results and respective analysis obtained from the application of the developed heuristic.

Finally, the sixth chapter concludes the dissertation by summarizing the main findings and conclusions drawn from the research.

Chapter 2

Case Study

This chapter presents a case study that serves as the basis for the development of this project. The way in which shoes are produced in a footwear industry was studied, as well as all the production, technical and operational processes used to produce shoes in this specific company. With this, the first step was to understand this problem, with the aim of studying and understanding how to create a model based on optimizing this production process.

2.1 Current Production System

This subchapter then explores the actual production system, divided into two parts, the production of a shoe and the process of putting a shoe together. While the first part provides an overview of the constitution of a shoe and the manufacturing process, highlighting the stages from initial design to final quality control, the second part focuses on the advanced techniques used to join the upper and lower parts of the shoe, with an emphasis on the direct injection method with PU.

2.1.1 Injected Shoes Production

In order to understand the manufacturing of a shoe, it is important to be aware of the constitution of an injected shoe. An injected shoe is divided into four parts: **Upper** (entire part above the sole that covers a foot, providing protection and support, outsourced by the company); **Insole** (part that has direct contact with the bottom of the foot, giving comfort to the shoe); **Midsole** (injected component, foamed and soft part, responsible for the cushion of a shoe); **Outsole** (also an injected component, compact and hard material in contact with the outside surfaces), as in Figure 2.1 (Technologies [2024]).

Figure 2.1: Shoe Components

The manufacturing of footwear is a combination of innovation, production technology, tradition, and skill. The shoe manufacturing process take several steps:

1. **Mould creation and Cutting:** This process of converting sketches into 3D data and models is defined by precision and rigor, which enables manufacturers to assess the real shoe design and make decisions on materials and measurements.
2. **Assembly and forming:** As the essential form of the shoe takes shape, the upper material gets formed using moulds.
3. **Sole Attachment:** Through the use of an adhesive (Polyurethane) the midsole and outsole are attached to the upper.
4. **Finishing and quality control:** The upper is washed, creamed and polished and the sole and shoe edges are colored and polished. The quality standards need to be ensured.

2.1.2 Injection Moulding Process

To join the upper with the lower part of the shoe, PU is used, it is a polymer chemistry composed by Polyol and Isocyanate. Polyurethane is used working as an adhesive defining the quality and durability of the products. In this process, liquid PU is injected directly into moulds, where it solidifies and bonds the different parts of the shoe together. At the heart of this transformative process lies the direct injection method, a game changer in the world of footwear production, propelled by the cutting-edge capabilities of DESMA rotating machines, shown in Figure 2.2 (GmbH [2024]). The use of DESMA rotating machines further improves this process by automating the injection and molding stages, improving efficiency and reducing the margin for error. These machines are capable of processing several molds simultaneously, each adapted to specific shoe designs and sizes. The rotation mechanism ensures that the molds are filled precisely, leading to a high-quality finish.

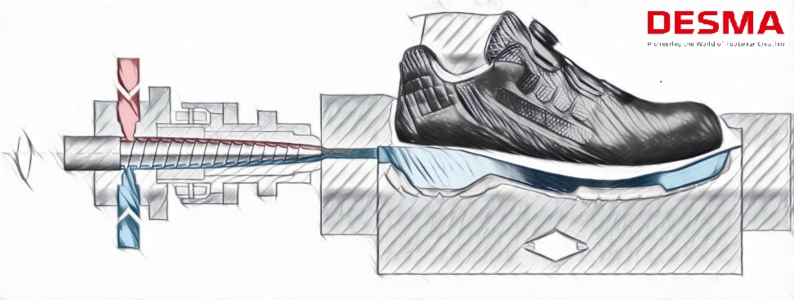


Figure 2.2: Injection of the Midsole

The direct injection of PU is made by a DESMA rotating machine (Figure 2.3). This machine has 24 positions, but only a set of 12 is considered, since shoes are produced in pairs. In each position a mould is placed, characterized by type, size and transition time, which refers to the machine's rotation time between two positions. The model defined by the company is characterized by a reference, sole type (PU-PU or PU-Rubber), sole color, midsole color and the mould required for production. The machine has 2 injectors, one for the sole and one for the midsole, where the sole injector is only used if the type of sole is PU-PU. Each production order (PO) is characterized by the quantities to be produced of different sizes of a model and has a priority associated with it (defined according to the delivery dates restricted to the company).

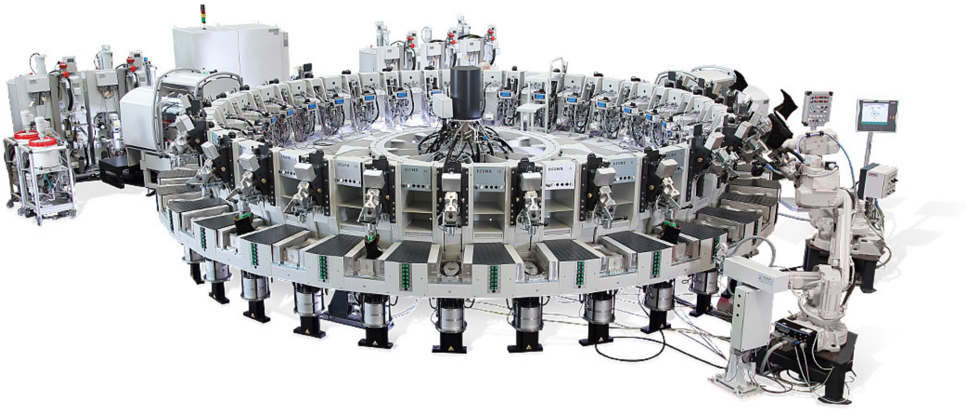


Figure 2.3: DESMA Rotating Machine (DESMA [2024])

2.2 System Features

In footwear manufacturing at AMF Safety Shoes, small irregularities or inefficiencies can lead to significant bottlenecks, delays or defects in the final product. Therefore, a thorough knowledge of the system's characteristics becomes important in order to optimize production planning. This section describes the main features of the production system, focusing on the machine, the moulds and the injection colors, which must be carefully managed in order to achieve an efficient and flawless manufacturing process.

2.2.1 Machine Features

The injection moulding machine has 24 stations, whereas only 12 stations are considered as it works with pairs of shoes. The cycle time of the machine is the duration of one full rotation and the transition time is the gap between two successive locations (cycle time is 24 times the transition time). The transition time might range from 18 to 20 seconds, depending on whatever moulds are in the machine, which means the longest transition time will be taken into consideration in such a scenario, meaning the shoes with the shortest processing times will spend more time in the machine than the shoes with the longest processing times. In many cases, the machine can run moulds with different transition times at the same time. It's critical to reduce transition time variances when multiple shoe kinds and sizes are loaded together.

The machine is not fully automatic as there is still the need of 2 operators, so the availability of machine depends on the operators' schedule. Moreover, the PO selected will be the best one to increase the efficiency and the machine usage, however, sometimes the machine is not completely full and it only injects if there is an associated mould, which creates some inefficiency.

2.2.2 Mould Features

There are six types of moulds: Mould 1, Mould 2, Mould 3, Mould 4, Mould 5, Mould 6, and they are distinguished by size. Usually, the mould name is associated with the model name, but there are some exceptions.

There are some mould exceptions in terms of size, for example, Mould 4 size 45 can inject size 44 and Mould 3 size 44 can inject Mould 1 size 44. The availability of certain mould types or sizes can constrain production flexibility.

The planning is done in a way to minimize mould changes, since each mould change takes around 10 minutes, so when there is a mould change, its position is the bottleneck of that lap. In addition, the moulds come on a trolley in a set of 10, so the mould change can only be done every 10 laps.

2.2.3 Injection Color Features

The machine has 2 injectors, one for the sole and the other for the midsole. The sole injector is not used when the type of sole is PU-Rubber. Each injector can handle both parts but only one at a time, necessitating a switching mechanism between them. Switching between colors for the outsole and midsole entails a specific process.

- **Incompatibility:** This occurs when the machine cannot transition between the required colors. In other words, the machine is unable to change from one color to another seamlessly.

- **Compatibility with purging:** In this scenario, the machine can change the injection color, but it requires cleaning the injector, which results in material waste. This cleaning process, known as purging, ensures that there is no residue of the previous color in the injection process, thereby maintaining the integrity of the new color. However, this additional step leads to material wastage and increases production time.

- **Compatibility without purging:** This situation arises when there is no need for a color change between injections. In such cases, the machine can continue production without the need for purging, thereby saving time and minimizing material wastage. This scenario is the most efficient in terms of production continuity and resource utilization.

2.3 Current Planning Method

The current planning method consists on the production planning of sequentially allocating a given set of POs in order to minimize both mould changes and color changes in the injectors. Planning is often done on a weekly basis, and for this reason it is very rarely carried out with the machine completely empty. In this way, both the initial moulds and the color present in each of the injectors are predefined characteristics. Therefore, the machine already has moulds in all positions at the start of the planning process.

Color changes are a much faster processes with fewer restrictions and can be made in any lap of the machine taking only a few seconds, however, mould changes can only be made in multiple laps of 10, since the trolleys arrive with the moulds for production in multiple quantities of 10 (the trolley must be finished first) and take 10 minutes for each mould changing. Therefore, whenever the algorithm starts with a new PO, it locks the position, not allowing the algorithm to allocate a new PO until all 10 moulds have been completed.

The decision of which PO to allocate follows several conditions. If the position is not locked, depending on the mould that is in the position and taking into account the priority orders (each PO has a priority associated from 1 to 5), starting for the lower ones, the following conditions are then verified sequentially:

- **1º:** the possibility of allocating a PO that **does not involve any type of change** (change of mould or color). If this is possible, the PO found is allocated and the machine moves on to the next position, otherwise the next condition is analyzed.

- **2º:** the possibility of allocating a PO that only **involves changing the color of the sole injector**. If this is possible, the injector color is changed to the desired color, the PO found is allocated and the machine moves on to the next position, otherwise the next condition is analyzed.

- **3º:** the possibility of allocating a PO that only **involves changing the color of the midsole injector**. If this is possible, the color of the injector is changed to the desired color, the PO found is allocated and the machine runs forward to the next position, otherwise the following condition will be analyzed.
- **4º:** the possibility of allocating an PO that **involves changing both colors in the injectors**. If this is possible, the color in the injectors is changed to the desired colors, the PO found is allocated and the machine runs forward to the next position, otherwise it will check if the mould changing is possible.

Color changes are given priority over mould changes, as it is a faster process with fewer restrictions. Thus, after checking all the previous conditions, the possibility of a mould changing is analyzed (only if the position is not locked ,which means, the current lap is a multiple of 10). If the position is locked, the mould changing is not possible, the algorithm proceeds to the next priority (if there are no higher priorities the position remains empty), otherwise, if mould changing is required, the decision of which PO to place again follows similar conditions to the previous ones:

- **1º:** the possibility of allocating a PO that **involves changing the mould, but which has both colors compatible**. If this is possible, the mould in the position is changed, the PO found is allocated and the machine runs forward to the next position, otherwise the next condition will be analyzed.
- **2º:** the possibility of allocating a PO that **involves changing the mould and the color of the sole injector**, but which has a compatible midsole color. If this is possible, the mould in the position and the color in the sole injector are changed, the PO found is allocated and the machine runs forward to the next position, otherwise the next condition is analyzed.
- **3º:** the possibility of allocating a PO that **involves changing the mould and the color of the midsole injector**, but which has a compatible sole color. If this is possible, the mould in the position and the color in the midsole injector are changed, the PO found is allocated and the machine runs forward to the next position, otherwise the next condition is analyzed.
- **4º:** the possibility of allocating a PO that **involves changing the mould and both colors**. If this is possible, the mould in the position and the color in the injectors are changed, the PO found is allocated and the machine runs forward to the next position, otherwise it is checked for higher priority POs. If there are, the whole process of changing colors and moulds is repeated, otherwise the position will be empty..

After these analyses and if there are no higher priorities, the position remains empty. After the 12 positions remain empty, the algorithm finishes and all the PO are allocated. To easier understand this scheduling process, a flowchart developed by INESC TEC under the Bioshoes4All Project is presented in Figure 2.4.

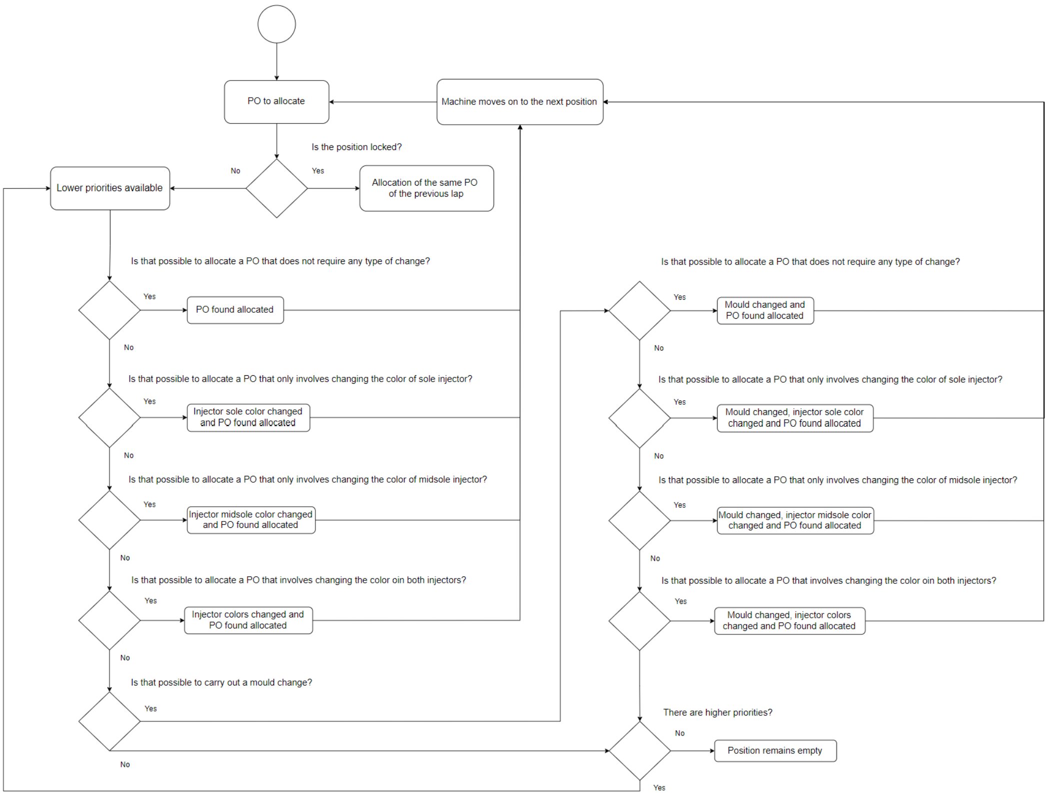


Figure 2.4: Current Planning Method (Developed by INESC TEC under the Bioshoes4All Project)

2.3.1 BioShoes4All Project

The BioShoes4All project is an aspiring initiative that aims to transform the footwear industry through the development of sustainable practices and innovative technologies. The aim of BioShoes4All is to place significant emphasis on the creation of new bio-based materials, the design of ecological footwear and the strengthening of circularity in production processes, sustainability being an important issue for companies today. The project aims to reduce dependence on fossil-based materials, improve resource efficiency and eliminate critical substances. It also seeks to regenerate production waste and start recovering post-consumer products, thus increasing the sustainability of the entire value chain.

The key component of the project is the introduction of advanced production technologies that support the digitalization of the footwear sector, enabling more efficient and automated manufacturing processes. These technologies include solutions for tracking production processes, advanced planning and the integration of eco-processes that contribute to reducing the environmental footprint of footwear production.

The focus of this dissertation is the development of a decision support tool for eco-efficient production planning and, for this reason, the BioShoes4All project is especially pertinent. The research conducted in this thesis is aligned with the fourth pillar of the project, which involves the digitalization and optimization of production processes, since the aim is to develop an eco-efficient planning system that incorporates energy consumption profiles. The following background chapter will delve into the theoretical and technical foundations that support the development of economical and efficient production systems, providing the necessary context to understand the meaning and implementation of the strategies proposed in this case study.

Chapter 3

Background

This chapter presents the relevant literature on production planning and scheduling in the footwear industry, taking into account the case study under discussion.

This project provides information about production planning and scheduling, as it seeks to balance the objectives of maximizing production efficiency and minimizing energy consumption, and therefore enable eco-efficient production, combining sustainability with productivity.

Heuristics and mathematical models were analyzed to determine the most suitable approach for optimizing production efficiency and reducing energy consumption in the project.

3.1 Production Planning and Scheduling

Production planning aggregates a set of activities defined by an industry, with the aim of satisfying customer needs by optimizing the use of resources and managing the company's tasks, thus ensuring that production runs as expected. It is the basis of production, defining times and quantities of what needs to be produced in order to meet customer needs, taking into account inventory costs and order delays. The process of organizing activities includes forecasting demand to ensure that products are available when needed, managing stocks to balance inventory levels and minimize costs, and planning capacity to ensure the resources needed to meet production objectives (Sule [2007]).

As discussed in Chapter 2, production planning in the footwear industry is particularly complex due to the high level of customization required and the diverse variety of products, each of which can have different models, sizes and restrictions, which complicates the planning process. The aim is to ensure that a given product is finished in the defined time, minimizing inventory costs and, principally, in the context of this project, avoiding delays.

The planning process must take into account the unique requirements of each production phase. For example, in the case of a shoe injection machine, which is a critical component in the production process, optimizing its use can have a significant impact on overall production efficiency. The planning process must therefore be structured in detail to incorporate these factors, ensuring that resources such as materials, personnel and machinery are optimally managed (Cerveira et al. [2024]).

Scheduling, on the other hand, is characterized by the act of defining rules and organizing activities to meet specific requirements, constraints and objectives. Or, in case of objectives can't be met, how to set new objectives that are optimal and practical with the resources available. In everyone's day-to-day life, time is a significant constraint and so people organize and define the way they carry out their activities in order to optimize their tasks.

Scheduling activities range from simple tasks involving graphs and diagrams to sophisticated algorithms that require substantial knowledge, such as mathematical programming methods or heuristics. Therefore effective scheduling balances the need for simplicity with the benefits of advanced techniques, thus ensuring accessibility for all industry professionals (Sule [2007]).

Given the project in question, shoe injection machine scheduling is fundamental to the production process, requiring a careful balance between minimizing setup times and maximizing machine utilization. One of the main challenges is dealing with the changeover times associated with changing moulds on the machines, as they can significantly affect production efficiency, making it necessary to develop schedules that minimize interruptions while meeting production objectives. Based on the study of Parisa et al. [2021], an integer optimization model was developed to respond to these scheduling challenges. The model aimed to minimize changeovers and inventory levels in order to keep production operations running smoothly. The study demonstrated that, using advanced scheduling techniques, it is possible to optimize the use of resources in the footwear industry, thus improving overall efficiency and profitability.

In industries such as footwear, where the production process is highly specialized, effective scheduling ensures that production runs smoothly and meets market demands (Cerveira et al. [2024]), involving:

- **Calculation of processing time:** Considering setup time, processing time of units and quantities for production.

- **Machine occupancy rate:** Planning machine activity time.

- **Data integration:** Combining information about schedules, delivery times, machine conditions and customer orders.

According to Huang et al. [2011], scheduling rotating machines with dependent processing times offers valuable information on managing the complexities of scheduling in environments where processing times are not constant, but depend on the combination of tasks being processed. The article highlights the importance of advanced algorithms, such as genetic algorithms, in optimizing programs under such constraints, highlighting an elaborate approach to managing scheduling in footwear manufacturing.

3.2 Traditional Approaches in Scheduling

In the context of production planning and scheduling, the use of mathematical programming and heuristics is common, as they provide the best optimized results for a given problem. On the one hand, mathematical programming involves formulating planning problems as mathematical models, which use methods to rigorously analyze all possible decisions and construct optimal solutions. On the other hand, heuristics are more efficient at constructing several alternative solutions to complex, large-scale problems. Unlike mathematical programming, this approach, especially Single-Solution Based heuristics, do not present only one optimal solution, but find solutions that are good enough to solve problems with a wide search space and complex restrictions, where exact methods become impractical (Cerveira et al. [2024]).

3.2.1 Mathematical Programming

Mathematical programming, as previously mentioned, encompasses a series of techniques used to solve optimization problems by formulating them as mathematical models. These models usually include:

Linear Programming (LP): Uses linear equations to represent constraints and objectives, suitable for problems in which the decision variables are continuous.

Integer Programming (IP): Similar to LP in that the variables are integers, making it useful for discrete decisions, such as assigning tasks.

Mixed integer linear programming (MILP): Combines integer and continuous variables and can therefore provide flexibility for complex programming scenarios.

Mathematical programming is applied to various scheduling problems, such as task scheduling, flow scheduling and project scheduling. This method produces optimal solutions and takes into account complex constraints and objectives, however, it may not be the best method to use as it may not be suitable in some cases where decision-makers need a series of solutions rather than a single optimal solution. Firstly, it makes analysis difficult for highly complex problems, since analyzing an optimal solution ends up requiring significant processing capacity and time. In addition, it requires a precise formulation of the problem and exact data, which can be difficult to obtain in real situations (Klemmt [2009]).

3.2.2 Heuristic Approaches

Heuristics offer an effective alternative, guiding the search process toward good or near-optimal solutions through a balance of exploration (often seen in population-based metaheuristics) and exploitation (commonly found in single-solution-based heuristics) of the solution space. These methods are highly adaptable, capable of dealing with multiple conflicting objectives and can generate several solutions, which makes them more suitable for complex and dynamic programming problems, in contrast to mathematical models situations where the search space is large and complex, as they find high-quality solutions without the need to carry out exhaustive searches.

However, they do not guarantee that a solution is optimal, meaning that it satisfies all the conditions (unlike mathematical models), this method is therefore effective in finding solutions and can provide high-quality results for scheduling problems (Klemmt [2009]).

There are two types of heuristics: **Single Solution Based heuristics** and **Population Based heuristics**. On one hand, Single Solution Based heuristics, also known as trajectory methods, are heuristics based on a single solution, taking advantage of that solution, iteratively improving that solution and finding a better solution to the problem. These methods are particularly effective when starting with a reasonably good solution that requires further optimization. The objective is to exploit the current solution's neighborhood to find better solutions progressively (Boussaïd et al. [2013]).

On the other hand, Population Based heuristics are heuristics based on a population (set of solutions), exploring the solution space through multiple simultaneous solutions. These methods are suitable for exploring a large and diverse space of solutions, as they can avoid getting stuck in local optima by considering several candidate solutions in each iteration (Boussaïd et al. [2013]).

In this case, Single Solution Based heuristics are particularly suitable for the problem, since the starting point is based on a solution built on the heuristic, and it is necessary to improve this solution. There are some examples of its uses: **Simulated Annealing (SA)**, **Microcanonical Annealing (MA)**, **Threshold Accepting (TA)**, **Noising Method (NM)**, **Tabu Search (TS)**, **GRASP (Greedy Randomized Adaptive Search Procedure)**, **Variable Neighborhood Search (VNS)**, **Guided Local Search (GLS)** and **Iterated Local Search (ILS)** (Boussaïd et al. [2013]).

According to Arroyo and Pereira [2011], in the planning of shoe injection moulding machines, the GRASP method has been successfully applied to optimize production plans, minimizing setup times and maximizing machine utilization. Therefore, this method was used for this project in a similar way and with a solution improvement heuristic. The following subsection presents its characteristics as well as its algorithm, both for GRASP and the adaptation to the constructive heuristic used.

3.2.2.1 GRASP (Greedy Randomized Adaptive Search Procedure)

This heuristic is used for combinatorial optimization problems. Its algorithm has two important steps, **construction** and **local search**, with the objective of finding the best solution (Boussaïd et al. [2013]). In the first step, it construct a feasible solution using a randomized greedy heuristic and in the second step, a local search procedure is done using the feasible solution as an initial solution. The Algorithm 1 represents this method (Cerveira et al. [2024]).

This algorithm shows the two different phases of the process. The construction phase uses a heuristic approach to build the solution, which can be a random search or a more targeted heuristic that uses a restricted list of candidates (RCL) to guide the selection of operations.

To further increase the effectiveness of GRASP, an Improvement Heuristic is incorporated during the local search phase. The Improvement Heuristic, specifically the Swap Slots strategy, focuses on refining the initial solution generated in the construction phase by making systematic changes to the sequence of operations rules. Local search aims to improve the solution through

```
input  : Jobs, Moulds, maxItGrasp
output: bestSolution
it ← 0;
f(bestSolution) ← +∞;
while it < maxItGrasp do
    solution_it ← ∅;
    RandomizedConstructiveHeuristic(Jobs, Moulds, solution_it);
    LocalSearch(solution_it);
    if f(solution_it) < f(bestSolution) then
        bestSolution ← solution_it;
    end
    it ← it + 1;
end
```

Algorithm 1: Pseudocode of the GRASP approach (Cerveira et al. [2024])

small changes that reduce costs, minimize delays or optimize energy consumption. The process continues until no further improvements can be made, which indicates that a local optimum has been reached. The Algorithm 2 presents these described steps.

GRASP repeats the construction and local search phases over a predefined number of iterations (*maxItGrasp*). Each iteration starts with a new or varied initial solution, ensuring that different regions of the solution space are explored.

```
input  : An initial feasible solution (initialSolution)
output: The best solution found (bestSolution)
bestSolution ← initialSolution;
improvements ← true;
while improvements do
    improvements ← false;
    for each feasible move do
        solution ← bestSolution;
        ApplySwapSlotOperator(solution);
        Reschedule(solution);
        if f(solution) < f(bestSolution) then
            bestSolution ← solution;
            improvements ← true;
            exit for;
        end
    end
end
```

Algorithm 2: Pseudocode of the improvement heuristic (Cerveira et al. [2024])

The Swap Slots strategy, according to Cerveira et al. [2024], is a targeted heuristic that changes the sequencing order in the machine's slots. This strategy is particularly useful for minimizing the setup costs associated with changes such as color transitions in a shoe injection molding machine.

3.3 Multiple Objectives in Optimization

Multi-objective optimization (MOO) is a mathematical approach used to solve problems that involve several objectives being optimized simultaneously. Unlike single-objective optimization, in which only one objective is optimized,in MOO, several criteria are analyzed collectively and not individually. The result of MOO is a set of Pareto optimal solutions, where no single solution can improve one objective without worsening another. This analysis is relevant in manufacturing processes, where the trade-offs between different objectives, such as cost, time and resource efficiency, must be carefully managed (Marler and Arora [2010]).

In the context of this project, the MOO will be required to find a balance between the various KPIs. Each of these criteria represents a different objective that the scheduling model must optimize, and therefore has an associated weight depending on the scenario in question (Marler and Arora [2010]).

3.3.1 Weighted Sum Model

The Weighted Sum Method (WSM) is one of the oldest and simplest approaches used in multi-objective optimization. Its origins and evolution go back to the fundamental concepts of optimization and decision making, where it is necessary to balance or optimize several objectives simultaneously (Marler and Arora [2010]).

The WSM method works by assigning a weight to each indicator based on its relative importance in each alternative, where the weighted performance values are added together to produce a total score for each alternative. Before applying the WSM, each objective is usually normalized to ensure equal comparability. Normalization adjusts the scale of the different objectives so that one does not disproportionately influence the results simply because of its magnitude (Thokala and Madhavan [2018]).

The basic formula of WSM is presented in Equation 3.1.

$$U = \sum_{i=1}^{k} w_i \cdot F_i(x) \tag{3.1}$$

where:

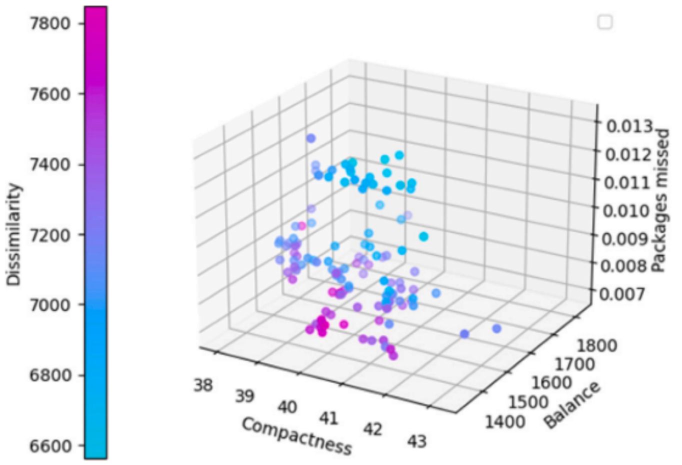
- U is the total score.
- w_i is the weight assigned to each function.
- $F_i(x)$ represents the different objective functions.

3.3.2 Pareto Optimal Frontier

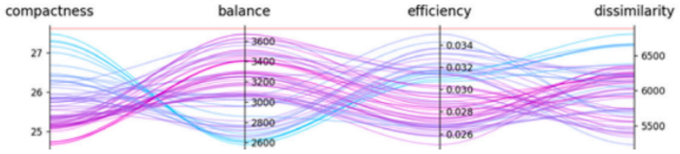
The Pareto Optimal Frontier represents the set of all Pareto optimal solutions. These solutions are visualized as a curve (or a surface in higher dimensions) in the objective space, where each point on the curve represents a compromise between different objectives. In engineering and decision-making problems, particularly in production planning and scheduling, this approach helps decision-makers to understand the range of possible compromise solutions between conflicting objectives (Lopes et al. [2023]).

For multi-objective optimization problems with three or more objectives, the representation of the Pareto frontier becomes a challenge due to the limitations of graph presentation (Figure 3.1 (a)). In these cases, parallel coordinate graphs offer a more effective way of visualizing and interpreting the compromise solutions (Figure 3.1 (b)). Parallel coordinates allow multiple objectives to be represented on a single graph, where each objective is presented as a vertical axis. By representing each solution as a line that crosses all the axes, decision-makers can easily compare the performance of different solutions across all objectives simultaneously and more easily plot the Pareto frontier curve (Lopes et al. [2023]).

The graphical representation of both approaches can be seen from Figure 3.1, extracted from Lopes et al. [2023].



(a) Three-dimensional



(b) Parallel Coordinates Plot

Figure 3.1: Different Representation of multi-objective optimal solutions (Lopes et al. [2023])

3.4 Eco-Efficient Objectives

The two primary objectives of this project delve into increasing the production efficiency, minimizing disruptions to the production process by optimizing the scheduling of tasks on the rotating injection machine, and enhancing sustainability of the production system by optimizing energy consumption.

According to Parisa et al. [2021], scheduling in injection moulding machines is a complex task due to the high levels of customization and the variety of products that must be processed. These machines are prone to interruptions, especially during mould and color changes, which can significantly extend the production cycle and lead to inefficiencies. The study highlights the importance of optimizing the programming process to minimize these interruptions, underlining that even small delays can have a chain effect on the entire production line, leading to bottlenecks and a failure to meet delivery deadlines.

Furthermore, disruptions often arise from the intricate dependencies between the different production phases and are sometimes unforeseen. A complete scheduling framework is therefore needed that can adapt to these dependencies and mitigate the impact of any disruptions (Cerveira et al. [2024]).

The article Huang et al. [2011] provides information on genetic algorithms for the scheduling of rotating machines, providing further insight into how machine-specific constraints, such as processing times dependent on the sequence of operations, can contribute to interruptions in production. These constraints must be carefully managed to avoid inefficiencies, especially in environments where machines such as injection molders are involved. The study suggests that by integrating advanced scheduling algorithms that take these constraints into account, it is possible to reduce the likelihood of these interruptions and improve the overall production flow.

In the context of sustainable production, energy consumption is a primary KPI in production planning. In the footwear industry, optimizing energy use serves to reduce operating costs and minimize environmental impact. The aim is to explore strategies for managing and reducing energy consumption in production processes, including energy reduction objectives and ensuring the consistent application of sustainable best practices. To achieve these goals, regular assessments are often carried out to identify areas where energy savings can be made and improvement measures implemented (Flores Lazo and Rosales Molina [2023]).

Injection molding machines consume significant amounts of energy, especially during the mold heating and cooling phases. Non-productive energy consumption can be as high as 60%, which highlights the importance of optimizing energy use in the manufacturing cycle (Flores Lazo and Rosales Molina [2023]). By reducing non-productive energy consumption, not only can costs be cut, but the environmental impact of the production process can be significantly reduced. This implies not only optimizing the machine's operating characteristics, but also considering the broader context of production scheduling, in which the efficient use of energy must be balanced with the need to maintain a consistent production flow.

Chapter 4

Methodology

The main objective of this project is to develop a planning and optimization tool adapted to the footwear manufacturing process. The tool was built to improve the efficiency of production systems, taking into account key Operational factors such as energy consumption, production delays and the effective allocation of POs considering the constraints of the manufacturing environment.

To achieve this goal, a comprehensive heuristic approach was developed, focusing on multi-objective optimization. This approach is important for balancing multiple performance indicators that exhibit different behaviors, ensuring that the final production plan is not only efficient, but also adaptable to different Operational priorities. This methodology combines heuristic and meta-heuristic techniques, integrating the knowledge of the initial heuristic model with sophisticated optimization strategies that allow the exploration of a wider solution space.

In order to simplify the presentation of the data throughout the paper, the KPIs have been represented in abbreviated form: the Number of Late Orders has been designated by N, the Total Delay by T, and the Energy Consumption per Pair by E.

4.1 Proposed Approach

In this work, a production plan was built for the injection machine, and so, this chapter describes the methodological approach adopted, in which improvements were made to the current algorithm by defining performance indicators in order to quantify the machine's performance.

The Background carried out in the previous chapter served as the basis for building the heuristic implemented. In this work, an approach was developed that made it possible to obtain several compromise solutions, using multi-objective analysis. The decision to avoid using mathematical programming was mainly due to the complexity of the problem and the need for multi-objective analysis, since using this approach would simplify the model and require excessive computational time.

The first step was to define the key performance indicators that would be used to build the solutions. A multi-objective model was thus built in which there would not be just one best solution, but rather a set of best solutions which would then be chosen according to what the decision-maker intended. Firstly, these indicators were normalized through a rule change analysis in the scaling and then different weights were assigned to the indicators, thus combining them in various combinations of weights so that, after running the algorithm, these various solutions were obtained.

The optimization model was then structured in two key phases to respond effectively to the scheduling challenges. In the first phase, a Random Search was used to explore a wide range of solutions, with the aim of identifying a viable initial solution that could serve as a starting point for further refinement. In this phase 2 solutions were compared. The first solution was derived from the initial heuristic, which followed the company's current planning method (Figure 2.4). The second solution was generated by assigning random priorities to the POs. This phase allowed the model to consider several possible alternatives for initially allocate POs.

Once the best initial solution had been calculated, the model would move on to the second phase, defined as Neighborhood Search, in which the focus would shift to improving the initial solution. The Neighborhood Search involved small strategic swaps, swapping the priorities of the POs within predefined groups. These swaps aimed to improve key performance metrics, such as minimizing energy consumption, reducing total delay time and optimizing other relevant indicators. This methodology, which combines initial research with a solution improvement process, ensured that the final solution was efficient. The detailed steps and logic behind each phase are explained in the following sections.

The methodological approach is presented in the schema in Figure 4.1.

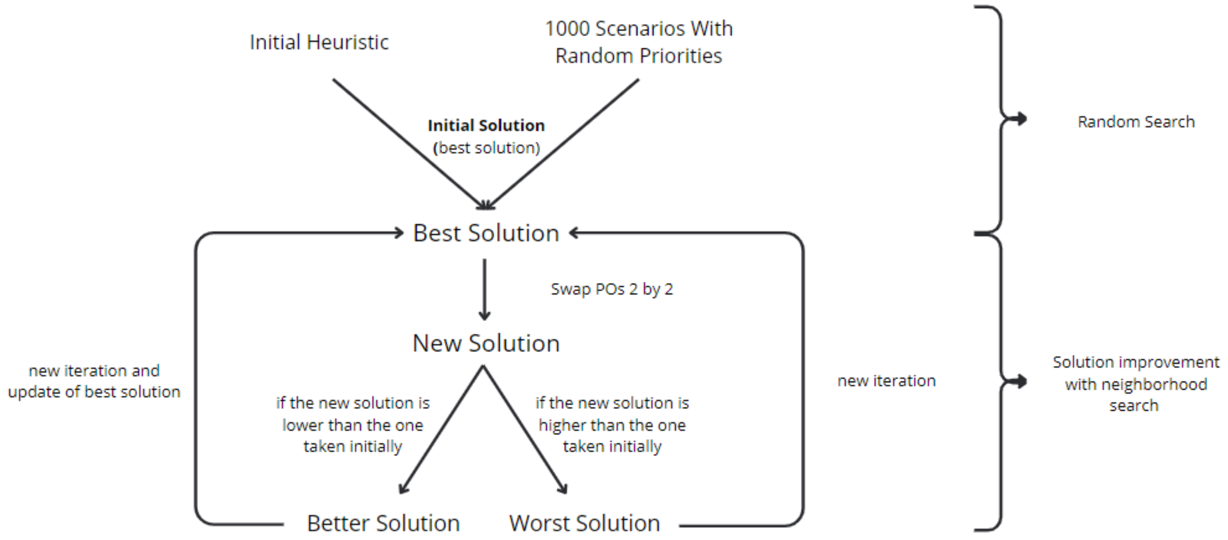


Figure 4.1: Developed decision support approach

4.2 Key Performance Indicators

In order to evaluate the effectiveness of the optimization process, several Key Performance Indicators (KPIs) were analyzed, focusing on how different strategies impacted overall performance and solution quality. Three main indicators were then defined:

- **Number of Late Orders:** This indicator was calculated in order to analyze the number of POs in which the production of a pair of shoes was not completed in the expected time. The company has an expected delivery date for each PO, so the expected time was calculated taking into account this time in hours. The production time for each pair of shoes in each lap of the machine was calculated by adding up the production time until the previous lap with the transition time (characteristic of each PO) and the mold change time (10 minutes), if it took place. The delay for each PO was then calculated by subtracting the estimated delivery time to the production time for each lap.

- **Total Delay:** This indicator adds up the delays of all the POs once they have been allocated to the machine and finished being produced. Similar to calculating the number of delayed orders, this indicator analyzes the excess time needed to complete each PO, adding up these times to obtain a total measure of delay, and is beneficial for understanding how this result can affect the outcome of the final solution. For this calculation, the delay for each PO (Di) is defined as the difference between the actual production time and the expected production time, represented in the Equation 4.1 (units in hours). If the result is negative (indicating that the production was completed ahead of schedule), the delay is set to zero.

  $$D_i = \max\left(\left[A_i - (5 \times 16 \times E_i)\right], 0\right) \tag{4.1}$$

  Where:

  - A_i is the actual production time for PO i in hours, which includes the sum of time each lap takes, considering transition time and mold changes.
  - E_i is the expected delivery time for PO i in weeks.
  - The term $5 \times 16 \times E_i$ calculates the total expected production time in hours, assuming a workweek of 5 days with 16 working hours per day.
  - The function $\max(\cdot, 0)$ ensures that if the calculated delay is negative, it is set to zero (indicating no delay).

  The Total Delay for all POs, represented in Equation 4.2 (units in hours), is then calculated by summing the delays for each individual order.

  $$\text{Total Delay} = \sum_{i=1}^{n} D_i \tag{4.2}$$

  Where:

  - n is the total number of POs.
  - D_i is the delay for PO i, as calculated above.

- **Energy Consumption per Pair:** Given the importance of this problem in minimizing the energy efficiency of the injection machine, the energy consumed was calculated by the ratio between the energy consumed and the number of pairs produced. The energy consumption is proportional to the number of laps of the machine, since each lap of the machine consumes a certain amount of energy. The formula calculated is presented in Equation 4.3, with units in Watts/Number of pairs.

$$\text{Energy Consumption per Pair} = \frac{EnergyConsumedperlap \times Numberoflaps}{Numberofpairs} \tag{4.3}$$

4.2.1 Normalization of Indicators

After the 3 KPIs have been defined, they were normalized, adapting the values to a range between 0 and 1. In the context of multi-objective optimization, it is necessary to normalize the indicators to ensure that they are on a comparable scale. Normalization allows the different objectives with different units, to be combined in a meaningful way during the optimization process. Without normalization, an indicator with a larger range could disproportionately influence the results, leading to biased or non-optimal decisions. In this way, the KPIs were organized as follows:

N: Vector N with the total number of late orders
N': Normalization of Vector N, presented in Equation 4.4

$$N' = \frac{N - N_{\min}}{N_{\max} - N_{\min}}, \quad 0 < N' < 1 \tag{4.4}$$

T: Vector T with the total delay of the PO
T': Normalization of Vector T, presented in Equation 4.5

$$T' = \frac{T - T_{\min}}{T_{\max} - T_{\min}}, \quad 0 < T' < 1 \tag{4.5}$$

E: Vector E with the energy consumed per pair of shoes
E': Normalization of Vector E, presented in Equation 4.6

$$E' = \frac{E - E_{\min}}{E_{\max} - E_{\min}}, \quad 0 < E' < 1 \tag{4.6}$$

In order to normalize the indicators, a minimum value and a maximum value needed to be defined. The minimum value was simple to calculate, as it represents the best theoretical case in which the indicator achieves its most favorable result. This value was determined based on the inherent characteristics of the production system.

However, determining the maximum value required a more careful approach since, due to the nature of scheduling, it is never possible to know with certainty whether the worst case scenario has actually been achieved. Therefore, this maximum value was analyzed based on a series of hypothetical scenarios that explored the worst behavior of the system, in order to understand the upper limits of each indicator can have in adverse situations. In this case, a scenario refers to a set of sequencing rules applied to the algorithm that allocate POs within the production plan.

To generate these scenarios, the algorithm for allocating POs to the injection machine was modified. The original algorithm worked with three primary rules to prioritize the assignment of POs:

- **Priority:** POs were allocated based on their priority level, starting by lower priority numbers (ranging from 1 to 5);
- **Quantity:** POs with higher quantities were allocated first;
- **Size:** POs with higher sizes were allocated first.

4.3 Heuristic Approach

After defining and normalizing the Key Performance Indicators, a multi-objective heuristic was constructed. As previously mentioned, the scheduling process of the problem was based on the priorities of the tasks, and the quantities and sizes of the items. The quantities and sizes only served as tie-breakers criteria for the allocation of the POs in the machine, therefore, this heuristic would base on the priorities of the POs. From a Multi-Objective Analysis perspective, various weight distributions were implemented with the aim of presenting several optimal solutions, in which the decision agent could choose the best solution for the company's purposes.

For each distribution of weights, the aim of this heuristic was to find the best solution and so was divided into 2 parts. In the first part, a **Random Search** was implemented, where the goal was to find the best solution to start the second part. It compared two values, the solution of the Current Heuristic (developed by INESC before this project that follows the scheduling of Figure 2.4) and the minimum score of the Random Search. The solution with minimum score would then be used to start as an initial solution for the second phase. In this second part, **Neighborhood Search**,a solution improvement was done in order to find better solutions for the problem, and so the neighborhood of the problem would focus on changing the priorities in order to find this better solution.

4.3.1 Multi-Objective Analysis

In the context of the developed heuristic, Multi-Objective Analysis serves to evaluate and select the best possible solutions based on multiple different criteria. The aim is to find balanced solutions that satisfy several performance measures, rather than optimizing a single criterion or a single solution. As this approach is particularly useful in complex decision-making scenarios, it ultimately fits in with production planning for injected shoe manufacturing, where the various indicators, number of late orders, total delay and energy consumption, must be considered simultaneously in this model.

Thus, with this multi-objective analysis, solutions are evaluated holistically, considering multiple performance indicators, balancing trade-offs between objectives that can be seen as inverse, building a set of optimal solutions (Pareto optimal solutions) for decision makers to choose from, based on their preferences and company priorities.

The Table 4.1 therefore shows the weights assigned to the three key performance indicators, indicating the relative importance of each in the decision-making process, resulting in 21 combination of weights. With this variation in weights, different scenarios can be analyzed to understand how prioritizing one KPI over another affects overall performance. This helps to identify the best possible compromises and provides decision makers with a comprehensive set of solutions to choose from, depending on their strategic priorities and objectives.

Table 4.1: Performance Weight Analysis Distribution

Combination	w_N	w_T	w_E
1	0%	0%	100%
2	0%	20%	80%
3	0%	40%	60%
4	0%	60%	40%
5	0%	80%	20%
6	0%	100%	0%
7	20%	0%	80%
8	20%	20%	60%
9	20%	40%	40%
10	20%	60%	20%
11	20%	80%	0%
12	40%	0%	60%
13	40%	20%	40%
14	40%	40%	20%
15	40%	60%	0%
16	60%	0%	40%
17	60%	20%	20%
18	60%	40%	0%
19	80%	0%	20%
20	80%	20%	0%
21	100%	0%	0%

In few words, this analysis ensures that all the criteria are properly measured, making it possible to compare the performance of each objective in different solutions. After executing the algorithm and calculating each indicator, the construction of this multi-objective analysis requires two phases. Firstly, for each set of weights, the indicators were normalized, multiplied by their respective weights and the three indicators were summed to obtain a final score. In the final stage, the scores of all the solutions were compared, and a graph was constructed to show which solutions would form part of the Pareto frontier, thus allowing the decision-maker to have a set of solutions and make a choice according to the objectives.

4.3.2 Random Search

In this phase, the objective was to find a solution for each weight distribution in Table 4.1, which would serve as the initial solution for the next phase, the Neighborhood Search.

Thus, two solutions were compared, the first being found using the company's Current Heuristics and the second through a Random Search for solutions. The company's Current Heuristic has not had any multi-objective analysis and therefore only presents a solution minimizing mould changes and color changes. For each combination of weights, the values for each of the objectives are the same, with only the score changing for each distribution of weights.

For the second solution, it was decided to change the priorities of the previously defined POs, giving some randomness between the values of 1 and 5, allowing the allocation of POs to be done randomly. In this case, since the result would be completely random, it was decided to run 100 scenarios, for each weight distribution, in which the best solution would then be used as the final solution of this Random Search.

For each weight distribution, the minimum score obtained between these two solutions would then be the initial solution used for the next phase. To easily understand the scheme, a flowchart is presented in Figure 4.2.

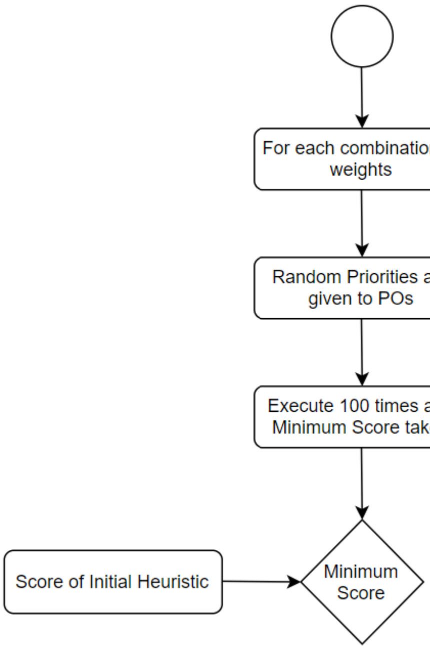


Figure 4.2: Flowchart of Random Search

4.3.2.1 Solution Improvement Analysis

Before starting the Neighborhood Search process, the strategy to be adopted to improve the solution was analyzed by swapping two POs with different priorities. In this process, a multi-objective analysis was not applied in order to simplify the process and avoid the excessive consumption of time. Instead, the focus was on optimizing the solution for a specific scenario. In this way, the values of the Current Heuristic were used as a basis for formulating the strategy to be used in the model, with no interference in the outcome of the final solutions.

The algorithm was executed with two stopping criteria: maximum number of iterations or number of iterations without improvement, with the aim of balancing the scope of the optimization process with consumption time. Due to the complexity of the problem and the computational time, would not be worth to waste time on iterations that would not bring significant improvements and would only serve as a choice for the next phase.

Once the stopping criterion to be used had been defined, three swapping strategies were then analyzed, and the algorithm was run three times in order to effectively improve the solution. The decision of executing the algorithm three times is due to the fact that the algorithm randomly selects POs and swaps between them, even though this strategy is constructive and meaningful, each swap can potentially improve the final solution, but it can also introduce inefficiencies, since a specific swap may seem beneficial in isolation, however, it can limit the effectiveness of subsequent swaps, making the algorithm biased from the moment that initial swap is made. After an initial trade-off, the solution space can be restricted, preventing the discovery of other potentially better solutions that could have been achieved with a different sequence of trade-offs. In other words, an initial trade-off can create a trajectory in the solution space that, although it improves the result immediately, can block access to other more efficient solutions in the long term.

Therefore, by executing the algorithm three times, an attempt was made to mitigate this tendency, with each independent execution allowing the algorithm to explore different paths in the solution space, increasing the probability of finding an overall better solution. Thus, at the end of the three runs, the best solution would be the one with the lowest minimum score. Although this method is not 100% effective in guaranteeing the Optimum solution, it allows for a broader exploration of the solution space and enables the Optimization process. As such, the three strategies analyzed for swapping priorities were:

- **Swap Priorities Randomly:** POs with different priorities were swapped randomly, without any strategy, in order to see if it would be effective to swap them. While offering a broad exploration of possible solutions, often introduces inefficiencies due to the lack of a structured approach.
- **Swap Adjacent Priorities:** Instead of swapping priorities randomly, which would not bring any strategic improvement to the solution, it was decided to swap adjacent priorities, so that an PO with a certain priority would only be swapped with another PO that had the immediately higher or lower priority value, allowing for a more precise optimization of the solution.

- **Swap Priorities by Group:** POs were divided into 2 groups, priorities 4 and 5, due to the large number of PO with these priorities, and priorities 1, 2 and 3, where the POs could only be swapped with others within the same group. Ensures that optimizations were made within defined groups without disturbing the overall hierarchy of POs.

After evaluating the performance of these strategies, it became clear which was the most strategic approach that would produce the best results and would therefore be adopted in the Neighborhood Search phase.

4.3.3 Neighborhood Search

At this stage, we continued with the multi-objective analysis and followed the process described above in which the POs were swapped, with the same stopping criteria and the same number of runs. The idea behind this process, through an analyzed swapping strategy, was to explore the possibility of improving the current solution by trying to reduce the score value, minimizing delays and energy consumption. For each set of weights, the initial solution to be used in this process, as mentioned before, was the result of the final Random Search solution.

In each iteration, the algorithm swaps two OPs and calculates the new score resulting from this change and then compares it with the minimum score recorded up to that point in the process. If the new score was lower than the previous minimum score, it indicated that the swap resulted in an improvement in the solution, and the minimum score was updated to reflect this new, better solution. On the other hand, if the new score was greater than or equal to the previous minimum score, it meant that the change had not contributed to an improvement in the solution. In this case, the minimum score remained unchanged and the algorithm continued to the next iteration, trying another swap between two different POs.

The Figure 4.3 presents a flowchart, in which this process is detailed.

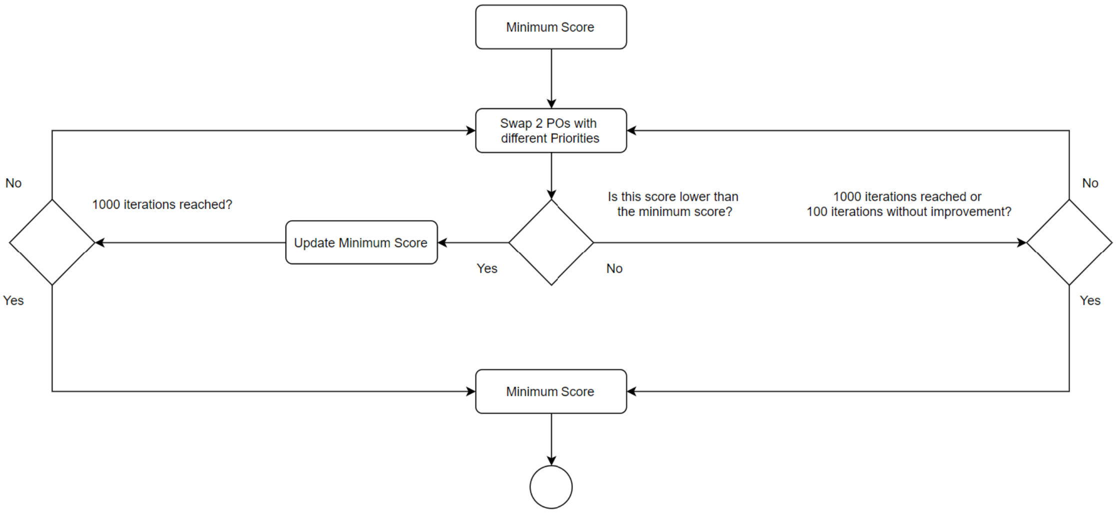


Figure 4.3: Neighborhood Search

Chapter 5

Computational Results

Once the entire methodology for this project had been carried out, the results were obtained for all the stages of the process. These results were analysed with the aim of maximizing production efficiency, in this case by reducing the number of late orders and their total time in hours, and minimizing energy consumption by reducing the number of machine laps and increasing the machine's occupancy rate. To evaluate the effectiveness of the proposed decision suport tool, a specific production instance was used.

5.1 Test Instance

This instance provides a detailed description of all the data involved in the problem, allowing an understanding of the sizing of the project and the high processing time of each stage of the process. This data was provided by the company and represents a real set of POs that have to be scheduled, depending on their specifications. This set of data is determinant for simulating the production planning process, as it reflects the real constraints and requirements faced by the company in its daily operations.

The company assigns priorities to POs based on delivery times and the urgency of production, with the highest priority orders (starting with priority 1) corresponding to more immediate delivery needs. These deadlines are usually set at weekly intervals, which means that each PO must be completed and delivered within a specific number of weeks. The data provided includes not only information about the POs, but also operational specifications relating to the machine's characteristics and capacity.

The availability of this dataset is required for defining the scheduling process, calculating the KPIs, and executing the optimization process effectively. Therefore the instance used was: **Number of POs by priority**: 30, (2 POs of priority 1; 2 POs of priority 5; 1 POs of priority 3; 21 POs of priority 4; 4 POs of priority 5); **Total Number of POs**: 170; **Total Number of Sole Colors**: 5; **Total Number of Insole Colors**: 4; **Total Number of Moulds**: 1547; **Energy Consumed per Lap** = 100 Watts; and **Number of Pairs** = 29930 pairs.

5.2 Key Performance Indicators

The KPIs served as tools for assessing the effectiveness of the optimization process, acting as a link between the theoretical optimization strategies and their practical application. By analyzing these indicators, it was possible to measure the extent to which the proposed sequencing strategies met the project's objectives, taking into account an eco-efficient environment. In addition, they made it possible to assess the improvements brought about by the optimization, as well as the overall performance and efficiency of the production process.

Given the different scales and units of these KPIs, normalize them was necessary to ensure that each indicator could be meaningfully compared and combined during the optimization process. This normalization method required the definition of minimum and maximum values for each KPI based on a series of scenarios presented in the following subsection.

5.2.1 Scenario Analysis

To accurately define the minimum and maximum values for normalization, several scenarios were created, analyzing the impact of various sequencing rules on production performance. Each scenario represents a different set of rules applied to the allocation of POs. The Table 5.1, with units as previously mentioned, summarizes the results for each scenario:

Table 5.1: Scenarios used for Normalization

Number of Scenario	Scenario	N	T (hours)	E (Watts/ Number of pairs)
1	Current Heuristic	6	241,26	10,29
2	Descending order of Quantity and Ascending order of Size	3	37,03	9,22
3	Ascending order of Quantity and Descending order of Size	4	165,08	11,16
4	Ascending order of Quantity and Ascending order of Size	6	272,53	11,23
5	Critical Ratio	8	476,73	11,76
6	Inverted Priorities	16	1692,25	10,96

The first scenario (**Current Heuristic**) refers to the operation of the initial algorithm, before any changes were made to the rules, and therefore only served as a comparison to the results obtained in the future. These values were also used in the Random Search, where considering each weight distribution, these values were compared with the randomly generated values and, consequently, the minimum score was then used for the next phase, Neigbhorhood Search.

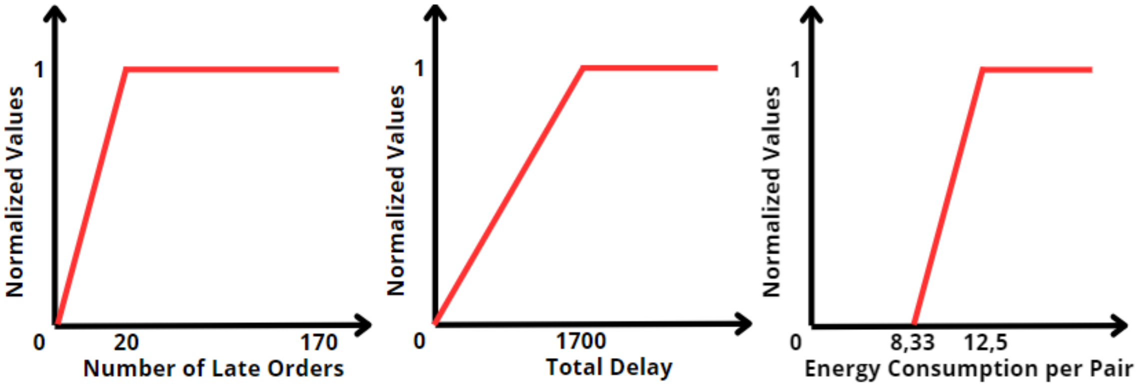
Next, quantities and size were taken into account, where was decided to see how changing these parameters would affect allocation. So starting from this first scenario, in which the POs were allocated starting with higher quantities and sizes (in a descending way) and created 3 more scenarios. Then, the second scenario would follow a descending form of quantity allocation and ascending form of size allocation, the third scenario would follow an ascending form of quantity and descending form of size allocation, and the fourth scenario would follow an ascending form for both quantities and sizes.

The fifth scenario (**Critical Ratio**) was built on the basis of the first scenario as well (priorities established as in the previous algorithm) and a critical ratio was defined, with the ratio between quantity/priority. This ratio helped to prioritize orders that were at higher risk of being delayed, trying to ensure that orders close to their deadlines are completed on time. While the use of the critical ratio is intended to reduce the number of delays by focusing on the most time sensitive orders, this approach could have consequences particularly on energy consumption. However, the delay indicators were worse than expected, which has to do with the behavior of the machine and the associated rules.

Despite of the good results, comparing the scenarios relating to the quantity and size ordering swaps, the only scenario that could make the indicators vary more would be the first scenario. Therefore, another scenario (**Inverted Priorities**) was created based on the first one, reversing the priorities, which means the POs that had lower priorities would now have higher priorities and would therefore be the last to be allocated. In this scenario, the expected results were obtained for the indicators, since high values were obtained and so it was the scenario used to normalize them.

5.2.2 Normalization of Indicators

After analysing and comparing different scenarios from Table 5.1, the minimum and maximum values were then defined. The minimum value was easily calculated since the minimum theoretical value was assigned to the 3 indicators. The maximum values that were set for the normalization of the indicators were not only obtained through the analysis of the different scenarios in the figure, but also with a view to them being equally comparable to each other, thus not allowing their values to influence the future analysis in a unexpected way, and so maximum values were given higher than the values listed. Since there was no defined maximum value for the indicators and there could be cases in which the indicators exceeded the maximum values, any value above the defined maximums were approximated to 1, as shown in Figure 5.1, since it would happen rarely. Considering a perfect environment, the minimum values would be: Nmin = Tmin = 0, considering that there are no delays; Emin = $\frac{100}{12} = 8.33$ Watts/Number of pairs, considering a machine occupancy rate of 100%. Looking to the Table 5.1, the maximum values were then: Nmax = 20 (as there were 170 POs and the maximum value observed was 16); Tmax = 1700 hours (since this indicator has a wide range of values and can therefore take on higher values than the first 5 scenarios observed, but cannot take much higher values than the last scenario; Emax = 12,5, ensuring any unexpected spikes in this parameter, which is common.



(a) Number of Late Orders (b) Total Delay (c) Energy Consumption per Pair

Figure 5.1: Plots of Normalization

5.3 Developed Heuristic

The heuristic developed combined the construction of a heuristic in which weights were assigned to the 3 objectives (Number of Late Orders, Total Delay and Energy Consumed per Pair). This subchapter begins by analyzing the results obtained in the first phase of the process, the Random Search, followed by the solution improvement analysis and, finally, the final results after the Neighborhood Search were analyzed.

5.3.1 Random Search

As mentioned in the previous chapter, for each distribution of weights, two scores were compared, the score of the Current Heuristic and the score obtained by randomly attributing priorities to POs.

At this stage, the indicators for the Current Heuristic were calculated as presented in the first row of Table 5.1. This heuristic was built with the aim of minimizing the number of mould and color changes, so it would be expected that the results of the KPIs would not be ideal for starting the next phase of improvement of solution, since mould and color changes do not directly affect the three main optimization objectives. Although minimizing mould changes can reduce total production time (since each change takes around 10 minutes), the order in which POs are allocated to the machine can create bottlenecks in the production process, thus increasing production time. This bottleneck is related to the specific limitations of the machine, in which some POs can only be processed in certain positions, which leads to an increase in production time and can cause delays in other POs with shorter delivery times.

The second procedure was then carried out, in which each solution was obtained by assigning random priorities to the POs (the algorithm was executed 100 times for each set of weights and the minimum score and respective indicators were obtained). Thus, as expected, the best results were derived from the second procedure, where there was variation in the objectives set, as can be seen in the Table 5.2.

Table 5.2: Results after Random Search Process

	Weights			Random Search			
Combination	N	T	E	N	T	E	Minimum Score
1	0%	0%	80%	7	666,7	8,553	0,042
2	0%	20%	80%	4	391,67	8,553	0,088
3	0%	40%	60%	4	165,63	8,553	0,071
4	0%	60%	40%	2	27,74	9,255	0,098
5	0%	80%	20%	6	214,86	8,553	0,112
6	0%	100%	0%	4	141,79	8,954	0,083
7	20%	0%	80%	4	473,2	8,553	0,082
8	20%	20%	60%	5	210,55	8,720	0,131
9	20%	40%	40%	2	353,37	8,553	0,124
10	20%	60%	20%	5	186,89	9,088	0,152
11	20%	80%	0%	4	251,8	9,088	0,158
12	40%	0%	60%	5	447,91	8,553	0,132
13	40%	20%	40%	4	382,79	8,654	0,156
14	40%	40%	20%	3	97,33	8,988	0,114
15	40%	60%	0%	4	280	9,723	0,179
16	60%	0%	40%	3	372,8	8,720	0,127
17	60%	20%	20%	3	356,9	8,654	0,147
18	60%	40%	0%	3	142,64	8,854	0,124
19	80%	0%	20%	3	423,8	8,553	0,131
20	80%	20%	0%	3	269,29	9,322	0,152
21	100%	0%	0%	2	86,36	9,322	0,100

Although in some cases the results of some of the Current Heuristic indicators were more interesting, specially the Total Delay values, this had a low effect on the final solution, since the weights of these indicators were insignificant.

In the case of the energy consumed, it was found that these variations were effectively insignificant, and a minimum of energy consumed in the process could have been observed (8,553), with the next phase being important for drawing these conclusions. The number of late orders also showed negligible variation, as the values for this indicator ranged from 2 to 7. However, a more interesting variation was observed in the case of the total delay, where this parameter took on more dispersed values, since it takes greater account of the characteristics of each of the 170 POs (transition time and number of mold changes).

5.3.2 Solution Improvement Analysis

For this analysis, the algorithm was executed with two stopping criteria: maximum number of iterations or number of iterations without improvement, where 1000 and 100 iterations were considered, respectively. The application of this stopping criterion not only ensures the quality of the solution, but also optimizes execution time. In the Figure 5.2, the area outlined in red shows the period in which the algorithm would continue to execute without providing further improvements.

As already mentioned, this analysis was based on the Current Heuristic, since the choice of the initial solution had no direct influence on this analysis, and without a multi-objective analysis. Through this analysis, the initial solution was then improved through three methods, for each of which the algorithm was executed three times. From these three executions, the result with the minimum score was selected and two different sets of graphs were presented. The first set,

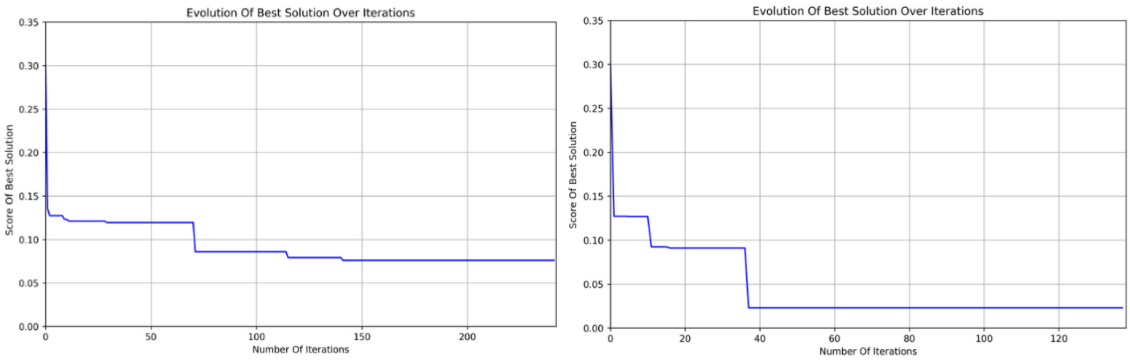
Figure 5.2: Stop Criteria Analysis

presented in Figure 5.3 shows the evolution of the best solution, illustrating how the algorithm reacted to each swap made, allowing to see if the swaps implemented really helped to improve the solution. The second set, presented in Figure 5.4 is composed by scatter plots, used to verify the accuracy of the results, helping in the evaluation of whether the swaps made were successful or if the apparent improvements may have been the product of pure chance. The results obtained from this improvement solution analysis were:

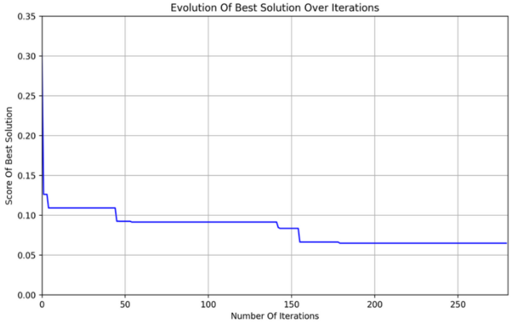
- **Swap Priorities Randomly:** As predicted, random swaps of POs' priorities can improve the solution as shown in Figure 5.3 (a), however, there is no meaning behind this swap, it doesn't add value to the model built and, therefore, from Figure 5.4 (a)it's understandable that the distribution of solutions is extensive. This analysis only served as a comparison for the following analyses.

- **Swap Adjacent Priorities:** This method is more systematic than random swap, since by making small swaps, it is less likely to disturb good solutions and more likely to find better solutions. This strategy is interesting from the point of view of a heuristic, since it aims to explore local optima. As seen from Figure 5.3 (b), there is a gradual decrease in the value of the best solution over the course of the iterations. In addition, the solutions of Figure 5.4 (b) shows the search for these local optima, since the solution from iteration to iteration is generally close to the best solution so far.

- **Swap Priorities by Group:** This method allows for structured exploration in sub-regions of the solution space, by dividing into 2 groups and swapping within them. This allows small swaps to be made, but avoids too many swaps between all the priorities, ando so Figure 5.4 (c) shows the proximity of new solutions. Figure 5.3 (c) shows that this is a good solution improvement strategy, although it ends up being worse than the previous strategy.

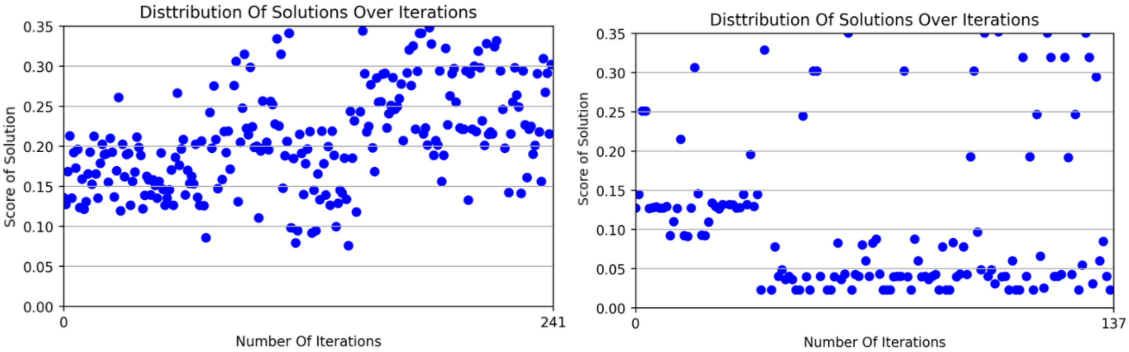


(a) Random Priorities Swaps
(b) Adjacent Priorities Swaps

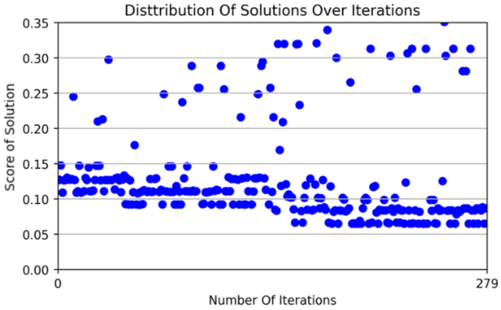


(c) Grouped Priorities Swaps

Figure 5.3: Evolution Of Best Solution Over Iterations



(a) Random Priorities Swaps
(b) Adjacent Priorities Swaps



(c) Grouped Priorities Swaps

Figure 5.4: Distribution Of Solutions Over Iterations

Concluding, through the analysis of Figure 5.3, there was a better solution improvement in Swapping Adjacent Priorities strategy and so was defined to use during the Neighborhood Search phase.

5.3.3 Neighborhood Search

Throughout the process, the aim was to improve the solutions, minimizing their scores. After performing a solution improvement analysis and deciding to use the Swapping Adjacent Priorities strategy, this method was incorporated into this phase in order to arrive at a set of optimal solutions from the multi-objective analysis. For each of the weight distributions, a graph was built for each of the 3 executions, showing the evolution of the solution obtained when the priorities were swapped, and only the best score was taken into account. At the end of this process, these solutions were compared with the solutions obtained from the Random Search, as shown in Table 5.3.

Table 5.3: Results after Neighborhood Search Process

	Weights			Random Search				Neighborhood Search			
Combination	**N**	**T**	**E**	**N**	**T**	**E**	**Minimum Score**	**N**	**T**	**E**	**Minimum Score**
1	0%	0%	100%	7	666,70	8,553	0,053	7	666,70	8,553	0,053
2	0%	20%	80%	4	391,67	8,553	0,088	5	97,95	8,553	0,054
3	0%	40%	60%	4	165,63	8,553	0,071	2	45,03	8,553	0,042
4	0%	60%	40%	2	27,74	9,255	0,098	2	47,40	8,553	0,038
5	0%	80%	20%	6	214,86	8,553	0,112	3	29,03	8,553	0,024
6	0%	100%	0%	4	141,79	8,954	0,083	1	7,77	8,954	0,005
7	20%	0%	80%	4	473,20	8,553	0,082	3	467,90	8,553	0,072
8	20%	20%	60%	5	210,55	8,720	0,131	3	138,97	8,553	0,078
9	20%	40%	40%	2	353,37	8,553	0,124	2	182,34	8,553	0,084
10	20%	60%	20%	5	186,89	9,088	0,152	3	25,01	8,553	0,049
11	20%	80%	0%	4	251,80	9,088	0,158	1	24,37	9,222	0,021
12	40%	0%	60%	5	447,91	8,553	0,132	4	476,70	8,553	0,112
13	40%	20%	40%	4	382,79	8,654	0,156	3	198,20	8,553	0,104
14	40%	40%	20%	3	97,33	8,988	0,114	1	0,97	8,754	0,040
15	40%	60%	0%	4	280,00	9,723	0,179	1	25,43	9,255	0,029
16	60%	0%	40%	3	372,80	8,720	0,127	2	327,74	8,553	0,081
17	60%	20%	20%	3	356,90	8,654	0,147	2	261,06	8,553	0,101
18	60%	40%	0%	3	142,64	8,854	0,124	2	119,03	8,854	0,088
19	80%	0%	20%	3	423,80	8,553	0,131	2	399,96	8,553	0,091
20	80%	20%	0%	3	269,29	9,322	0,152	2	68,06	9,322	0,088
21	100%	0%	0%	2	86,36	9,322	0,100	1	31,93	9,422	0,050

This whole process turned out to be very advantageous, since, except when E = 100%, the values of this last search turned out to be better than the initial search. In this way, this exchange strategy was effective, allowing the algorithm to find better solutions and meet the objectives of this project.

5.4 Analysis of Results

Once the results had been presented, they were analyzed, taking into account both the parameter values and some trends that emerged during the process.

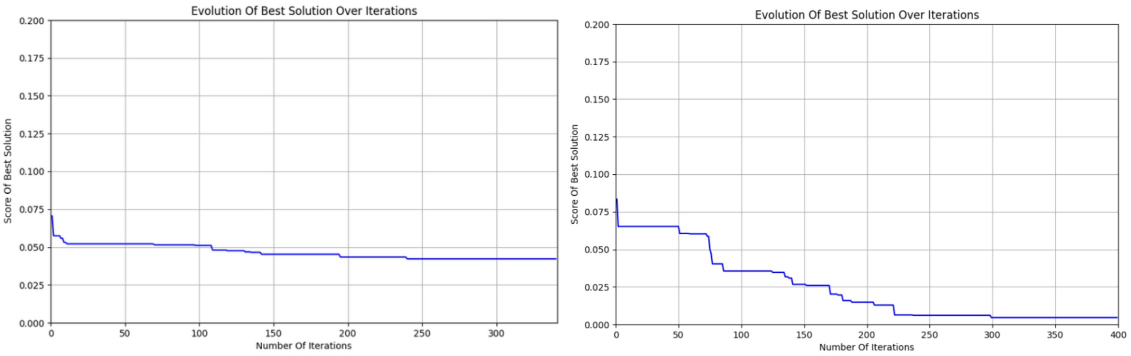
Firstly, the results for each of the objectives of Table 5.3 were analyzed, as well as the evolution of the solutions presented. Next, the influence that the multi-objective analysis had on each of the objectives were analyzed, especially how they reacted to the increase in their weights in the final solution. In addition, the relationship between the indicators were analyzed, since, given a multi-objective analysis, the emphasis would be on having solutions in which the indicators behaved differently, in order to present a final set of solutions and, therefore, possible existence of a trade-off was also analyzed. Finally, the optimal results of this solution were analyzed and how they would be delivered to a decision agent. Thus, a parallel coordinates plot with the results of the 3 objectives was constructed, giving a more clear analysis of the results when compared to a 3D plot. In order to help a decision-maker, the “Pareto frontier” was constructed, showing the optimal solutions.

5.4.1 Evolution of Solutions

To analyze how these solutions evolved, several graphs have been drawn up, but due to their complexity, they are all presented in the Appendices chapter. This subsection then presents the analysis made of the final results after the Neighborhood Search process as well as some pertinent commentary graphs, showing the trends of the algorithm and the results.

With the results, several conclusions were drawn:

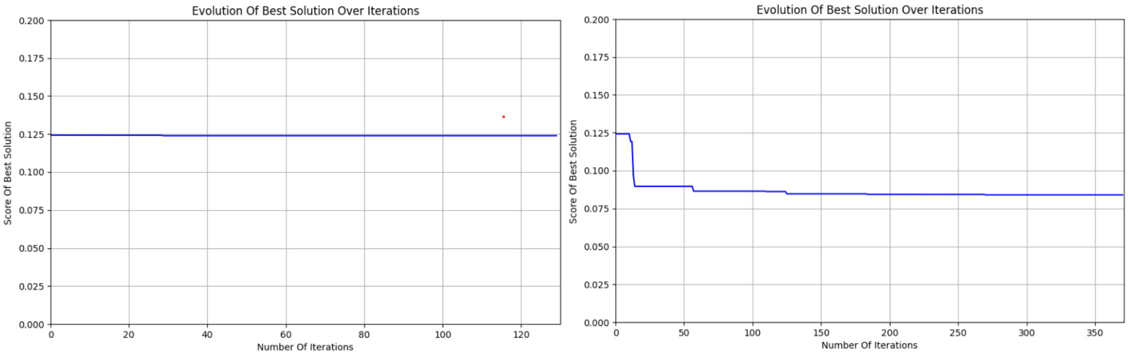
- Only in the first case, where the energy weight is 100%, there were no improvements in the final solution; in the remaining cases, there was always space for improvement. These swaps show that there can always be better values for each of the KPI, however, the energy value was not reduced for the remaining sets of weights, so the first conclusion is that the **minimum value of energy is 8,553 Watts/Number of pairs, equivalent to 2560 laps**. The theoretical minimum calculated was 2500 laps, but it is clear that this value is impossible to achieve, as this difference is due to the machine’s characteristics. When allocating POs that meet its characteristics, the machine cannot be fully maximized (12 pairs in each lap, for all laps). These situations occur towards the end of the allocation process, which means that after a certain point the POs that could fit into a certain position on the machine have already been produced, and if there are no more, the machine is empty in those positions.
- **Energy consumption has an important influence in this project**. As the weight of the energy consumed decreases, its value remains constant or increases, so when its weight is significant, there is less energy consumption, which is why it can remain constant, because this value refers to the minimum energy consumed. In addition, there is also a more efficient swap process when the weight is lower, since the improvement of the solution does not depend much on energy. Thus, 2 plots in Figure 5.5 have been presented showing the evolution of the solution in which the weight of energy is 60% (a) and 0% (b).
- As mentioned above, for each weight distribution, the algorithm was run 3 times in the exchange process, with the aim of making this process more efficient, thus avoiding solutions



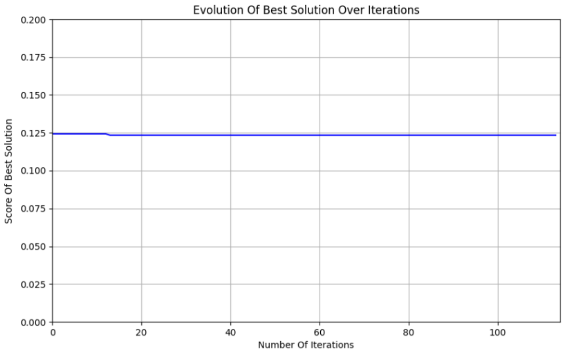
(a) Energy’s weight = 60% (b) Energy’s weight = 0%

Figure 5.5: Comparison of Best Solution Evolution between different Energy´s weights

derived from dependencies on the algorithm and thus achieving better results. For each of these executions, the values were recorded and analyzed using a graph of the evolution of the best solution over the course of each swap iteration. The tree executions of Weight Combination 9 (N = 20%; T = 40%; E = 40%) are used in Figure 5.6 to explain why these criteria were defined.



(a) 1st Execution (b) 2nd Execution



(c) 3rd Execution

Figure 5.6: Best Solution Evolution between different executions, for Weight Combination 9 (N = 20%; T = 40%; E = 40%)

In the first and third runs, the algorithm did not identify any swaps that resulted in significant improvements to the solution, only marginally reducing the minimum score. However, in the second run, the algorithm found some trade-offs that led to substantial improvements in the solution. This result shows that the criterion of carrying out three executions was justified. Increasing the number of executions, although it could potentially generate slightly better solutions, would result in an excessive amount of time for improvements that ultimately might not be significant, especially considering that the final result will be represented by the Pareto frontier. The values of indicators in the final solution are presented in Table 5.4.

Table 5.4: Values of indicators for Weight Combination 9 (N = 20%; T = 40%; E = 40%)

Execution	Number of Late Orders	Total Delay	Energy Consumption
1	2	353,37	8,553
2	2	182,34	8,553
3	2	349,77	8,553

This Table presents the corresponding values for each of the indicators, where the Total Delay shows greater variability, unlike the other indicators. This variation depends on the weights assigned to each objective, however, this indicator offers a greater margin of decision for the final solutions.

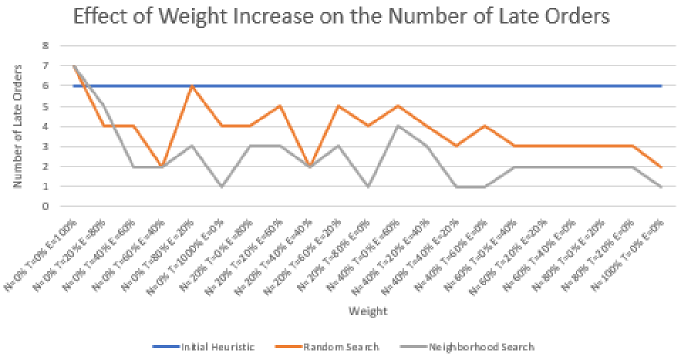
In order to analyze the influence that each weight has on the different values of each KPI, they were then analyzed individually in order to understand the effect of increasing the weight on their values.

5.4.2 KPIs Analysis

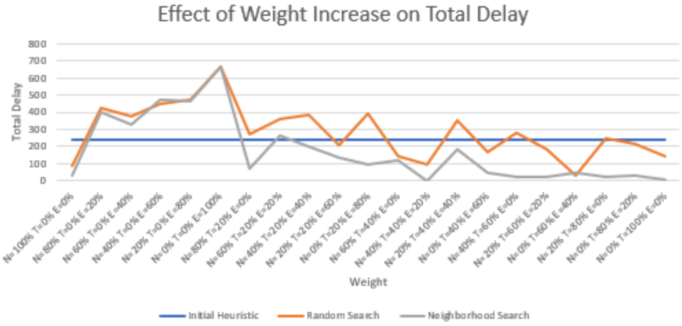
The aim of this analysis was to understand the differences between Current Heurisitc, Random Search and Neighborhood Search. As expected, when the weight of an indicator increases, the tendency is for its value to decrease, which can vary within the same weight, as it also depends on other variables. Thus, three graphs were created, analyzing the variation in the values of each indicator when its weight increased. Each point refers to the value of the indicator for a given distribution of weights, with the weight of the indicator in question increasing in xx.The three plots are presented in Figure 5.7.

With the multi-objective analysis, the aim was to be able to have several different answers to the defined indicators. The Initial Heuristic solution was not used at any stage of the process, as the Random Search solutions proved to be better at meeting the defined objectives. Thus, looking at the graphs (a) and especially (b) in the Figure 5.7, some indicators of the Initial Heuristic were better, however, taking into account this multi-objective analysis and the respective weights, the other indicators prevailed in the final result of the solution. In addition, the Neigborhood Search process proved to be effective, since its line is particularly below the rest, except in a few cases, also explained by the results of others indicators.

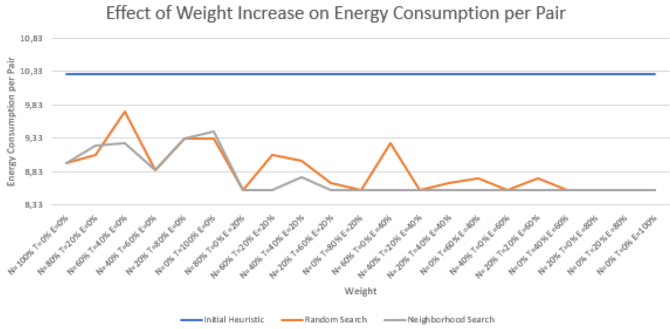
From the Initial Heuristic line, there is a clear difference between the energy consumed and the other objectives, since the values of this indicator are always below the blue line, making it clear that this criterion has a lot of influence on the final results. In the case of the number of late



(a) Number of Late Orders



(b) Total Delay



(c) Energy Consumption per Pair

Figure 5.7: Effect of Weight Increase on KPIs

orders, only one value is below the blue line. On the other hand, in the case of the total delay, there is a difference, where it can vary over a wider range of values (its units are in hours and the production of a PO can take minutes), its values tend to vary more, and is also the criterion that varies the most in the final solution, which is why its values are above when its weigh is low and moves downwards of the Current Heuristic line as its weight increases, having more relevance in the final solution.

In a final analysis, the values of energy consumed are very low in relation to the Initial Heruristics line, positive results considering the objectives of this project since more than half of the values are minimized.

In this analysis, the impact of weight's objectives was observed and showed that a higher value in a given indicator may or may not impact the final solution due to the multi-objective nature of the evaluation. Therefore, this analysis was not intended to compare the indicators against each other but rather to understand how the criteria vary according to changes in their respective weights. Consequently, the next step in the analysis involves examining the relationship between the indicators, taking into account the implemented multi-objective framework.

5.4.3 Trade-off Analysis

In multi-objective optimization problems, where decisions are made based on several criteria, trade-off analysis are important to understand the balance between different objectives. The existing trade-offs are not clear from the results obtained, as this would require a more in-depth study. However, the behavior of the indicators between the results obtained should be analyzed in order to understand some trends in this model.

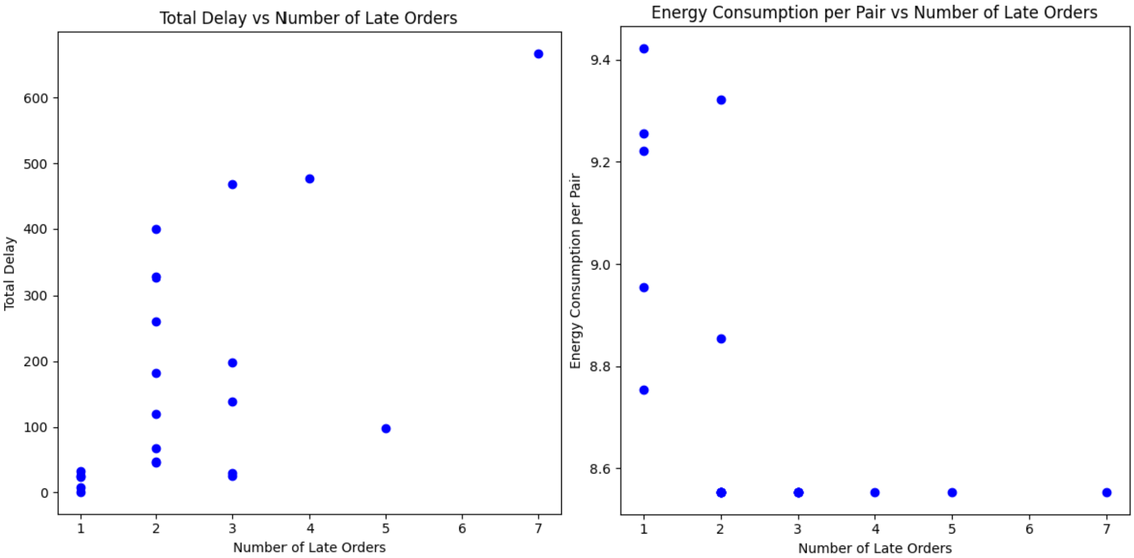
To investigate this, three scatter plots comparing the various indicators were analyzed, as observed in Figure 5.8. In these graphs, each point represents a different combination of weights applied to the objectives.

From the first scatter plot (Figure 5.8 (a)), can't be concluded that there is a positive correlation between the number of late orders and the total delay, since it doesn't mean that an increase in the number of late orders always results in an increase in the total delay. However, the total delay is related to each late orders, as it is the sum of the delays of late orders, and so this correlation highlights the importance of minimizing the number of late orders in order to reduce the total delay. However, as already mentioned, this relationship cannot be clearly explained as machine's and POs' characteristics affect results.

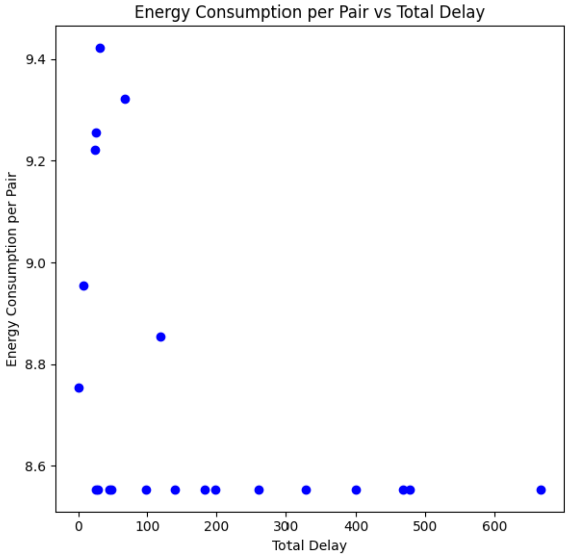
The second scatter plot (Figure 5.8 (b)), which compares energy consumption per pair with the number of delays, reveals a more complex relationship, showing that no clear trend is evident due to the variability of the solutions. Thus, when the energy is minimal, the number of late orders can vary between 2 and 7, and when the number of late orders is minimal, the energy can also vary between a large range, so no clear trade-off can be assumed. However, there is an indication that higher energy consumption, despite being associated with a higher number of machine laps, leading to a longer production time, rather than increasing the number of late orders, may be associated with a lower number of late orders. The opposite is not true, when there is lower energy consumption, there may or may not be more late orders. These results can be explained by the way POs are allocated to the machine, and these aspects are due to the specific characteristics of the machine itself, which the model cannot change.

In the third plot (Figure 5.8 (c)), where energy consumption is related to total delay, the analysis is similar to the previous one, since when energy is minimal, delay can take on a wide range of values and when total delay is minimized, energy consumption also takes on a wide range of values. These similar plots show that show that Number of Late Orders and Total Delay are related.

The scatter plots suggest that although there are relationships between the indicators defined, these relationships are not strictly linear or consistent. The complexity of the production environment, including the attribution of weights to different objectives and the inconsistencies that occur



(a) Total Delay and Number of Late Orders (b) Energy Consumption per Pair and Number of Late Orders



(c) Energy Consumption per Pair and Total Delay

Figure 5.8: Trade-off between objectives

during the allocation of POs related with machine features, means that these indicators can behave unpredictably under different conditions.

This concludes the analysis and explanation of the results, and the next subsection presents the results to be taken into account for a decision-maker.

5.4.3.1 Pareto Optimal Frontier Analysis

In this subsection, the results are presented in a parallel coordinates plot instead of a three-dimensional diagram, as the use of parallel coordinates makes it easier to understand and compare the results. This approach allows a clearer analysis for the construction of the Pareto frontier, since the interpretation of multiple dimensions in parallel coordinates is more intuitive and accessible than in complex 3D representations. The 21 results provided from Table 5.3 were then presented in the Figure 5.9.

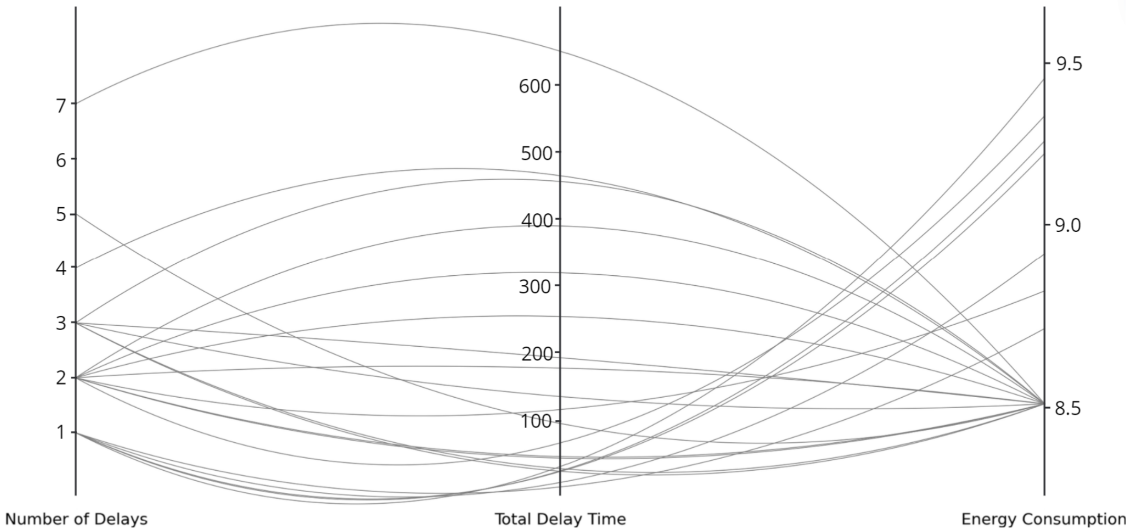


Figure 5.9: Solutions presented in Parallel Coordinates Plot

The Pareto frontier, also known as the Pareto front, represents a set of non-dominated solutions in multi-objective optimization. A solution is considered non-dominated if there is no other solution that improves one objective without worsening at least one other objective. The aim of this construction of the Pareto frontier for this project is to provide decision-makers with a set of good or near-optimal solutions, each representing a different compromise between the objectives (Number of Late Orders, Total Delay and Energy Consumption per Pair). The Pareto frontier provides a powerful tool for decision-makers, enabling them to select the most appropriate solution based on the specific needs and constraints of the production environment.

Table 5.5 was constructed with the good or near-optimal solutions in this project, making it possible to construct the approximate Pareto Frontier Curve presented in the Figure 5.10, with the three solutions, marked in green, that make up the optimal set of solutions from the solutions presented in Figure 5.9.

Table 5.5: Solutions of Pareto Optimal Frontier

Number of Late Orders	Total Delay	Energy Consumption
1	0,97	8,754
2	45,03	8,553
3	25,01	8,553

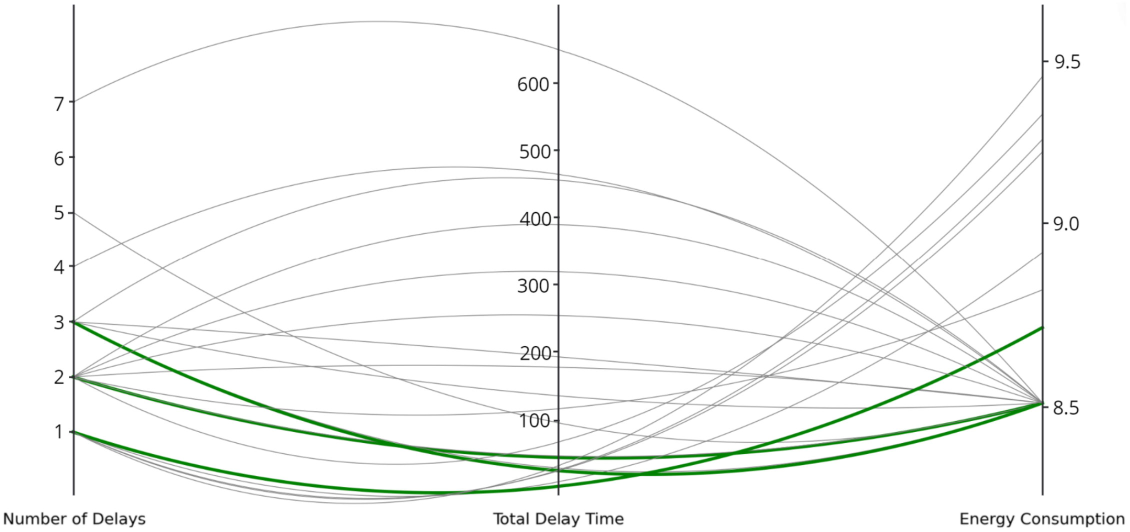


Figure 5.10: Pareto Near-Optimal Frontier

Chapter 6

Conclusion

This dissertation focused on creating a decision support tool for optimizing the planning and operation of a rotary machine used in shoe manufacturing, specifically addressing the challenges of minimizing energy consumption and improving production efficiency. The approach combined heuristic techniques in a multi-objective optimization framework, allowing for a detailed exploration of trade-offs between KPIs, number of late orders, total delay and energy consumption per produced pair.

The main results of this research reveal several improvements achieved. Firstly, during the production process, the energy consumed was properly optimized, as it proved to be minimal in several scenarios, taking into account the multi-objective analysis defined. Secondly, the model produced demonstrated its ability to minimize production delays, especially when the optimization process gave priority to time-sensitive POs. However, it was also found that the relationship between energy consumption and delays is complex and non-linear, emphasizing the need for a balanced approach in multi-objective optimization. Furthermore, the combination of Random Search followed by Neighborhood Search, taking into account the GRASP method, explored a wide space of solutions and the solutions performed better in several objectives. The strategy of exchanging adjacent priorities was particularly successful in improving the quality of the final solutions. Finally, the construction of the Pareto frontier was a valuable tool for decision-makers, enabling them to decide on the best solution taking into account the company's preferences and needs.

During the course of the project, some difficulties were encountered. Firstly, the limited availability of data, as the dataset provided by the company was incomplete. The fact that BioShoes4All is a recent initiative that is scheduled to end in 2025 and is still under analysis for implementation in the footwear industry limited the depth and breadth of the analysis. This limitation is typical of new projects, where the initial phase involves collecting and understanding the data, which makes it difficult to fully assess the project's potential at this stage. In addition, there is still uncertainty as to whether the project will progress to full-scale implementation, as the initial analyses are still ongoing.

Another significant difficulty faced was calculating energy consumption, also due to the lack of data provided. The energy consumption of the injection machine is not an easy metric to estimate, as it tends to vary and is not consistent. Despite these variations, an average value of around 100 Watts was assumed, although this is only an approximation. This assumption introduced an element of uncertainty into the optimization model, since the exact energy consumption could not be established definitively.

From an algorithmic point of view, the excessive execution time of the heuristic developed posed a challenge, with any unexpected error leading to longer execution and resolution times. Due to time constraints, several analyses were adapted or omitted, such as the statistical analysis of the stopping criteria, the results of the OP exchanges, the analysis of the mold exchanges and the examination of the dependency indicators. In addition, more sophisticated standardization could have been used in the process. These omissions, although necessary due to practical constraints, highlighted areas where the project could be further improved.

Despite these challenges, the project provided relevant information about the production process, particularly with regard to the heuristic approach. The exploration of solution improvement techniques and the application of methodologies derived from the Chapter 3 have enriched the project's framework.

6.1 Future Work

In order to foster benefits from the work developed, it's important to continue developing some of the ideas taken from the project. The BioShoes4All project, despite its initial challenges, offers significant opportunities for further exploration and development, as it is a project to be used in Portugal and not just by the company, so it has already been properly analyzed and substantiated for possible progress. Several points of future work were identified that could improve the accuracy and applicability of the optimization model.

As the project progresses and more data becomes available, a deeper analysis of the dependencies between the defined criteria should be carried out. For example, the relationship between the number of late orders and the total delay needs to be explored further, taking into account the machine's characteristics to determine whether, for example, two 100-hour delays might be more beneficial than a single 200-hour delay. This type of analysis will provide more detailed information on optimizing production plans.

In addition, the influence of mold changes on production efficiency, which was only examined at the end of the project, deserves a more comprehensive analysis. Before this project, the scheduling algorithm used by the company took into account the minimization of mould and color changes, so in the current project we tried to study mould changes as a consequence rather than an objective. Since the objectives were defined at the start of building the model for this project, it was not possible to analyze this parameter as an objective. Future work should include an in-depth exploration of how mould changes affect both results and indicators, exploring their potential as predictive indicators within the optimization model.

Moreover, the process of normalizing the KPIs could be done using some specific normalization. Future efforts could focus on validating the normalization approach used and exploring alternative methods to guarantee the accuracy and reliability of the optimization results. Given the excessive running time of the current algorithm, it is also essential to prioritize improving its efficiency in future work. This could involve exploring alternative heuristic or metaheuristic approaches, improving the existing algorithm or even considering parallel processing techniques. In addition, a more rigorous statistical analysis of the stopping criteria could be carried out to ensure that the algorithm finishes at the most optimal point, balancing execution time with the quality of the solution.

The heuristic approach used in this project has provided a solid foundation, but there are still many opportunities to explore other heuristic or metaheuristic methods that could offer better or faster solutions.

The results of this dissertation highlight the importance of a multi-objective approach to production planning in the footwear manufacturing industry. By providing a decision support tool that balances key performance indicators, this research has contributed to more efficient and sustainable production practices. Continued development in this area holds promise for further advances in production optimization, with wider implications for the industry in general.

References

AMF Shoes (2023). Amf shoes website. Accessed: 2023-07-24.

APICCAPS/INE (2022). Portuguese footwear industry.

Arroyo, J. E. C. and Pereira, A. A. S. (2011). A grasp heuristic for the multi-objective permutation flowshop scheduling problem. *International Journal of Advanced Manufacturing Technology*, 55:741–753.

Boussaïd, I., Lepagnot, J., and Siarry, P. (2013). A survey on optimization metaheuristics. *Information Sciences*, 237:82–117.

Cerveira, A., e Silva, E. C., Gonçalves, N., Lopes, R. B., and Nogueira, C. (2024). Ground planning optimisation of a shoe injection machine. *Mathematics in Industry Reports (MIIR).*

DESMA (2024). Desma official website.

Flores Lazo, C. M. and Rosales Molina, E. I. (2023). Energy consumption in injection moulding: A case study. In *34th DAAAM International Symposium on Intelligent Manufacturing and Automation*, Vienna, Austria.

GmbH, D. S. (2024). Desma multi-section injection (msi).

Huang, J., Süer, G. A., and Urs, S. B. R. (2011). Genetic algorithm for rotary machine scheduling with dependent processing times. *Journal of Intelligent Manufacturing*, 23(6):1931–1948.

Klemmt, A. (2009). Simulation-based optimization vs. mathematical programming: A hybrid approach for optimizing scheduling problems. *Robotics and Computer-Integrated Manufacturing*, 25(6):917–925.

Lopes, C., Rodrigues, A. M., Romanciuc, V., Ferreira, J. S., Öztürk, E. G., and Oliveira, C. (2023). Divide and conquer: A location-allocation approach to sectorization. *Mathematics*, 11(11):2553.

Marler, R. T. and Arora, J. S. (2010). The weighted sum method for multi-objective optimization: new insights. *Structural and Multidisciplinary Optimization*, 41:853–862.

Marques, A. and Guedes, G. (2015). Innovation in the portuguese footwear industry. In *15th AUTEX World Textile Conference*, pages 10–12, Bucharest, ROMANIA.

Neves, R. (2022). Amf de guimarães cumpre tradição e dá salário extra aos mais de 100 trabalhadores.

Parisa, S., Guardão, L., Rebelo, R. D., and Ferreira, J. S. (2021). Scheduling footwear moulding injection machines for a long time horizon. In *Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management*.

Portuguese Shoes (2024a). Portuguese footwear invests 140 million euros and prepares the industry of the future. Accessed: 2024-08-31.

Portuguese Shoes (2024b). Portuguese shoes website. Accessed: 2024-08-31.

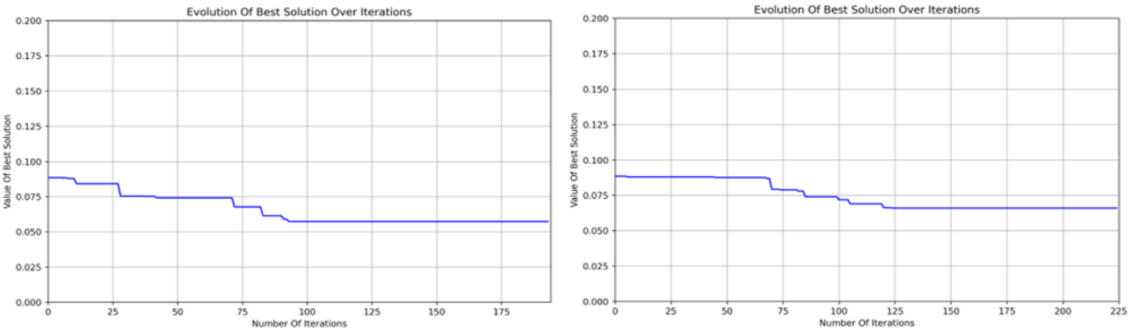
Sule, D. (2007). *Production Planning and Industrial Scheduling*. CRC Press.

Technologies, S. (2024). Anatomy of the shoe.

Thokala, P. and Madhavan, G. (2018). Stakeholder involvement in multi-criteria decision analysis. *Cost Effectiveness and Resource Allocation*, 16(Suppl 1).

Appendix A

Appendixes



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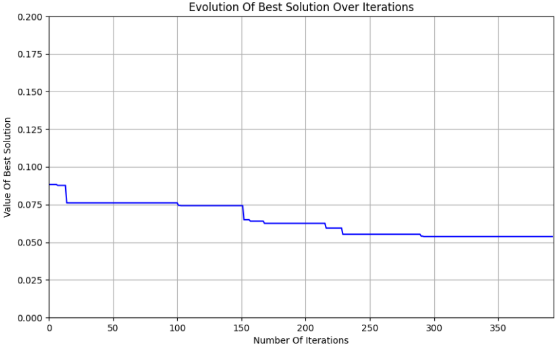

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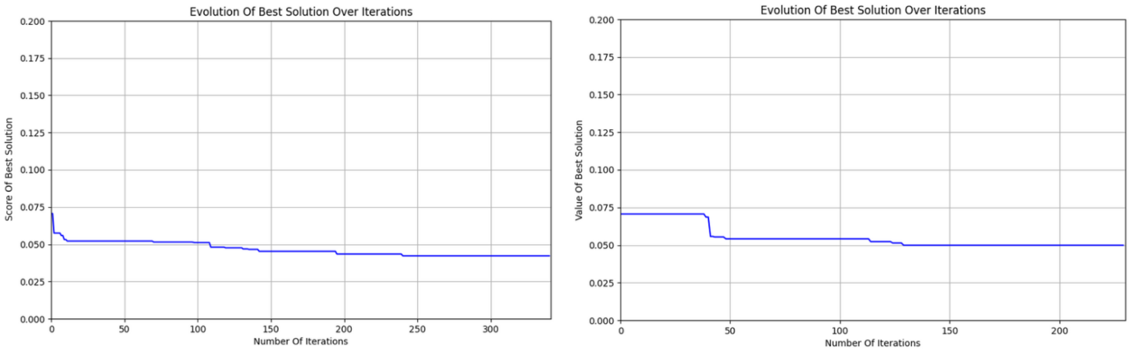
Figure A.1: Best Solution Evolution between different executions, for Weight Combination 2 (N = 0%; T = 20%; E = 80%)



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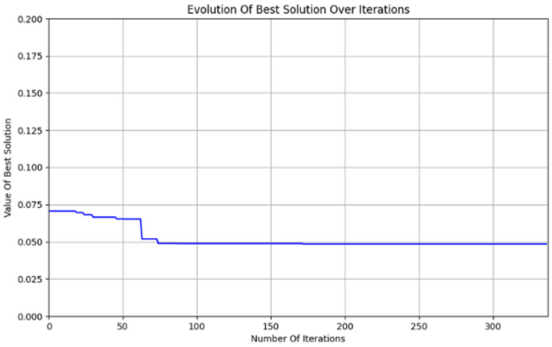

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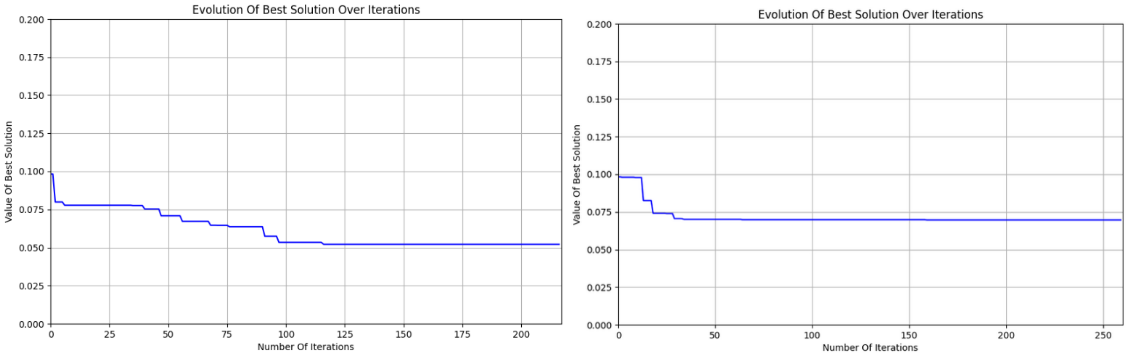
Figure A.2: Best Solution Evolution between different executions, for Weight Combination 3 (N = 0%; T = 40%; E = 60%)



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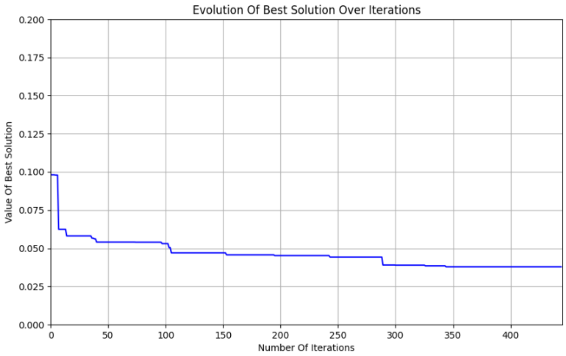

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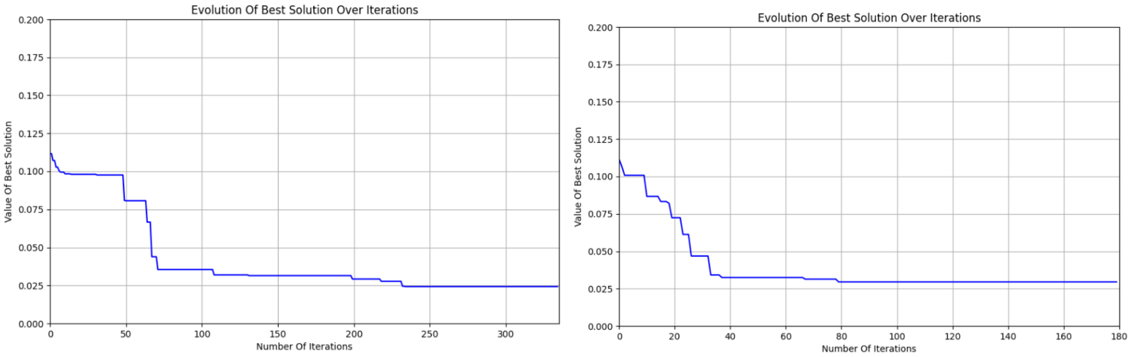
Figure A.3: Best Solution Evolution between different executions, for Weight Combination 4 (N = 0%; T = 60%; E = 40%)



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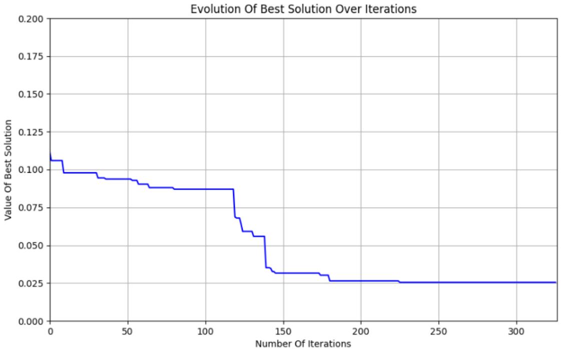

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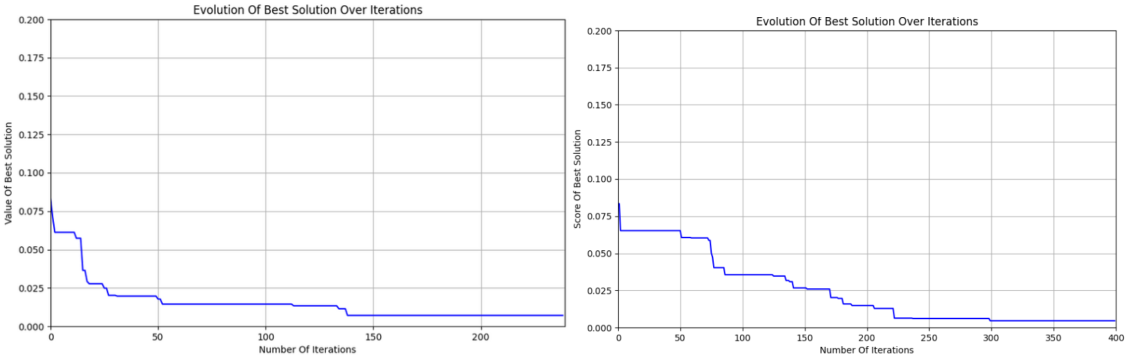
Figure A.4: Best Solution Evolution between different executions, for Weight Combination 5 (N = 0%; T = 80%; E = 20%)



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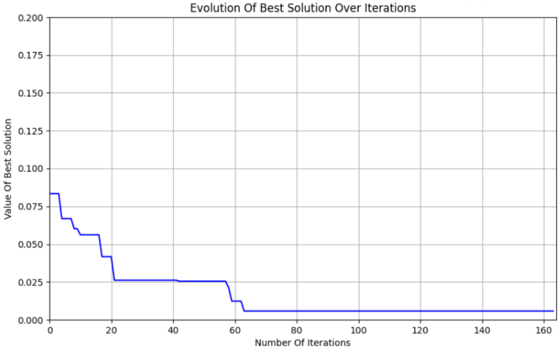

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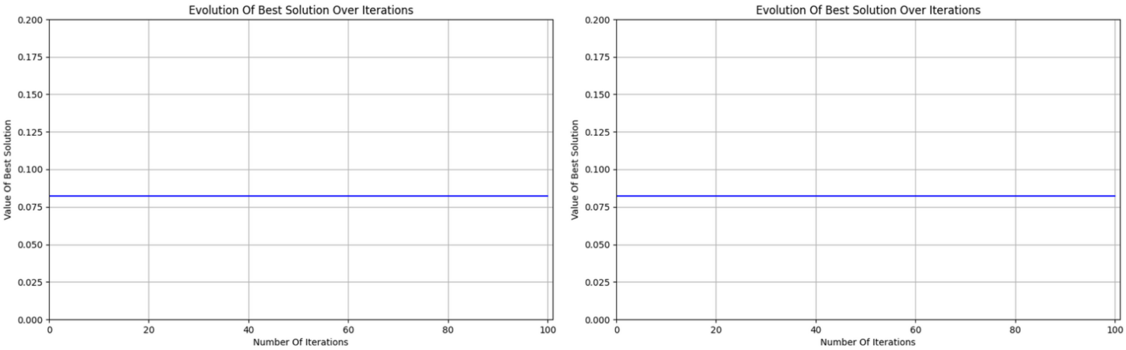
Figure A.5: Best Solution Evolution between different executions, for Weight Combination 6 (N = 0%; T = 100%; E = 0%)



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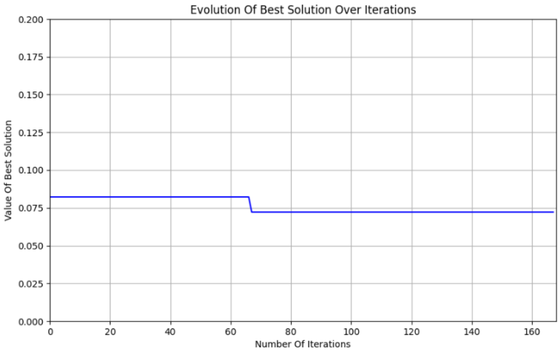

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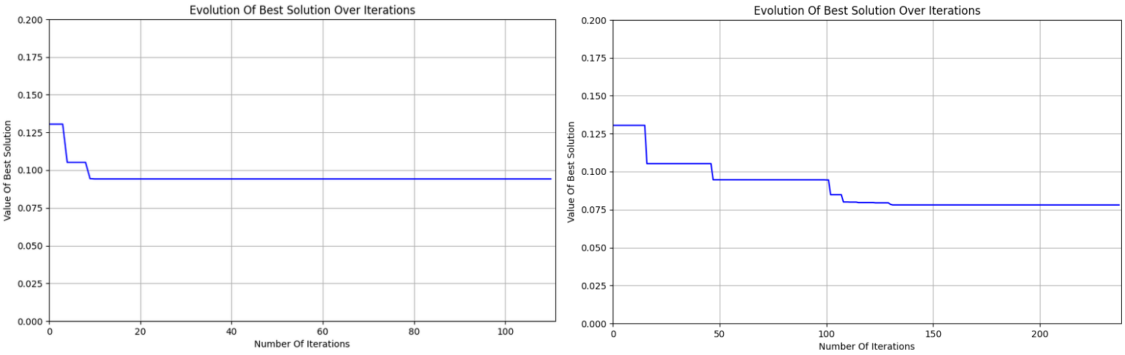
Figure A.6: Best Solution Evolution between different executions, for Weight Combination 7 (N = 20%; T = 0%; E = 0%)



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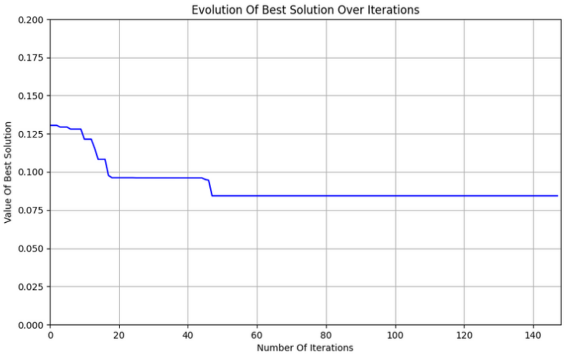

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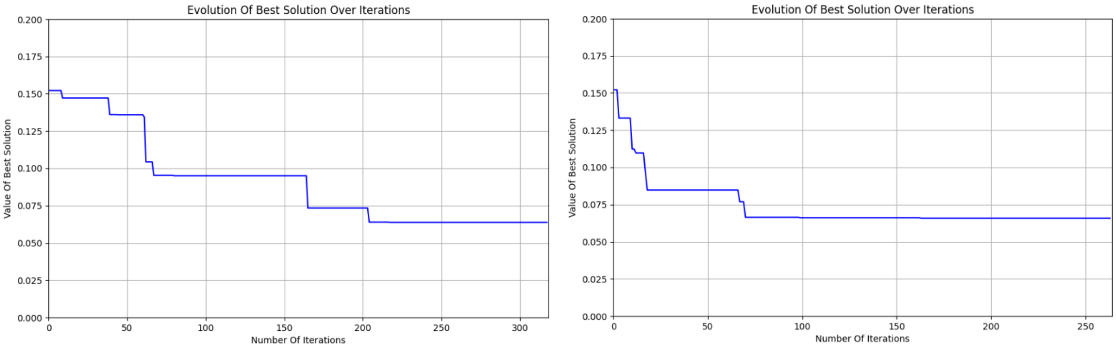
Figure A.7: Best Solution Evolution between different executions, for Weight Combination 8 (N = 20%; T = 20%; E = 60%)



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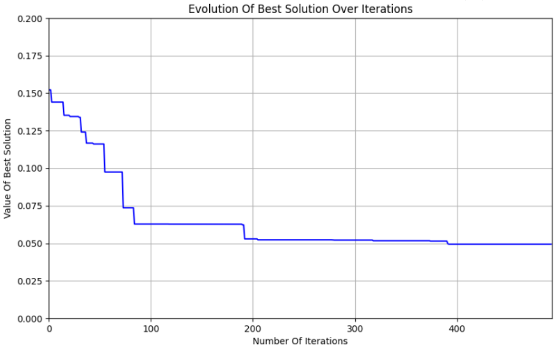

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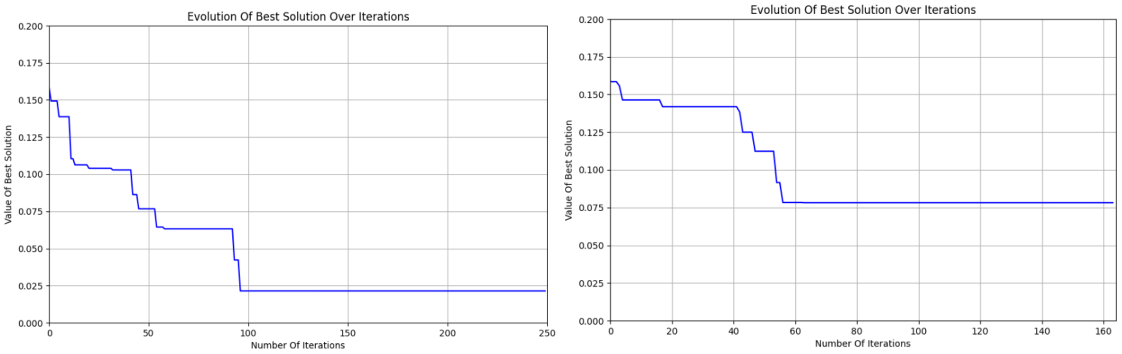
Figure A.8: Best Solution Evolution between different executions, for Weight Combination 10 (N = 20%; T = 60%; E = 20%)



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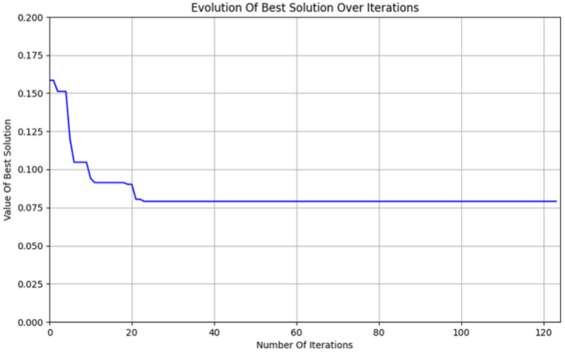

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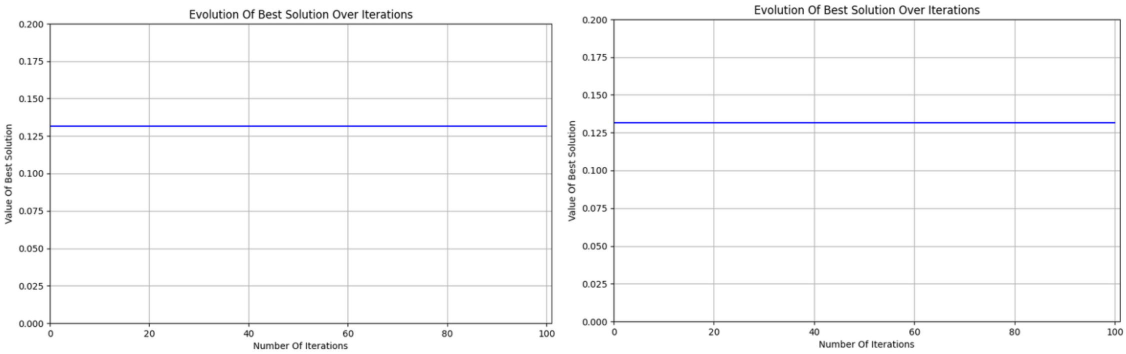
Figure A.9: Best Solution Evolution between different executions, for Weight Combination 11 (N = 20%; T = 80%; E = 0%)



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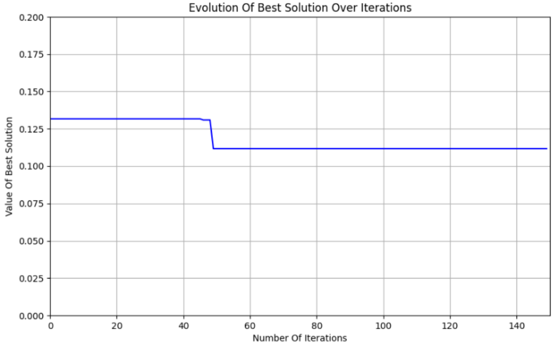

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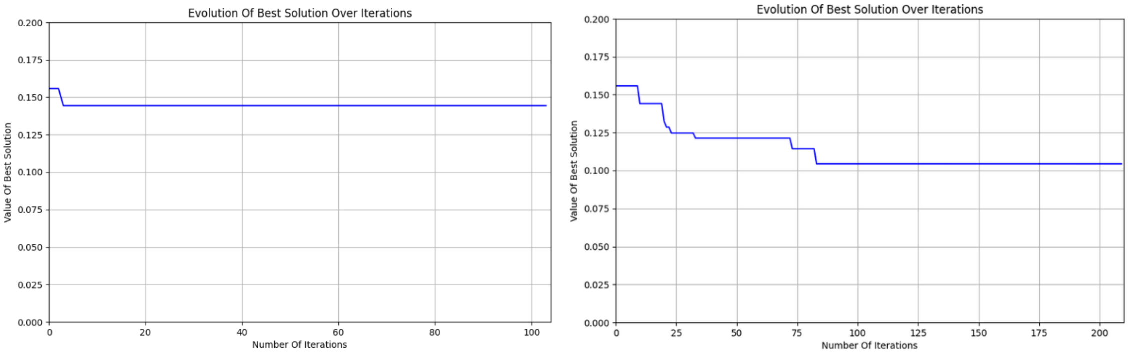
Figure A.10: Best Solution Evolution between different executions, for Weight Combination 12 (N = 40%; T = 0%; E = 60%)



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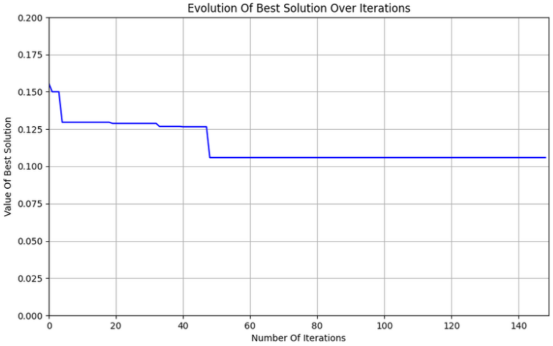

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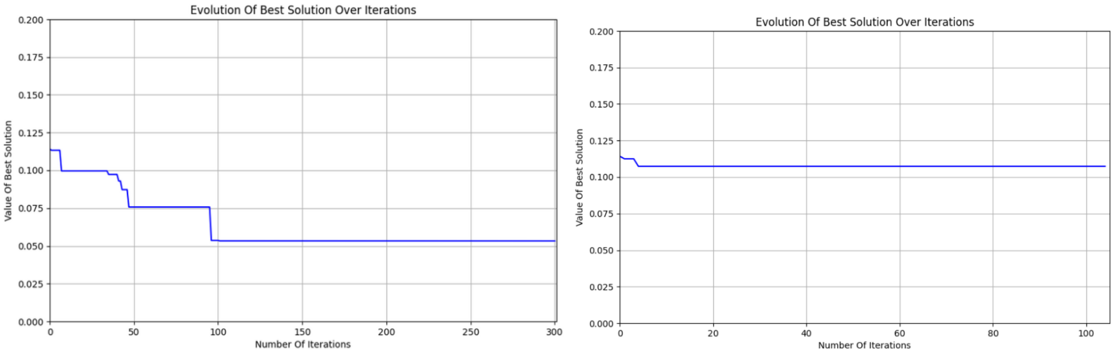
Figure A.11: Best Solution Evolution between different executions, for Weight Combination 13 (N = 40%; T = 20%; E = 40%)



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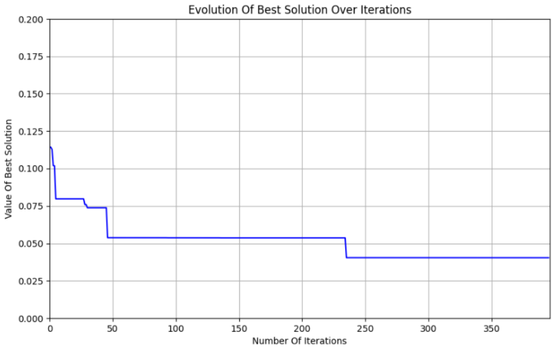

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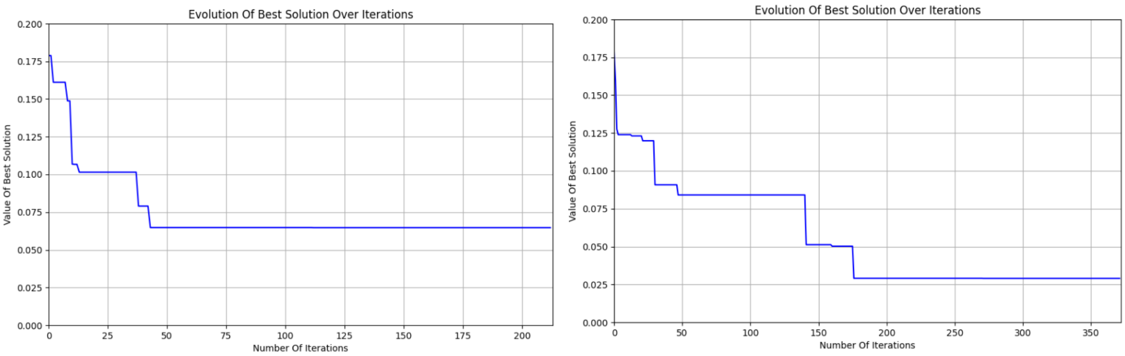
Figure A.12: Best Solution Evolution between different executions, for Weight Combination 14 (N = 40%; T = 40%; E = 20%)



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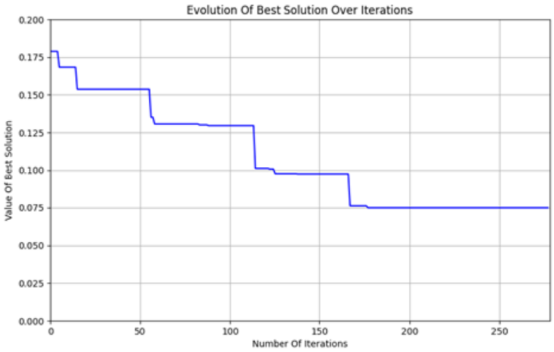

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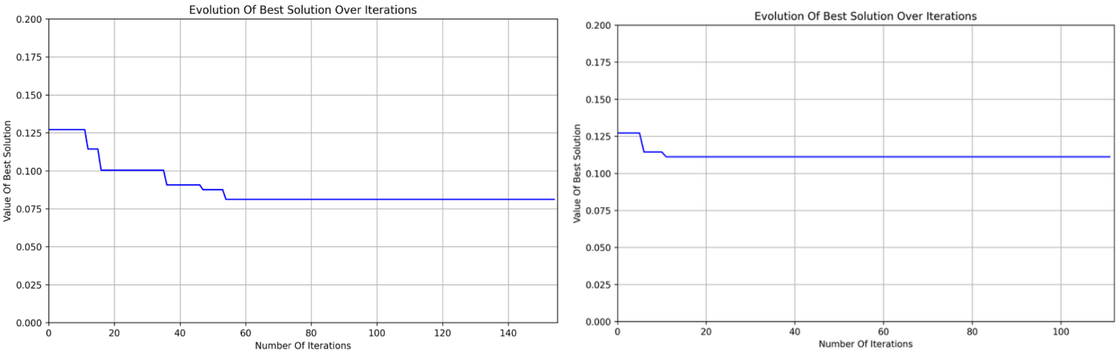
Figure A.13: Best Solution Evolution between different executions, for Weight Combination 15 (N = 40%; T = 60%; E = 40%)



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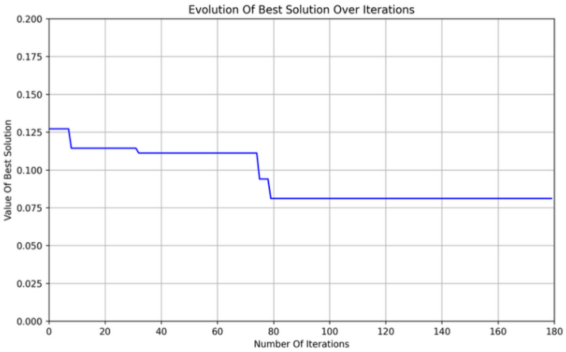

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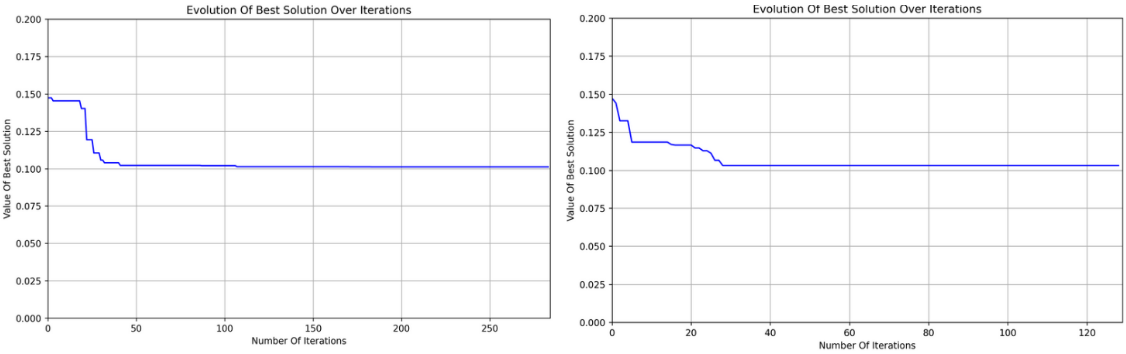
Figure A.14: Best Solution Evolution between different executions, for Weight Combination 16 (N = 60%; T = 0%; E = 40%)



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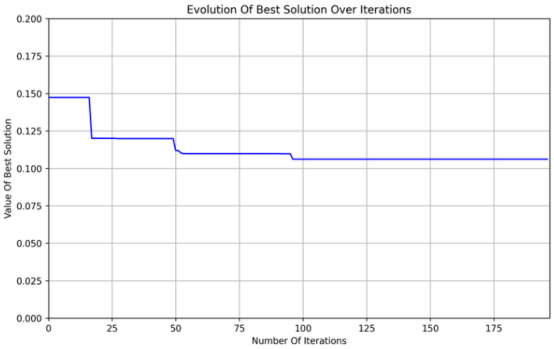

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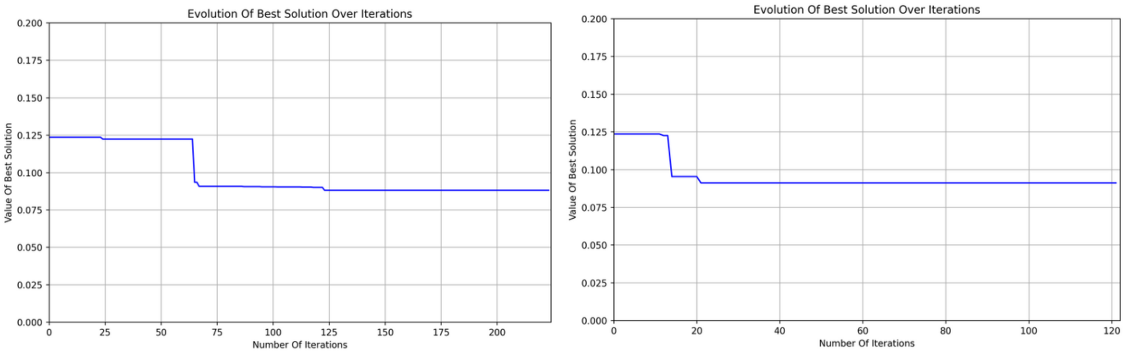
Figure A.15: Best Solution Evolution between different executions, for Weight Combination 17 (N = 60%; T = 20%; E = 20%)



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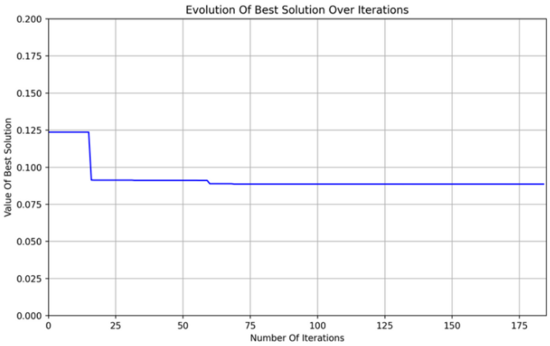

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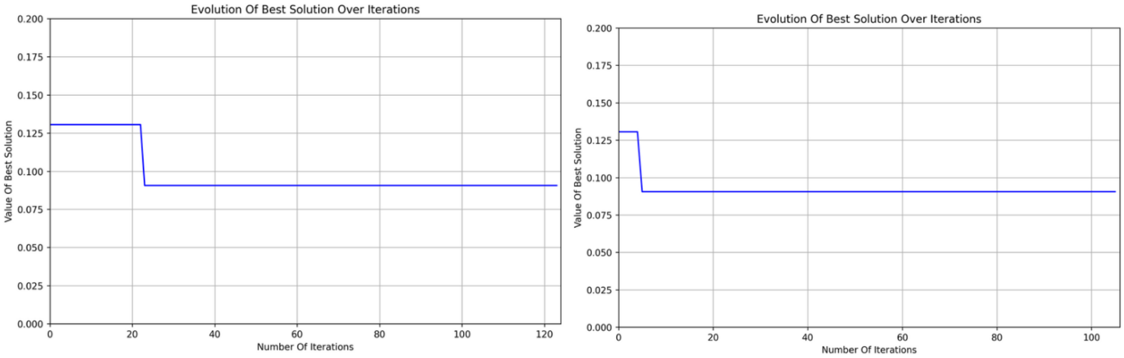
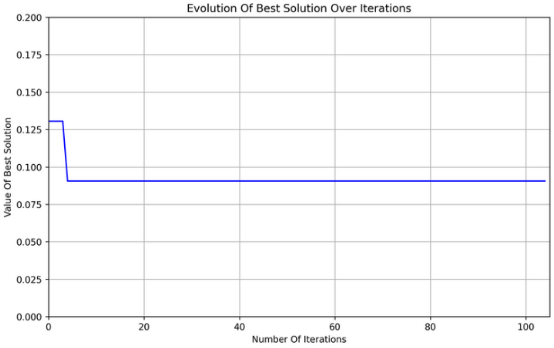
Figure A.16: Best Solution Evolution between different executions, for Weight Combination 18 (N = 60%; T = 40%; E = 0%)

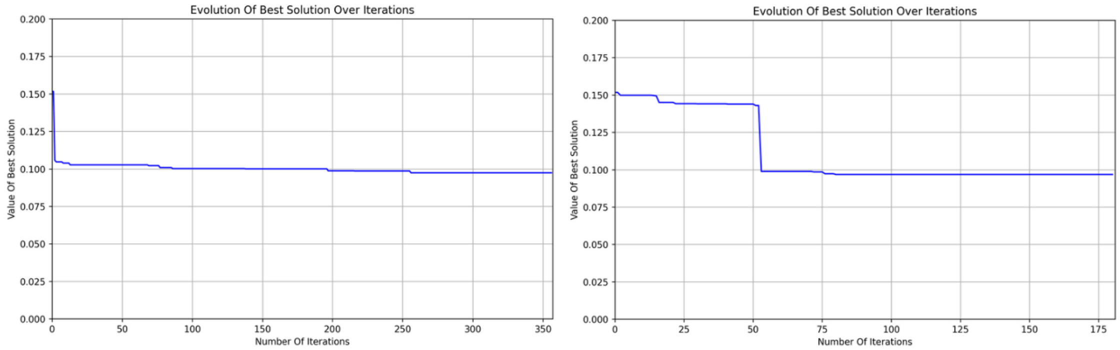


(a) 1st Execution (b) 2nd Execution

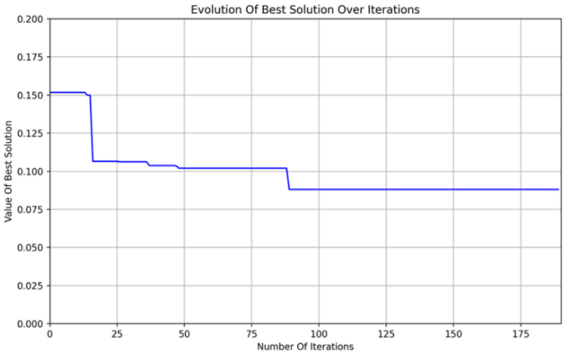


(c) 3rd Execution

Figure A.17: Best Solution Evolution between different executions, for Weight Combination 19 (N = 80%; T = 0%; E = 20%)

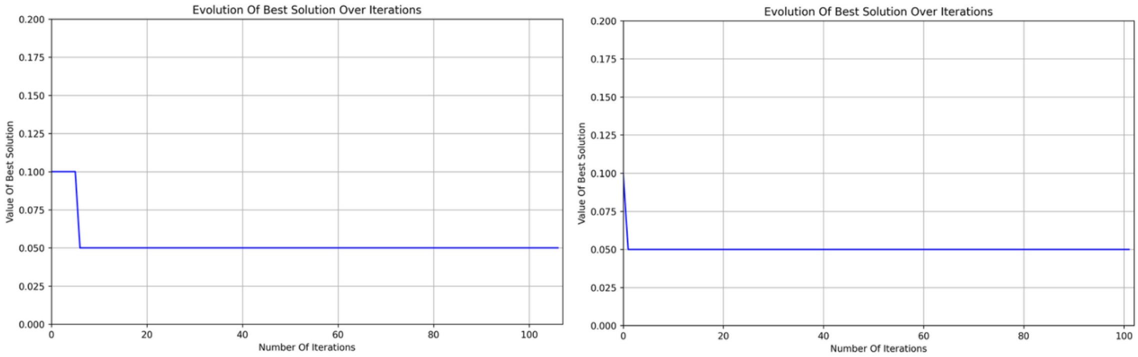


(a) 1st Execution (b) 2nd Execution

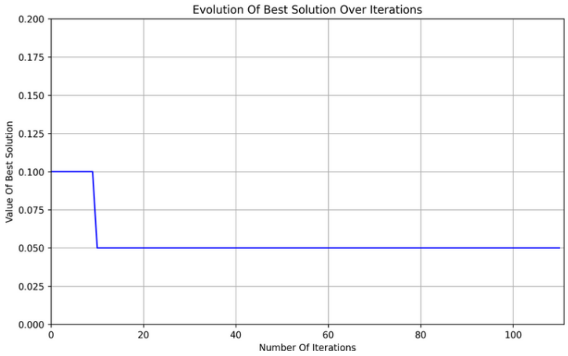


(c) 3rd Execution

Figure A.18: Best Solution Evolution between different executions, for Weight Combination 20 (N = 80%; T = 20%; E = 0%)



(a) 1st Execution (b) 2nd Execution



(c) 3rd Execution

Figure A.19: Best Solution Evolution between different executions, for Weight Combination 21 (N = 100%; T = 0%; E = 0%)