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Master's Degree

in Management and Engineering

Master's Degree Thesis

Data-driven Overall Equipment Effectiveness modelling and optimal scheduling in GSK Oak Hill (NY, US) Production Site

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Declaration

I hereby declare that every information revealed in this dissertation about GlaxoSmithKline/Haleon is fictitious. Therefore, algorithms exhibited are re-adapted to dummy data in order to highlight their functionalities and potentialities. However, they are developed accordingly to real manufacturing processes performed in GSK Oak Hill Production Site. Therefore, they are tested and validated in real industrial settings.

Angelo Cinquemani
December 2022

Abstract

Overall Equipment Effectiveness (OEE) is a core Key Performance Indicator (KPI) in industrial manufacturing. The downtime experienced by production resources negatively affects it. Root cause analysis from data retrieved highlights that combinations of products and packaging materials impact unplanned maintenance time of manufacturing and packaging lines. The main idea of the project is to create an optimal scheduling model whose aim is to maximise the resource utilisation recommending combinations of products, mixers, packaging materials and packaging lines. It has been developed with the constant support of GlaxoSmithKline(Consumer Healthcare)/Haleon Data Science Team whose Dr. Mihaylov is the Principal Data Scientist.

The development process starts collecting and analysing real data-sets about GSK Oak Hill (NY, US) Production Site. Process Mining is exploited in order to discover the end-to-end production flow. Then, information about hard and soft constraints, which the model enforces, are retrieved. They are related to production, maintenance, changeovers, shifts and breaks, inventory management and spare capacity. The objective function minimizes the machine downtime. The model is designed and developed using Python as programming language and exploiting the library "ortools.sat.python" as background optimization environment.

The solution space is explored using Greedy Insertion. The heuristic allocates production blocks minimizing their impact on the objective function. Blocks are

scheduled starting from packaging lines and going backward.

Relevant insights emphasize that metaheuristics such as Large Neighborhood Search (LNS) can lead to outstanding results in improving the solution quality [1, Pisinger et al., 2010]. LNS works implementing a *destroy* and *repair* method. As a result, some blocks of the current solution are removed and located in new positions [1, Pisinger et al., 2010]. Its application often allows to escape from local optima and hopefully finding a global optima solution.

Furthermore, a practical implementation of Agglomerative Hierarchical Clustering is developed. It aims at identifying product families based on operational flows. This would make the procedure of inserting metadata more robust, leading to higher Data Integrity which is a relevant concern in the pharmaceutical industry.

Sommario

L'Overall Equiment Effectiveness (OEE) è un fondamentale Key Performance Indicator (KPI) nell'ambito della produzione industriale. Esso è influenzato negativamente dal tempo di inattività delle risorse di produzione. Analizzando in maniera approfondita i dati si evince che gli interventi di manutenzione straordinaria dipendono dalle combinazioni di prodotti e materiali usati per l'impacchettamento. L'idea principale del progetto è di schedulare la produzione in modo da massimizzare il grado di utilizzo delle risorse, raccomandando combinazioni di prodotti, mixers, materiali di impacchettamento e linee di confezionamento. Il modello è stato sviluppato con il costante supporto di GlaxoSmithKline(Consumer Healthcare)/Haleon Data Science Team, di cui il Dottor Mihaylov è il Principal Data Scientist.

I primi step necessari per realizzare il progetto richiedono di acquisire e analizzare datasets contenenti informazioni reali sul sito produttivo di GSK locato in Oak Hill (NY, US). Il Process Mining è utilizzato per scoprire il flusso di produzione end-to-end. Successivamente, sono state raccolte le informazioni relative ai vincoli che il modello deve rispettare. Essi riguardano aspetti legati alla produzione, manutenzione, cambi, turni e pause, gestione dell'area di stoccaggio e capacità inutilizzata. La funzione obiettivo minimizza i tempi di inattività dei macchinari. Il modello è progettato e sviluppato usando Python come linguaggio di programmazione e la libreria "ortools.sat.python" come ambiente di ottimizzazione.

Lo spazio di soluzioni viene esplorato usando l'algoritmo Greedy Insertion. Tale euristica alloca i blocchi di produzione minimizzando il loro impatto sulla funzione obiettivo. Tali blocchi sono schedulati partendo dal termine del processo produttivo, ossia le linee di impacchettamento, e "andando all'indietro" verso le linee di miscelazione.

Alcuni risultati recenti enfatizzano che l'utilizzo di metaeuristiche, quali la Large Neighborhood Search (LNS), possono migliorare in maniera sostanziale la qualità della soluzione [1, Pisinger et al., 2010]. La LNS si sviluppa usando un metodo di "distruzione e riparazione". Tale metodo rimuove alcuni blocchi dalla soluzione corrente e li colloca in una nuova posizione [1, Pisinger et al., 2010]. Spesso, la sua applicazione permette di "sfuggire" da punti di ottimo locale e trovare una soluzione globalmente ottima.

Inoltre, è stata sviluppata un'implementazione pratica del Hierarchical Clustering Agglomerativo. Essa ha lo scopo di identificare famiglie di prodotto sulla base dei flussi operativi. Questo rende la procedura di inserimento dei metadata più robusta, aumentando l'integrità dei dati, un aspetto importante nel settore farmaceutico.

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Chapter 1

Introduction

1.1 Research Motivation

Nowadays, manufacturing efficiency and effectiveness are critical requirements to survive in fierce competitive environments. Production resources, being the heart of industrial activities and deeply influencing the related KPIs, represent the main point of interest. Therefore, companies, subject to competitive pressure, strive to achieve the maximum machine utilisation reducing downtime duration and frequency.

Equipment downtime refers to time windows where the machine incurs scheduled or unplanned stops. Planned breaks reduce the risk of failures while keeping an optimal rate of production. They are often performed at regular intervals and their duration exhibits a low variance. Conversely, unexpected downtime reasons are several. In addition, they change from one resource to another [2, Nwanya et al., 2017]. In industrial sites, unplanned breakdown factors cover, among the others, supply shortage, worker unavailability and sudden demand changes [3, Yang et al., 2005]. Such deviations could lead to business disruption if not tackled properly [3, Yang et al., 2005]. Resource availability and in turn throughput, manufacturing lead time, and product quality are just few measures deeply influenced by machine downtime. Hopefully, Total Predictive Maintenance (TPM) discipline claims that companies can control and decrease a large percentage of it.

GSK Oak Hill Production Site downtime experienced by resources, manufacturing consumer healthcare products, is deeply analysed in the project. There is an expectation that an end-to-end view on the process can provide better opportunities for downtime root cause analysis and equipment utilisation optimisation. Critical combinations of products, manufacturing and packaging lines are studied. Finally, an optimal scheduling problem, whose objective is to increase the overall equipment effectiveness (OEE) of the plant, is designed and developed.

1.2 GlaxoSmithKline(CH)/Haleon

Research, technology and expertise are brought together by GlaxoSmithKline to get ahead of disease. This approach makes GSK a leading player in the pharmaceutical industry. It supports people's health discovering, developing and producing state-of-the-art vaccines, drugs, and consumer healthcare products. Last year, it supplied more than 767 million vaccines and 1.7 billion medicines. Next decade future goal sets the ambitious target to improve the well-being of over 2.5 billion people.

Several profitable investments and strategic adjustments to its consumer healthcare division lead to the creation of Haleon. The new independent organization is a global leader in its sector. It offers prominent product brands which embrace Centrum, Voltaren, Sensodyne and Panadol. They are highly trusted means to enhance the health of people.

GSK Consumer Healthcare and Haleon, collaborating with Politecnico di Torino, constantly and tirelessly supported the development of the master thesis. In particular, the work benefits from the knowledge of the Data Science Team settled in Brentford headquarter (London, UK). Experts involved have a background in Mathematics, Physics and Biomedical Engineering. Such cross-disciplinary environment, made up by people with outstanding hard and soft skills, is the perfect place to continuously learn and grow. It is truly inspiring seeing people coming from all over the world (Bulgaria, Greece, Ireland, England, China, France, etc.,) being highly motivated to achieve common goals. Another relevant aspect concerns the working atmosphere, which is very comfortable. Smiling, grabbing a coffee and eating all together are common practices. Therefore, collaboration among team members is excellent which results in high quality project outcomes.

The thesis content is further enriched thanks to weekly virtual meetings with GSK Oak Hill Production Site technicians. During meetings, a general overview of the core processes related to toothpastes manufacturing was provided. In addition, real datasets, which feed the optimal scheduling algorithm, are deeply analysed. Finally, relevant insights about operational hard and soft constraints are discussed. A released picture of the manufacturing site is shown in figure 1.1.

Figure 1.1: GSK Oak Hill Production Site.

The production site began its activities manufacturing dermatological products. Toothpastes production started in 2010 with the well known Sensodyne brand. Two years later the annual production volume of 23 millions of tubes was achieved. Demand kept growing driven by an increased attention on health and well-being of elderly population and emerging middle-class. In 2014 the target of supplying in one year 200 million of tubes was reached. In 2016 the product portfolio was further enriched by famous toothpaste brands Pronamel and Aquafresh. In 2018 the transition to Enterprise Resource Planning (ERP) system, and the relative change management, lead to an output reduction. After this period, the growth proceeded towards the ambition of exceeding the threshold of 400 million tubes in 2027. Figure 1.2 briefly introduces the production site's achievements.

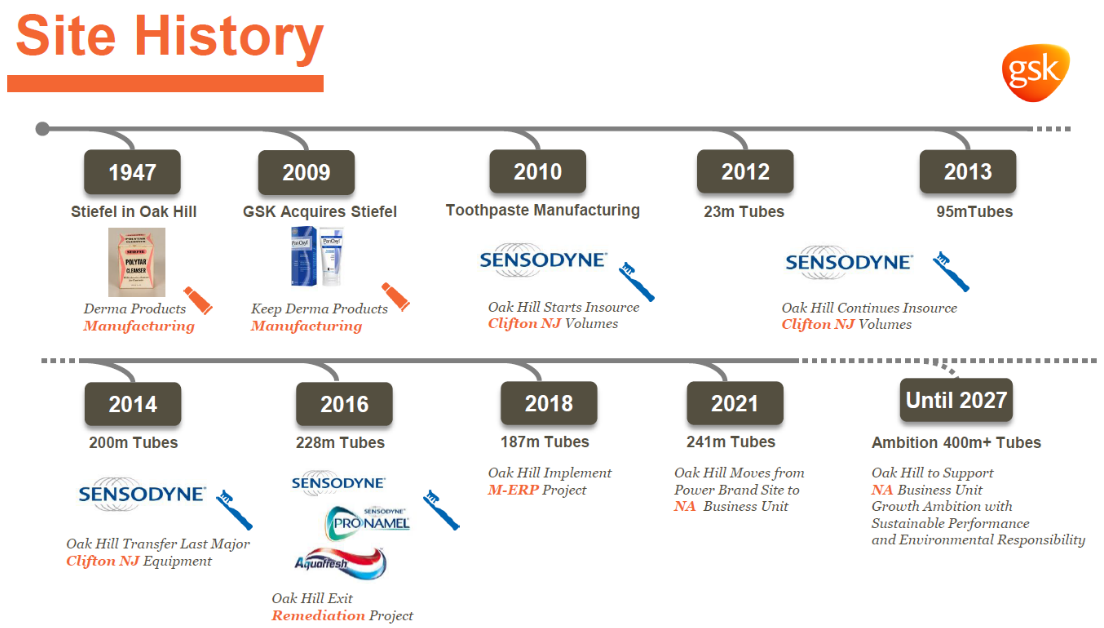

Figure 1.2: Brief History of GSK Oak Hill Production Site.

1.3 Thesis Structure

The project embraces five chapters starting from the introduction.

The second section explores the main concepts of process mining. It contains valuable insights to discover the end-to-end production flow of toothpastes. In addition, it introduces a practical application of Agglomerative Hierarchical Clustering. It is a famous data mining unsupervised learning technique useful to identify product clusters based on operational path similarity.

The third chapter provides information related to the GSK/Haleon Oak Hill Production Site. Then, the goal of the project, which is improving the Overall Equipment Effectiveness of production resources, is formally discussed. Afterwards, the python optimal scheduling model is described. Therefore, the objective function and the relevant constraints, variables, parameters and subscripts are explained. Finally, the chapter covers heuristics, such as Greedy Insertion, used to explore the solution space.

The fourth chapter delivers the results of the optimal scheduling model. It starts showing the input parameters which feed the algorithm. Then, three different simulations are explored. The first shows a scheduling solution relative to a planning horizon of four weeks. The second extends the previous solution performing a weekly review. The third keeps on extending previous results implementing another weekly review, and it is further enriched dealing with an unexpected long machine failure.

The thesis terminates with relevant final conclusions and discussing advanced local search techniques, known as metaheuristics, which should enhance the scheduling solution provided.

Unfortunately, the software developed cannot be released because of confidentiality reasons. However, a sample script is available in the shared disk.

Chapter 2

Process Mining

This chapter examines some of the relevant literature about process mining. It contains five sections. They are organized in a similar way, beginning exploring the literature of previous research in that area and concluding illustrating the practical application of the theory in the project developed.

Specifically, the first section (2.1) explains the key concepts of process mining and the reasons behind its success. The second section (2.2) is relative to the importance of data for process mining. It considers the main obstacles to get the *right data*, then it formally defines *event logs*, and finally it shows an event log comparable to the one analysed in the project. The third section (2.3) further explores one branch of process mining which is Process Discovery. It focuses on the metrics designed to evaluate the quality of the results, afterwards it briefly goes through the key elements of the model Business Process Modeling Notation (BPMN) and it closes revealing the BPMN extracted from the project's event log. The fourth section (2.4) introduces the nowadays need of companies to manage product variety. As it will be possible to understand, surviving in environments where the competition is fierce requires providing customers a broad array of choices. This has benefits, but also several challenges. The last section (2.5) offers a solution to product variety challenges. It highlights the concept of *product family* exploring four valuable methods to create product groups. It starts with Intuitive Grouping (2.5.1) showing a method to cluster products based on Bill-of-Material (BOM) similarity. Then, it describes the Parts Classification and Coding method (2.5.2) with the well-known *Opitz coding scheme*. Thereafter, it introduces the Production Flow Analysis (2.5.3) as another clustering criteria. In conclusion, it explains the Networked Operations Sequence Analysis (2.5.4). This last sub-section beyond a brief theoretical explanation, contains a possible application of Agglomerative Hierarchical Clustering as unsupervised learning technique to create family of products based on production path similarity.

2.1 Concepts of Process Mining

Transforming raw materials into finished products usually involves multiple manufacturing steps. Furthermore, production processes are not the same for each material, but they may change depending on product specifications [4, Mayr et al., 2021]. Thus, it is vital to know which are the expected flows each material should follow to become final product. This would be valuable in order to increase production efficiency and survive in competitive environments.

A discipline that assists managers and decision makers to discover and monitor manufacturing activities is process mining. It provides a family of techniques focused on supporting organizations to gain valuable information from data [5, Munoz-Gama et al., 2022]. Process mining is strongly related to both Process Science (whose main topics are, among others, business process management and operations research) and Data Science (which includes areas such as data mining and predictive analytics). Indeed, it conceives *data-driven* forces and *process-centric* forces as complementary, interconnected, and interdependent [5, Munoz-Gama et al., 2022]. Process mining is *domain-agnostic*, thus it is not linked to a particular process or industry. The only requirements to apply this discipline are that processes are present and data generated by them is available [5, Munoz-Gama et al., 2022]. Nowadays, having data available is not challenging, especially in industrial manufacturing where the production of information is rising continuously. This is mainly due to the so-called *Industry 4.0 revolution* enabling a massive source of complex sensor data [4, Mayr et al., 2021].

Process mining exploits event data to create process models having the aim of answering to performance and conformance related questions [6, Aalst, 2016]. Process models highlight the sequence of activities to accomplish in order to get a certain output. Also, they show the different possible paths that can be followed [5, Munoz-Gama et al., 2022]. Many formal notations - such as Petri nets, Business Process Model and Notation (BPMN), Unified Modelling Language (UML) and Event-driven Process Chain (EPC) - can be used to model operational (business) processes. The formalisms mentioned have in common that processes are described in terms of activities whose ordering is modelled by casual dependencies [6, Aalst, 2016].

Value inside process-generated data can be extracted by three prominent branches of process mining.

- Process Discovery: it has the aim of creating a process model from an event log, without exploiting any a-priori information [6, Aalst, 2016]. Although most discovery techniques have the goal of showing the sequence of activities in the process (control-flow, trajectories, activity paths and care pathways), others focus on gaining valuable knowledge about the functions of resources employed. They are applied to get insights about role discovery, social networks, and task prioritisation [5, Munoz-Gama et al., 2022].

- Conformance Checking: it is adopted to understand if real processes are compliant with the model and vice versa. For instance, conformance checking can be useful to verify the so-called "four-eyes" rule which signals that specific tasks should be performed by at least two people [6, Aalst, 2016]. Hence, Conformance Checking is a valuable tool to detect, locate and reason *deviations*, and to assess their impact [6, Aalst, 2016].

- Process Enhancement: it is a powerful technique to extend and enhance already developed process models. This is possible exploiting additional information about the real process recorded in some event logs. Thus, while Conformance Checking is mostly used to assess the level of alignment between model and reality, Process Enhancement aims at *repairing* or *extending* the a-priori model. Repairing aims at changing the model to better reflect reality. Extending tries to further enrich information conveyed by process models. Indeed, exploiting timestamps it is possible to gain further insights on bottlenecks, service levels, throughput times, and frequencies [6, Aalst, 2016].

Process mining discipline is made even richer by various perspectives that can be identified orthogonally to its three sections [7, Huser, 2012].

- Control-flow perspective: it studies the ordered sequence of activities relevant to the process and identifies the various paths it may take.
- Organizational perspective: it extracts knowledge about resources hidden in the dataset. For example, which actors (people, systems, roles and departments) are relevant and the relationship among them. Its aim is to find the organizational structure by sorting people in terms of roles and organizational units or highlighting the social network.
- Case perspective: it is based on cases' properties. They can be classified according to the values of their data elements. For instance, having a case showing a refilling order, it could be valuable to discover the supplier or the amount of material requested.

- Time perspective: it is related to timing and frequency of events. Information about timestamps is precious because they allow to discover bottlenecks, quantify service levels, monitor the utilization of resource, and foresee the residual process time of running cases.

2.2 Data-Driven process

Process mining establishes links between the actual processes and their data on the one hand and process models on the other hand [6, Aalst, 2016]. Event logs constitute the primary input for this discipline [5, Munoz-Gama et al., 2022]. Based on the principle of *garbage in, garbage out* process mining's outcome is highly reliant on it [6, Aalst, 2016].

However, the task of getting the *right data* is made challenging by the plethora of sources which may contain it and by the different perspectives required to find answers [6, Aalst, 2016]. Sometimes, the information relevant to the analysis may be scattered due to technical or organizational reasons making the tasks of finding and extracting it particularly difficult [6, Aalst, 2016]. Meta data, which well describes structured datasets, could be a valuable support. However, often data is unstructured or lacking of relevant meta data [6, Aalst, 2016]. In this case, scoping is vital since it would be pointless to attempt to exhaustively extract event logs from countless tables and other data sources. The task of getting answers should be guided by questions instead of being influenced by the presence of lots of data [6, Aalst, 2016].

Introducing *event logs*, it is possible to formally define them as a collection of *traces*. Conversely, a trace is a set of events - ordered chronologically - referring to the same *case* [8, Choueiri et al., 2021]. A case refers to the various entities under study. They are unambiguously identified using an alphanumeric code. Each event can mark the beginning or finishing of an activity involved in the manufacturing process. Indeed, activities may be not instantaneous and having information about start time and completion time can be valuable to assess performance related properties, such as cycle time and waiting time [6, Aalst, 2016]. Thus, process mining discovers insightful information based on datasets where every instance is relative to a case, an activity and a point in time [6, Aalst, 2016]. Additionally, event logs can be further enriched by supplementary features which include [5, Munoz-Gama et al., 2022]:

- *transaction type*, which signals the type of the event. Possible records are 'start', 'resume', 'complete', etc;

- *resource*, which refers to the subject who should perform the activity. It can be a person or a production machine;

- *cost*, which refers to the costs associated to events;

- *other attributes*, referring to supplementary case or event features such as the size of an order.

In the dataset which contains transactional data about the end-to-end manufacturing process to make toothpaste in GSK Oak Hill Production Site, the case ID refers to the Stock Keeping Unit (SKU) code. Moreover, possible activities may be *dispense materials*, *mix materials*, *feed tubes* and *pack tubes*. Timestamps would record when each case started and finished being processed. Finally, additional attributes may reveal the quantity manufactured, the production resource, and the machine downtime. Table 2.1 shows a simplified event log, similar to the one being studied in the project.

Case ID	**Start Time**	**End Time**	**Activity**	**Additional Attibutes**
1AA0	4-5-22 15:02	4-5-22 15:07	Dispense Materials	Process-state & product-state characteristics
1AA0	4-5-22 15:07	4-5-22 15:18	Mix Materials	Process-state & product-state characteristics
2AB0	4-5-22 15:02	4-5-22 15:06	Dispense Materials	Process-state & product-state characteristics
1AA0	4-5-22 15:20	4-5-22 15:22	Feed tubes	Process-state & product-state characteristics
1AA0	4-5-22 15:22	4-5-22 15:24	Pack tubes	Process-state & product-state characteristics
2AB0	4-5-22 15:06	4-5-22 15:17	Mix Materials	Process-state & product-state characteristics
2AB0	4-5-22 15:22	4-5-22 15:24	Feed tubes	Process-state & product-state characteristics

Table 2.1: Toothpaste production event log.

2.3 Process Discovery

Recent discoveries in the fields of computing and communications deeply affected companies' workflow, leading to an increase in the complexity of business processes. As a result, understanding how the organization is running is vital [9, Process and Data Science Group - RWTH Aachen University, 2020]. Process Discovery, which is the first section of process mining, supports organizations to achieve this task. Indeed, its main goal is to develop a process model which is aligned - *"representative"* - to the behaviour observed in the event log. Its output can be evaluated using four quality criteria. Satisfying all of them is impossible since they are conflicting with one another [6, Aalst, 2016].

- Fitness: the discovered model should be able to reply the pattern observed in the data set.

- Precision: the identified model should avoid behaviours entirely different from what is recorded in the event log. If the output of process discovery has a poor level of this metric, then it is *underfitting*.

- Generalization: it is a measure of the degree to which the developed model would be capable of replicating the process' future pattern. A model having a low level of generalization is *overfitting*.

- Simplicity: it measures how much the model is straightforward. This last requirement is linked to Occam's razor statement: *"One should not increase, beyond what is necessary, the number of entities required to explain anything"*.

The end-to-end toothpaste manufacturing process is analysed adopting the perspective *control-flow*. In addition, the production path is represented using the Business Process Model Notation formalism (BPMN) which is the de-facto standard in the industry [4, Mayr et al., 2021]. It is possible to briefly introduce its key concepts referring to figure 2.1. In particular, the beginning of the process is marked with the *start event*. Conversely, its finishing point is identified with the *end event*. More complex models often involve also gateways which represent alternative paths: a *parallel gateway* constrains to follow all the routes, whereas an *exclusive gateway* implies that just one path can be taken. Finally, the *task* is displayed with a box.

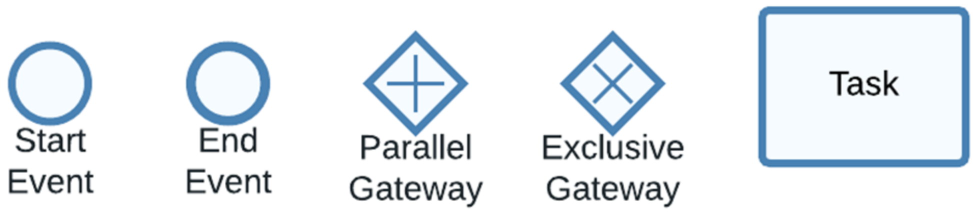

Figure 2.1: Key elements of BPMN.

The output of process discovery techniques applied to the project's event data is the model represented in figure 2.2. It highlights the production flow inside the manufacturing plant. As it is possible to notice, the main production activities are dispensing, mixing, feeding and packaging. Dispensers feed mixers with several toothpaste ingredients, where they are blended to make the material paste. Afterwards, the batch is stored in containers and deposited in an inventory area. Finally, the toothpaste is pumped (feeding) into tubes and the final product is packed. Concerning production resources, several manufacturing lines and packaging lines work in parallel.

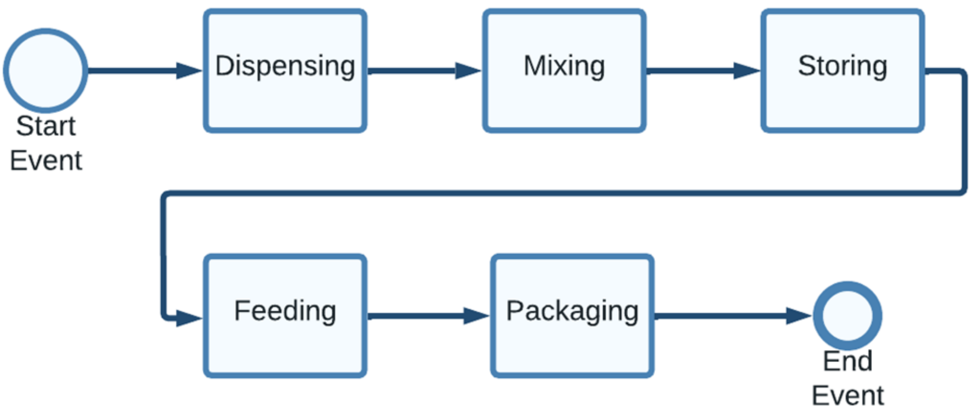

Figure 2.2: Process model representing the production-flow to make toothpastes.

2.4 Product Variety

Products are designed and manufactured in order to satisfy customers' expectations. However, meeting perceived needs of users is not trivial. They highly vary due to differences in social values, usage scenarios, constraints and other factors [10, Elmaraghy et al., 2013]. Organizations able to catch these changing tastes and fulfil them promptly, offering appropriate products, gain considerable advantage over their competitors [11, MacDuffie et al., 1996]. Furthermore, offering a wide range of products potentially leads to differentiation, market expansion, higher revenues and sales volume.

However, sometimes product variety decisions do not ensure such desirable outcomes. Experimental research, interestingly, found that a broad array of choices leads to customers confusion. Also, often users do not have the adequate level of knowledge to catch differentiation among solutions [10, Elmaraghy et al., 2013]. Along to financial uncertain benefits, decisions about the breadth and depth of product lines result in significant supply chain challenges. Indeed, as the production variety increases, materials planning and scheduling end up being more problematic [11, MacDuffie et al., 1996]. The issues mentioned may lead to a reduction of manufacturing productivity and lower part quality. Furthermore, producing a wider assortment of materials requires having more product platforms which translates in an increase of setup costs [11, MacDuffie et al., 1996]. Other operative side effects involve line balancing - required to ensure consistent cycle times at each workstation - which becomes more challenging because of multiple models and several option combinations [11, MacDuffie et al., 1996]. The multitude of financial and manufacturing issues above-mentioned makes product variety management particularly difficult.

In the project, product variety challenges are encountered firstly in dataset analysis. Indeed, event logs that present many different cases and high diversity of behaviour, if not pre-processed adequately, may lead to process diagrams very confusing and difficult to understand (*spaghetti models*), as it is shown in figure 2.3.

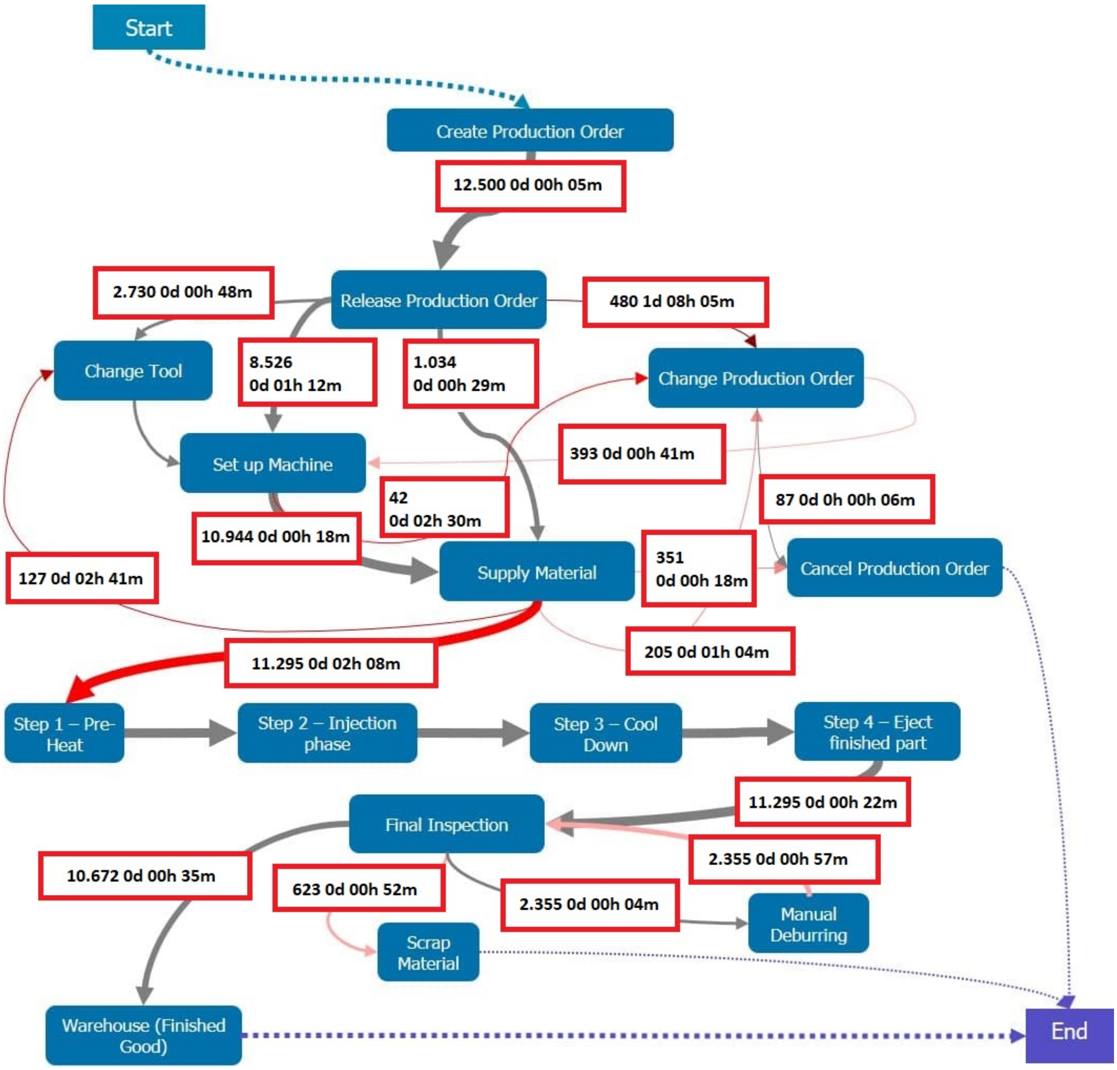

Figure 2.3: Example of *spaghetti model* [12, Celver].

Clustering algorithms, by grouping products into families, are useful means to deal with such complexity, leading to less confusing outputs. Furthermore, managing efficiently the production of a wide array of materials should result in a reduction of setup and changeover times/costs and, in turn, increase the Overall

Equipment Efficiency (OEE) which is coherent with the goal of the thesis [13, Navaei et al., 2016].

2.5 Product Families

When manufacturing processes are highly dependent on similarity and commonality among products, it may be beneficial - in terms of efficiency and productivity - to divide materials into clusters creating product families [14, Kashkoush et al., 2015]. They are group of products whose roots are on a certain design concept or obtained from a standard parent and whose design or manufacturing process is comparable [10, Elmaraghy et al., 2013].

They have boundaries that can change overtime. Evolving product families capture new elements whose characteristics overlap, to some extent, to the ones of entities in the original family [10, Elmaraghy et al., 2013]. Afterwards, succession of various product generations leads to the appearance of new materials quite different to the ones present in the original parent cluster [15, Elmaraghy, 2009].

The task of associating materials and finding clusters can be accomplished exploiting some general methods. Often they take time and require data analysis carried out by experts [16, Groover, 2001]. Here, the following techniques are briefly introduced:

- Intuitive Grouping 2.5.1
- Parts Classification and Coding 2.5.2
- Production Flow Analysis 2.5.3
- Networked Operations Sequence Analysis 2.5.4

2.5.1 Intuitive Grouping

This method, also called *visual inspection*, is famous for its simplicity and affordability [16, Groover, 2001]. It links products based on physical elements similarities, discovered by skilled technical personnel, generating clusters. Commonality can be established by [16, Groover, 2001]:

- design attributes, relative to features such as size, geometry and material;

- manufacturing attributes, concerned to characteristics including the processing steps to make a part, the cycle time, the batch size, the annual production, and the setup required.

Given that a part's shape is mainly defined by the industrial processes performed on it, there is some overlap between design and manufacturing features [16, Groover, 2001].

One application of visual inspection reliant on design attributes involves the use of similarity measures relative to Bill-of-Material (BOM) trees [14, Kashkoush et al., 2015]. This association approach simultaneously addresses three major clustering criteria [14, Kashkoush et al., 2015]:

1. components similarity;

2. assembly structure, which often denotes assembly sequence;

3. commonality in required amount of elements.

For illustrative purposes, figure 2.4 highlights grouping based on Bill-of-Material.

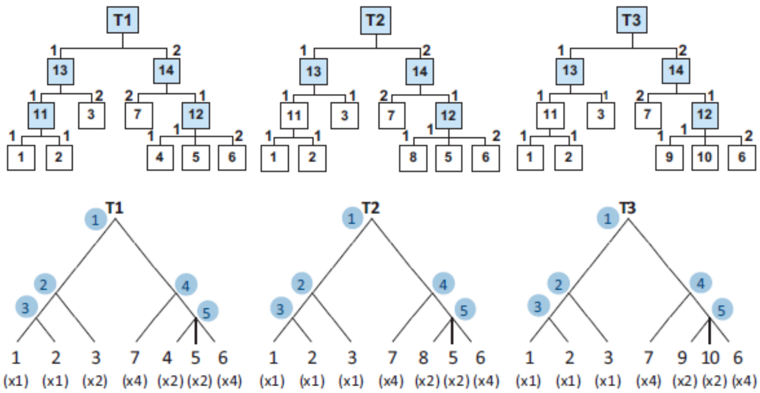

Figure 2.4: Three products belonging to the same family based on BOM similarity [14, Kashkoush et al., 2015].

In the project, a product family based on BOM can include the various toothpastes that can be produced from the same paste of material. They slightly change in terms of weight or packaging type.

Intuitive grouping is considered as the least accurate methodology to make product families. Despite this, one of the earliest significant group technology success stories in the United States employed this technique, the Langston Division of Harris-Intertype in New Jersey [16, Groover, 2001].

2.5.2 Parts Classification and Coding

This technique assesses commonalities among elements and relates them in a coding system. Reasons for using a coding scheme include [16, Groover, 2001]:

- design retrieval, which can be exploited by designers - facing the task of building a new product - to check if a similar element was already developed. Indeed, slightly modifying an existing item would often require substantially less time than designing an entire new product from scratch;
- automated process planning, meaning that the process plan to make the new

element can be retrieved with a simple code comparison. Indeed, often, process plans of existing materials can be re-adapted to produce new parts having similar codes;

- machine cell design, based on part codes, able to make all elements of a specific product family.

Successful performing parts classification and coding takes a plenty of time. It requires analysing design and/or manufacturing characteristics of every element [16, Groover, 2001]. The *Opitz coding scheme*, developed by H. Opitz of the University of Aachen in Germany, represents one of the most well known systems, if not the most widely employed, to accomplish this task [16, Groover, 2001]. It adopts the following alphanumerical sequence:

12345 6789 ABCD

This series of digits can be divided into three sections based on the type of attributes described [16, Groover, 2001].

1. The first section is called *form code* and consists of five numbers. It defines the primary design features of the part.

2. The second section is known as *supplementary code* and is made up of four digits. It describes some attributes which would be beneficial in production.

3. The last group, which is made up of four letters, is labelled as *secondary code*. Its aim is indicating the manufacturing operation type and sequence. The user company may design it to meet its specific requirements.

Figure 2.5 provides an overview of the first nine digits.

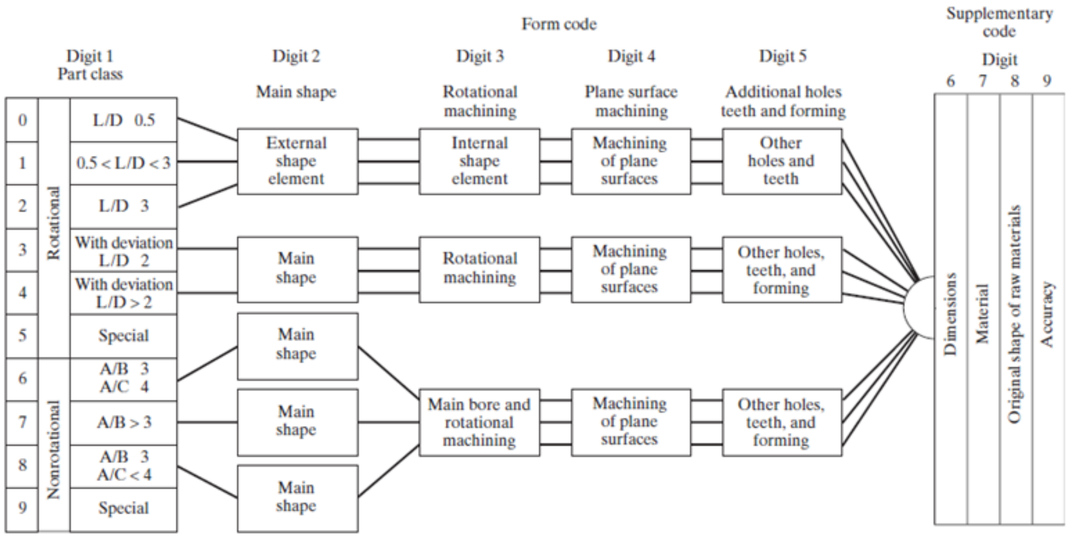

Figure 2.5: Basic structure of the Opitz system of parts classification and coding [16, Groover, 2001].

2.5.3 Production Flow Analysis

Production Flow Analysis (PFA) aims at detecting clusters of materials and relative machine groupings exploiting data retrieved from production route sheets instead of product drawings. Families are discovered collecting work parts presenting equal or comparable routings [16, Groover, 2001]. Referencing to production data, in place of design information, allows PFA to overcome relevant drawbacks of parts classification and coding [16, Groover, 2001].

- Despite having different geometries, materials may require similar or even the same process routings.
- Although some elements have comparable geometries, they may involve quite different process routings.

The following procedure needs to be applied in order to carry out a Production Flow Analysis [16, Groover, 2001].

1. Data collection: it requires information such as material number and manufacturing sequence. They are included in shop documents known as route sheets or operation sheets.

2. Sortation of process routings: clusters of elements - called *"packs"* - are created based on commonality of their process routings.

3. PFA chart: it is a tabulation having production resources j in the rows and parts i in the columns. It is also known as *part-machine incidence matrix*. Values of the matrix comply with rule 2.1.

$$x_{ji} = \begin{cases} 1 & \text{if resource } j \text{ manufactures material } i \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

   An oversimplified PFA chart is highlighted in figure 2.6.

	Parts (i)								
Machines (j)	A	B	C	D	E	F	G	H	I
1	1			1				1	
2					1				1
3			1		1				1
4		1				1			
5	1							1	
6			1						1
7		1				1	1		

Figure 2.6: Example of PFA chart [16, Groover, 2001].

4. Cluster analysis: it is performed analysing the entries of the *part-machine incidence matrix*. Materials with comparable patterns are grouped together into families. One feasible output of cluster analysis applied on the initial PFA chart is shown in figure 2.7. It displays various resource groups inside blocks.

	Parts (i)								
Machines (j)	C	E	I	A	D	H	F	G	B
3	1	1	1						
2		1	1						
6	1		1						
1				1	1	1			
5				1		1			
7							1	1	1
4							1		1

Figure 2.7: Output of cluster analysis [16, Groover, 2001].

2.5.4 Networked Operations Sequence Analysis

An extension of Production Flow Analysis would-be the Networked Operations Sequence Analysis. It builds clusters according to operation flow similarity [13, Navaei et al., 2016]. Also, it overcomes the limit of PFA having the ordering of processing operations *flexible*, rather than *fixed*. Networked Operations Sequence Analysis has various benefits such as reduction of changeover time and ease of system reconfiguration [17, Youssef, et al., 2006]. Furthermore, being able to discover the product manufactured based on its operation flow allows to increase *data integrity*. The reason behind this can be explained taking a step back, and in particular focusing on datasets. As it was mentioned in chapter 2.2, structured datasets record transactional data and meta data. Transactional data is obtained automatically exploiting sensors installed in resources involved in the process. Therefore, they are highly reliant. On the other hand, meta data is often inserted manually by operators. Errors or failures which may occur in the task of recording information lead to lower data consistency. This is particularly problematic in the pharmaceutical industry where data consistency is vital. Thus, being able of automatically assessing the product manufactured by looking at its operational path makes the whole procedure more reliant.

In order to create product families *Agglomerative Hierarchical Clustering* (AHC) can be employed as unsupervised learning algorithm. The final goal is grouping instances in a way that they are similar to each other and dissimilar to entities belonging to other clusters. AHC is a *distance-based* clustering algorithm. Thus, it measures dissimilarity in terms of distance [6, Aalst, 2016]. It is preferred over *k-means clustering* because it does not require any assumptions on the amount of clusters to be generated: they are variable. AHC begins allocating every entity to a particular singleton cluster. Then, iteratively, the two clusters closest to each other are merged, until all instances are in the same cluster [6, Aalst, 2016].

The output of the process is displayed through a dendrogram. Cutting it with a horizontal line corresponds to a concrete clustering [6, Aalst, 2016]. Indeed, each intersection point between horizontal and vertical segment consists in a family having as elements the leaves of the vertical line. Thus, moving up and down the cutting line is possible to vary the abstraction level [6, Aalst, 2016].

For illustrative purposes, a case study showing the application of Agglomerative Hierarchical Clustering to create product families was developed. The analysis focuses on nine hundred materials to be manufactured. Several production operations are required to transform them into final products. Overall, the possible manufacturing activities are ten. For the sake of clarity, each of them can be encoded with alphabetic letters going from A to J. The production path followed by every item i is shown using a symmetrical 10x10 matrix whose elements $x_{i,j,k}$ comply with equation 2.2. The subscript j is relative to the rows, whereas k to the columns.

$$x_{i,j,k} = \begin{cases} 1 & \text{if material } i \text{ flows from resource } j \text{ to resource } k \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

To make the application crystal-clear, based on equation 2.2, it is possible to consider a random material i and develop the fictitious matrix 2.3 representing its production operation path which is also displayed in figure 2.8.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.3}
$$

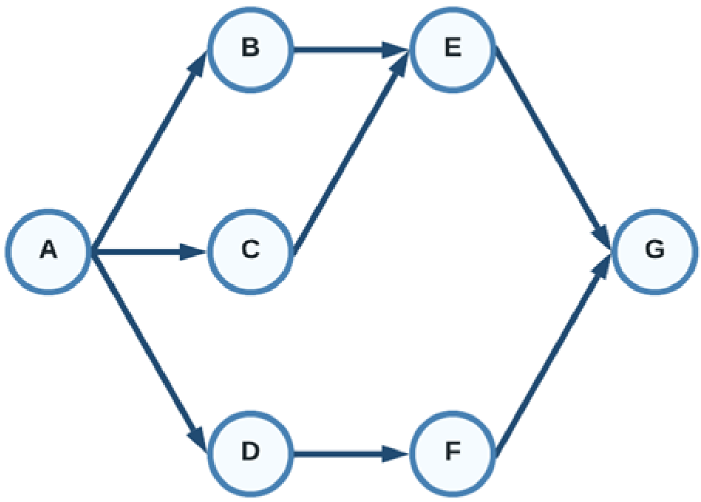

Figure 2.8: Production operation path based on matrix 2.3.

Returning to the analysis, materials are evenly split into the following variant categories according to the number of successors each activity can have, and production paths not allowed. With the purpose of further highlighting the differences among variant categories some matrices are displayed. Each of them is obtained summing all the matrices of materials belonging to the relative category.

1. Materials whose operations have maximum two successors and diagonals from the sixth to the ninth cut.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 19 & 14 & 20 & 18 & 31 & 0 & 0 & 0 & 0 \\
0 & 0 & 17 & 24 & 22 & 18 & 20 & 0 & 0 & 0 \\
0 & 0 & 0 & 19 & 16 & 25 & 30 & 23 & 0 & 0 \\
0 & 0 & 0 & 0 & 16 & 15 & 18 & 25 & 17 & 0 \\
0 & 0 & 0 & 0 & 0 & 16 & 12 & 17 & 21 & 28 \\
0 & 0 & 0 & 0 & 0 & 0 & 13 & 15 & 13 & 18 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 14 & 22 & 24 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 23 & 19 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 39 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.4}
$$

2. Materials whose operations have maximum three successors and diagonals from the sixth to the ninth cut.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 32 & 34 & 28 & 28 & 37 & 0 & 0 & 0 & 0 \\
0 & 0 & 36 & 26 & 27 & 31 & 28 & 0 & 0 & 0 \\
0 & 0 & 0 & 36 & 34 & 22 & 28 & 31 & 0 & 0 \\
0 & 0 & 0 & 0 & 25 & 19 & 26 & 32 & 30 & 0 \\
0 & 0 & 0 & 0 & 0 & 29 & 20 & 23 & 29 & 26 \\
0 & 0 & 0 & 0 & 0 & 0 & 31 & 22 & 29 & 19 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 37 & 32 & 33 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 37 & 42 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 36 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.5}
$$

3. Materials whose operations have maximum four successors and diagonals from the sixth to the ninth cut.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 48 & 41 & 42 & 34 & 28 & 0 & 0 & 0 & 0 \\
0 & 0 & 36 & 47 & 36 & 42 & 38 & 0 & 0 & 0 \\
0 & 0 & 0 & 39 & 32 & 40 & 35 & 41 & 0 & 0 \\
0 & 0 & 0 & 0 & 30 & 32 & 34 & 50 & 43 & 0 \\
0 & 0 & 0 & 0 & 0 & 30 & 29 & 36 & 31 & 37 \\
0 & 0 & 0 & 0 & 0 & 0 & 29 & 32 & 51 & 43 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 39 & 39 & 42 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 39 & 42 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 38 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.6}
$$

4. Materials whose operations have maximum two successors, and the first three diagonals cut.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 0 & 0 & 0 & 17 & 19 & 13 & 30 & 22 & 13 \\
0 & 0 & 0 & 0 & 0 & 23 & 16 & 23 & 19 & 27 \\
0 & 0 & 0 & 0 & 0 & 0 & 31 & 20 & 24 & 29 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 27 & 31 & 37 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 26 & 31 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 24 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.7}
$$

5. Materials whose operations have maximum three successors, and the first

three diagonals cut.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 0 & 0 & 0 & 31 & 31 & 34 & 30 & 34 & 32 \\
0 & 0 & 0 & 0 & 0 & 36 & 35 & 33 & 43 & 41 \\
0 & 0 & 0 & 0 & 0 & 0 & 36 & 39 & 31 & 37 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 29 & 37 & 39 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 46 & 38 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 38 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.8}
$$

6. Materials whose operations have maximum four successors, and the first three diagonals cut.

$$
\begin{array}{c c}
 & \begin{array}{cccccccccc} A & B & C & D & E & F & G & H & I & J \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{array} &
\begin{pmatrix}
0 & 0 & 0 & 38 & 38 & 35 & 35 & 42 & 39 & 38 \\
0 & 0 & 0 & 0 & 46 & 41 & 35 & 42 & 30 & 47 \\
0 & 0 & 0 & 0 & 0 & 45 & 33 & 46 & 47 & 40 \\
0 & 0 & 0 & 0 & 0 & 0 & 44 & 40 & 46 & 43 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 32 & 36 & 42 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 50 & 44 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 43 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.9}
$$

7. Materials whose operations have maximum two successors and the first four

antidiagonals cut.

$$
\begin{array}{c}
\\
\begin{matrix} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{matrix}
\end{array}
\begin{array}{c}
\begin{matrix} A & B & C & D & E & F & G & H & I & J \end{matrix} \\
\begin{pmatrix}
0 & 0 & 0 & 0 & 5 & 23 & 9 & 19 & 19 & 30 \\
0 & 0 & 0 & 9 & 17 & 4 & 18 & 20 & 20 & 23 \\
0 & 0 & 0 & 16 & 9 & 16 & 20 & 14 & 21 & 34 \\
0 & 0 & 0 & 0 & 14 & 10 & 14 & 18 & 17 & 17 \\
0 & 0 & 0 & 0 & 0 & 14 & 15 & 11 & 16 & 28 \\
0 & 0 & 0 & 0 & 0 & 0 & 10 & 18 & 20 & 24 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 17 & 19 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.10}
$$

8. Materials whose operations have maximum three successors and the first four antidiagonals cut

$$
\begin{array}{c}
\\
\begin{matrix} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{matrix}
\end{array}
\begin{array}{c}
\begin{matrix} A & B & C & D & E & F & G & H & I & J \end{matrix} \\
\begin{pmatrix}
0 & 0 & 0 & 0 & 27 & 23 & 30 & 27 & 25 & 40 \\
0 & 0 & 0 & 14 & 14 & 22 & 29 & 25 & 25 & 35 \\
0 & 0 & 0 & 26 & 16 & 23 & 19 & 31 & 35 & 38 \\
0 & 0 & 0 & 0 & 20 & 16 & 24 & 14 & 26 & 33 \\
0 & 0 & 0 & 0 & 0 & 21 & 18 & 29 & 22 & 31 \\
0 & 0 & 0 & 0 & 0 & 0 & 22 & 25 & 31 & 30 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 28 & 37 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
\tag{2.11}
$$

9. Materials whose operations have maximum four successors and the first four

antidiagonals cut

$$\begin{array}{c|c} & \begin{matrix} A & B & C & D & E & F & G & H & I & J \end{matrix} \\ \begin{matrix} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \\ I \\ J \end{matrix} & \begin{pmatrix} 0 & 0 & 0 & 0 & 34 & 32 & 39 & 42 & 31 & 50 \\ 0 & 0 & 0 & 28 & 32 & 34 & 32 & 24 & 44 & 40 \\ 0 & 0 & 0 & 40 & 28 & 27 & 31 & 37 & 40 & 40 \\ 0 & 0 & 0 & 0 & 30 & 25 & 32 & 35 & 35 & 44 \\ 0 & 0 & 0 & 0 & 0 & 32 & 22 & 30 & 38 & 43 \\ 0 & 0 & 0 & 0 & 0 & 0 & 31 & 31 & 34 & 44 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 37 & 41 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{2.12}$$

The next step is applying hierarchical clustering which requires setting up two key parameters. They are the *linkage* technique and the *distance* metric.

Some well known linkage methods are [18, Virtanen, et al., 2020]:

- *single* or *Nearest Point Algorithm*, which computes the distance between two clusters considering their closest elements;

- *complete* or *Farthest Point Algorithm*, which defines the distance between two clusters referencing to their furthest entities;

- *average*, which assesses the distance between two clusters considering the mean gap of all couple of points. Every pair has one item of each cluster;

- *centroid*, which considers centroids to compute the distance between two clusters;

- *ward*, which - iteratively - merges couple of clusters together, minimizing the increase of the *Sum of Squares Error* (ESS).

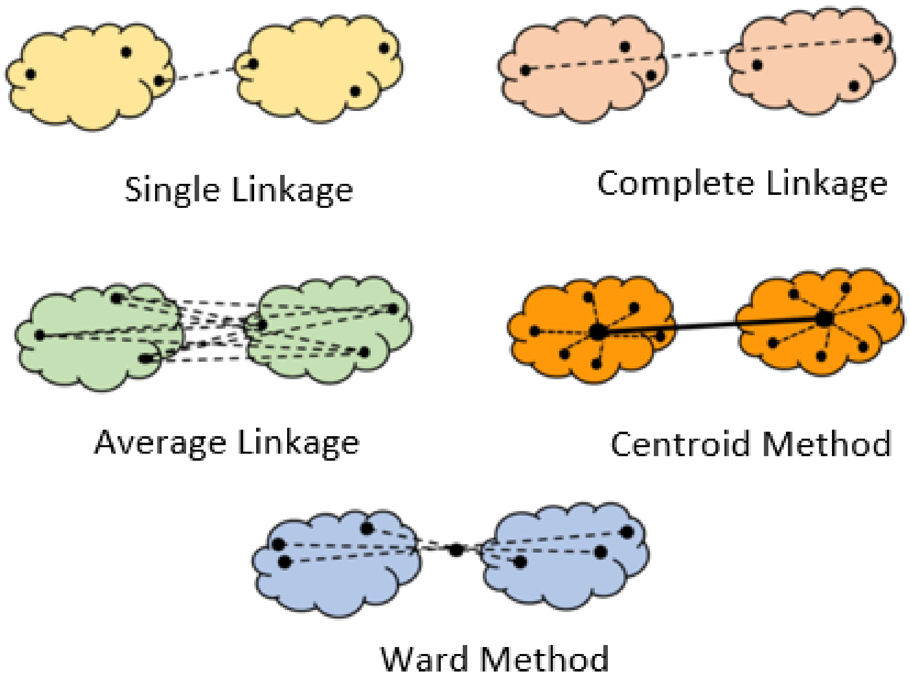

Figure 2.9: Graphical representation of linkage methods [19, Kijewska, et al., 2021].

Among the various distance metrics, it is possible to highlight [20, Sampaio, 2022]:

- Euclidean, it computes the distance considering the length of the line passing between two points;
- Manhattan, it assesses the distance as the sum of absolute differences between the measures in every dimesion of two points;
- Minkowski, it considers distance as absolute differences to the order of the Minkowski metric p ($p > 0$). If $p = 1$ it corresponds to the Manhattan distance, instead if $p = 2$ it is the same of the Euclidean distance;
- Chebyshev, it is the ultimate instance of Minkowski distance having $p = +\infty$;

- Cosine, it quantifies distance between points considering the angular cosine.

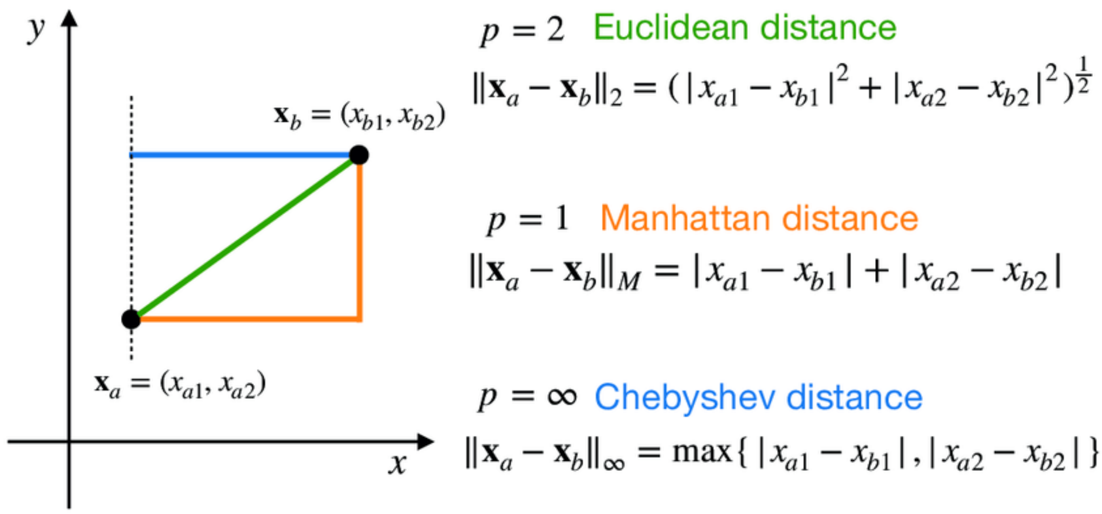

Figure 2.10: Graphical representation of some well-known Minkowski distances, i.e., Euclidean, Manhattan and Chebyshev metrics [21, Fu et al., 2021].

To apply the Agglomerative Hierarchical Clustering algorithm it has been chosen *Ward* as linkage method and *Euclidean* as distance metric. The reasons behind this decision are due to their largely adoption, efficiency in providing satisfactory results, errors minimization, and fitting well in lower dimensions.
After having grouped materials into variants according to the before mentioned rules, the results of the experiment can be shown through a dendrogram in figure 2.11. In order to pick the right number of clusters there are a number of heuristics and rules-of-thumb. For instance, drawing a horizontal line in between 240 and 250 would lead to group variants, and in turn the relative materials, into *three* product families.

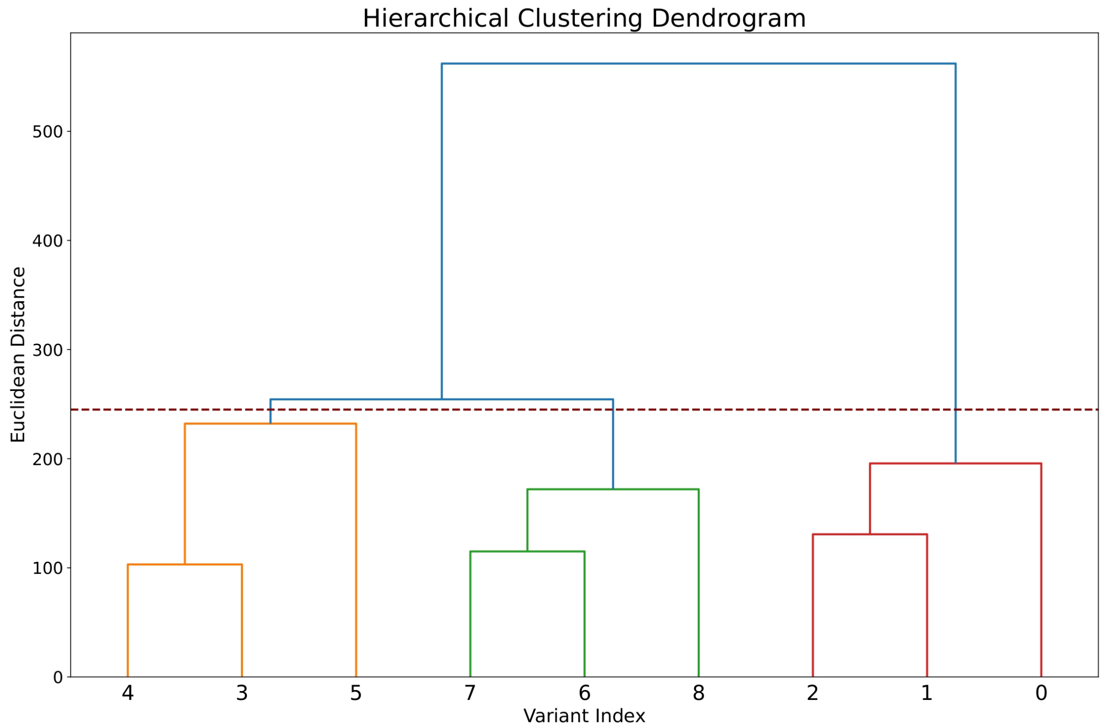

Figure 2.11: Dendrogram showing the results of the experiment.

Chapter 3

Optimal Scheduling

This chapter is related to the Optimal Scheduling model developed in order to effectively plan the production of toothpastes. It is divided into four sub-chapters.

The first section (3.1) provides an overview of the production site where toothpastes are made. In particular, it describes the toothpaste as final product, and lists the raw materials involved in the process. Then, it introduces a comparison between the end-to-end manufacturing process, as it is described in literature, and the real production process which takes place in GSK Oak Hill Production Site. Thus, the main production resources and the activities performed are mentioned.

The second section (3.2) focuses on the goals of the model. It explores the Overall Equipment Effectiveness, which is a Key Performance Indicator (KPI) that the proposed solution tries to improve. Here, the main components of the OEE are described and practical formulae to compute them are provided.

The third section (3.3) highlights the python model designed and developed in order to represent the real manufacturing process. In particular, the relevant subscripts (3.3.1), parameters (3.3.2) and decision variables (3.3.3) are listed. Then, the set of rules enforced are described (3.3.4). Finally, the objective function is shown (3.3.5).

The last section (3.4) refers to the approach adopted in order to explore the solution space. In particular, it emphasizes the importance of approximated methods, such as dispatching rules (3.4.1). They are extremely useful to find satisfactory results while keeping at an acceptable level the computational complexity. Finally, the heuristic Greedy Insertion (3.4.2), which is implemented in the project, is described.

3.1 Production Site Description

GSK production site located in Oak Hill (NY) manufactures mainly toothpastes. This item is a key part of people's daily oral hygiene routine, indeed it maintains and enhances oral healthcare and aesthetics. Historically, first toothpastes appeared thousand years ago, and since then their composition has evolved remarkably. Indeed, they moved from suspensions of crushed egg shells or ashes to sophisticated formulations involving often more than twenty ingredients [22, van Loveren C, 2013]. Today, a rising awareness on oral health is pushing the toothpaste industry, speeding its growth particularly in developing economies [23, Boukoutaya].
The end-to-end manufacturing process involves several activities and resources. Exploiting process mining, the list of materials relevant to the analysis and their production flow has been discovered. However, thoroughly investigating every manufacturing activity is outside the scope of the project. For this reason, some production steps are grouped together. In order to provide a clear picture, following figures (3.1 and 3.2) illustrate respectively the *standard* end-to-end production process as it is described in literature, and the *simplified* one. Focusing on the simplified process, it bundles production steps upstream mixing considering them as dispensing activities. Also, operations of filling, capping, labeling and printing are analysed collectively as a unique packaging step. In addition, to get more familiar with the process, a brief description of the main production resources and

their role is following provided.

- Dispenser: it mechanically weighs raw materials. Its aim is to ensure that the exact quantity of each ingredient is distributed into mixers. Its cycle time is negligible. Because of this, it is assumed that inbound materials are immediately dispensed and available to be manufactured in mixers. As a result, dispensers' management only marginally influence the optimal schedule model.
- Mixers: they get several types of ingredients and blending them together they make batches of paste. Two critical parameters are temperature and humidity, which are closely monitored. Indeed, they ensure that the mix comes together adequately. The production site exploits several mixers which work in parallel. Their production time is relevant and it changes with the type of paste being manufactured. A certain load capacity - around 10.000+ lbs - constrains the maximum weight of output batches. It is common practice to fully exploit it, achieving a load utilization of 100%, when mixers are manufacturing.
- Packaging lines: they fill tubes with toothpaste, but before this a blower and a vacuum machine are employed to guarantee tube cleanliness. As a result, dust and particles are swept away. Then, the tube is capped and the opposite part is opened, so that the pumping machine can load the toothpaste. After the filling step, the tube is packed. Batches of paste are received from the storage area which is located between manufacturing and packaging. Similarly to mixers, also packaging lines work in parallel. Each line has a throughput (i.e., number of items produced in a unit of time) which can accomplish the production of more than 100.000+ tubes per day. It does not depend on the product, although it varies across lines. In particular, some machines, called *High Volume Pace* (HVP), can outperform the others. Indeed, they are designed to reach much higher speed. This is particularly useful to satisfy

demand peaks and to mitigate the effects of unexpected breakdowns of other packaging resources.

Focusing on waiting areas, it is particularly relevant to mention the storage between mixers and packaging lines. Its effective management is vital in order to reach target Key Performance Indicators (KPIs) and achieve satisfactory results. Indeed, incoming batches of paste are stored in containers and wait in this area until their packaging scheduled time arrives. Containers, called *"totes"*, have a load capacity of 10.000+ lbs. Often, some totes are not available for regular use because they are tied up with quality issues or leftover paste that did not get fully consumed. Furthermore, when a packaging line is using totes it will require at least one extra tote to act as a static container for each formula it is running.

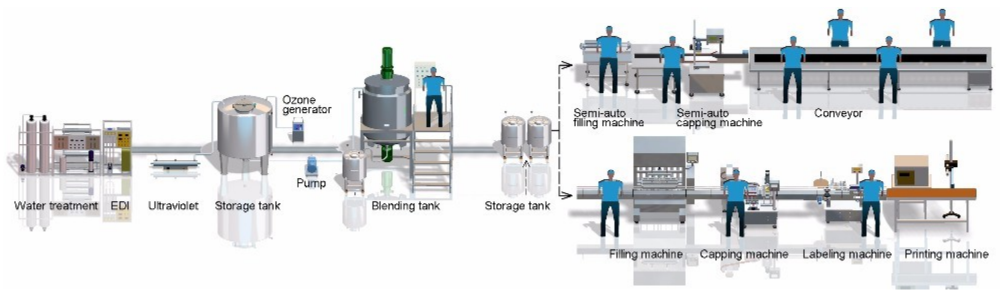

Figure 3.1: Picture of the end-to-end production process [23, Boukoutaya].

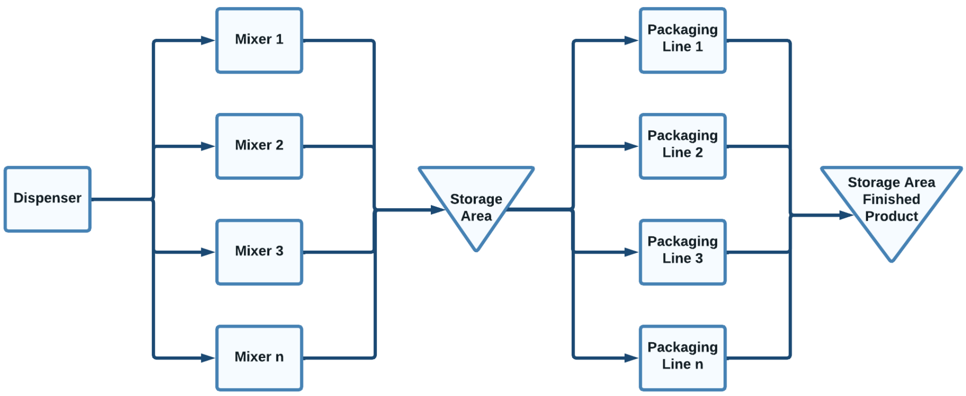

Figure 3.2: Flow chart diagram of the end-to-end production process.

As it was mentioned toothpastes have a complex chemical composition because of the wide array of properties they should have. Some of them are compounds to combat dental caries, gum disease, calculus, decay and dentin hypersensitivity [22, van Loveren C, 2013]. Furthermore, toothpastes contain abrasives to clean and whiten teeth, flavors for the purpose of breath freshening and dyes for better visual appeal. To ensure the above-cited characteristics, as listed in table 3.1, several ingredients are required. For the sake of simplicity, they can be referred as *raw materials*. Whereas the output of the blending operation is named as *material paste* which is, in turn, the input of packaging activities to make the *final product*. Final products differ in terms of material paste, weight and packaging type. It is relevant to mention that the same material paste can fill several final products, being the relation between them *one-to-many*.

Ingredient Type	**Relative Weight**
Liquid Base	White - 30% Gel - up to 80%
Fillers and Abrasives	White - 20% - 50% Gel - 15% - 25%
Rheology Modifiers	0.5% - 2%
Detergent	0.5% - 2.5%
Active Ingredient	0.3%
Flavor	0.5% - 2%
Sweetener	0.2%
Coloring	0.1%
Preservative	0.2%

Table 3.1: Toothpaste ingredients [23, Boukoutaya].

3.2 Scheduling Goals

The main goal of the project is to determine whether the implementation of an optimal scheduling model would improve the production efficiency measured in terms of the OEE (Overall Equipment Effectiveness) indicator. Nowadays, several Key Performance Indicators support decision making processes at various organizational layers. Mainly, they assess process deviations and guarantee that corrective responses can be implemented [24, Corrales, 2020]. OEE is a KPI designed by Nakajima in 1988 [24, Corrales, 2020]. It is a quantitative index considered as one of the focal points of the Total Productive Maintenance (TPM) discipline and of production planning [25, pp. Li, 2021]. It is largely employed, particularly in manufacturing management, to quantify the unexploited production capacity of resources and increase the performances of the operations site [26, Šajdlerová, 2020]. In addition, OEE is widely used as a mechanism to monitor and control equipment performances when lean manufacturing programs or maintenance plans are implemented. It aims at minimizing the widely known *Six Big Losses in lean manufacturing* [27, Kripya]:

- Equipment Failure;
- Setup and Adjustments;
- Idling and Minor Stops;
- Reduced Speeds;
- Process Defects;
- Reduced Yield.

The Overall Equipment Effectiveness, in compliance with the main concepts of TPM, is computed dividing the real manufacturing output by what could be theoretically produced [24, Corrales, 2020]. It depends on three sub-indicators which refer to the Six Big Losses (figure

$$OEE = AR \times PE \times QR \tag{3.1}$$

Where the relative factors are respectively assessed applying mathematical formulae 3.2, 3.3, 3.4.

$$AR = \frac{OT}{LT} \tag{3.2}$$

$$PE = SCT \times \frac{TO}{OT} \tag{3.3}$$

$$QR = \frac{QP}{TO} \tag{3.4}$$

Therefore, the OEE, in its primary terms, can be computed using equation 3.5 [25, pp. Li, 2021].

$$OEE = \frac{OT}{LT} \times SCT \times \frac{TO}{OT} \times \frac{QP}{TO} \tag{3.5}$$

Which can be further simplified becoming as written in equation 3.6 [25, pp. Li, 2021].

$$OEE = SCT \times \frac{QP}{LT} \tag{3.6}$$

In order to fully understand the several formulae introduced, it is necessary to explain the meaning of each acronym.

- AR means Availability Rate. It is related to the level of exploitation of production planning time.

- PE stands for Performance Effectiveness. It considers the degree of utilization of equipment's design performance.

- QR is Quality Rate. It is the relative amount of conforming products with respect to the overall number of items manufactured.

- LT denotes Loading Time. It is assessed considering the Factory Planning Working Time lowered by the Site Planning Downtime.
- SCT refers to Single Cycle Time.
- OT represents the Operating Time. It can be computed diminishing the Loading Time by the Equipment Downtime which should incorporate, among others, also Adjustment Time and Failure Time.
- TO denotes the Total Output.
- QP means Qualified Products. They are the result of Total Output minus the number of non-conforming items.

As bottom line, it was possible to understand that the implications of OEE theory cover several research fields. They embrace the Internet of Things, Tool Management, Sustainable Manufacturing and many others [25, pp. Li, 2021].

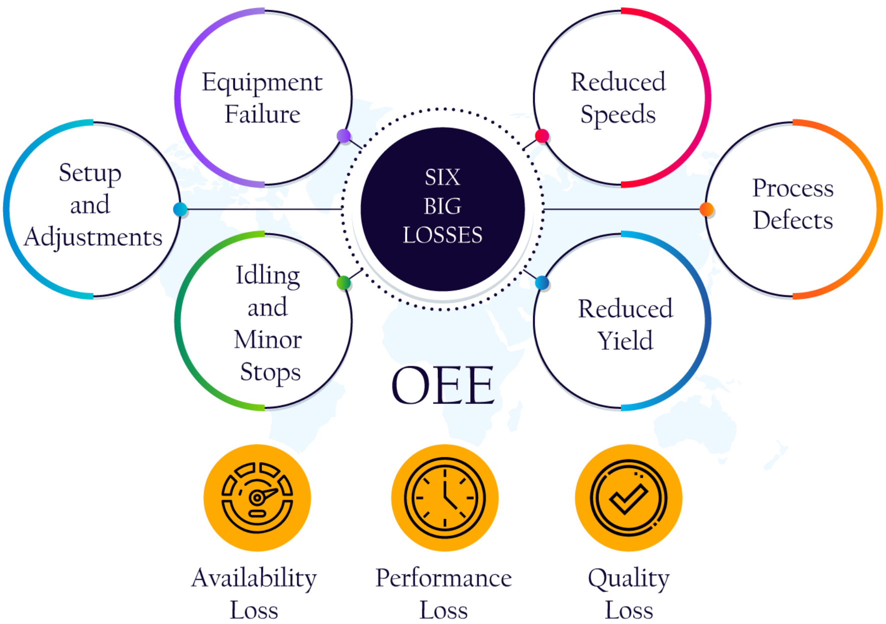

Figure 3.3: Six Big Losses in Lean Manufacturing [27, Kripya].

3.3 Final Model

Exploiting data and insights about the production site, a constraint programming model is designed to develop an optimal scheduling plan which maximizes the OEE while respecting several constraints.

In order to clear understand it, the main reasoning behind the algorithm built is provided. The process starts considering data about final products demand. Therefore, if there is enough production capacity in resources, every SKU's production block is allocated in the packaging line which experiences the lowest expected downtime. Afterwards, the SKU's bill-of-material provides information about the code and the quantity of the relative material paste required to fulfill its demand. Thus, the demand of every final product is translated into the demand of the relative material paste which is manufactured in mixers. As before, every batch is made in the resource which goes through the lowest expected failure time. A relevant constraint is that the material paste demand must be fulfilled before packaging lines start. Indeed, it would be impossible to feed toothpaste tubes without paste.

Furthermore, as it will be possible to notice from Gantt Charts in results section, production blocks are left aligned. It means that they start as soon as possible. This way of thinking should reduce the machine downtime due to unutilized capacity.

A python library called "ortools.sat.python" provides the background optimization environment to find the optimal solution. The solution space is explored using Greedy Insertion as constructive heuristic algorithm. It builds the solution scheduling before fixed non-production activities such as maintenance, spare capacity and shifts. Then, it adds production blocks starting from the ones which lead to the lowest expected machine downtime. The main methods imported are:

- CpModel, which is able to create models having variables and constraints;

- CPSolver, which allows to solve models and explore the solution space.

Developing an optimal scheduling plan requires to introduce the following sections:

1. Subscripts 3.3.1;
2. Parameters 3.3.2;
3. Variables 3.3.3;
4. Constraints 3.3.4;
5. Objective Function 3.3.5.

3.3.1 Subscripts

Information extracted from datasets involves several objects belonging to same classes. Indeed, the model considers several material pastes, final products, and many production resources. Thus, using subscripts in order to differentiate elements of the same family results essential. The main subscripts explored are:

- material paste index, $i \in [1, I]$;
- final product (SKU) index, $p \in [1, P]$;
- mixer index, $j \in [1, J]$;
- packaging line index, $k \in [1, K]$;
- index which counts how many times a certain action (production row, shift, maintenance, etc.) is repeated $t \in [1, T]$.

3.3.2 Parameters

Several input parameters are involved in order to effectively schedule the production in the manufacturing plant. They are grouped together based on the function to which they are related. In particular they involve:

- Production parameters;
- Inventory parameters;
- Shift parameters;
- Maintenance parameters;
- Changeover parameters;
- Spare Capacity parameters.

Following, an overview of the major production related parameters is provided.

- The time horizon which should be covered by the optimal scheduling program. In the model it is defined as an object called *"horizon"*.

$$horizon = const.$$

- The set of pastes needed as raw materials to make final products. Every paste can fulfill the development of several SKUs given the *one-to-many* relation. A list, called *"pastes"*, introduces them in the model.

$$pastes = [pasteID_1, \dots, pasteID_I]$$

- The set of final products demanded in the planning horizon. In the model this parameter is defined as a list, called *"final_products"*, whose elements represent each SKU code.

$$final\_products = [SKU_1, \dots, SKU_P]$$

- The whole set of materials, comprehensive of pastes and final products. In the model it is defined as a list, called *"materials"*. The first I elements are relative to the code of pastes, whereas last P objects list the SKUs of final products.

$$materials = [pasteID_1, \dots, pasteID_I,\ SKU_1, \dots, SKU_P]$$

- The list of mixers.

$$mixers = [mixer_1, \dots, mixer_J]$$

- The list of packaging lines.

$$packaging = [packaging_1, \dots, packaging_K]$$

- The list of production resources, such as mixers and packaging lines. In the model it is called *"resources"*.

$$resources = [mixer_1, \dots, mixer_J, packaging_1, \dots, packaging_K]$$

- The load capacity of mixers. It changes among machines. In the model it is called *"capacity"*.

$$capacity = [load\_capacity_1, \dots, load\_capacity_J]$$

- The production time of mixers to manufacture one batch. It varies with the material paste to be manufactured. In the model it is called *"production_time"*.

$$production\_time = \begin{bmatrix} \begin{bmatrix} time_{1,1}, & \dots, & time_{1,J} \end{bmatrix} \\ \begin{bmatrix} time_{2,1}, & \dots, & time_{2,J} \end{bmatrix} \\ \begin{bmatrix} time_{I,1}, & \dots, & time_{I,J} \end{bmatrix} \end{bmatrix}$$

- The expected downtime of mixers when producing each paste. In the model it is called *"downtime_mixers"*.

$$downtime\_mixers = \begin{bmatrix} \begin{bmatrix} down\_m_{1,1}, & ..., & down\_m_{1,J} \end{bmatrix} \\ \begin{bmatrix} down\_m_{2,1}, & ..., & down\_m_{2,J} \end{bmatrix} \\ \begin{bmatrix} down\_m_{I,J}, & ..., & down\_m_{I,J} \end{bmatrix} \end{bmatrix}$$

- The throughput of packaging lines. It differs among machines. In the model it is called *"throughput"*.

$$throughput = [throughput_1, ..., throughput_K]$$

- The expected downtime loss of packaging lines when dealing with final items. In the model it is called *"downtime_packaging"*.

$$downtime\_packaging = \begin{bmatrix} \begin{bmatrix} down\_p_{1,1}, & ..., & down\_p_{1,K} \end{bmatrix} \\ \begin{bmatrix} down\_p_{2,1}, & ..., & down\_p_{2,K} \end{bmatrix} \\ \begin{bmatrix} down\_p_{P,1}, & ..., & down\_p_{P,K} \end{bmatrix} \end{bmatrix}$$

- The demand of material pastes needed to satisfy the desired production of final items. It is measured in lbs. In the model it is called *"demand_pastes"*.

$$demand\_pastes = [demand\_paste_1, ..., demand\_paste_I]$$

- The demand of units of final products. It is relative to the planning horizon above-specified. In the model it is called *"demand"*.

$$demand = [demand\_SKU_1, ..., demand\_SKU_P]$$

Concerning parameters required to deal with inventory management, some of them are following introduced.

- The storage capacity of inventory containers. In the model it is called *"storage_capacity"*.

$$storage\_capacity = const.$$

- The maximum time each paste can stay in the storage area. In the model it is called *"max_storage_time"*.

$$max\_storage\_time = const.$$

The next parameters focus on shift planning. Among them is necessary to define the following.

- The time between two consecutive production stops in mixers due to employee breaks. In the model it is called *"gap_shifts_mixers"*.

$$gap\_shifts\_mixers = const.$$

- The average duration of breaks in mixers. In the model it is called *"duration_shift_mixers"*.

$$duration\_shift\_mixers = const.$$

- The time between two consecutive production stops in packaging lines due to employee breaks. In the model it is called *"gap_shifts_packaging"*.

$$gap\_shifts\_packaging = const.$$

- The average duration of breaks in packaging lines. In the model it is called *"duration_shift_packaging"*.

$$duration\_shift\_packaging = const.$$

Focusing on parameters related to preventive maintenance planning, a list of them is here provided.

- The time interval between two consecutive preventive maintenance stops in mixers. In the model it is called *"gap_maintenance_mixers"*.

$$gap\_maintenance\_mixers = const.$$

- The average duration of preventive maintenance in mixers. In the model it is called *"duration_maintenance_mixers"*.

$$duration\_maintenance\_mixers = const.$$

- The time interval between two consecutive preventive maintenance stops in packaging lines. In the model it is called *"gap_maintenance_packaging"*.

$$gap\_maintenance\_packaging = const.$$

- The average duration of preventive maintenance in packaging lines. In the model it is called *"duration_maintenance_packaging"*.

$$duration\_maintenance\_packaging = const.$$

Dealing with changeover requirements, it is needed to introduce the following parameters.

- The duration of changeovers in mixers. In the model it is called *"duration_changeover_mixers"*.

$$duration\_changeover\_mixers = const.$$

- The duration of changeovers in packaging lines. In the model it is called *"duration_changeover_packaging"*.

$$duration\_changeover\_packaging = const.$$

Concerning with spare capacity related parameters, the most important is the following.

- The spare capacity required in the planning horizon. In the model it is called *"duration_spare_capacity"*.

$$duration\_spare\_capacity = const.$$

3.3.3 Variables

Solving a model is equivalent to finding, for each variable, a single value belonging to its initial domain, such that the model is feasible, or optimal based on the objective function and the relative constraints.

Mostly three types of variables are employed in the model [28, Perron, 2022].

- Boolean, which has just two admissible values (often defined as *true* and *false*). Thus, it works focusing on a conditional statement which identifies different paths by changing control flow based on whether the code evaluates the variable as true or false.

- Integer, which is an object that can assume any integer value belonging to a specified domain.

- Interval, which has the function of both constraints and variables. It is determined by three integer variables: start, duration, and finish. The reason behind the fact that it is a constraint is that it respects equation 3.7.

$$Start + Duration = Finish \tag{3.7}$$

  In addition, it is considered a variable given that it can be employed in planning rules such as NoOverlap, NoOverlap2D and Cumulative.

Several variables are exploited to develop the model. It is possible to divide them into different categories based on the purpose they have. Main groups are:

- Production variables;
- Inventory variables;
- Shift variables;
- Maintenance variables;
- Changeover variables;
- Spare Capacity variables.

Following, an overview of the major production related variable is provided.

- $y\_mixers_{i,j,t}$ which is a boolean variable. It gets true if mixer j manufactures production row t of material paste i.

$$y\_mixers_{i,j,t} = \begin{cases} 1 & \text{if mixer } j \text{ makes production row } t \text{ of paste } i \\ 0 & \text{otherwise} \end{cases}$$

- $production\_mixers_{i,j,t}$ which is an integer variable. It quantifies the lbs of material paste i manufactured in mixer j during the production row t.

$$production\_mixers_{i,j,t} \geq 0 \quad \forall\ i, j, t$$

- $duration\_mixers_{i,j,t}$ which is an integer variable. It defines the time required to manufacture production row t of material paste i in mixer j.

$$duration\_mixers_{i,j,t} \geq 0 \quad \forall\ i, j, t$$

- $start\_mixers_{i,j,t}$ which is an integer variable. It defines the start time of production row t of material paste i in mixer j.

$$start\_mixers_{i,j,t} \geq 0 \quad \forall\ i, j, t$$

- $end\_mixers_{i,j,t}$ which is an integer variable. It defines the end time of production row t of material paste i in mixer j.

$$end\_mixers_{i,j,t} \geq 0 \quad \forall\ i, j, t$$

- $interval\_mixers_{i,j,t}$ which is an interval variable. It is defined by variables $start\_mixers_{i,j,t}$, $duration\_mixers_{i,j,t}$ and $end\_mixers_{i,j,t}$.

$$interval\_mixers_{i,j,t} \in [0, horizon] \quad \forall\ i, j, t$$

- $y\_packaging_{p,k,t}$ which is a boolean variable. It gets true if packaging line k makes production row t of final item p.

$$y\_packaging_{p,k,t} = \begin{cases} 1 & \text{if packaging line } k \text{ makes production row } t \text{ of SKU } p \\ 0 & \text{otherwise} \end{cases}$$

- $production\_packaging_{p,k,t}$ which is an integer variable. It assesses the number of tubes of SKU p made in packaging line k during production row t.

$$production\_packaging_{p,k,t} \geq 0 \quad \forall\ p, k, t$$

- $duration\_packaging_{p,k,t}$ which is an integer variable. It defines the time required to make production row t of final product p in packaging line k.

$$duration\_packaging_{p,k,t} \geq 0 \quad \forall\ p, k, t$$

- $start\_packaging_{p,k,t}$ which is an integer variable. It defines the start time of production row t of SKU p in packaging line k.

$$start\_packaging_{p,k,t} \geq 0 \quad \forall\ p, k, t$$

- $end\_packaging_{p,k,t}$ which is an integer variable. It defines the end time of production row t of final product p in packaging line k.

$$end\_packaging_{p,k,t} \geq 0 \quad \forall\ p, k, t$$

- $interval\_packaging_{p,k,t}$ which is an interval variable. It is defined by variables $start\_packaging_{p,k,t}$, $duration\_packaging_{p,k,t}$ and $end\_packaging_{p,k,t}$.

$$interval\_packaging_{p,k,t} \in [0, horizon] \quad \forall\ p, k, t$$

Concerning variables required to deal with inventory management, some of them are following introduced.

- $start\_SA_{p,j,t}$ which is an integer variable. After having completed production row t of material paste i in mixer j, the material paste i enters in inventory and is available to be used in packaging lines to make final product p. Thus, $start\_var\_SA_{p,j,t}$ defines the point in time in which production of final product p can start.

$$start\_SA_{p,j,t} \geq 0 \quad \forall\ p, j, t$$

- $end\_SA_{p,j,t}$ which is an integer variable. It defines the end time in which the material paste required to make final product p is available in inventory. Thus, from that moment on, that material paste is not anymore in inventory.

$$end\_SA_{p,j,t} \geq 0 \quad \forall\ p, j, t$$

- $duration\_SA_{p,j,t}$ which is an integer variable. It defines the amount of time in which it was possible to start producing final product p in packaging lines.

$$duration\_SA_{p,j,t} \geq 0 \quad \forall\ p, j, t$$

- $interval\_SA_{p,j,t}$ which is an interval variable. It depends on $start\_SA_{p,j,t}$, $duration\_SA_{p,j,t}$ and $end\_SA_{p,j,t}$.

$$interval\_SA_{p,j,t} \in [0, horizon] \quad \forall\ p, j, t$$

The next variables focus on shift planning. Among them is necessary to define the following.

- $start\_shift\_mixers_{j,t}$ which is an integer variable. It defines the start time of shift t in mixer j.

$$start\_shift\_mixers_{j,t} \geq 0 \quad \forall\ j, t$$

- $end\_shift\_mixers_{j,t}$ which is an integer variable. It defines the end time of shift t in mixer j.

$$end\_shift\_mixers_{j,t} \geq 0 \quad \forall\ j, t$$

- $interval\_shift\_mixers_{j,t}$ which is an interval variable. It defines the time frame related to break t in mixer j. It depends on $start\_shift\_mixers_{j,t}$, $duration\_shift\_mixers$ and $end\_shift\_mixers_{j,t}$.

$$interval\_shift\_mixers_{j,t} \in [0, horizon] \quad \forall\ j, t$$

- $start\_shift\_packaging_{k,t}$ which is an integer variable. It defines the start time of shift t in packaging line k.

$$start\_shift\_packaging_{k,t} \geq 0 \quad \forall\ k, t$$

- $end\_shift\_packaging_{k,t}$ which is an integer variable. It defines the end time of shift t in packaging line k.

$$end\_shift\_packaging_{k,t} \geq 0 \quad \forall\ k, t$$

- $interval\_shift\_packaging_{k,t}$ which is an interval variable. It assesses the interval of time in which there is break t in packaging line k. It is defined by $start\_shift\_packaging_{k,t}$, $duration\_shift\_packaging$ and $end\_shift\_packaging_{k,t}$.

$$interval\_shift\_packaging_{k,t} \in [0, horizon] \quad \forall\ k, t$$

Focusing on variables related to preventive maintenance planning, a list of them is here provided.

- $start\_maintenance\_mixers_{j,t}$ which is an integer variable. It defines the start time of maintenance t in mixer j.

$$start\_maintenance\_mixers_{j,t} \geq 0 \quad \forall\ j, t$$

- $end\_maintenance\_mixers_{j,t}$ which is an integer variable. It defines the end time of maintenance t in mixer j.

$$end\_maintenance\_mixers_{j,t} \geq 0 \quad \forall\ j, t$$

- $interval\_maintenance\_mixers_{j,t}$ which is an interval variable. It defines the interval of time in which there is maintenance t in mixer j. It considers $start\_maintenance\_mixers_{j,t}$, $duration\_maintenance\_mixers$ and $end\_maintenance\_mixers_{j,t}$.

$$interval\_maintenance\_mixers_{j,t} \in [0, horizon] \quad \forall\ j, t$$

- $start\_maintenance\_packaging_{k,t}$ which is an integer variable. It defines the start time of maintenance t in packaging line k.

$$start\_maintenance\_packaging_{k,t} \geq 0 \quad \forall\ k, t$$

- $end\_maintenance\_packaging_{k,t}$ which is an integer variable. It defines the end time of maintenance t in packaging line k.

$$end\_maintenance\_packaging_{k,t} \geq 0 \quad \forall\ k, t$$

- $interval\_maintenance\_packaging_{k,t}$ which is an interval variable. It shows the time where maintenance t in packaging k happens. It is defined by

$start\_maintenance\_packaging_{k,t}$, $duration\_maintenance\_packaging$ and $end\_maintenance\_packaging_{k,t}$.

$$interval\_maintenance\_packaging_{k,t} \in [0, horizon] \quad \forall\, k, t$$

Dealing with changeover requirements, it is needed to introduce the following variables.

- $start\_changeover\_mixers_{i,j,t}$ which is an integer variable. It defines the start time of changeover in mixer j before production row t of material paste i.

$$start\_changeover\_mixers_{i,j,t} \geq 0 \quad \forall\, i, j, t$$

- $end\_changeover\_mixers_{i,j,t}$ which is an integer variable. It defines the end time of changeover in mixer j before production row t of material paste i.

$$end\_changeover\_mixers_{i,j,t} \geq 0 \quad \forall\, i, j, t$$

- $interval\_changeover\_mixers_{i,j,t}$ which is an interval variable. It defines the interval of time allocated to changeover, which is required to manufacture production row t of material paste i in mixer j. It considers $start\_changeover\_mixers_{i,j,t}$, $duration\_changeover\_mixers$ and $end\_changeover\_mixers_{i,j,t}$.

$$interval\_changeover\_mixers_{i,j,t} \in [0, horizon] \quad \forall\, i, j, t$$

- $start\_changeover\_packaging_{p,k,t}$ which is an integer variable. It defines the start time of changeover in packaging line k before making production row t of final item p.

$$start\_changeover\_packaging_{p,k,t} \geq 0 \quad \forall\, p, k, t$$

- $end\_changeover\_packaging_{p,k,t}$ which is an integer variable. It defines the end time of changeover in packaging line k before making production row t of final item p.

$$end\_changeover\_packaging_{p,k,t} \geq 0 \quad \forall\ p, k, t$$

- $interval\_changeover\_packaging_{p,k,t}$ which is an interval variable. It defines the timeslot allocated to changeover, which is required to make production row t of SKU p in packaging line k. It considers $start\_changeover\_packaging_{p,k,t}$, $duration\_changeover\_packaging$ and $end\_changeover\_packaging_{p,k,t}$.

$$interval\_changeover\_packaging_{p,k,t} \in [0, horizon] \quad \forall\ p, k, t$$

Concerning with spare capacity related variables , the most important are the following.

- $start\_spare\_capacity\_mixers_{j,t}$ which is an integer variable. It defines the start time of spare capacity t in mixer j.

$$start\_spare\_capacity\_mixers_{j,t} \geq 0 \quad \forall\ j, t$$

- $end\_spare\_capacity\_mixers_{j,t}$ which is an integer variable. It defines the end time of spare capacity t in mixer j.

$$end\_spare\_capacity\_mixers_{j,t} \geq 0 \quad \forall\ j, t$$

- $interval\_spare\_capacity\_mixers_{j,t}$ which is an interval variable. It defines the interval of time where spare capacity t of mixer j is allocated. It is defined by $start\_spare\_capacity\_mixers_{j,t}$, $duration\_spare\_capacity$ and $end\_spare\_capacity\_mixers_{j,t}$.

$$interval\_spare\_capacity\_mixers_{j,t} \in [0, horizon] \quad \forall\ j, t$$

- $start\_spare\_capacity\_packaging_{k,t}$ which is an integer variable. It defines the start time of spare capacity t in packaging line k.

$$start\_spare\_capacity\_packaging_{k,t} \geq 0 \quad \forall\ k, t$$

- $end\_spare\_capacity\_packaging_{k,t}$ which is an integer variable. It defines the end time of spare capacity t in packaging line k.

$$end\_spare\_capacity\_packaging_{k,t} \geq 0 \quad \forall\ k, t$$

- $interval\_spare\_capacity\_packaging_{k,t}$ which is an interval variable. It considers the time-slot where spare capacity t of packaging line k is allocated. It is defined by $start\_spare\_capacity\_packaging_{k,t}$, $duration\_spare\_capacity$ and $end\_spare\_capacity\_packaging_{k,t}$.

$$interval\_spare\_capacity\_packaging_{k,t} \in [0, horizon] \quad \forall\ k, t$$

3.3.4 Constraints

Several constraints are developed in order to effectively enforce the production rules. They are created exploiting methods such as “Add”,“AddDivisionEquality”,“AddModuloEquality” and automatically inserted in the problem. In order to make clear how they work, a brief description of each of them is here provided [28, Perron, 2022].

- Add inserts a bounded linear expression to the model.

- AddDivisionEquality allows to make divisions and constrains the result setting a certain target value. It takes as input parameters “target”, “numerator” and “denominator”. Then it enforces equation 3.8.

$$target = \frac{numerator}{denominator} \tag{3.8}$$

- AddModuloEquality allows to constrain the division's modulo to a certain target value. It takes as input parameters "target","var" and "mod". Then, it adds constraint 3.9.

$$target = var \ \% \ mod \tag{3.9}$$

- AddNoOverlap avoids that intervals variable, being passed as parameters to this method, overlap in time.

Several constraints are designed to make the model as much representative of the reality as possible. They are divided into categories based on the role they have. The main constraint groups are:

- Production constraints;
- Inventory constraints;
- Shift constraints;
- Maintenance constraints;
- Changeover constraints;
- Spare Capacity constraints;
- Overlap constraints.

Among production constraints, the model is designed in order to satisfy the following rules.

- Production in mixers lead the boolean variable $y\_mixers_{i,j,t}$ getting the value of one. This is a *Big M constraint*, given that the parameter M gets a very high value.

$$model.Add(production\_mixers_{i,j,t} \leq M \times y\_mixers_{i,j,t})$$

- Mixer lbs manufacturing equals load capacity - given that they produce at full capacity - multiplied by the number of batches made in a production row.

$$model.Add(production\_mixers_{i,j,t} = capacity_j \times batches_{i,t})$$

- Production length in mixers equals the time required to manufacture one batch times the number of batches made in one production row.

$$model.Add(duration\_mixers_{i,j,t} = production\_time_{i,j} \times batches_{i,t})$$

- Avoid production of final products in mixers.

$$model.Add(production\_mixers_{p,j,t} = 0)$$

- Start production row t after having completed *t-1* in mixers.

$$model.Add(start\_mixers_{i,j,t} > end\_mixers_{i,j,t-1})$$

- Each material paste must be produced in a way that its overall demand is satisfied.

$$model.Add(sum(production\_mixers_{i,j,t} \text{ for } j \text{ in mixers} \\ \text{for } t \text{ in T} \geq demand\_pastes_i))$$

- If final product p demand, as raw material, paste i then production in packaging line can start just after having completed manufacturing in mixer.

$$model.Add(start\_packaging_{p,k,t} > end\_mixers_{i,j,t})$$

- If there is production in packaging lines the boolean variable $y\_packaging_{p,k,t}$ gets the value of one.

$$model.Add(production\_packaging_{p,k,t} \leq M \times y\_packaging_{p,k,t})$$

- Packaging duration should be an integer number.

$$model.AddModuloEquality(0, production\_packaging_{p,k,t}, throughput_k)$$

- The length of production in packaging lines equals the ratio between the output tubes divided by the average machine throughput.

$$model.AddDivisionEquality(duration\_packaging_{p,k,t},$$
$$production\_packaging_{p,k,t}, throughput_k)$$

- Avoid production of material pastes in packaging lines.

$$model.Add(production\_packaging_{i,k,t} = 0)$$

- Start production row *t* after having completed *t-1* in packaging lines.

$$model.Add(start\_packaging_{p,k,t} > end\_packaging_{p,k,t-1})$$

- Packaging lines overall production must satisfy final items relative demand.

$$model.Add(sum(production\_packaging_{p,k,t}\text{for } k \text{ in packaging\_lines}$$
$$\text{for } t \text{ in T} \geq demand_p)$$

Among inventory constraints, the model is designed in order to satisfy the following rules.

- Material paste enters in storage area once mixer production has finished. Thus, every final product p requiring material paste i starts simultaneously being available for packaging lines in that moment.

$$model.Add(start\_SA_{p,j,t} = end\_mixers_{i,j,t})$$

- Material paste ends being available in inventory when packaging line finishes.

$$model.Add(end\_SA_{p,j,t} = end\_packaging_{p,j,t})$$

- Material paste stays available in inventory from when it enters to when it exits.

$$model.Add(duration\_SA_{p,j,t} = end\_SA_{p,j,t} - start\_SA_{p,j,t})$$

Among shift constraints, the model is designed in order to satisfy the following rules.

- The interval of time between two subsequent shifts in mixers is constant.

$$model.Add(start\_shift\_mixers_{j,t} - start\_shift\_mixers_{j,t-1} = gap\_shifts\_mixers)$$

- The interval of time between two subsequent shifts in packaging lines is constant.

$$model.Add(start\_shift\_packaging_{k,t} - start\_shift\_packaging_{k,t-1} = gap\_shift\_packaging)$$

Among maintenance constraints, the model is designed in order to satisfy the following rules.

- The interval of time between two subsequent maintenance in mixers is constant.

$$model.Add(start\_maintenance\_mixer_{j,t} - start\_maintenance\_mixer_{j,t-1} = gap\_maintenance\_mixer)$$

- the duration of maintenance in mixers is constant.

$$model.Add(end\_maintenance\_mixer_{j,t} - start\_maintenance\_mixer_{j,t} = duration\_maintenance\_mixer)$$

- The interval of time between two subsequent maintenance in packaging line is constant.

$$model.Add(start\_maintenance\_packaging_{k,t} - start\_maintenance\_packaging_{k,t-1} = gap\_maintenance\_packaging)$$

- the duration of maintenance in packaging lines is constant.

$$model.Add(end\_maintenance\_packaging_{k,t} - star\_maintenance\_packaging_{k,t} = duration\_maintenance\_packaging)$$

Among changeover constraints, the model is designed in order to satisfy the following rules.

- The changeover in mixers starts when each production row of material paste finishes.

$$model.Add(start\_changeover\_mixers_{i,j,t} = end\_mixers_{i,j,t})$$

- The changeover in mixers lasts for a constant average duration.

$$model.Add(end\_changeover\_mixers_{i,j,t} - start\_changeover\_mixers_{i,j,t} = duration\_changeover\_mixers)$$

- The changeover in packaging lines starts when each production row of final product ends.

$$model.Add(start\_changeover\_packaging_{p,k,t} = end\_packaging_{p,k,t})$$

- The changeover in packaging lines lasts for a constant average duration.

$$model.Add(end\_changeover\_packaging_{p,k,t} - start\_changeover\_packaging_{p,k,t} = duration\_changeover\_packaging)$$

Among spare capacity constraints, the model is designed in order to satisfy the following rules.

- In mixers a constant percentage of time should be left as spare capacity.

$$\begin{aligned}model.Add(&end\_spare\_capacity\_mixer_{j,t} - \\ &start\_spare\_capacity\_mixer_{j,t} = \\ &duration\_spare\_capacity)\end{aligned}$$

- In mixers spare capacity is scheduled to start at a certain point of time.

$$model.Add(start\_spare\_capacity\_mixers_{j,t} = const.)$$

- In packaging lines a constant percentage of time should be left as spare capacity.

$$\begin{aligned}model.Add(&end\_spare\_capacity\_packaging_{k,t} - \\ &start\_spare\_capacity\_packaging_{k,t} = \\ &duration\_spare\_capacity)\end{aligned}$$

- In packaging lines spare capacity is scheduled to start at a certain point of time.

$$model.Add(start\_spare\_capacity\_packaging_{k,t} = const.)$$

Among avoid overlap constraints, the model is designed in order to satisfy the following rules.

- Each mixer can manufacture just one material at a time. Thus, overlap between each pair of material pastes *i* and *i'*, and each production row *t* and *t'* must be avoided.

$$model.AddNoOverlap(interval\_mixers_{i,j,t}, interval\_mixers_{i',j,t'})$$

- In mixers overlap between material pastes production, shift, maintenance, changeovers, and spare capacity must be avoided.

$$model.AddNoOverlap(interval\_mixers_{i,j,t}, interval\_shift\_mixers_{j,t'},$$
$$interval\_maintenance\_mixers_{j,t'},$$
$$interval\_changeover\_mixers_{i',j,t'},$$
$$interval\_spare\_capacity\_mixers_{j,t'})$$

- Each packaging line can fill and pack just one production row of SKU at a time. Thus, overlap between each pair of final items *p* and *p'*, and each production row *t* and *t'* must be avoided.

$$model.AddNoOverlap(interval\_packaging_{p,k,t}, interval\_packaging_{p',k,t'})$$

- In packaging lines overlap between SKU production, shift, maintenance, changeovers, and spare capacity must be avoided.

$$model.AddNoOverlap(interval\_packaging_{p,k,t},$$
$$interval\_shift\_packaging_{k,t'},$$
$$interval\_maintenance\_packaging_{k,t'},$$
$$interval\_changeover\_packaging_{p',k,t'},$$
$$interval\_spare\_capacity\_packaging_{k,t'})$$

3.3.5 Objective Function

The goal of the optimal scheduling model is to find a solution which maximizes the Overall Equipment Effectiveness while respecting the constraints highlighted above. Thus, the objective function minimizes the OEE components which affect negatively this indicator. In particular, the model tries to schedule the production in order to minimize the expected time each production resource results unavailable because of unplanned downtime. It is computed multiplying the expected duration of production by the average percentage of downtime incurred while manufacturing. Other factors which affect the machine availability such as production breaks and planned maintenance are seen as constants by the objective function. Indeed, production rules enforce them to happen with a certain frequency.

$$model.Minimize(sum(duration\_mixers_{i,j,t} \times downtime\_mixers_{i,j}$$

$$\text{for } i \text{ in pastes for } j \text{ in mixers for } t \text{ in T})+$$

$$sum(duration\_packaging_{p,k,t} \times downtime\_packaging_{p,k}$$

$$\text{for } p \text{ in final\_products for } k \text{ in packaging\_lines for } t \text{ in T}))$$

3.4 Solution Approach

In a nutshell, scheduling aims at allocating activities to resources over a certain time window. Often, resources are not infinite, therefore jobs are forced to share or, more likely, compete with each other to get them [29, Ruiz, 2015]. Scheduling is carried out with a certain objective to optimize, it may involve one or more criteria such as resource utilization or production costs [29, Ruiz, 2015].

Unfortunately, solving scheduling models is dramatically hard. Indeed, the vast majority of them fall into the NP-Hard class of computational problems [30, Grabot et al., 1994]. The reason behind this lies on their combinatorial nature which is relative to binary decisions. Generally, they involve activity-job allocations, task sequencing, changeovers, maintenance, and inventory management [30, Grabot et al., 1994]. Solving models, which involve several tasks, resources and jobs over a long time horizon, may be challenging using exact methods [31, Moniz et al., 2014]. Thus, at this point it is relevant to wonder if optimal solutions are truly needed in practice or not. In fact, scheduling models always reflect reality introducing a certain degree of approximation [31, Moniz et al., 2014]. It is due to real data estimation which then fed the algorithms. In addition, sometimes in order to avoid dramatically high computational complexity, constraints are designed as linear approximations or aggregations [31, Moniz et al., 2014]. As a result, finding a global optimal solution which sorts out an approximated problem may be pointless [30, Grabot et al., 1994]. In this case, it is possible to tackle real problems using alternative techniques such as heuristics [30, Grabot et al., 1994]. A possible definition of heuristic is a process which exploits the structure of the problem being studied in the most efficient way to reach a high quality solution while taking the lowest computational time [32, Widmer et al.]. They offer prompt answers even for highly complex scheduling models. Notably, solutions proposed are nearly optimal, despite this achievement can be demonstrated just if the optimality gap can be computed or forecasted [30, Grabot et al., 1994].

3.4.1 Dispatching Rules

Improving the productivity was the need which first scheduling methods tried to satisfy. At the beginning of the 20th century, they started being implemented in up-to-date manufacturing sites. Production planning was performed by hand, simply using pen and paper [29, Ruiz, 2015]. Nowadays, in several companies the scheduling mechanism is almost the same. Mainly, manufacturing scheduling is developed exploiting spreadsheets and straightforward methods to get acceptable results [29, Ruiz, 2015]. Trivial rules are often termed as dispatching rules, sequencing laws, or priority rules [29, Ruiz, 2015]. They are widely adopted in the industrial world in order to tackle scheduling problems [33, Kaban et al., 2013].

Dispatching rules are simple heuristics which involve activities or entities ordering when they arrive or when it becomes feasible to manufacture them. They are based on choices made over a collection of admissible activities [29, Ruiz, 2015].

In the course of time, several dispatching rules have been designed by scientists [34, Holthaus et al., 1997]. Interestingly, experimental results highlight that it does not exist a single rule which leads to higher performance considering all relevant objectives such as average processing time, mean and variance tardiness. Thus, the selection of the proper methodology is relative to the criterion which the model aims to improve upon [34, Holthaus et al., 1997].

A standard classification of dispatching rules divides them into *static* and *dynamic* [33, Kaban et al., 2013]. Static rules order entities assigning priority values which are not variable as time passes. Thus, they are not a function of time, but just of entity and/or resource data. Conversely, dynamic rules consider also the passage of time.

Most common dispatching rules include the following [29, Ruiz, 2015].

- *First Come First Served* (FCFS), it schedules entities based on arrival order. Thus, jobs are sequenced using a First In First Out (FIFO) policy.

- *Shortest Processing Time* (SPT), it orders jobs starting from the ones with lowest processing time. The opposite methodology is the *Longest Processing Time* (LPT) rule. SPT procedure leads to mean processing time minimization [34, Holthaus et al., 1997].

- *Earliest Due Date* (EDD), it allocates first the items with earliest due date.

It is worth to mention that dispatching rules are incredibly quick. Their computational complexity is around $\mathcal{O}(n \log n)$, where n is relative to the number of entities or activities to plan [29, Ruiz, 2015]. Other strength points embrace being straightforward to develop and understand. These features are very appreciated by human schedulers [29, Ruiz, 2015]. On the other hand, the widely known trade-off cost-quality predicts their main disadvantage, which refers to the difficulty to find global optimal solutions. It is mainly due to the fact that just local information is exploited in order to take a decision [33, Kaban et al., 2013]. Overall, considering benefits and drawbacks it is possible to conclude saying that they find large adoption especially because of their easiness to develop and use, and responsiveness to the dynamic environment of production systems [33, Kaban et al., 2013].

3.4.2 Greedy Insertion

Greedy Insertion (GI), similar to dispatching rules, is a *construction heuristic* which generates a solution incrementally [35, Tavares et al., 2009]. In every iteration the solution is enriched with a new product until each of them has been scheduled [35, Tavares et al., 2009]. Every material is allocated starting from the one which leads to the lowest expected downtime. In this way an initial scheduling solution is generated. The greedy heuristics are widely employed to decrease the time required to get results [36, Bekkar et al., 2016]. Indeed, largely, greedy techniques need reduced polynomial time complexity and they often reach higher quality local optima [36, Bekkar et al., 2016]. In addition, they are not challenging to implement and scalable [36, Bekkar et al., 2016]. The GI technique implemented in the project iteratively assigns final products to packaging lines and material pastes to mixers. Items are ordered starting from the one which has the lowest impact on the minimization problem. Blocks are scheduled going backward from packaging lines until the whole production has been planned. The solver run simulations until a local optimum is attained. As it will be detailed explained in section 5, the initial solution developed can be further enhanced applying metaheuristics [35, Tavares et al., 2009]. They are particularly powerful because, with little parameters setting, they are able to discover global optimal solutions, escaping from the traps of local optimal points, in reduced CPU times.

Chapter 4

Results

This chapter provides the relevant results of the optimal scheduling model developed. It contains four sub-chapters.

The first section (4.1) goes through the input parameters which are used to feed the algorithm. Knowing them is essential to understand the scheduling plans shown afterwards.

The second section (4.2) exhibits the results of the first simulation. It contains a step by step process to effectively schedule materials. Then, the local optimal solution is shown using a Gantt Chart.

The third section (4.3) explores the results of the second simulation. The previous solution is updated implementing a weekly review which extends the production plan of one week.

The fourth section (4.4) introduces the last simulation. It extends the model considering another weekly review. In addition, it deals with an unexpected machine failure.

4.1 Input Parameters

The main results of the optimal scheduling model developed can be explored feeding the algorithm with dummy data. Real information about GSK Oak Hill Production Site are not shared because of confidentiality reasons. However, the model is well aligned with its real process.

The end-to-end fictitious operational flow involves six mixers and six packaging lines. Final products are the output of packaging lines, whereas material pastes are manufactured in mixers. The model schedules toothpastes production over a time window of four weeks which starts on January 1st 2023 and ends on January 29th 2023.

Thirty-two SKUs, in various amount, are demanded by customers. Producing them requires fourteen pastes. This section explains the input parameters required to build a scheduling plan for the first three final products (SKU_1, SKU_2 and SKU_3). However, detailed information about other materials involved in simulations is displayed in appendix A.

The optimal scheduling process starts feeding the algorithm with data relative to the relationship between final products and pastes. For this purpose, table 4.1 shows which input materials are needed to produce the first three SKUs.

Final Product	**Material Paste**
SKU_1	$Paste_1$
SKU_2	$Paste_2$
SKU_3	$Paste_2$

Table 4.1: SKU_1, SKU_2, SKU_3 Bill of Materials.

Several constraints are introduced in the model in order to align it to reality. In particular, it includes as hard constraint the complete satisfaction of customers' demand over the planning horizon. Therefore, production blocks of each toothpaste are created in order to achieve this objective.

Target final product output, for the three SKUs considered, is illustrated in table 4.2.

Final Product	**Demand [tubes]**
SKU_1	300.000
SKU_2	300.000
SKU_3	600.000

Table 4.2: SKU_1, SKU_2, SKU_3 target demand.

The next step is to compute, for each paste, the production amount needed to satisfy SKUs demand. To accomplish this task, it is not enough to know which material is required to make every final product. The missing piece of data is the conversion rate. It states the number of toothpaste tubes made with one lib of material paste. Relevant information about conversion rate of SKU_1, SKU_2 and SKU_3 is shown in table 4.3.

Final Product	**Material Paste**	**Conversion Rate [tubes/lb]**
SKU_1	$Paste_1$	3
SKU_2	$Paste_2$	2
SKU_3	$Paste_2$	3

Table 4.3: SKU_1, SKU_2, SKU_3, conversion rate.

At this point, having available the proper data, pastes demand can be computed. The target output relative to the first two materials is displayed in table 4.4. It should be be fulfilled as soon as possible, otherwise packaging lines cannot start. Indeed, pastes, after being manufactured, are stored in containers and kept in inventory. Then, they are moved near to packaging lines to continuously feed them.

Material Paste	**Demand [lbs]**
$Paste_1$	100.000
$Paste_2$	350.000

Table 4.4: $Paste_1$, $Paste_2$ target demand.

Switching the attention on packaging lines, they are described by a key indicator, which is the throughput. It assesses the expected quantity of toothpastes made in one hour. This metric is function of the packaging line and not of the SKU being produced. Relevant information about average throughput is shown in table 4.5.

Packaging Line	**Throughput [tubes/hour]**
$Packaging_1$	6.000
$Packaging_2$	5.000
$Packaging_3$	5.000
$Packaging_4$	5.000
$Packaging_5$	5.000
$Packaging_6$	4.000

Table 4.5: Average throughput packaging lines.

Considering manufacturing lines, they have a maximum load capacity which cannot be exceeded. In addition, it is common practice to work at full capacity. Therefore, batches produced by mixers have a weight which equals the maximum load capacity. Data about this parameter is displayed in table 4.6.

Manufacturing Line	**Load Capacity [lbs]**
$Mixer_1$	20.000
$Mixer_2$	20.000
$Mixer_3$	20.000
$Mixer_4$	20.000
$Mixer_5$	20.000
$Mixer_6$	20.000

Table 4.6: Average mixers load capacity.

Another relevant indicator, to comprehensively describe mixers, is the processing time. It represents the average number of hours needed to manufacture each batch. It depends on both, mixer and material paste. Average processing times of $Paste_1$ and $Paste_2$ are displayed in table 4.7.

Paste	$\boldsymbol{Mixer_1}$	$\boldsymbol{Mixer_2}$	$\boldsymbol{Mixer_3}$	$\boldsymbol{Mixer_4}$	$\boldsymbol{Mixer_5}$	$\boldsymbol{Mixer_6}$
$Paste_1$	12	12	12	12	12	12
$Paste_2$	10	10	10	10	10	10

Table 4.7: $Paste_1$, $Paste_2$ processing time [hh].

Focusing on the final goal of the scheduling model, the machine downtime is introduced. It is split in failures affecting manufacturing lines and breakdowns relative to packaging lines. It is computed considering all the relevant causes which lead to production stoppages. Thus, the result is a percentage indicator obtained dividing the amount of time spent in breakdown status by the total available production time, for every resource and for every material paste.

In manufacturing lines the downtime depends on the material paste and on the mixer employed. Information about expected likelihood of unplanned maintenance in mixers, when manufacturing the first two pastes, is represented in table 4.8.

Paste	$\boldsymbol{Mixer_1}$	$\boldsymbol{Mixer_2}$	$\boldsymbol{Mixer_3}$	$\boldsymbol{Mixer_4}$	$\boldsymbol{Mixer_5}$	$\boldsymbol{Mixer_6}$
$Paste_1$	0.15	0.56	0.55	0.60	0.49	0.48
$Paste_2$	0.59	0.21	0.35	0.54	0.42	0.46

Table 4.8: Mixers expected percentage downtime.

As it was mentioned above, unfortunately, also packaging lines experience machine failures related to SKUs production. The likelihood of downtime is a function of both packaging line and final product. Data relative to packaging downtime when dealing with SKU_1, SKU_2, and SKU_3 is shown in table 4.9.

Final Product	$\boldsymbol{Line_1}$	$\boldsymbol{Line_2}$	$\boldsymbol{Line_3}$	$\boldsymbol{Line_4}$	$\boldsymbol{Line_5}$	$\boldsymbol{Line_6}$
SKU_1	0.47	0.44	0.40	0.25	0.34	0.38
SKU_2	0.44	0.21	0.28	0.34	0.32	0.14
SKU_3	0.43	0.25	0.29	0.23	0.21	0.23

Table 4.9: Packaging lines expected percentage downtime.

Despite the project aims at minimizing unplanned maintenance experienced by machines, there are other reasons which lead to production stoppage. They include interruptions due to shifts and breaks, planned maintenance, changeover, and spare capacity. They are characterized by duration and frequency and measured in hours.

Expected duration of every non-value-added activity is provided in table 4.10. It is possible to see that manufacturing lines do not incur in stops due to shifts. On the other hand, they are required in packaging lines where they take one hour. Planned maintenance, changeover and spare capacity account respectively for eight, six and fourteen hours, regardless the resource.

Interruption Cause	**Manufacturing Lines**	**Packaging Lines**
Shift	0	1
Maintenance	8	8
Changeover	6	6
Spare Capacity	14	14

Table 4.10: Planned non-productive time [hh].

Concerning frequency, the expected values are shown in table 4.11. It is possible to notice that shift in manufacturing lines does not happen. As a result, blank field is left. Whereas, in packaging lines it should happen every half day. Maintenance is expected to occur every two and four weeks, respectively in mixers and packaging lines. Changeover frequency is blank because it happens every time there is a product switch in the machine. Thus, its frequency is not a-priori fixed. Finally, spare capacity is left every week in every production resource.

Interruption Cause	**Manufacturing Lines**	**Packaging Lines**
Shift	-	12
Maintenance	336	672
Changeover	-	-
Spare Capacity	168	168

Table 4.11: Planned shutdown frequency [hh/stop].

Implementing inventory management constraints would significantly increase the computational time. In addition, the optimal scheduling model would be very hard to understand. Thus, it is avoided. It is assumed that there is plenty of space to store containers. As a result, storage area capacity is almost infinite. Furthermore, no material degradation is considered. Therefore, material pastes can remain in inventory for long time before being used.

4.2 Scheduling Results

This section provides the solution of the optimal scheduling model. It meets all the constraints provided. It is judged by the solver as optimal. Run time is around twenty minutes.

Results are described beginning with the allocation of non-production blocks such as maintenance, spare capacity and shift. Changeover depends on materials switching in machines. Therefore, it will be added simultaneously to them. A step by step procedure to schedule the production of SKU_1, SKU_2 and SKU_3 is highlighted. Finally, the whole scheduling plan, comprehensive of every material, is provided and the relevant failure time is computed.

Maintenance planning involves both manufacturing and packaging lines. In order to meet constraints, it is performed in mixers and packaging lines once every two and four weeks respectively. Its expected duration is eight hours. Concerning spare capacity, it is allocated in every resource. Its length is fourteen hours. It is exploited, eroding the relative block, if actual production time exceeds the schedule. It may happen in case of unexpected demand peaks, or machine breakdowns. Packaging activities interruption because of shifts is expected to happen every half day for a duration of one hour. They are related to workers lunch and breaks needs. Mixing activities, being highly automated do not incur in such kind of stoppages. Table 4.12 provides all information related to start time and finish time of the above-mentioned non-value-added activities. This schedule, useful for illustrative purposes, involves just $Mixer_1$ and $Packaging_1$. However, an exhaustive plan is exhibited in appendix A.

Production Resource	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_1$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_1$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_1$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_1$	Shift	2023-01-01 12:00	2023-01-01 13:00
$Packaging_1$	Shift	2023-01-02 00:00	2023-01-02 01:00
$Packaging_1$	Shift	2023-01-02 12:00	2023-01-02 13:00
$Packaging_1$	Shift	2023-01-03 00:00	2023-01-03 01:00
$Packaging_1$	Shift	2023-01-03 12:00	2023-01-03 13:00
$Packaging_1$	Shift	2023-01-04 00:00	2023-01-04 01:00
$Packaging_1$	Shift	2023-01-04 12:00	2023-01-04 13:00
$Packaging_1$	Shift	2023-01-05 00:00	2023-01-05 01:00
$Packaging_1$	Shift	2023-01-05 12:00	2023-01-05 13:00
...	...	...	...
$Packaging_1$	Shift	2023-01-28 00:00	2023-01-28 01:00
$Packaging_1$	Shift	2023-01-28 12:00	2023-01-28 13:00

Table 4.12: $Mixer_1$ and $Packaging_1$ non-production blocks four weeks schedule.

The optimal scheduling of maintenance, spare capacity and shift is displayed in figure 4.1. The Gantt Chart plotted shows that maintenance (dark gray blocks) is carried out simultaneously in all production resources which need it. Spare capacity (blue blocks) is planned in the last part of the week in each machine. Shift stops (thin light gray blocks) happen just in packaging lines, twice per day.

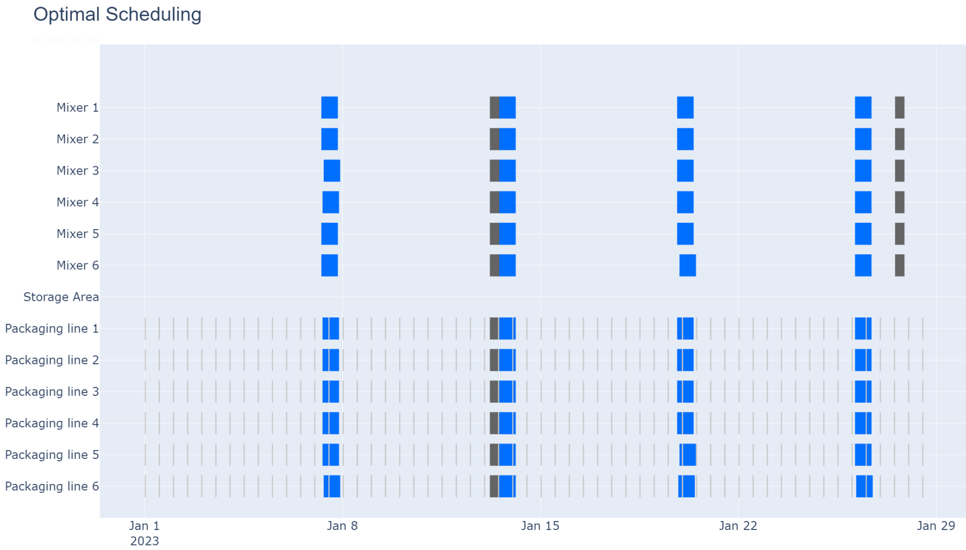

Figure 4.1: Non-production blocks four weeks schedule.

Production blocks are scheduled in order to meet constraints and minimize the overall plant downtime. They are allocated using greedy insertion. Thus, each material is made where the expected failure time is the lowest.

Considering SKU_1, it is produced in $Packaging_4$.

The reason behind this choice is that making 300.000 tubes takes 60 hours in that resource. Having an expected percentage downtime of 0.25, the machine breakdown time would be 15 hours. $Packaging_2$, $Packaging_3$, $Packaging_5$ and $Packaging_6$ have higher expected percentage downtime and equal or lower throughput. Therefore, the time lost would be more relevant. $Packaging_1$ has a higher throughput, but it would need 50 hours to produce the output demanded, and the downtime is expected to be 23.5 hours. Thus, $Packaging_4$ guarantees the best local result.

Similar reasoning leads to choose $Mixer_1$ to manufacture $Paste_1$.

Another consideration is related to the mixer production row. Indeed, dividing the production quantity by the load capacity, it is possible to see that five batches are made, one after the other. Relevant information about production amount (measured in lbs in case of pastes and in tubes in case of SKUs), start time and end time is shown in table 4.13.

Resource	Activity	Production	Start Time	End Time
$Mixer_1$	$Paste_1$	100.000	2023-01-17 02:00	2023-01-19 14:00
$Packaging_4$	SKU_1	300.000	2023-01-22 18:00	2023-01-25 06:00

Table 4.13: Production schedule to make SKU_1.

The Gantt Chart in figure 4.2 graphically displays the production schedule to make the first final product. Both items involved, $Paste_1$ and SKU_1 are represented through a blue colour bar.

In addition, the output contains information about the storage area. It correctly highlights that an inventory block is created. It starts when $Paste_1$ exits from $Mixer_1$, whereas it ends in the point in time where $Packaging_4$ finishes producing the demanded quantity of SKU_1.

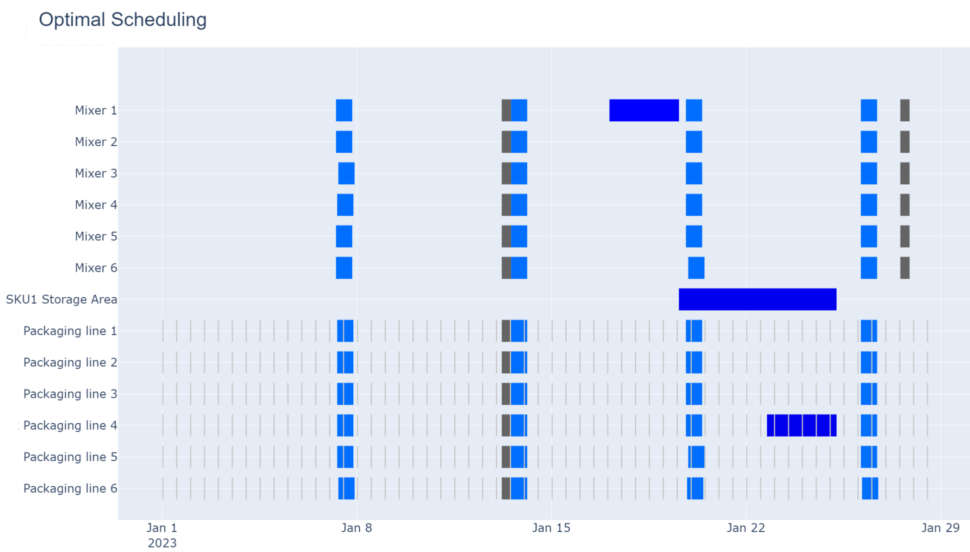

Figure 4.2: SKU_1 Optimal Scheduling Plan.

Considering SKU_2 and SKU_3, the choice of where producing them depends on production demand, throughput and expected percentage downtime.

The requirement to minimize downtime leads to make SKU_2 in $Packaging_6$, leading to 10.5 hours of expected time losses.

Similarly, SKU_3 achieves the lowest downtime (12.6 hours) in $Packaging_5$.

Applying the same reasoning in manufacturing lines, production rows of $Paste_2$ are scheduled in $Mixer_2$ and $Mixer_3$. Production rows consist of ten batches made one after the other in both resources.

In mixers the allocation choice depends on the lowest expected likelihood of downtime. Indeed, the other factors (load capacity and processing time) which could influence the decision do not vary with respect to the material paste.

Additional insights about output quantity, start time and end time are shown in table 4.14.

Resource	**Activity**	**Production**	**Start Time**	**End Time**
$Mixer_2$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_3$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Packaging_5$	SKU_3	300.000	2023-01-07 21:00	2023-01-12 21:00
$Packaging_6$	SKU_2	300.000	2023-01-07 22:00	2023-01-11 01:00

Table 4.14: Production schedule to make SKU_2, SKU_3.

The previous Gantt Chart is further enriched adding production blocks relative to SKU_2 (light aquamarine bar) and SKU_3 (dark aquamarine bar). They both require as input $Paste_2$ (aquamarine bar). The result is shown in figure 4.3.

As before, it is interesting to analyse storage area blocks. Indeed, the inventory now stocks two more set of containers, which are respectively used to continuously feed $Packaging_6$ and $Packaging_5$. The first ones store the amount of $Paste_2$ needed to make SKU_2. Conversely, the others contain the quantity of input material required to fully satisfy the demand of SKU_3. As before, they start when the mixer finishes manufacturing $Paste_2$, and they last until the relative SKU production in packaging line ends.

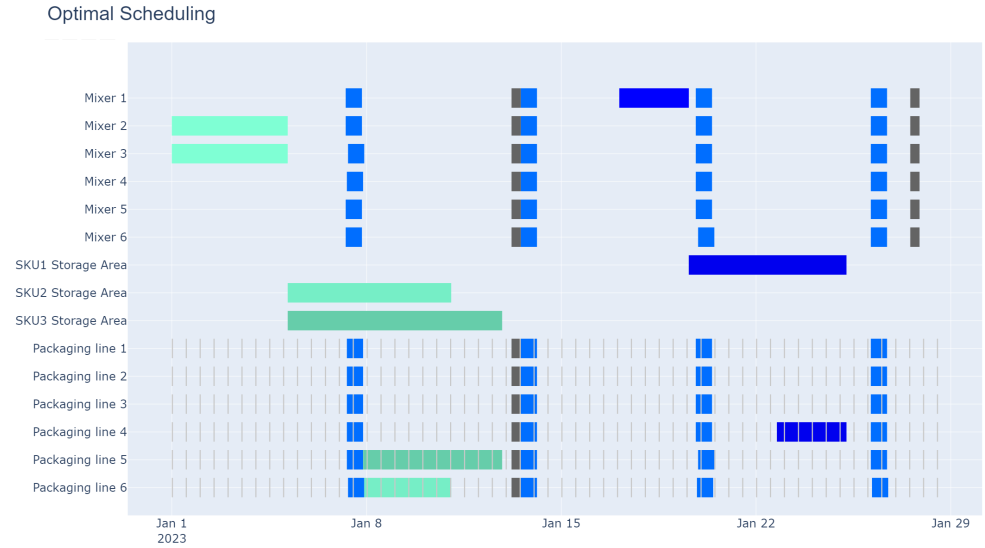

Figure 4.3: SKU_2, SKU_3 Optimal Scheduling Plan.

The complete set of information about material production scheduling is provided in appendix A. It exhibits several tables showing, for every resource, details about the item produced, the relative quantity, the scheduled start time and finish time.

Following, it is displayed the Gantt Chart which exhaustively shows production and non-production blocks allocated to every resource.

In figure 4.4 changeovers (black bars) are required every time a production row (set of batches being manufactured one after the other) ends.

Considering storage area blocks, they are covered to make the output visualization as clear as possible. However, the final figure, which also embraces storage area bars, is shown in appendix A.

In order to easily understand which is the input material related to every SKU, the colour of every final product resembles the colour of the relative paste (i.e., the material paste in purple manufactured in $Mixer_6$ feeds purple shade SKUs in $Packaging_5$). The legend is contained appendix A.

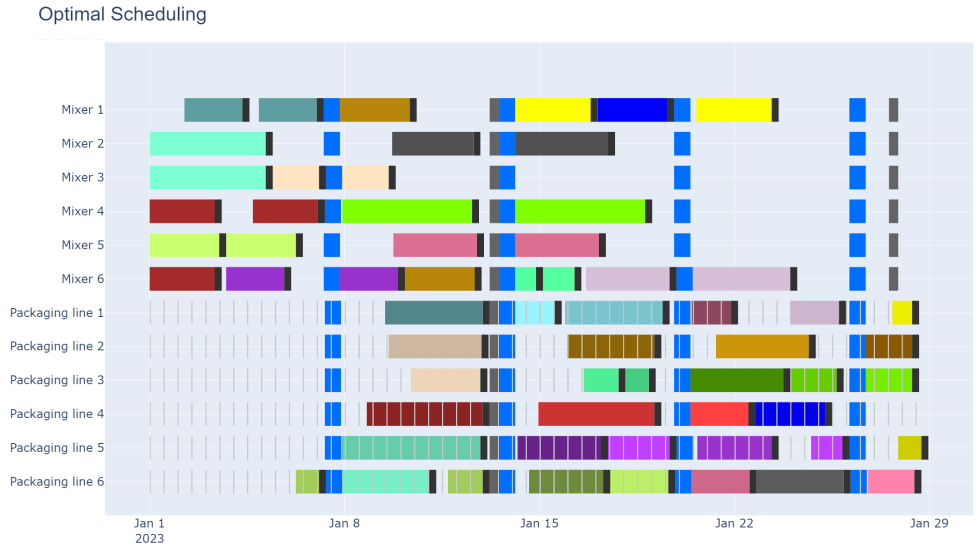

Figure 4.4: Production resources four weeks schedule.

After production planning, it is mandatory to check that all constraints are satisfied. A stringent rule, the algorithm must be compliant to, is the complete fulfilment of customers' demand. Achieving this target requires producing enough lbs of pastes. Having inputs available, expected quantity of toothpastes can be made. Table 4.15 shows that minimum productions of pastes and SKUs are achieved. It is worth to mention that total quantities are obtained aggregating either the output of manufacturing lines in case of pastes, or the output of packaging lines in case of final products.

Material Paste	Total Production	Target Demand
$Paste_1$	100.000	100.000
$Paste_2$	400.000	350.000
SKU_1	300.000	300.000
SKU_2	300.000	300.000
SKU_3	600.000	600.000

Table 4.15: $Paste_1$, $Paste_2$ comparison between production and demand.

The last output of the scheduling model provides insights about the expected non-value-added time experienced by every resource 4.16. Planned stops such as maintenance, shift and spare capacity lead to a fixed contribution, based on hard constraints, which cannot be optimized. What the algorithm minimizes is the loss of productivity due to changeover and downtime.

Resource	**Downtime**	**Changeover**	**Maintenance**	**Shift**	**S. Capacity**
$Mixer_1$	38	36	16	0	56
$Mixer_2$	43	18	16	0	56
$Mixer_3$	55	18	16	0	56
$Mixer_4$	53	24	16	0	56
$Mixer_5$	36	24	16	0	56
$Mixer_6$	119	48	16	0	56
$Packaging_1$	49	36	8	56	56
$Packaging_2$	44	24	8	56	56
$Packaging_3$	42	36	8	56	56
$Packaging_4$	67	24	8	56	56
$Packaging_5$	81	36	8	56	56
$Packaging_6$	75	48	8	56	56

Table 4.16: Four weeks non-value-added time per resource [hh].

4.3 First Weekly Review

It is interesting to show that the optimal scheduling model provided is not static. Indeed, among the various input parameters which feed the algorithm, it is possible to choose the review frequency. It allows to get updated information about expected demand and availability of resources. A rolling review period of one week is adopted to reschedule the solution based on the additional data retrieved. As a result, the new planning horizon covers the four weeks between January 8th 2023 and February 5th 2023.

The revised plan satisfies all the manufacturing constraints while minimizing the production site downtime. It is supposed that the demand of nine additional SKUs (SKU_{33}, SKU_{34},..,SKU_{41}) should be satisfied. In order to do so, four new material pastes ($Paste_{15}$, $Paste_{16}$, $Paste_{17}$, $Paste_{18}$) must be manufactured. Relevant data about them is introduced in appendix B. The solver takes around two hours to explore the search space and find a local optimal solution.

Concerning non-production blocks, spare capacity and shift schedule is updated. The reason is the one week extension of the planning period. Indeed, previous scheduling plan ends on 29th January 2023. Conversely, the updated plan finishes on February 5th 2023. Thus, it is needed to cover the additional week. Therefore, new spare capacity blocks and machine stoppages due to shifts are introduced. On the other hand, planned maintenance is not required. Indeed, in manufacturing lines it should be performed once every two weeks, whereas in packaging lines every four. Being last ones scheduled respectively on January 27th 2023 and January 13th 2023, it is not needed to plan a new maintenance before February 5th 2023. The scheduling plan of non-value-added activities in $Mixer_1$ and $Packaging_1$ is illustrated in table 4.17. The complete version which includes all production resources is provided in appendix B.

Production Resource	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Mixer_1$	Maintenance	2023-01-27 15:00	2023-01-27 23:00
$Mixer_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_1$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Mixer_1$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Mixer_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_1$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Packaging_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_1$	Spare Capacity	2023-02-01 12:00	2023-02-02 02:00
$Packaging_1$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_1$	Shift	2023-01-01 12:00	2023-01-01 13:00
...	...	...	...
$Packaging_1$	Shift	2023-02-04 00:00	2023-02-04 01:00
$Packaging_1$	Shift	2023-02-04 12:00	2023-02-04 13:00

Table 4.17: $Mixer_1$ and $Packaging_1$ non-production blocks five weeks schedule.

The scheduling can be effectively visualized using the Gantt Chart in figure 4.5.

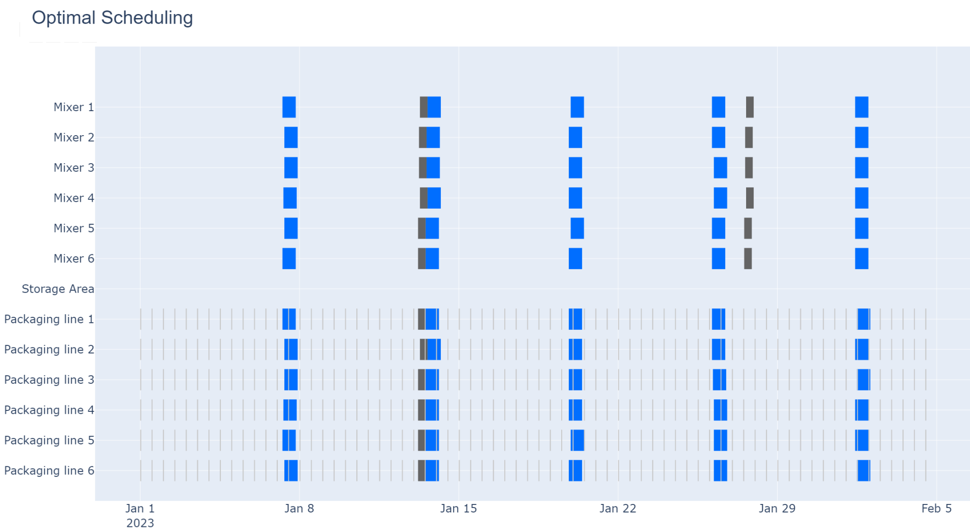

Figure 4.5: Non-production blocks five weeks schedule.

Focusing on production blocks, given that the new planning horizon starts on January 8th 2023, the old schedule before that day results frozen (i.e., unchanged). It is still displayed, but it belongs to the past. What the model optimizes is the production plan in the new time window. A remarkable difference is that mixers manufacture four new pastes which afterwards feed packaging lines to meet the additional demand of SKU_{33}, SKU_{34}, .. ,SKU_{41}. It should be noticed that the updated plan does not merely insert new production blocks leaving the others unaffected. For instance, it happens to $Paste_6$ (green bar) which moves from $Mixer_4$ to $Mixer_3$, whereas the second production row of $Paste_9$ (purple bar) switches from $Mixer_6$ to $Mixer_1$. They are reallocated in order to provide the overall lowest plant downtime. The Gantt Chart in figure 4.6 displays the complete scheduling plan related to every production resource. As before, storage area blocks are covered. However, they are illustrated in appendix B. Concerning the legend which links every bar colour with the relative material, it is also displayed in appendix B.

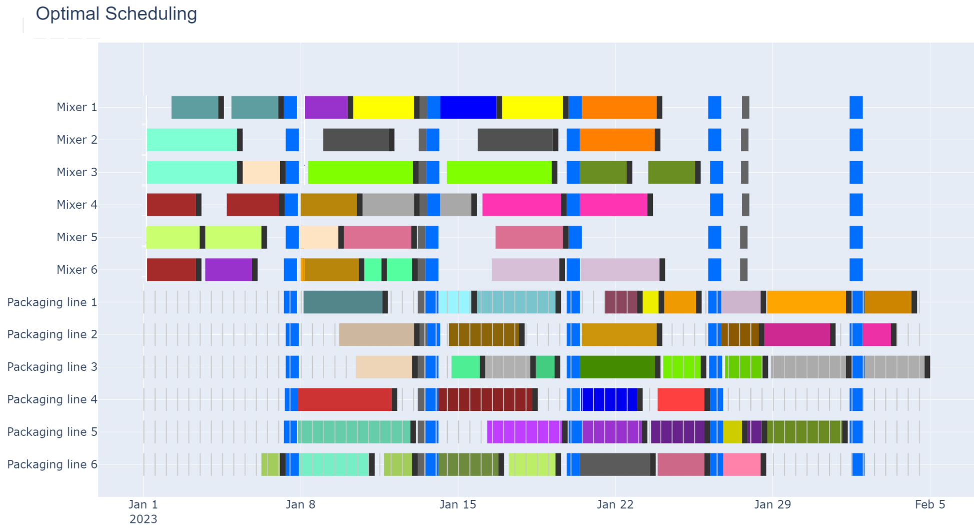

Figure 4.6: Production resources five weeks schedule.

Relevant information about non-value-added time experienced by every resource is contained in table 4.18. This result updates table 4.16. Indeed, it is related to the five week period starting from January 1st 2023.

It is relatively easy to forecast fixed contributions such as spare capacity, shift, and maintenance. Being spare capacity planned once per week with a duration of fourteen hours, then in five weeks it leads to an expected production loss of seventy hours. Manufacturing lines do not incur in shift stoppages, whereas packaging lines experience two hour of break per day. As a result, they waste seventy hours in five weeks. Concerning maintenance, it keeps the plan of the previous model.

Focusing on variable contributions such as changeover and downtime, they are always higher than previous values shown in table 4.16. The main reasons of this fact are the following. This table covers five weeks whereas the other four. Increasing the amount of SKUs demanded, it is needed to switch from one product to another more often (higher setup contribution). Finally, it is known that downtime is computed multiplying the historical percentage of time a machine spent in breakdown with the production time. Therefore, given that making more materials requires higher production time, then the downtime increases.

Resource	Downtime	Changeover	Maintenance	Shift	S. Capacity
$Mixer_1$	66	42	16	0	70
$Mixer_2$	51	24	16	0	70
$Mixer_3$	166	36	16	0	70
$Mixer_4$	122	42	16	0	70
$Mixer_5$	52	30	16	0	70
$Mixer_6$	100	42	16	0	70
$Packaging_1$	102	54	8	70	70
$Packaging_2$	66	36	8	70	70
$Packaging_3$	87	54	8	70	70
$Packaging_4$	67	24	8	70	70
$Packaging_5$	113	42	8	70	70
$Packaging_6$	75	48	8	70	70

Table 4.18: Five weeks total non-value-added time per resource [hh].

4.4 Second Weekly Review

Moving forward in time until January 14th 2023, the optimal scheduling model goes through a second weekly review. The new planning horizon considered covers the period between January 15th 2023 and February 12th 2023. Conversely, the schedule of the weeks before, belonging to the past, results frozen. This simulation is enriched dealing with a relatively long machine failure.

Recent information retrieved highlights that additional SKU_{42}, SKU_{43},..,SKU_{50} are demanded by customers. Their bill-of-materials involve new material pastes ($Paste_{19}$, $Paste_{20}$, $Paste_{21}$) which need to be manufactured in order to satisfy the relative final products demand. Detailed information about relevant input parameters of new materials is exhibited in appendix C.

The solver is able to explore the search space and find a local optimal solution in two hours. All constraints are respected while minimizing the overall production site downtime.

Starting analysing non-value-added activities, they should be extended to cover the additional week (from February 5th 2023 to February 12th 2023) which the new model is planning. Therefore, one spare capacity block is scheduled to be left in every production resource in the new week. Also, shifts in packaging lines are extended to embrace the new period. Finally, another maintenance is required to be performed in both manufacturing and packaging lines since last ones are scheduled respectively more than two and four weeks before February 12th 2023. The illustrative plan of non-production blocks in $Mixer_1$ and $Packaging_1$ is shown in table 4.19. The complete six weeks schedule is exhibited in appendix C.

Production Resource	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Mixer_1$	Maintenance	2023-01-27 15:00	2023-01-27 23:00
$Mixer_1$	Maintenance	2023-02-10 15:00	2023-02-10 23:00
$Mixer_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_1$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Mixer_1$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Mixer_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_1$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_1$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_1$	Maintenance	2023-02-10 06:00	2023-02-10 14:00
$Packaging_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Packaging_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_1$	Spare Capacity	2023-02-01 12:00	2023-02-02 02:00
$Packaging_1$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_1$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_1$	Shift	2023-01-01 12:00	2023-01-01 13:00
...	...	...	...
$Packaging_1$	Shift	2023-02-11 00:00	2023-02-11 01:00
$Packaging_1$	Shift	2023-02-11 12:00	2023-02-11 13:00

Table 4.19: $Mixer_1$ and $Packaging_1$ non-production blocks six weeks schedule.

Displaying non-production blocks using a Gantt Chart, it is possible to visualize that the planning horizon has been extended until February 12th 2023.

Consequently, maintenance , spare capacity and shift plans cover the additional week. What is interesting to highlight is that the model deals with the case of an unplanned machine breakdown. Indeed, figure 4.7 shows a dark red bar in $Mixer_5$. It is due to a mixer failure whose duration is expected to be five days. As a result, the algorithm should reschedule production blocks taking into account the unavailability of this resource from January 15th 2023 to January 20th 2023.

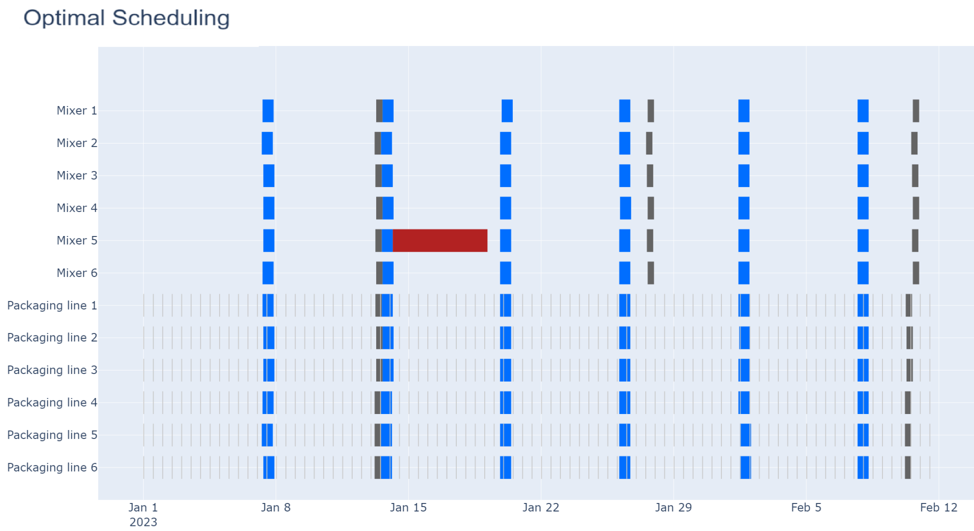

Figure 4.7: Non-production blocks six weeks schedule.

Focusing on production blocks, the relative scheduling plan is updated in order to produce the additional SKUs demanded. It means that, to best integrate them, the others may change their production resource in order to find the global lowest downtime. Also, the solution provided should promptly react to the failure of $Mixer_5$. Therefore, materials previously scheduled in that resource must be reallocated. This happens to the second production row of $paste_{10}$ (pink block) which is rescheduled to be manufactured in $Mixer_4$. Conversely, as it was previously announced, the scheduling before January 15th 2023 is unchanged.

Considering storage area blocks, they are not included in figure 4.8. They are covered in order to allow a clear visualization of the optimal scheduling model provided. However, a six weeks scheduling, comprehensive of inventory blocks, is represented in a Gantt Chart in appendix C.

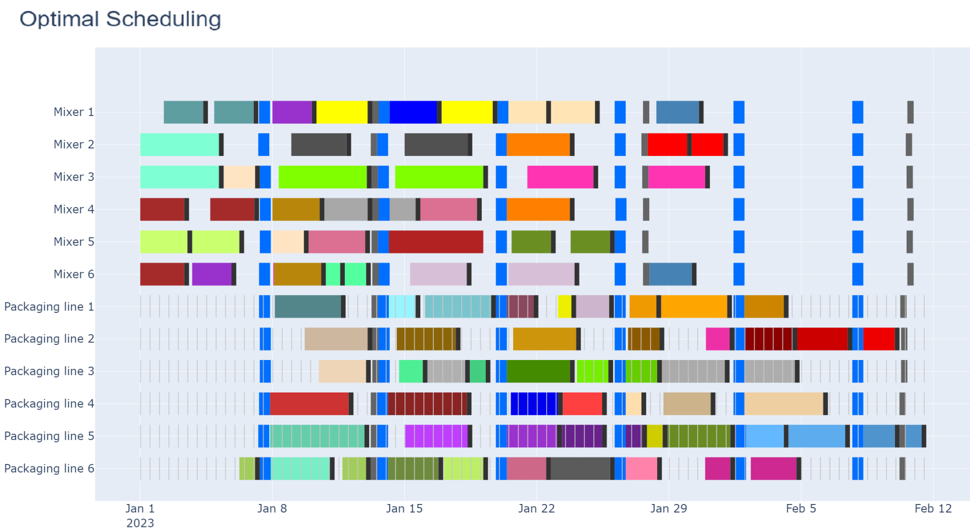

Figure 4.8: Production resources six weeks schedule.

Finally, the algorithm displays the expected non-value-added time experienced by every production resource. The output is shown in table 4.20.

Covering six weeks leads to eighty-four hours of spare capacity (fourteen hours per week). In addition, packaging lines should stop because of shifts twice per day for one hour. Therefore, the total production loss is eighty-four hours.

Concerning maintenance, being performed three times in mixers and twice in packaging lines, it respectively accounts for twenty-four and sixteen hours. $Mixer_5$ exhibits 144 maintenance hours because of the failure which is expected to last 120 hours.

Finally, the expected downtime and changeover required are computed. As it is possible to see, among critical manufacturing lines there is $Mixer_3$ with 182 hours of downtime and $Packaging_5$ with 145 hours.

Resource	**Downtime**	**Changeover**	**Maintenance**	**Shift**	**S. Capacity**
$Mixer_1$	70	54	24	0	84
$Mixer_2$	65	36	24	0	84
$Mixer_3$	182	36	24	0	84
$Mixer_4$	147	42	24	0	84
$Mixer_5$	80	36	144	0	84
$Mixer_6$	101	48	24	0	84
$Packaging_1$	102	54	16	84	84
$Packaging_2$	86	48	16	84	84
$Packaging_3$	87	54	16	84	84
$Packaging_4$	108	42	16	84	84
$Packaging_5$	145	66	16	84	84
$Packaging_6$	75	60	16	84	84

Table 4.20: Six weeks total non-value-added time per resource [hh].

Chapter 5

Conclusion and Future Work

The project explores the end-to-end optimal scheduling model which, hopefully in the future, would support industrial manufacturing sites to plan toothpastes production. Working side-by-side with GSK(CH)/Haleon Data Science Team the complete real operational flow has been discovered. Weekly meetings with site technicians and proper data analysis resulted in the design of several, production related, hard and soft constraints. Concerning the objective function, it aims at maximizing the OEE by minimizing the whole plant expected downtime. Therefore, it covers manufacturing and packaging lines. The development phase is carried out using python constraint programming packages. Given that scheduling belongs to the class of NP-Hard computational problems, cloud computing - Azure - is used to run three simulations. The first suggests a scheduling solution which covers a planning horizon of four weeks. The second extends the previous solution performing a weekly review. The third keeps on extending previous results implementing another weekly review, and it is further enriched dealing with an unexpected long machine failure. Greedy Insertion is the heuristic chosen to explore the solution space leading to local optimal results. Future research includes the application of metaheuristics such as Large Neighbourhood Search or Simulated Annealing. They may further improve the solution quality discovering a global optima scheduling. In addition, the thesis embraces a practical application of Agglomerative Hierarchical Clustering which groups products into families based on process flow similarities.

5.1 Metaheuristics

Conventionally, scheduling - belonging to the class of NP-Hard computational problems - has been tackled using heuristics like descent algorithms [32, Widmer et al., 2008]. They move through the solution space X switching, at every iteration, the old solution with a better new one. This loop continues until the objective function does not improve anymore. Therefore, the exploration ends when a local minimum is found [32, Widmer et al., 2008]. Being incapable of getting away from the first local minimum discovered is the main drawback of descent processes [32, Widmer et al., 2008]. Indeed, combinatorial optimization problems often have several local optima points which lead to sub-optimal results [32, Widmer et al., 2008]. Referencing to an objective function whose pattern is displayed in figure 5.1, descent methods starting from an initial solution s_0 would stop in s_3. However, $f(s_3)$ differ greatly from the global optimal value $f(s^*)$.

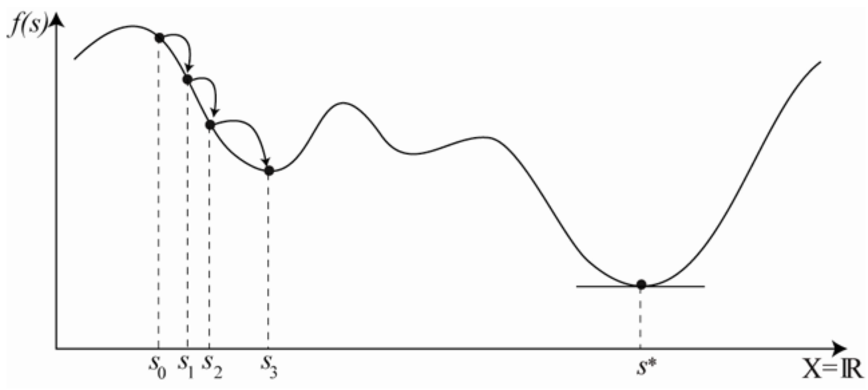

Figure 5.1: Illustrative objective function curve [32, Widmer et al., 2008].

In addition, the algorithm developed create a scheduling plan starting from packaging lines and going backward. Therefore, every SKU is assigned to the packaging line which experiences the lowest expected downtime. As a result, the relative material paste is constrained to be manufactured before the production of that SKU. This may lead to solution which are optimal considering just packaging downtime, but sub-optimal if the system is the whole production plant.

Considering for example SKU_2 which is produced in $packaging_1$ from February 2th 2023 to February 4th 2023 and the relative input material, $paste_1$, which is manufactured in $mixer_1$ from January 31th 2023 to February 1th 2023. They lead to 15 and 10 hours of downtime respectively in packaging lines and mixers. Therefore, 25 hours of plant downtime. What may happen is that if $paste_1$ were not constrained to be ready before February 2th 2023 a better solution could be producing it in $mixer_2$ (which was manufacturing $paste_3$ from January 31th 2023 to February 2th 2023) from February 2th 2023 to February 3th 2023. Then, SKU_2 would have been produced in $packaging_2$ from February 3th 2023 to February 5th 2023. This new solution would lead to 18 and 6 hours of downtime respectively in packaging lines and mixers. Therefore, 24 hours of plant downtime. Thus, a sub-optimal solution in packaging lines (15 against 18 hours of downtime) potentially leads to better overall results.

Walking through this weakness is possible using advanced local search techniques, which are usually known as metaheuristics [32, Widmer et al., 2008]. They exploit heuristics and control them with higher level strategies. The goal is to efficiently inspect the solution space [37, Blum et al., 2001]. It is possible given that they embrace methods able to escape from objective function valleys (local minima). For instance, they may allow the algorithm to switch to worse solutions (producing SKU_2 in $packaging_2$ rather than $packaging_1$) to find global optima (producing $paste_1$ in $mixer_2$ rather than $mixer_1$) [32, Widmer et al., 2008]. Furthermore, they are often stochastic and do not involve problem-related knowledge [37, Blum et al., 2001]. This class of algorithms includes Large Neighborhood Search (LNS) and Simulated Annealing (SA).

5.1.1 Large Neighborhood Search

Large Neighborhood Search is a metaheuristic introduced by Shaw in 1998 [1, Pisinger et al., 2010]. Broadly, the algorithm starts implementing Local Search (LS) on an initial solution to optimize it. Then, the solution is perturbed to avoid being trapped into local optima. Iterations end when the termination condition is met [37, Blum et al., 2001].

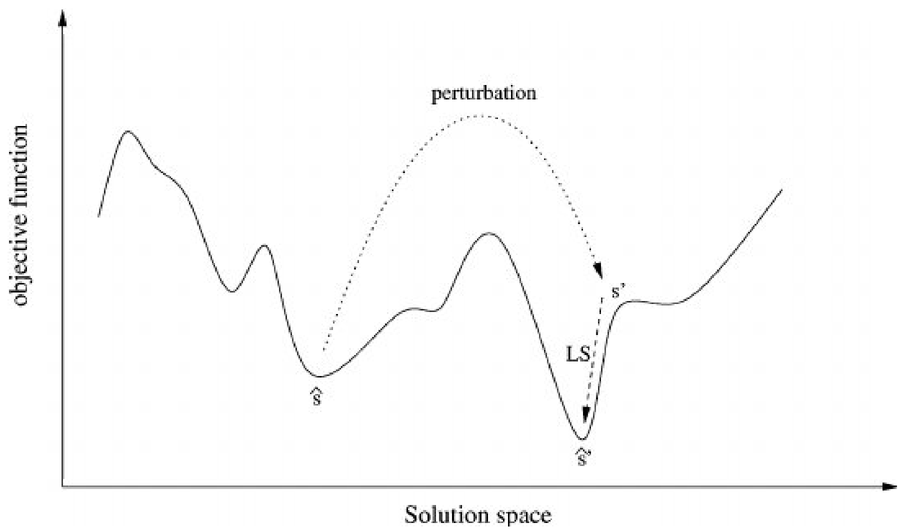

Figure 5.2: Perturbation effect [37, Blum et al., 2001].

The perturbation is performed using the *destroy and repair* method. Destroy randomly removes from the current solution a certain percentage of blocks, while repair relocates them exploiting a greedy heuristic [1, Pisinger et al., 2010].

Focusing on the destroy phase, it often embraces a randomness element which ensures that blocks removed in every iteration are different [1, Pisinger et al., 2010]. The crucial parameter is the percentage of destruction [1, Pisinger et al., 2010].

If it is too low, then the heuristic may not effectively explore the solution space. Conversely, a relevant perturbation would lead LS to restart from a casual point [1, Pisinger et al., 2010]. Approaches to deal with the degree of destruction include either the possibility to progressively increase it, or picking it casually from a certain range which depends on the instance size [1, Pisinger et al., 2010].

Considering repair, it can be *optimal* meaning that the destroyed solution is completely rebuilt in the most effective way [1, Pisinger et al., 2010]. Another option is choosing a *heuristic* repair [1, Pisinger et al., 2010]. It assumes that a good enough solution, developed from the partial one, is also acceptable. In choosing, it should be considered that optimal repair takes a plenty of computational time, but could hopefully find the global best solution [1, Pisinger et al., 2010]. However, taking into account diversification aspects, optimal repair may not be interesting given that just enhancing solutions will be produced. This would make challenging leaving local minima unless relevant percentage of destruction is accepted [1, Pisinger et al., 2010].

LNS algorithm is shown in figure 5.3. It employs the variable x^b which contains the optimal value found during the exploration, the actual solution is x, whereas x^t refers to a transitional solution which may be rejected or accepted as current one [1, Pisinger et al., 2010]. Destroy is accomplished using function $d()$, whereas $r()$ implements repair [1, Pisinger et al., 2010]. Thus, $d(x)$ yields the solution x destroyed, whereas $r(d(x))$ returns the rebuilt destroyed solution x. Explaining the process step by step, it starts initializing the optimal solution. Then, a while loop begins. It ends when the termination condition is met [1, Pisinger et al., 2010]. In line four the destroy and repair methods are executed leading to the transitional solution x^t. In line five, the heuristic analyses x^t and eventually accepts it [1, Pisinger et al., 2010]. If this happens the current solution x is updated. Acceptance criterion may be approving just better solutions [1, Pisinger et al., 2010]. Finally, if the objective function improves the optimal solution is updated. The termination condition can be related to maximum computational time or number of loops [1, Pisinger et al., 2010]. It is worth to highlight that LNS does not explore the whole neighbourhood of a solution, but just samples of it [1, Pisinger et al., 2010].

Algorithm 1 Large neighborhood search

input: a feasible solution x
$x^b = x$;
repeat
  $x^t = r(d(x))$;
  if accept(x^t, x) **then**
    $x = x^t$;
  end if
  if $c(x^t) < c(x^b)$ **then**
    $x^b = x^t$;
  end if
until stop criterion is met
return x^b

Figure 5.3: Large Neighborhood Search algorithm [1, Pisinger et al., 2010].

Concluding remarks are that LNS fluctuates between infeasible and feasible solutions. The first are due to the destroy method. Whereas, repair guarantees feasibility requirement [1, Pisinger et al., 2010].

5.1.2 Simulated Annealing

Simulated Annealing (SA) is often employed to deal with optimization problems [38, Yavuz et al., 2017]. It is a probabilistic technique which emulates the annealing process in metallurgy. A key control parameter is the temperature [39, Sieniutycz et al., 2018]. In annealing, it is gradually lowered keeping in mind that quick cooling leads to anomalies in the crystal structures. Conversely, too slow cooling leads to excellent crystals spending the lowest energy, but it also takes exorbitant processing time [39, Sieniutycz et al., 2018].

SA technique stochastically accepts a worse solution [39, Sieniutycz et al., 2018].

The likelihood of this acceptance follows the same pattern of the temperature in the metallurgy process above described. It starts taking a high value and then it gradually decreases up to almost zero in the last iterations [40, Arora, 2004]. As a result, the algorithm allows worse solutions in early stages. However, when it approaches the termination, having a marginal likelihood ensures that non-improving designs are nearly always discarded [40, Arora, 2004]. This strategy supports the model to escape from valleys [40, Arora, 2004].

The algorithm begins setting the initial temperature T_0 (which approximates the global optimal value of the objective function) [40, Arora, 2004]. Afterwards, it selects casual points in the neighbourhood of the actual solution and computes the objective value there [40, Arora, 2004]. If the solution improves, then the point is accepted and the optimal value is updated. Otherwise, the point may be accepted or rejected. Acceptance criterion of non-improving solutions is related to the value of the probability density function of the Bolzman-Gibbs distribution which again depends on the temperature parameter [40, Arora, 2004]. If this value is higher than a certain threshold, the point is accepted and the optimal current solution is updated. Finally, if the termination condition is not met, the temperature is lowered and a new iteration begins. The algorithm can stop based on several rules. The most widely adopted are the following [40, Arora, 2004].

- Termination because the solution has improved below a certain threshold during the most recent N iterations.
- Termination because the maximum number of attempts has been reached.
- Termination because a certain solution value has been achieved.

SA does not demand function continuity and differentiability [40, Arora, 2004]. Therefore, this technique finds application also in non-differentiable problems. Having available plenty of time, it is able to find global optimal solutions regardless the variable types involved (continous, discrete, integer) [40, Arora, 2004]. In case there is a tight time window, parallel computing can be a valuable mean to boost calculations [40, Arora, 2004].

Appendix A

Optimal Scheduling Results

Final Product	**Material Paste**	**Final Product**	**Material Paste**
SKU_1	$Paste_1$	SKU_{17}	$Paste_7$
SKU_2	$Paste_2$	SKU_{18}	$Paste_8$
SKU_3	$Paste_2$	SKU_{19}	$Paste_8$
SKU_4	$Paste_3$	SKU_{20}	$Paste_8$
SKU_5	$Paste_3$	SKU_{21}	$Paste_9$
SKU_6	$Paste_4$	SKU_{22}	$Paste_9$
SKU_7	$Paste_4$	SKU_{23}	$Paste_9$
SKU_8	$Paste_4$	SKU_{24}	$Paste_{10}$
SKU_9	$Paste_5$	SKU_{25}	$Paste_{10}$
SKU_{10}	$Paste_5$	SKU_{26}	$Paste_{10}$
SKU_{11}	$Paste_5$	SKU_{27}	$Paste_{11}$
SKU_{12}	$Paste_6$	SKU_{28}	$Paste_{11}$
SKU_{13}	$Paste_6$	SKU_{29}	$Paste_{12}$
SKU_{14}	$Paste_6$	SKU_{30}	$Paste_{12}$
SKU_{15}	$Paste_7$	SKU_{31}	$Paste_{13}$
SKU_{16}	$Paste_7$	SKU_{32}	$Paste_{14}$

Table A.1: Complete Bill of Materials.

Final Product	**Demand [tubes]**	**Final Product**	**Demand [tubes]**
SKU_1	300.000	SKU_{17}	375.000
SKU_2	300.000	SKU_{18}	200.000
SKU_3	600.000	SKU_{19}	200.000
SKU_4	300.000	SKU_{20}	255.000
SKU_5	400.000	SKU_{21}	400.000
SKU_6	250.000	SKU_{22}	320.000
SKU_7	500.000	SKU_{23}	360.000
SKU_8	500.000	SKU_{24}	160.000
SKU_9	200.000	SKU_{25}	200.000
SKU_{10}	500.000	SKU_{26}	200.000
SKU_{11}	500.000	SKU_{27}	150.000
SKU_{12}	200.000	SKU_{28}	100.000
SKU_{13}	200.000	SKU_{29}	100.000
SKU_{14}	400.000	SKU_{30}	100.000
SKU_{15}	200.000	SKU_{31}	300.000
SKU_{16}	400.000	SKU_{32}	250.000

Table A.2: Target demand.

Final Product	**Material Paste**	**Conversion Rate [tubes/lb]**
SKU_1	$Paste_1$	3
SKU_2	$Paste_2$	2
SKU_3	$Paste_2$	3
SKU_4	$Paste_3$	3
SKU_5	$Paste_3$	4
SKU_6	$Paste_4$	5
SKU_7	$Paste_4$	10
SKU_8	$Paste_4$	5
SKU_9	$Paste_5$	4
SKU_{10}	$Paste_5$	5
SKU_{11}	$Paste_5$	10
SKU_{12}	$Paste_6$	2
SKU_{13}	$Paste_6$	2
SKU_{14}	$Paste_6$	4
SKU_{15}	$Paste_7$	8
SKU_{16}	$Paste_7$	4
SKU_{17}	$Paste_7$	5
SKU_{18}	$Paste_8$	4
SKU_{19}	$Paste_8$	8
SKU_{20}	$Paste_8$	3
SKU_{21}	$Paste_9$	4
SKU_{22}	$Paste_9$	8
SKU_{23}	$Paste_9$	6
SKU_{24}	$Paste_{10}$	4
SKU_{25}	$Paste_{10}$	2
SKU_{26}	$Paste_{10}$	2
SKU_{27}	$Paste_{11}$	3
SKU_{28}	$Paste_{11}$	2
SKU_{29}	$Paste_{12}$	1
SKU_{30}	$Paste_{12}$	1
SKU_{31}	$Paste_{13}$	1
SKU_{32}	$Paste_{14}$	1

Table A.3: Conversion rate final product - material paste.

Material Paste	Demand [lbs]
$Paste_1$	100.000
$Paste_2$	350.000
$Paste_3$	200.000
$Paste_4$	200.000
$Paste_5$	200.000
$Paste_6$	300.000
$Paste_7$	200.000
$Paste_8$	160.000
$Paste_9$	200.000
$Paste_{10}$	240.000
$Paste_{11}$	100.000
$Paste_{12}$	200.000
$Paste_{13}$	300.000
$Paste_{14}$	250.000

Table A.4: Target material paste demand.

Paste	$Mixer_1$	$Mixer_2$	$Mixer_3$	$Mixer_4$	$Mixer_5$	$Mixer_6$
$Paste_1$	12	12	12	12	12	12
$Paste_2$	10	10	10	10	10	10
$Paste_3$	8	8	8	8	8	8
$Paste_4$	14	14	14	14	14	14
$Paste_5$	10	10	10	10	10	10
$Paste_6$	14	14	14	14	14	14
$Paste_7$	12	12	12	12	12	12
$Paste_8$	15	15	15	15	15	15
$Paste_9$	10	10	10	10	10	10
$Paste_{10}$	12	12	12	12	12	12
$Paste_{11}$	9	9	9	9	9	9
$Paste_{12}$	13	13	13	13	13	13
$Paste_{13}$	10	10	10	10	10	10
$Paste_{14}$	12	12	12	12	12	12

Table A.5: Mixers processing time [hh].

Paste	$Mixer_1$	$Mixer_2$	$Mixer_3$	$Mixer_4$	$Mixer_5$	$Mixer_6$
$Paste_1$	0.15	0.56	0.55	0.60	0.49	0.48
$Paste_2$	0.59	0.21	0.35	0.54	0.42	0.46
$Paste_3$	0.52	0.58	0.25	0.54	0.41	0.41
$Paste_4$	0.51	0.50	0.40	0.18	0.40	0.43
$Paste_5$	0.10	0.53	0.45	0.38	0.44	0.48
$Paste_6$	0.30	0.51	0.43	0.15	0.45	0.49
$Paste_7$	0.10	0.53	0.47	0.42	0.43	0.41
$Paste_8$	0.50	0.55	0.46	0.42	0.12	0.35
$Paste_9$	0.42	0.45	0.20	0.48	0.52	0.39
$Paste_{10}$	0.35	0.51	0.45	0.43	0.15	0.46
$Paste_{11}$	0.32	0.45	0.44	0.47	0.38	0.16
$Paste_{12}$	0.10	0.42	0.45	0.45	0.40	0.31
$Paste_{13}$	0.52	0.15	0.41	0.41	0.41	0.36
$Paste_{14}$	0.50	0.45	0.43	0.41	0.43	0.16

Table A.6: Mixers expected percentage downtime.

Final Product	$\boldsymbol{Line_1}$	$\boldsymbol{Line_2}$	$\boldsymbol{Line_3}$	$\boldsymbol{Line_4}$	$\boldsymbol{Line_5}$	$\boldsymbol{Line_6}$
SKU_1	0.47	0.44	0.40	0.25	0.34	0.38
SKU_2	0.44	0.21	0.28	0.34	0.32	0.14
SKU_3	0.43	0.25	0.29	0.23	0.21	0.23
SKU_4	0.43	0.34	0.22	0.33	0.31	0.43
SKU_5	0.22	0.13	0.23	0.42	0.22	0.44
SKU_6	0.43	0.33	0.35	0.25	0.37	0.23
SKU_7	0.20	0.43	0.46	0.18	0.44	0.31
SKU_8	0.43	0.45	0.32	0.22	0.38	0.32
SKU_9	0.15	0.37	0.34	0.24	0.26	0.29
SKU_{10}	0.21	0.26	0.23	0.32	0.36	0.34
SKU_{11}	0.15	0.45	0.35	0.43	0.45	0.46
SKU_{12}	0.38	0.23	0.16	0.33	0.53	0.35
SKU_{13}	0.47	0.31	0.12	0.47	0.22	0.23
SKU_{14}	0.31	0.49	0.13	0.26	0.39	0.33
SKU_{15}	0.21	0.18	0.24	0.45	0.47	0.48
SKU_{16}	0.22	0.18	0.36	0.24	0.24	0.32
SKU_{17}	0.33	0.16	0.47	0.43	0.41	0.26
SKU_{18}	0.45	0.28	0.32	0.28	0.29	0.27
SKU_{19}	0.52	0.33	0.33	0.47	0.33	0.26
SKU_{20}	0.42	0.30	0.24	0.36	0.48	0.21
SKU_{21}	0.33	0.41	0.35	0.34	0.26	0.36
SKU_{22}	0.43	0.36	0.46	0.33	0.25	0.45
SKU_{23}	0.57	0.47	0.37	0.42	0.23	0.34
SKU_{24}	0.36	0.23	0.37	0.37	0.22	0.21
SKU_{25}	0.42	0.35	0.34	0.46	0.38	0.13
SKU_{26}	0.17	0.25	0.22	0.35	0.47	0.25
SKU_{27}	0.22	0.33	0.11	0.44	0.35	0.25
SKU_{28}	0.48	0.44	0.23	0.32	0.31	0.33
SKU_{29}	0.17	0.33	0.20	0.33	0.32	0.42
SKU_{30}	0.36	0.22	0.44	0.36	0.16	0.27
SKU_{31}	0.24	0.34	0.55	0.24	0.35	0.14
SKU_{32}	0.13	0.37	0.26	0.23	0.32	0.25

Table A.7: Packaging lines expected percentage downtime.

Manufacturing Line	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_1$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_2$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_2$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_3$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_3$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_4$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_4$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_5$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_5$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_6$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_6$	Maintenance	2023-01-27 13:00	2023-01-27 21:00

Table A.8: Manufacturing lines four weeks maintenance plan.

Packaging Line	**Activity**	**Start Time**	**End Time**
$Packaging_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_2$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_3$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_4$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_5$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_6$	Maintenance	2023-01-13 05:00	2023-01-13 13:00

Table A.9: Packaging lines four weeks maintenance plan

Manufacturing Line	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_2$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_2$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_2$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_2$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_3$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_3$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_3$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_3$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_4$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Mixer_4$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_4$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_4$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_5$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_5$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_5$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_5$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_6$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_6$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_6$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Mixer_6$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00

Table A.10: Manufacturing lines four weeks spare capacity plan.

Packaging Line	Activity	Start Time	End Time
$Packaging_1$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_2$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_2$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_2$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_2$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_3$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_3$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_3$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_3$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_4$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_4$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_4$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_4$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_5$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_5$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_5$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Packaging_5$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_6$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_6$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_6$	Spare Capacity	2023-01-19 21:00	2023-01-20 11:00
$Packaging_6$	Spare Capacity	2023-01-26 04:00	2023-01-26 18:00

Table A.11: Packaging lines four weeks spare capacity plan.

Packaging Line	Activity	Start Time	End Time
$Packaging_1$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_1$	Shift	2023-01-01 12:00	2023-01-01 13:00
$Packaging_1$	Shift	2023-01-02 00:00	2023-01-02 01:00
$Packaging_1$	Shift	2023-01-02 12:00	2023-01-02 13:00
...	...	...	...
...	...	...	...
$Packaging_6$	Shift	2023-01-27 00:00	2023-01-27 01:00
$Packaging_6$	Shift	2023-01-27 12:00	2023-01-27 13:00
$Packaging_6$	Shift	2023-01-28 00:00	2023-01-28 01:00
$Packaging_6$	Shift	2023-01-28 12:00	2023-01-28 13:00

Table A.12: Packaging lines four weeks shift plan.

Tables from A.13 to A.24 show production schedule of material pastes and SKUs. In particular, for each resource it is shown the material manufactured, the relative amount produced, the start time and the end time. After every production, the changeover is required. Its duration is six hours in both manufacturing and packaging lines.

Resource	**Activity**	**Production [lbs]**	**Start Time**	**End Time**
$Mixer_1$	$Paste_5$	100.000	2023-01-02 06:00	2023-01-04 08:00
$Mixer_1$	Changeover	-	2023-01-04 08:00	2023-01-04 14:00
$Mixer_1$	$Paste_5$	100.000	2023-01-04 22:00	2023-01-07 00:00
$Mixer_1$	Changeover	-	2023-01-07 00:00	2023-01-07 06:00
$Mixer_1$	$Paste_7$	100.000	2023-01-07 20:00	2023-01-10 08:00
$Mixer_1$	Changeover	-	2023-01-10 08:00	2023-01-10 14:00
$Mixer_1$	$Paste_{12}$	100.000	2023-01-14 03:00	2023-01-16 20:00
$Mixer_1$	Changeover	-	2023-01-16 20:00	2023-01-17 02:00
$Mixer_1$	$Paste_1$	100.000	2023-01-17 02:00	2023-01-19 14:00
$Mixer_1$	Changeover	-	2023-01-19 14:00	2023-01-19 20:00
$Mixer_1$	$Paste_{12}$	100.000	2023-01-20 15:00	2023-01-23 08:00
$Mixer_1$	Changeover	-	2023-01-23 08:00	2023-01-23 14:00

Table A.13: $Mixer_1$ four weeks production schedule.

Resource	**Activity**	**Production [lbs]**	**Start Time**	**End Time**
$Mixer_2$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_2$	Changeover	-	2023-01-05 04:00	2023-01-05 10:00
$Mixer_2$	$Paste_{13}$	140.000	2023-01-09 17:00	2023-01-12 15:00
$Mixer_2$	Changeover	-	2023-01-12 15:00	2023-01-12 21:00
$Mixer_2$	$Paste_{13}$	160.000	2023-01-14 03:00	2023-01-17 11:00
$Mixer_2$	Changeover	-	2023-01-17 11:00	2023-01-17 17:00

Table A.14: $Mixer_2$ four weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_3$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_3$	Changeover	-	2023-01-05 04:00	2023-01-05 10:00
$Mixer_3$	$Paste_3$	100.000	2023-01-05 10:00	2023-01-07 02:00
$Mixer_3$	Changeover	-	2023-01-07 02:00	2023-01-07 08:00
$Mixer_3$	$Paste_3$	100.000	2023-01-07 22:00	2023-01-09 14:00
$Mixer_3$	Changeover	-	2023-01-09 14:00	2023-01-09 20:00

Table A.15: $Mixer_3$ four weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_4$	$Paste_4$	80.000	2023-01-01 00:00	2023-01-03 08:00
$Mixer_4$	Changeover	-	2023-01-03 08:00	2023-01-03 14:00
$Mixer_4$	$Paste_4$	80.000	2023-01-04 17:00	2023-01-07 01:00
$Mixer_4$	Changeover	-	2023-01-07 01:00	2023-01-07 07:00
$Mixer_4$	$Paste_6$	160.000	2023-01-07 22:00	2023-01-12 14:00
$Mixer_4$	Changeover	-	2023-01-12 14:00	2023-01-12 20:00
$Mixer_4$	$Paste_6$	160.000	2023-01-14 03:00	2023-01-18 19:00
$Mixer_4$	Changeover	-	2023-01-18 19:00	2023-01-19 01:00

Table A.16: $Mixer_4$ four weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_5$	$Paste_8$	80.000	2023-01-01 00:00	2023-01-03 12:00
$Mixer_5$	Changeover	-	2023-01-03 12:00	2023-01-03 18:00
$Mixer_5$	$Paste_8$	80.000	2023-01-03 18:00	2023-01-06 06:00
$Mixer_5$	Changeover	-	2023-01-06 06:00	2023-01-06 12:00
$Mixer_5$	$Paste_{10}$	120.000	2023-01-09 18:00	2023-01-12 18:00
$Mixer_5$	Changeover	-	2023-01-12 18:00	2023-01-13 00:00
$Mixer_5$	$Paste_{10}$	120.000	2023-01-14 03:00	2023-01-17 03:00
$Mixer_5$	Changeover	-	2023-01-17 03:00	2023-01-17 09:00

Table A.17: $Mixer_5$ four weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_6$	$Paste_4$	80.000	2023-01-01 00:00	2023-01-03 08:00
$Mixer_6$	Changeover	-	2023-01-03 08:00	2023-01-03 14:00
$Mixer_6$	$Paste_9$	100.000	2023-01-03 18:00	2023-01-05 20:00
$Mixer_6$	Changeover	-	2023-01-05 20:00	2023-01-06 02:00
$Mixer_6$	$Paste_9$	100.000	2023-01-07 20:00	2023-01-09 22:00
$Mixer_6$	Changeover	-	2023-01-09 22:00	2023-01-10 04:00
$Mixer_6$	$Paste_7$	100.000	2023-01-10 04:00	2023-01-12 16:00
$Mixer_6$	Changeover	-	2023-01-12 16:00	2023-01-12 22:00
$Mixer_6$	$Paste_{11}$	40.000	2023-01-14 03:00	2023-01-14 21:00
$Mixer_6$	Changeover	-	2023-01-14 21:00	2023-01-15 03:00
$Mixer_6$	$Paste_{11}$	60.000	2023-01-15 03:00	2023-01-16 06:00
$Mixer_6$	Changeover	-	2023-01-16 06:00	2023-01-16 12:00
$Mixer_6$	$Paste_{14}$	120.000	2023-01-16 16:00	2023-01-19 16:00
$Mixer_6$	Changeover	-	2023-01-19 16:00	2023-01-19 22:00
$Mixer_6$	$Paste_{14}$	140.000	2023-01-20 12:00	2023-01-24 00:00
$Mixer_6$	Changeover	-	2023-01-24 00:00	2023-01-24 06:00

Table A.18: $Mixer_6$ four weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_1$	SKU_{11}	504.000	2023-01-09 11:00	2023-01-12 23:00
$Packaging_1$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_1$	SKU_9	204.000	2023-01-14 03:00	2023-01-15 13:00
$Packaging_1$	Changeover	-	2023-01-15 13:00	2023-01-15 19:00
$Packaging_1$	SKU_{10}	504.000	2023-01-15 22:00	2023-01-19 10:00
$Packaging_1$	Changeover	-	2023-01-19 10:00	2023-01-19 16:00
$Packaging_1$	SKU_{26}	204.000	2023-01-20 11:00	2023-01-21 21:00
$Packaging_1$	Changeover	-	2023-01-21 21:00	2023-01-22 03:00
$Packaging_1$	SKU_{32}	252.000	2023-01-24 00:00	2023-01-25 18:00
$Packaging_1$	Changeover	-	2023-01-25 18:00	2023-01-26 00:00
$Packaging_1$	SKU_{29}	102.000	2023-01-27 16:00	2023-01-28 09:00
$Packaging_1$	Changeover	-	2023-01-28 09:00	2023-01-28 15:00

Table A.19: $Packaging_1$ four weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_2$	SKU_5	400.000	2023-01-09 14:00	2023-01-12 22:00
$Packaging_2$	Changeover	-	2023-01-12 22:00	2023-01-13 04:00
$Packaging_2$	SKU_{17}	375.000	2023-01-16 00:00	2023-01-19 03:00
$Packaging_2$	Changeover	-	2023-01-19 03:00	2023-01-19 09:00
$Packaging_2$	SKU_{16}	400.000	2023-01-21 08:00	2023-01-24 16:00
$Packaging_2$	Changeover	-	2023-01-24 16:00	2023-01-24 22:00
$Packaging_2$	SKU_{15}	200.000	2023-01-26 17:00	2023-01-28 09:00
$Packaging_2$	Changeover	-	2023-01-28 09:00	2023-01-28 15:00

Table A.20: $Packaging_2$ four weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_3$	SKU_4	300.000	2023-01-10 09:00	2023-01-12 21:00
$Packaging_3$	Changeover	-	2023-01-12 21:00	2023-01-13 03:00
$Packaging_3$	SKU_{27}	150.000	2023-01-16 14:00	2023-01-17 20:00
$Packaging_3$	Changeover	-	2023-01-17 20:00	2023-01-18 02:00
$Packaging_3$	SKU_{28}	100.000	2023-01-18 02:00	2023-01-18 22:00
$Packaging_3$	Changeover	-	2023-01-18 22:00	2023-01-19 04:00
$Packaging_3$	SKU_{14}	400.000	2023-01-20 10:00	2023-01-23 18:00
$Packaging_3$	Changeover	-	2023-01-23 18:00	2023-01-24 00:00
$Packaging_3$	SKU_{13}	200.000	2023-01-24 00:00	2023-01-25 16:00
$Packaging_3$	Changeover	-	2023-01-25 16:00	2023-01-25 22:00
$Packaging_3$	SKU_{12}	200.000	2023-01-26 17:00	2023-01-28 09:00
$Packaging_3$	Changeover	-	2023-01-28 09:00	2023-01-28 15:00

Table A.21: $Packaging_3$ four weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_4$	SKU_8	500.000	2023-01-08 19:00	2023-01-12 23:00
$Packaging_4$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_4$	SKU_7	500.000	2023-01-14 23:00	2023-01-19 03:00
$Packaging_4$	Changeover	-	2023-01-19 03:00	2023-01-19 09:00
$Packaging_4$	SKU_6	250.000	2023-01-20 10:00	2023-01-22 12:00
$Packaging_4$	Changeover	-	2023-01-22 12:00	2023-01-22 18:00
$Packaging_4$	SKU_1	300.000	2023-01-22 18:00	2023-01-25 06:00
$Packaging_4$	Changeover	-	2023-01-25 06:00	2023-01-25 12:00

Table A.22: $Packaging_4$ four weeks production schedule.

Resource	**Activity**	**Output [tubes]**	**Start Time**	**End Time**
$Packaging_5$	SKU_3	300.000	2023-01-07 21:00	2023-01-12 21:00
$Packaging_5$	Changeover	-	2023-01-12 21:00	2023-01-13 03:00
$Packaging_5$	SKU_{23}	360.000	2023-01-14 05:00	2023-01-17 05:00
$Packaging_5$	Changeover	-	2023-01-17 05:00	2023-01-17 11:00
$Packaging_5$	SKU_{21}	265.000	2023-01-17 11:00	2023-01-19 16:00
$Packaging_5$	Changeover	-	2023-01-19 16:00	2023-01-19 22:00
$Packaging_5$	SKU_{22}	320.000	2023-01-20 16:00	2023-01-23 08:00
$Packaging_5$	Changeover	-	2023-01-23 08:00	2023-01-23 14:00
$Packaging_5$	SKU_{21}	135.000	2023-01-24 18:00	2023-01-25 21:00
$Packaging_5$	Changeover	-	2023-01-25 21:00	2023-01-26 03:00
$Packaging_5$	SKU_{30}	100.000	2023-01-27 21:00	2023-01-28 17:00
$Packaging_5$	Changeover	-	2023-01-28 17:00	2023-01-28 23:00

Table A.23: $Packaging_5$ four weeks production schedule.

Resource	**Activity**	**Output [tubes]**	**Start Time**	**End Time**
$Packaging_6$	SKU_{19}	80.000	2023-01-06 06:00	2023-01-07 02:00
$Packaging_6$	Changeover	-	2023-01-07 02:00	2023-01-07 08:00
$Packaging_6$	SKU_2	300.000	2023-01-07 22:00	2023-01-11 01:00
$Packaging_6$	Changeover	-	2023-01-11 01:00	2023-01-11 07:00
$Packaging_6$	SKU_{19}	120.000	2023-01-11 17:00	2023-01-12 23:00
$Packaging_6$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_6$	SKU_{20}	256.000	2023-01-14 15:00	2023-01-17 07:00
$Packaging_6$	Changeover	-	2023-01-17 07:00	2023-01-17 13:00
$Packaging_6$	SKU_{18}	200.000	2023-01-17 13:00	2023-01-19 15:00
$Packaging_6$	Changeover	-	2023-01-19 15:00	2023-01-19 21:00
$Packaging_6$	SKU_{25}	200.000	2023-01-20 11:00	2023-01-22 13:00
$Packaging_6$	Changeover	-	2023-01-22 13:00	2023-01-22 19:00
$Packaging_6$	SKU_{31}	300.000	2023-01-22 19:00	2023-01-25 22:00
$Packaging_6$	Changeover	-	2023-01-25 22:00	2023-01-26 04:00
$Packaging_6$	SKU_{24}	160.000	2023-01-26 19:00	2023-01-28 11:00
$Packaging_6$	Changeover	-	2023-01-28 11:00	2023-01-28 17:00

Table A.24: $Packaging_6$ four weeks production schedule.

Material Paste	**Total Production [lbs]**	**Target Demand [lbs]**
$Paste_1$	100.000	100.000
$Paste_2$	400.000	350.000
$Paste_3$	200.000	200.000
$Paste_4$	240.000	200.000
$Paste_5$	200.000	200.000
$Paste_6$	320.000	300.000
$Paste_7$	200.000	200.000
$Paste_8$	160.000	160.000
$Paste_9$	200.000	200.000
$Paste_{10}$	240.000	240.000
$Paste_{11}$	100.000	100.000
$Paste_{12}$	200.000	200.000
$Paste_{13}$	300.000	300.000
$Paste_{14}$	260.000	250.000

Table A.25: Material pastes comparison between production and demand.

Final Product	**Total Production [tubes]**	**Target Demand [tubes]**
SKU_1	300.000	300.000
SKU_2	300.000	300.000
SKU_3	600.000	600.000
SKU_4	300.000	300.000
SKU_5	400.000	400.000
SKU_6	250.000	250.000
SKU_7	500.000	500.000
SKU_8	500.000	500.000
SKU_9	204.000	200.000
SKU_{10}	504.000	500.000
SKU_{11}	504.000	500.000
SKU_{12}	200.000	200.000
SKU_{13}	200.000	200.000
SKU_{14}	400.000	400.000
SKU_{15}	200.000	375.000
SKU_{16}	400.000	200.000
SKU_{17}	375.000	200.000
SKU_{18}	200.000	255.000
SKU_{19}	200.000	400.000
SKU_{20}	256.000	255.000
SKU_{21}	400.000	400.000
SKU_{22}	320.000	320.000
SKU_{23}	360.000	360.000
SKU_{24}	160.000	160.000
SKU_{25}	200.000	200.000
SKU_{26}	204.000	200.000
SKU_{27}	150.000	150.000
SKU_{28}	100.000	100.000
SKU_{29}	102.000	100.000
SKU_{30}	100.000	100.000
SKU_{31}	300.000	300.000
SKU_{32}	252.000	250.000

Table A.26: Final products comparison between production and demand.

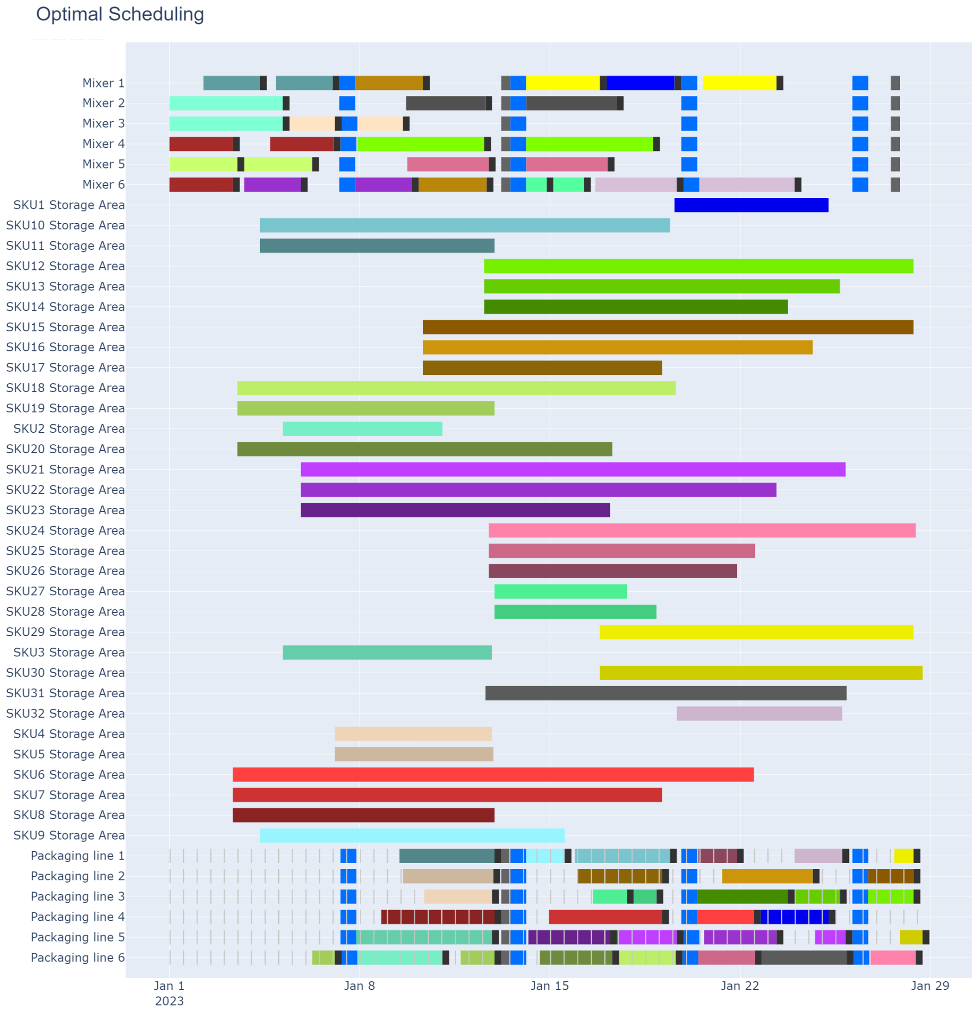

Figure A.1: Complete four weeks Optimal Scheduling Plan.

Material Paste	Colour
$Paste_1$	Blue
$Paste_2$	Aquamarine
$Paste_3$	Bisque
$Paste_4$	Brown
$Paste_5$	Cadet blue
$Paste_6$	Chartreuse
$Paste_7$	Dark goldenrod
$Paste_8$	Dark olive green
$Paste_9$	Dark orchid
$Paste_{10}$	Palevioletred
$Paste_{11}$	Sea green
$Paste_{12}$	Magenta
$Paste_{13}$	Dark Gray
$Paste_{14}$	Thistle

Table A.27: Material pastes legend.

Final Product	Colour Shade	Final Product	Colour Shade
SKU_1	Blue	SKU_{17}	Dark goldenrod
SKU_2	Light Aquamarine	SKU_{18}	Dark olive green
SKU_3	Dark Aquamarine	SKU_{19}	Dark olive green
SKU_4	Bisque	SKU_{20}	Dark olive green
SKU_5	Bisque	SKU_{21}	Dark orchid
SKU_6	Brown	SKU_{22}	Dark orchid
SKU_7	Brown	SKU_{23}	Dark orchid
SKU_8	Brown	SKU_{24}	Palevioletred
SKU_9	Cadet blue	SKU_{25}	Palevioletred
SKU_{10}	Cadet blue	SKU_{26}	Palevioletred
SKU_{11}	Cadet blue	SKU_{27}	Sea green
SKU_{12}	Chartreuse	SKU_{28}	Sea green
SKU_{13}	Chartreuse	SKU_{29}	Yellow
SKU_{14}	Chartreuse	SKU_{30}	Yellow
SKU_{15}	Goldenrod	SKU_{31}	Dark gray
SKU_{16}	Dark goldenrod	SKU_{32}	Thistle

Table A.28: SKUs legend.

Appendix B

First Weekly Review Results

Final Product	Material Paste	Final Product	Material Paste
SKU_{33}	$Paste_{15}$	SKU_{38}	$Paste_{17}$
SKU_{34}	$Paste_{15}$	SKU_{39}	$Paste_{18}$
SKU_{35}	$Paste_{16}$	SKU_{40}	$Paste_{18}$
SKU_{36}	$Paste_{17}$	SKU_{41}	$Paste_{18}$
SKU_{37}	$Paste_{17}$		

Table B.1: Additional Bill of Materials.

Final Product	Demand [tubes]	Final Product	Demand [tubes]
SKU_{33}	150.000	SKU_{38}	300.000
SKU_{34}	350.000	SKU_{39}	400.000
SKU_{35}	400.000	SKU_{40}	320.000
SKU_{36}	500.000	SKU_{41}	240.000
SKU_{37}	200.000		

Table B.2: Additional demand.

Final Product	Material Paste	Conversion Rate [tubes/lb]
SKU_{33}	$Paste_{15}$	2
SKU_{34}	$Paste_{15}$	2
SKU_{35}	$Paste_{16}$	2
SKU_{36}	$Paste_{17}$	5
SKU_{37}	$Paste_{17}$	2
SKU_{38}	$Paste_{17}$	3
SKU_{39}	$Paste_{18}$	8
SKU_{40}	$Paste_{18}$	8
SKU_{41}	$Paste_{18}$	4

Table B.3: Additional conversion rate final product - material paste.

Material Paste	Demand [lbs]
$Paste_{15}$	250.000
$Paste_{16}$	200.000
$Paste_{17}$	300.000
$Paste_{18}$	150.000

Table B.4: Additional material paste demand.

Paste	$Mixer_1$	$Mixer_2$	$Mixer_3$	$Mixer_4$	$Mixer_5$	$Mixer_6$
$Paste_{15}$	12	12	12	12	12	12
$Paste_{16}$	10	10	10	10	10	10
$Paste_{17}$	10	10	10	10	10	10
$Paste_{18}$	11	11	11	11	11	11

Table B.5: Mixers additional material processing time [hh].

Paste	$Mixer_1$	$Mixer_2$	$Mixer_3$	$Mixer_4$	$Mixer_5$	$Mixer_6$
$Paste_{15}$	0.43	0.56	0.15	0.30	0.49	0.48
$Paste_{16}$	0.59	0.35	0.25	0.54	0.42	0.46
$Paste_{17}$	0.23	0.10	0.21	0.43	0.48	0.41
$Paste_{18}$	0.20	0.12	0.38	0.34	0.34	0.23

Table B.6: Mixers additional expected percentage downtime.

Final Product	$\boldsymbol{Line_1}$	$\boldsymbol{Line_2}$	$\boldsymbol{Line_3}$	$\boldsymbol{Line_4}$	$\boldsymbol{Line_5}$	$\boldsymbol{Line_6}$
SKU_{33}	0.39	0.25	0.32	0.30	0.42	0.29
SKU_{34}	0.38	0.21	0.33	0.35	0.41	0.23
SKU_{35}	0.51	0.46	0.45	0.50	0.41	0.47
SKU_{36}	0.32	0.38	0.39	0.42	0.38	0.35
SKU_{37}	0.25	0.38	0.41	0.45	0.40	0.39
SKU_{38}	0.36	0.42	0.48	0.39	0.38	0.42
SKU_{39}	0.41	0.35	0.25	0.41	0.36	0.43
SKU_{40}	0.45	0.36	0.29	0.38	0.30	0.45
SKU_{41}	0.37	0.22	0.15	0.30	0.24	0.38

Table B.7: Packaging lines additional expected percentage downtime.

Manufacturing Line	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Mixer_1$	Maintenance	2023-01-27 15:00	2023-01-27 23:00
$Mixer_2$	Maintenance	2023-01-13 06:00	2023-01-13 14:00
$Mixer_2$	Maintenance	2023-01-27 14:00	2023-01-27 22:00
$Mixer_3$	Maintenance	2023-01-13 06:00	2023-01-13 14:00
$Mixer_3$	Maintenance	2023-01-27 14:00	2023-01-27 22:00
$Mixer_4$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Mixer_4$	Maintenance	2023-01-27 15:00	2023-01-27 23:00
$Mixer_5$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_5$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_6$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_6$	Maintenance	2023-01-27 13:00	2023-01-27 21:00

Table B.8: Manufacturing lines five weeks maintenance plan.

Packaging Line	**Activity**	**Start Time**	**End Time**
$Packaging_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_2$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Packaging_3$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_4$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_5$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_6$	Maintenance	2023-01-13 05:00	2023-01-13 13:00

Table B.9: Packaging lines five weeks maintenance plan.

Manufacturing Line	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_1$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Mixer_1$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Mixer_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_1$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_2$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_2$	Spare Capacity	2023-01-13 14:00	2023-01-14 04:00
$Mixer_2$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_2$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_2$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_3$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_3$	Spare Capacity	2023-01-13 14:00	2023-01-14 04:00
$Mixer_3$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_3$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_3$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_4$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Mixer_4$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Mixer_4$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_4$	Spare Capacity	2023-01-26 05:00	2023-01-26 19:00
$Mixer_4$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_5$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_5$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_5$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Mixer_5$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_5$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_6$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_6$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_6$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_6$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_6$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00

Table B.10: Manufacturing lines five weeks spare capacity plan.

Packaging Line	**Activity**	**Start Time**	**End Time**
$Packaging_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Packaging_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_1$	Spare Capacity	2023-02-01 12:00	2023-02-02 02:00
$Packaging_2$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_2$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Packaging_2$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_2$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_2$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_3$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_3$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_3$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_3$	Spare Capacity	2023-01-26 04:00	2023-01-26 18:00
$Packaging_3$	Spare Capacity	2023-02-01 12:00	2023-02-02 02:00
$Packaging_4$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_4$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_4$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_4$	Spare Capacity	2023-01-26 05:00	2023-01-26 19:00
$Packaging_4$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_5$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Packaging_5$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_5$	Spare Capacity	2023-01-19 03:00	2023-01-20 12:00
$Packaging_5$	Spare Capacity	2023-01-26 05:00	2023-01-26 19:00
$Packaging_5$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_6$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_6$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_6$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_6$	Spare Capacity	2023-01-26 05:00	2023-01-26 19:00
$Packaging_6$	Spare Capacity	2023-02-01 19:00	2023-02-02 02:00

Table B.11: Packaging lines five weeks spare capacity plan.

Packaging Line	Activity	Start Time	End Time
$Packaging_1$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_1$	Shift	2023-01-01 12:00	2023-01-01 13:00
$Packaging_1$	Shift	2023-02-04 00:00	2023-02-04 01:00
$Packaging_1$	Shift	2023-02-04 12:00	2023-02-04 13:00
...	...	...	...
...	...	...	...
$Packaging_6$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_6$	Shift	2023-01-01 12:00	2023-01-01 13:00
$Packaging_6$	Shift	2023-02-04 00:00	2023-02-04 01:00
$Packaging_6$	Shift	2023-02-04 12:00	2023-02-04 13:00

Table B.12: Packaging lines five weeks shift plan.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_1$	$Paste_5$	100.000	2023-01-02 06:00	2023-01-04 08:00
$Mixer_1$	Changeover	-	2023-01-04 08:00	2023-01-04 14:00
$Mixer_1$	$Paste_5$	100.000	2023-01-04 22:00	2023-01-07 00:00
$Mixer_1$	Changeover	-	2023-01-07 00:00	2023-01-07 06:00
$Mixer_1$	$Paste_9$	100.000	2023-01-08 00:00	2023-01-10 02:00
$Mixer_1$	Changeover	-	2023-01-10 02:00	2023-01-10 08:00
$Mixer_1$	$Paste_{12}$	100.000	2023-01-10 08:00	2023-01-13 01:00
$Mixer_1$	Changeover	-	2023-01-13 01:00	2023-01-13 07:00
$Mixer_1$	$Paste_1$	100.000	2023-01-14 05:00	2023-01-16 17:00
$Mixer_1$	Changeover	-	2023-01-16 17:00	2023-01-16 23:00
$Mixer_1$	$Paste_{12}$	100.000	2023-01-16 23:00	2023-01-19 16:00
$Mixer_1$	Changeover	-	2023-01-19 16:00	2023-01-19 22:00
$Mixer_1$	$Paste_{17}$	160.000	2023-01-20 12:00	2023-01-23 20:00
$Mixer_1$	Changeover	-	2023-01-23 20:00	2023-01-24 02:00

Table B.13: $Mixer_1$ five weeks production schedule.

Resource	**Activity**	**Production [lbs]**	**Start Time**	**End Time**
$Mixer_2$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_2$	Changeover	-	2023-01-05 04:00	2023-01-05 10:00
$Mixer_2$	$Paste_{13}$	140.000	2023-01-09 00:00	2023-01-11 22:00
$Mixer_2$	Changeover	-	2023-01-11 22:00	2023-01-12 04:00
$Mixer_2$	$Paste_{13}$	160.000	2023-01-15 21:00	2023-01-19 05:00
$Mixer_2$	Changeover	-	2023-01-19 05:00	2023-01-19 11:00
$Mixer_2$	$Paste_{17}$	160.000	2023-01-20 10:00	2023-01-23 18:00
$Mixer_2$	Changeover	-	2023-01-23 18:00	2023-01-24 00:00

Table B.14: $Mixer_2$ five weeks production schedule.

Resource	**Activity**	**Production [lbs]**	**Start Time**	**End Time**
$Mixer_3$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_3$	Changeover	-	2023-01-05 04:00	2023-01-05 10:00
$Mixer_3$	$Paste_3$	100.000	2023-01-05 10:00	2023-01-07 02:00
$Mixer_3$	Changeover	-	2023-01-07 02:00	2023-01-07 08:00
$Mixer_3$	$Paste_6$	160.000	2023-01-08 08:00	2023-01-13 00:00
$Mixer_3$	Changeover	-	2023-01-13 00:00	2023-01-13 06:00
$Mixer_3$	$Paste_6$	160.000	2023-01-14 12:00	2023-01-19 04:00
$Mixer_3$	Changeover	-	2023-01-19 04:00	2023-01-19 10:00
$Mixer_3$	$Paste_{16}$	100.000	2023-01-20 10:00	2023-01-22 12:00
$Mixer_3$	Changeover	-	2023-01-22 12:00	2023-01-22 18:00
$Mixer_3$	$Paste_{16}$	100.000	2023-01-23 11:00	2023-01-25 13:00
$Mixer_3$	Changeover	-	2023-01-25 13:00	2023-01-25 19:00

Table B.15: $Mixer_3$ five weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_4$	$Paste_4$	80.000	2023-01-01 00:00	2023-01-03 08:00
$Mixer_4$	Changeover	-	2023-01-03 08:00	2023-01-03 14:00
$Mixer_4$	$Paste_4$	80.000	2023-01-04 17:00	2023-01-07 01:00
$Mixer_4$	Changeover	-	2023-01-07 01:00	2023-01-07 07:00
$Mixer_4$	$Paste_7$	100.000	2023-01-08 00:00	2023-01-10 12:00
$Mixer_4$	Changeover	-	2023-01-10 12:00	2023-01-10 18:00
$Mixer_4$	$Paste_{18}$	100.000	2023-01-10 18:00	2023-01-13 01:00
$Mixer_4$	Changeover	-	2023-01-13 01:00	2023-01-13 07:00
$Mixer_4$	$Paste_{18}$	60.000	2023-01-14 05:00	2023-01-15 14:00
$Mixer_4$	Changeover	-	2023-01-15 14:00	2023-01-15 20:00
$Mixer_4$	$Paste_{15}$	140.000	2023-01-16 02:00	2023-01-19 14:00
$Mixer_4$	Changeover	-	2023-01-19 14:00	2023-01-19 20:00
$Mixer_4$	$Paste_{15}$	120.000	2023-01-20 10:00	2023-01-23 10:00
$Mixer_4$	Changeover	-	2023-01-23 10:00	2023-01-23 16:00

Table B.16: $Mixer_4$ five weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_5$	$Paste_8$	80.000	2023-01-01 00:00	2023-01-03 12:00
$Mixer_5$	Changeover	-	2023-01-03 12:00	2023-01-03 18:00
$Mixer_5$	$Paste_8$	80.000	2023-01-03 18:00	2023-01-06 06:00
$Mixer_5$	Changeover	-	2023-01-06 06:00	2023-01-06 12:00
$Mixer_5$	$Paste_3$	100.000	2023-01-08 00:00	2023-01-09 16:00
$Mixer_5$	Changeover	-	2023-01-09 16:00	2023-01-09 22:00
$Mixer_5$	$Paste_{10}$	120.000	2023-01-09 22:00	2023-01-12 22:00
$Mixer_5$	Changeover	-	2023-01-12 22:00	2023-01-13 04:00
$Mixer_5$	$Paste_{10}$	120.000	2023-01-16 16:00	2023-01-19 16:00
$Mixer_5$	Changeover	-	2023-01-19 16:00	2023-01-19 22:00

Table B.17: $Mixer_5$ five weeks production schedule.

Resource	**Activity**	**Production [lbs]**	**Start Time**	**End Time**
$Mixer_6$	$Paste_4$	80.000	2023-01-01 00:00	2023-01-03 08:00
$Mixer_6$	Changeover	-	2023-01-03 08:00	2023-01-03 14:00
$Mixer_6$	$Paste_9$	100.000	2023-01-03 18:00	2023-01-05 20:00
$Mixer_6$	Changeover	-	2023-01-05 20:00	2023-01-06 02:00
$Mixer_6$	$Paste_7$	100.000	2023-01-08 02:00	2023-01-10 14:00
$Mixer_6$	Changeover	-	2023-01-10 14:00	2023-01-10 20:00
$Mixer_6$	$Paste_{11}$	40.000	2023-01-10 20:00	2023-01-11 14:00
$Mixer_6$	Changeover	-	2023-01-11 14:00	2023-01-11 20:00
$Mixer_6$	$Paste_{11}$	60.000	2023-01-11 20:00	2023-01-12 23:00
$Mixer_6$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Mixer_6$	$Paste_{14}$	120.000	2023-01-16 12:00	2023-01-19 12:00
$Mixer_6$	Changeover	-	2023-01-19 12:00	2023-01-19 18:00
$Mixer_6$	$Paste_{14}$	140.000	2023-01-20 11:00	2023-01-23 23:00
$Mixer_6$	Changeover	-	2023-01-23 23:00	2023-01-24 05:00

Table B.18: $Mixer_6$ five weeks production schedule.

Resource	**Activity**	**Output [tubes]**	**Start Time**	**End Time**
$Packaging_1$	SKU_{11}	504.000	2023-01-08 03:00	2023-01-11 15:00
$Packaging_1$	Changeover	-	2023-01-11 15:00	2023-01-11 21:00
$Packaging_1$	SKU_9	204.000	2023-01-14 04:00	2023-01-15 14:00
$Packaging_1$	Changeover	-	2023-01-15 14:00	2023-01-15 20:00
$Packaging_1$	SKU_{10}	504.000	2023-01-15 20:00	2023-01-19 08:00
$Packaging_1$	Changeover	-	2023-01-19 08:00	2023-01-19 14:00
$Packaging_1$	SKU_{26}	204.000	2023-01-21 13:00	2023-01-22 23:00
$Packaging_1$	Changeover	-	2023-01-22 23:00	2023-01-23 05:00
$Packaging_1$	SKU_{29}	102.000	2023-01-23 05:00	2023-01-23 22:00
$Packaging_1$	Changeover	-	2023-01-23 22:00	2023-01-24 04:00
$Packaging_1$	SKU_{37}	204.000	2023-01-24 04:00	2023-01-25 14:00
$Packaging_1$	Changeover	-	2023-01-25 14:00	2023-01-25 20:00
$Packaging_1$	SKU_{32}	252.000	2023-01-26 17:00	2023-01-28 11:00
$Packaging_1$	Changeover	-	2023-01-28 11:00	2023-01-28 17:00
$Packaging_1$	SKU_{36}	504.000	2023-01-28 18:00	2023-02-01 06:00
$Packaging_1$	Changeover	-	2023-02-01 06:00	2023-02-01 12:00
$Packaging_1$	SKU_{38}	300.000	2023-02-02 02:00	2023-02-04 04:00
$Packaging_1$	Changeover	-	2023-02-04 04:00	2023-02-04 10:00

Table B.19: $Packaging_1$ five weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_2$	SKU_5	400.000	2023-01-09 17:00	2023-01-13 01:00
$Packaging_2$	Changeover	-	2023-01-13 01:00	2023-01-13 07:00
$Packaging_2$	SKU_{17}	375.000	2023-01-14 14:00	2023-01-17 17:00
$Packaging_2$	Changeover	-	2023-01-17 17:00	2023-01-17 23:00
$Packaging_2$	SKU_{16}	400.000	2023-01-20 12:00	2023-01-23 20:00
$Packaging_2$	Changeover	-	2023-01-23 20:00	2023-01-24 02:00
$Packaging_2$	SKU_{15}	200.000	2023-01-26 17:00	2023-01-28 09:00
$Packaging_2$	Changeover	-	2023-01-28 09:00	2023-01-28 15:00
$Packaging_2$	SKU_{34}	350.000	2023-01-28 15:00	2023-01-31 13:00
$Packaging_2$	Changeover	-	2023-01-31 13:00	2023-01-31 19:00
$Packaging_2$	SKU_{33}	150.000	2023-02-02 00:00	2023-02-03 06:00
$Packaging_2$	Changeover	-	2023-02-03 06:00	2023-02-03 12:00

Table B.20: $Packaging_2$ five weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_3$	SKU_4	300.000	2023-01-10 11:00	2023-01-12 23:00
$Packaging_3$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_3$	SKU_{27}	150.000	2023-01-14 17:00	2023-01-15 23:00
$Packaging_3$	Changeover	-	2023-01-15 23:00	2023-01-16 05:00
$Packaging_3$	SKU_{41}	240.000	2023-01-16 05:00	2023-01-18 05:00
$Packaging_3$	Changeover	-	2023-01-18 05:00	2023-01-18 11:00
$Packaging_3$	SKU_{28}	100.000	2023-01-18 11:00	2023-01-19 07:00
$Packaging_3$	Changeover	-	2023-01-19 07:00	2023-01-19 13:00
$Packaging_3$	SKU_{14}	400.000	2023-01-20 10:00	2023-01-23 18:00
$Packaging_3$	Changeover	-	2023-01-23 18:00	2023-01-24 00:00
$Packaging_3$	SKU_{12}	200.000	2023-01-24 03:00	2023-01-25 19:00
$Packaging_3$	Changeover	-	2023-01-25 19:00	2023-01-26 01:00
$Packaging_3$	SKU_{13}	200.000	2023-01-26 21:00	2023-01-28 13:00
$Packaging_3$	Changeover	-	2023-01-28 13:00	2023-01-28 19:00
$Packaging_3$	SKU_{39}	400.000	2023-01-28 22:00	2023-02-01 06:00
$Packaging_3$	Changeover	-	2023-02-01 06:00	2023-02-01 12:00
$Packaging_3$	SKU_{40}	320.000	2023-02-02 02:00	2023-02-04 18:00
$Packaging_3$	Changeover	-	2023-02-04 18:00	2023-02-05 00:00

Table B.21: $Packaging_3$ five weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_4$	SKU_7	500.000	2023-01-07 21:00	2023-01-12 01:00
$Packaging_4$	Changeover	-	2023-01-12 01:00	2023-01-12 07:00
$Packaging_4$	SKU_8	500.000	2023-01-14 03:00	2023-01-18 07:00
$Packaging_4$	Changeover	-	2023-01-18 07:00	2023-01-18 13:00
$Packaging_4$	SKU_1	300.000	2023-01-20 11:00	2023-01-22 23:00
$Packaging_4$	Changeover	-	2023-01-22 23:00	2023-01-23 05:00
$Packaging_4$	SKU_6	250.000	2023-01-23 21:00	2023-01-25 23:00
$Packaging_4$	Changeover	-	2023-01-25 23:00	2023-01-26 05:00

Table B.22: $Packaging_4$ five weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_5$	SKU_3	600.000	2023-01-07 21:00	2023-01-12 21:00
$Packaging_5$	Changeover	-	2023-01-12 21:00	2023-01-13 03:00
$Packaging_5$	SKU_{21}	400.000	2023-01-16 07:00	2023-01-19 15:00
$Packaging_5$	Changeover	-	2023-01-19 15:00	2023-01-19 21:00
$Packaging_5$	SKU_{22}	320.000	2023-01-20 12:00	2023-01-23 04:00
$Packaging_5$	Changeover	-	2023-01-23 04:00	2023-01-23 10:00
$Packaging_5$	SKU_{23}	285.000	2023-01-23 14:00	2023-01-25 23:00
$Packaging_5$	Changeover	-	2023-01-25 23:00	2023-01-26 05:00
$Packaging_5$	SKU_{30}	100.000	2023-01-26 19:00	2023-01-27 15:00
$Packaging_5$	Changeover	-	2023-01-27 15:00	2023-01-27 21:00
$Packaging_5$	SKU_{23}	75.000	2023-01-27 21:00	2023-01-28 12:00
$Packaging_5$	Changeover	-	2023-01-28 12:00	2023-01-28 18:00
$Packaging_5$	SKU_{35}	400.000	2023-01-28 18:00	2023-02-01 02:00
$Packaging_5$	Changeover	-	2023-02-01 02:00	2023-02-01 08:00

Table B.23: $Packaging_5$ five weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_6$	SKU_{19}	80.000	2023-01-06 06:00	2023-01-07 02:00
$Packaging_6$	Changeover	-	2023-01-07 02:00	2023-01-07 08:00
$Packaging_6$	SKU_2	300.000	2023-01-07 22:00	2023-01-11 01:00
$Packaging_6$	Changeover	-	2023-01-11 01:00	2023-01-11 07:00
$Packaging_6$	SKU_{19}	120.000	2023-01-11 17:00	2023-01-12 23:00
$Packaging_6$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_6$	SKU_{20}	256.000	2023-01-14 03:00	2023-01-16 19:00
$Packaging_6$	Changeover	-	2023-01-16 19:00	2023-01-17 01:00
$Packaging_6$	SKU_{18}	200.000	2023-01-17 06:00	2023-01-19 08:00
$Packaging_6$	Changeover	-	2023-01-19 08:00	2023-01-19 14:00
$Packaging_6$	SKU_{31}	300.000	2023-01-20 10:00	2023-01-23 13:00
$Packaging_6$	Changeover	-	2023-01-23 13:00	2023-01-23 19:00
$Packaging_6$	SKU_{25}	200.000	2023-01-23 21:00	2023-01-25 23:00
$Packaging_6$	Changeover	-	2023-01-25 23:00	2023-01-26 05:00
$Packaging_6$	SKU_{24}	160.000	2023-01-26 19:00	2023-01-28 11:00
$Packaging_6$	Changeover	-	2023-01-28 11:00	2023-01-28 17:00

Table B.24: $Packaging_6$ five weeks production schedule.

Material Paste	Total Production [lbs]	Target Demand [lbs]
$Paste_{15}$	260.000	250.000
$Paste_{16}$	200.000	200.000
$Paste_{17}$	320.000	300.000
$Paste_{18}$	160.000	150.000

Table B.25: Additional material pastes comparison between production and demand.

Final Product	**Total Production [tubes]**	**Target Demand [tubes]**
SKU_{33}	150.000	150.000
SKU_{34}	350.000	350.000
SKU_{35}	400.000	400.000
SKU_{36}	504.000	500.000
SKU_{37}	204.000	200.000
SKU_{38}	300.000	300.000
SKU_{39}	400.000	400.000
SKU_{40}	320.000	320.000
SKU_{41}	240.000	240.000

Table B.26: Additional SKUs comparison between production and demand.

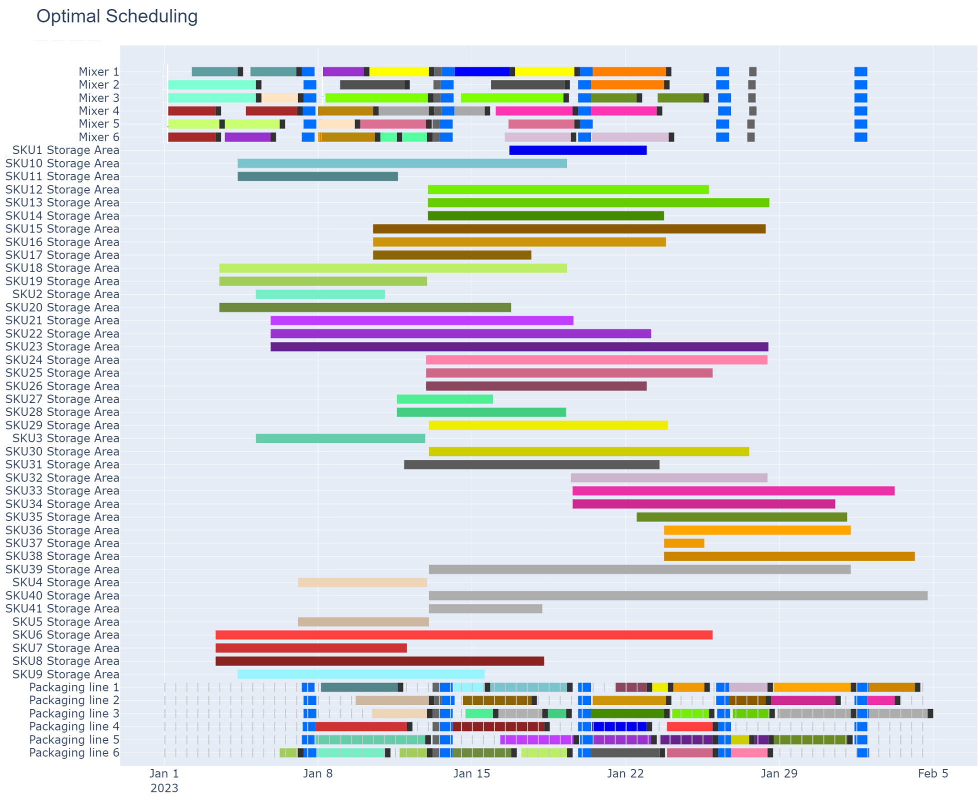

Figure B.1: Complete five weeks Optimal Scheduling Plan.

Material Paste	**Colour**
$Paste_{15}$	Maroon
$Paste_{16}$	Olive drab
$Paste_{17}$	Orange
$Paste_{18}$	Light gray

Table B.27: Material pastes updated legend.

Final Product	**Colour Shade**
SKU_{33}	Maroon
SKU_{34}	Maroon
SKU_{35}	Olive drab
SKU_{36}	Orange
SKU_{37}	Orange
SKU_{38}	Orange
SKU_{39}	Light gray
SKU_{40}	Light gray
SKU_{41}	Light gray

Table B.28: SKUs updated legend.

Appendix C

Second Weekly Review Results

Final Product	Material Paste	Final Product	Material Paste
SKU_{42}	$Paste_{19}$	SKU_{47}	$Paste_{20}$
SKU_{43}	$Paste_{19}$	SKU_{48}	$Paste_{21}$
SKU_{44}	$Paste_{19}$	SKU_{49}	$Paste_{21}$
SKU_{45}	$Paste_{20}$	SKU_{50}	$Paste_{21}$
SKU_{46}	$Paste_{20}$		

Table C.1: Additional Bill of Materials.

Final Product	Demand [tubes]	Final Product	Demand [tubes]
SKU_{42}	100.000	SKU_{47}	300.000
SKU_{43}	500.000	SKU_{48}	240.000
SKU_{44}	300.000	SKU_{49}	360.000
SKU_{45}	200.000	SKU_{50}	300.000
SKU_{46}	320.000		

Table C.2: Additional demand.

Final Product	**Material Paste**	**Conversion Rate [tubes/lb]**
SKU_{42}	$Paste_{19}$	2
SKU_{43}	$Paste_{19}$	5
SKU_{44}	$Paste_{19}$	3
SKU_{45}	$Paste_{20}$	4
SKU_{46}	$Paste_{20}$	4
SKU_{47}	$Paste_{20}$	5
SKU_{48}	$Paste_{21}$	2
SKU_{49}	$Paste_{21}$	6
SKU_{50}	$Paste_{21}$	5

Table C.3: Additional conversion rate final product - material paste.

Material Paste	**Demand [lbs]**
$Paste_{19}$	250.000
$Paste_{20}$	180.000
$Paste_{21}$	240.000

Table C.4: Additional material paste demand.

Paste	$\boldsymbol{Mixer_1}$	$\boldsymbol{Mixer_2}$	$\boldsymbol{Mixer_3}$	$\boldsymbol{Mixer_4}$	$\boldsymbol{Mixer_5}$	$\boldsymbol{Mixer_6}$
$Paste_{19}$	8	8	8	8	8	8
$Paste_{20}$	10	10	10	10	10	10
$Paste_{21}$	9	9	9	9	9	9

Table C.5: Mixers additional material processing time [hh].

Paste	$\boldsymbol{Mixer_1}$	$\boldsymbol{Mixer_2}$	$\boldsymbol{Mixer_3}$	$\boldsymbol{Mixer_4}$	$\boldsymbol{Mixer_5}$	$\boldsymbol{Mixer_6}$
$Paste_{19}$	0.10	0.56	0.45	0.30	0.49	0.48
$Paste_{20}$	0.28	0.16	0.49	0.47	0.36	0.31
$Paste_{21}$	0.14	0.28	0.24	0.46	0.51	0.30

Table C.6: Mixers additional expected percentage downtime.

Final Product	$\boldsymbol{Line_1}$	$\boldsymbol{Line_2}$	$\boldsymbol{Line_3}$	$\boldsymbol{Line_4}$	$\boldsymbol{Line_5}$	$\boldsymbol{Line_6}$
SKU_{42}	0.38	0.36	0.40	0.32	0.45	0.51
SKU_{43}	0.25	0.29	0.27	0.20	0.35	0.39
SKU_{44}	0.30	0.36	0.29	0.25	0.28	0.40
SKU_{45}	0.39	0.21	0.24	0.29	0.31	0.36
SKU_{46}	0.29	0.26	0.28	0.36	0.28	0.39
SKU_{47}	0.25	0.18	0.29	0.39	0.41	0.45
SKU_{48}	0.29	0.27	0.25	0.36	0.21	0.36
SKU_{49}	0.25	0.35	0.30	0.31	0.15	0.28
SKU_{50}	0.26	0.30	0.23	0.25	0.19	0.29

Table C.7: Packaging lines additional expected percentage downtime.

Manufacturing Line	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Mixer_1$	Maintenance	2023-01-27 15:00	2023-01-27 23:00
$Mixer_1$	Maintenance	2023-02-10 15:00	2023-02-10 23:00
$Mixer_2$	Maintenance	2023-01-13 06:00	2023-01-13 14:00
$Mixer_2$	Maintenance	2023-01-27 14:00	2023-01-27 22:00
$Mixer_2$	Maintenance	2023-02-10 13:00	2023-02-10 21:00
$Mixer_3$	Maintenance	2023-01-13 06:00	2023-01-13 14:00
$Mixer_3$	Maintenance	2023-01-27 14:00	2023-01-27 22:00
$Mixer_3$	Maintenance	2023-02-10 14:00	2023-02-10 22:00
$Mixer_4$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Mixer_4$	Maintenance	2023-01-27 15:00	2023-01-27 23:00
$Mixer_4$	Maintenance	2023-02-10 15:00	2023-02-10 23:00
$Mixer_5$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_5$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_5$	Maintenance	2023-02-10 14:00	2023-02-10 22:00
$Mixer_6$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Mixer_6$	Maintenance	2023-01-27 13:00	2023-01-27 21:00
$Mixer_6$	Maintenance	2023-02-10 15:00	2023-02-10 23:00

Table C.8: Manufacturing lines six weeks maintenance plan.

Packaging Line	Activity	Start Time	End Time
$Packaging_1$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_1$	Maintenance	2023-02-10 06:00	2023-02-10 14:00
$Packaging_2$	Maintenance	2023-01-13 07:00	2023-01-13 15:00
$Packaging_2$	Maintenance	2023-02-10 07:00	2023-02-10 15:00
$Packaging_3$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_3$	Maintenance	2023-02-10 07:00	2023-02-10 15:00
$Packaging_4$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_4$	Maintenance	2023-02-10 05:00	2023-02-10 13:00
$Packaging_5$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_5$	Maintenance	2023-02-10 05:00	2023-02-10 13:00
$Packaging_6$	Maintenance	2023-01-13 05:00	2023-01-13 13:00
$Packaging_6$	Maintenance	2023-02-10 05:00	2023-02-10 13:00

Table C.9: Packaging lines six weeks maintenance plan.

Manufacturing Line	**Activity**	**Start Time**	**End Time**
$Mixer_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_1$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Mixer_1$	Spare Capacity	2023-01-19 22:00	2023-01-20 12:00
$Mixer_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_1$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_1$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Mixer_2$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_2$	Spare Capacity	2023-01-13 14:00	2023-01-14 04:00
$Mixer_2$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_2$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_2$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_2$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Mixer_3$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_3$	Spare Capacity	2023-01-13 14:00	2023-01-14 04:00
$Mixer_3$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_3$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_3$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_3$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Mixer_4$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Mixer_4$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Mixer_4$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_4$	Spare Capacity	2023-01-26 04:00	2023-01-26 18:00
$Mixer_4$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_4$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Mixer_5$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Mixer_5$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_5$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_5$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_5$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_5$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Mixer_6$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Mixer_6$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Mixer_6$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Mixer_6$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Mixer_6$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Mixer_6$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00

Table C.10: Manufacturing lines six weeks spare capacity plan.

Packaging Line	**Activity**	**Start Time**	**End Time**
$Packaging_1$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Packaging_1$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_1$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_1$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_1$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_1$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_2$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_2$	Spare Capacity	2023-01-13 15:00	2023-01-14 05:00
$Packaging_2$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_2$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_2$	Spare Capacity	2023-02-01 11:00	2023-02-02 01:00
$Packaging_2$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_3$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_3$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_3$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_3$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_3$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_3$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_4$	Spare Capacity	2023-01-07 07:00	2023-01-07 21:00
$Packaging_4$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_4$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_4$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_4$	Spare Capacity	2023-02-01 10:00	2023-02-02 00:00
$Packaging_4$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_5$	Spare Capacity	2023-01-07 06:00	2023-01-07 20:00
$Packaging_5$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_5$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_5$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_5$	Spare Capacity	2023-02-01 12:00	2023-02-02 02:00
$Packaging_5$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00
$Packaging_6$	Spare Capacity	2023-01-07 08:00	2023-01-07 22:00
$Packaging_6$	Spare Capacity	2023-01-13 13:00	2023-01-14 03:00
$Packaging_6$	Spare Capacity	2023-01-19 20:00	2023-01-20 10:00
$Packaging_6$	Spare Capacity	2023-01-26 03:00	2023-01-26 17:00
$Packaging_6$	Spare Capacity	2023-02-01 12:00	2023-02-02 02:00
$Packaging_6$	Spare Capacity	2023-02-07 17:00	2023-02-08 07:00

Table C.11: Packaging lines six weeks spare capacity plan.

Packaging Line	**Activity**	**Start Time**	**End Time**
$Packaging_1$	Shift	2023-01-01 00:00	2023-01-01 01:00
$Packaging_1$	Shift	2023-01-01 12:00	2023-01-01 13:00
$Packaging_1$	Shift	2023-02-04 00:00	2023-02-04 01:00
$Packaging_1$	Shift	2023-02-04 12:00	2023-02-04 13:00
...	...	...	...
...	...	...	...
$Packaging_6$	Shift	2023-02-10 00:00	2023-02-10 01:00
$Packaging_6$	Shift	2023-02-10 12:00	2023-02-10 13:00
$Packaging_6$	Shift	2023-02-11 00:00	2023-02-11 01:00
$Packaging_6$	Shift	2023-02-11 12:00	2023-02-11 13:00

Table C.12: Packaging lines six weeks shift plan.

Resource	**Activity**	**Production [lbs]**	**Start Time**	**End Time**
$Mixer_1$	$Paste_5$	100.000	2023-01-02 06:00	2023-01-04 08:00
$Mixer_1$	Changeover	-	2023-01-04 08:00	2023-01-04 14:00
$Mixer_1$	$Paste_5$	100.000	2023-01-04 22:00	2023-01-07 00:00
$Mixer_1$	Changeover	-	2023-01-07 00:00	2023-01-07 06:00
$Mixer_1$	$Paste_9$	100.000	2023-01-08 00:00	2023-01-10 02:00
$Mixer_1$	Changeover	-	2023-01-10 02:00	2023-01-10 08:00
$Mixer_1$	$Paste_{12}$	100.000	2023-01-10 08:00	2023-01-13 01:00
$Mixer_1$	Changeover	-	2023-01-13 01:00	2023-01-13 07:00
$Mixer_1$	$Paste_1$	100.000	2023-01-14 05:00	2023-01-16 17:00
$Mixer_1$	Changeover	-	2023-01-16 17:00	2023-01-16 23:00
$Mixer_1$	$Paste_{12}$	100.000	2023-01-16 23:00	2023-01-19 16:00
$Mixer_1$	Changeover	-	2023-01-19 16:00	2023-01-19 22:00
$Mixer_1$	$Paste_{19}$	120.000	2023-01-20 12:00	2023-01-22 12:00
$Mixer_1$	Changeover	-	2023-01-22 12:00	2023-01-22 18:00
$Mixer_1$	$Paste_{19}$	140.000	2023-01-22 18:00	2023-01-25 02:00
$Mixer_1$	Changeover	-	2023-01-25 02:00	2023-01-25 08:00
$Mixer_1$	$Paste_{21}$	120.000	2023-01-28 08:00	2023-01-30 14:00
$Mixer_1$	Changeover	-	2023-01-30 14:00	2023-01-30 20:00

Table C.13: $Mixer_1$ six weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_2$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_2$	Changeover	-	2023-01-05 04:00	2023-01-05 10:00
$Mixer_2$	$Paste_{13}$	140.000	2023-01-09 00:00	2023-01-11 22:00
$Mixer_2$	Changeover	-	2023-01-11 22:00	2023-01-12 04:00
$Mixer_2$	$Paste_{13}$	160.000	2023-01-15 00:00	2023-01-18 08:00
$Mixer_2$	Changeover	-	2023-01-18 08:00	2023-01-18 14:00
$Mixer_2$	$Paste_{17}$	160.000	2023-01-20 10:00	2023-01-23 18:00
$Mixer_2$	Changeover	-	2023-01-23 18:00	2023-01-24 00:00
$Mixer_2$	$Paste_{20}$	100.000	2023-01-27 21:00	2023-01-29 23:00
$Mixer_2$	Changeover	-	2023-01-29 23:00	2023-01-30 05:00
$Mixer_2$	$Paste_{20}$	80.000	2023-01-30 05:00	2023-01-31 21:00
$Mixer_2$	Changeover	-	2023-01-31 21:00	2023-02-01 03:00

Table C.14: $Mixer_2$ six weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_3$	$Paste_2$	200.000	2023-01-01 00:00	2023-01-05 04:00
$Mixer_3$	Changeover	-	2023-01-05 04:00	2023-01-05 10:00
$Mixer_3$	$Paste_3$	100.000	2023-01-05 10:00	2023-01-07 02:00
$Mixer_3$	Changeover	-	2023-01-07 02:00	2023-01-07 08:00
$Mixer_3$	$Paste_6$	160.000	2023-01-08 08:00	2023-01-13 00:00
$Mixer_3$	Changeover	-	2023-01-13 00:00	2023-01-13 06:00
$Mixer_3$	$Paste_6$	160.000	2023-01-14 12:00	2023-01-19 04:00
$Mixer_3$	Changeover	-	2023-01-19 04:00	2023-01-19 10:00
$Mixer_3$	$Paste_{15}$	140.000	2023-01-21 12:00	2023-01-25 00:00
$Mixer_3$	Changeover	-	2023-01-25 00:00	2023-01-25 06:00
$Mixer_3$	$Paste_{15}$	120.000	2023-01-27 22:00	2023-01-30 22:00
$Mixer_3$	Changeover	-	2023-01-30 22:00	2023-01-31 04:00

Table C.15: $Mixer_3$ six weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_4$	$Paste_4$	80.000	2023-01-01 00:00	2023-01-03 08:00
$Mixer_4$	Changeover	-	2023-01-03 08:00	2023-01-03 14:00
$Mixer_4$	$Paste_4$	80.000	2023-01-04 17:00	2023-01-07 01:00
$Mixer_4$	Changeover	-	2023-01-07 01:00	2023-01-07 07:00
$Mixer_4$	$Paste_7$	100.000	2023-01-08 00:00	2023-01-10 12:00
$Mixer_4$	Changeover	-	2023-01-10 12:00	2023-01-10 18:00
$Mixer_4$	$Paste_{18}$	100.000	2023-01-10 18:00	2023-01-13 01:00
$Mixer_4$	Changeover	-	2023-01-13 01:00	2023-01-13 07:00
$Mixer_4$	$Paste_{18}$	60.000	2023-01-14 05:00	2023-01-15 14:00
$Mixer_4$	Changeover	-	2023-01-15 14:00	2023-01-15 20:00
$Mixer_4$	$Paste_{10}$	120.000	2023-01-15 20:00	2023-01-18 20:00
$Mixer_4$	Changeover	-	2023-01-18 20:00	2023-01-19 02:00
$Mixer_4$	$Paste_{17}$	160.000	2023-01-20 10:00	2023-01-23 18:00
$Mixer_4$	Changeover	-	2023-01-23 18:00	2023-01-24 00:00

Table C.16: $Mixer_4$ six weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_5$	$Paste_8$	80.000	2023-01-01 00:00	2023-01-03 12:00
$Mixer_5$	Changeover	-	2023-01-03 12:00	2023-01-03 18:00
$Mixer_5$	$Paste_8$	80.000	2023-01-03 18:00	2023-01-06 06:00
$Mixer_5$	Changeover	-	2023-01-06 06:00	2023-01-06 12:00
$Mixer_5$	$Paste_3$	100.000	2023-01-08 00:00	2023-01-09 16:00
$Mixer_5$	Changeover	-	2023-01-09 16:00	2023-01-09 22:00
$Mixer_5$	$Paste_{10}$	120.000	2023-01-09 22:00	2023-01-12 22:00
$Mixer_5$	Changeover	-	2023-01-12 22:00	2023-01-13 04:00
$Mixer_5$	Breakdown	-	2023-01-14 04:00	2023-01-19 04:00
$Mixer_5$	$Paste_{16}$	100.000	2023-01-20 16:00	2023-01-22 18:00
$Mixer_5$	Changeover	-	2023-01-22 18:00	2023-01-23 00:00
$Mixer_5$	$Paste_{16}$	100.000	2023-01-23 19:00	2023-01-25 21:00
$Mixer_5$	Changeover	-	2023-01-25 21:00	2023-01-26 03:00

Table C.17: $Mixer_5$ six weeks production schedule.

Resource	Activity	Production [lbs]	Start Time	End Time
$Mixer_6$	$Paste_4$	60.000	2023-01-01 00:00	2023-01-03 08:00
$Mixer_6$	Changeover	-	2023-01-03 08:00	2023-01-03 14:00
$Mixer_6$	$Paste_9$	100.000	2023-01-03 18:00	2023-01-05 20:00
$Mixer_6$	Changeover	-	2023-01-05 20:00	2023-01-06 02:00
$Mixer_6$	$Paste_7$	100.000	2023-01-08 02:00	2023-01-10 14:00
$Mixer_6$	Changeover		2023-01-10 14:00	2023-01-10 20:00
$Mixer_6$	$Paste_{11}$	40.000	2023-01-10 20:00	2023-01-11 14:00
$Mixer_6$	Changeover	-	2023-01-11 14:00	2023-01-11 20:00
$Mixer_6$	$Paste_{11}$	60.000	2023-01-11 20:00	2023-01-12 23:00
$Mixer_6$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Mixer_6$	$Paste_{14}$	120.000	2023-01-15 07:00	2023-01-18 07:00
$Mixer_6$	Changeover	-	2023-01-18 07:00	2023-01-18 13:00
$Mixer_6$	$Paste_{14}$	140.000	2023-01-20 12:00	2023-01-24 00:00
$Mixer_6$	Changeover	-	2023-01-24 00:00	2023-01-24 06:00
$Mixer_6$	$Paste_{21}$	120.000	2023-01-27 23:00	2023-01-30 05:00
$Mixer_6$	Changeover	-	2023-01-30 05:00	2023-01-30 11:00

Table C.18: $Mixer_6$ six weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_1$	SKU_{11}	504.000	2023-01-08 03:00	2023-01-11 15:00
$Packaging_1$	Changeover	-	2023-01-11 15:00	2023-01-11 21:00
$Packaging_1$	SKU_9	204.000	2023-01-14 04:00	2023-01-15 14:00
$Packaging_1$	Changeover	-	2023-01-15 14:00	2023-01-15 20:00
$Packaging_1$	SKU_{10}	504.000	2023-01-16 02:00	2023-01-19 14:00
$Packaging_1$	Changeover	-	2023-01-19 14:00	2023-01-19 20:00
$Packaging_1$	SKU_{26}	204.000	2023-01-20 10:00	2023-01-21 20:00
$Packaging_1$	Changeover	-	2023-01-21 20:00	2023-01-22 02:00
$Packaging_1$	SKU_{29}	102.000	2023-01-23 03:00	2023-01-23 20:00
$Packaging_1$	Changeover	-	2023-01-23 20:00	2023-01-24 02:00
$Packaging_1$	SKU_{32}	252.000	2023-01-24 02:00	2023-01-25 20:00
$Packaging_1$	Changeover	-	2023-01-25 20:00	2023-01-26 02:00
$Packaging_1$	SKU_{37}	204.000	2023-01-26 22:00	2023-01-28 08:00
$Packaging_1$	Changeover	-	2023-01-28 08:00	2023-01-28 14:00
$Packaging_1$	SKU_{36}	504.000	2023-01-28 14:00	2023-02-01 02:00
$Packaging_1$	Changeover	-	2023-02-01 02:00	2023-02-01 08:00
$Packaging_1$	SKU_{38}	300.000	2023-02-02 00:00	2023-02-04 02:00
$Packaging_1$	Changeover	-	2023-02-04 02:00	2023-02-04 08:00

Table C.19: $Packaging_1$ six weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_2$	SKU_5	400.000	2023-01-09 17:00	2023-01-13 01:00
$Packaging_2$	Changeover	-	2023-01-13 01:00	2023-01-13 07:00
$Packaging_2$	SKU_{17}	375.000	2023-01-14 14:00	2023-01-17 17:00
$Packaging_2$	Changeover	-	2023-01-17 17:00	2023-01-17 23:00
$Packaging_2$	SKU_{16}	400.000	2023-01-20 18:00	2023-01-24 02:00
$Packaging_2$	Changeover	-	2023-01-24 02:00	2023-01-24 08:00
$Packaging_2$	SKU_{15}	200.000	2023-01-26 20:00	2023-01-28 12:00
$Packaging_2$	Changeover	-	2023-01-28 12:00	2023-01-28 18:00
$Packaging_2$	SKU_{33}	150.000	2023-01-30 23:00	2023-02-01 05:00
$Packaging_2$	Changeover	-	2023-02-01 05:00	2023-02-01 11:00
$Packaging_2$	SKU_{47}	300.000	2023-02-02 01:00	2023-02-04 13:00
$Packaging_2$	Changeover	-	2023-02-04 13:00	2023-02-04 19:00
$Packaging_2$	SKU_{46}	320.000	2023-02-04 19:00	2023-02-07 11:00
$Packaging_2$	Changeover	-	2023-02-07 11:00	2023-02-07 17:00
$Packaging_2$	SKU_{45}	200.000	2023-02-08 07:00	2023-02-09 23:00
$Packaging_2$	Changeover	-	2023-02-09 23:00	2023-02-10 05:00

Table C.20: $Packaging_2$ six weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_3$	SKU_4	300.000	2023-01-10 11:00	2023-01-12 23:00
$Packaging_3$	changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_3$	SKU_{27}	150.000	2023-01-14 17:00	2023-01-15 23:00
$Packaging_3$	changeover	-	2023-01-15 23:00	2023-01-16 05:00
$Packaging_3$	SKU_{41}	240.000	2023-01-16 05:00	2023-01-18 05:00
$Packaging_3$	changeover	-	2023-01-18 05:00	2023-01-18 11:00
$Packaging_3$	SKU_{28}	100.000	2023-01-18 11:00	2023-01-19 07:00
$Packaging_3$	changeover	-	2023-01-19 07:00	2023-01-19 13:00
$Packaging_3$	SKU_{14}	400.000	2023-01-20 10:00	2023-01-23 18:00
$Packaging_3$	changeover	-	2023-01-23 18:00	2023-01-24 00:00
$Packaging_3$	SKU_{12}	200.000	2023-01-24 03:00	2023-01-25 19:00
$Packaging_3$	changeover	-	2023-01-25 19:00	2023-01-26 01:00
$Packaging_3$	SKU_{13}	200.000	2023-01-26 17:00	2023-01-28 09:00
$Packaging_3$	changeover	-	2023-01-28 09:00	2023-01-28 15:00
$Packaging_3$	SKU_{39}	400.000	2023-01-28 15:00	2023-01-31 23:00
$Packaging_3$	changeover	-	2023-01-31 23:00	2023-02-01 05:00
$Packaging_3$	SKU_{40}	320.000	2023-02-02 00:00	2023-02-04 16:00
$Packaging_3$	changeover	-	2023-02-04 16:00	2023-02-04 22:00

Table C.21: $Packaging_3$ six weeks production schedule.

Resource	**Activity**	**Output [tubes]**	**Start Time**	**End Time**
$Packaging_4$	SKU_7	500.000	2023-01-07 21:00	2023-01-12 01:00
$Packaging_4$	Changeover	-	2023-01-12 01:00	2023-01-12 07:00
$Packaging_4$	SKU_8	500.000	2023-01-14 03:00	2023-01-18 07:00
$Packaging_4$	Changeover	-	2023-01-18 07:00	2023-01-18 13:00
$Packaging_4$	SKU_1	300.000	2023-01-20 15:00	2023-01-23 03:00
$Packaging_4$	Changeover	-	2023-01-23 03:00	2023-01-23 09:00
$Packaging_4$	SKU_6	250.000	2023-01-23 09:00	2023-01-25 11:00
$Packaging_4$	Changeover	-	2023-01-25 11:00	2023-01-25 17:00
$Packaging_4$	SKU_{42}	100.000	2023-01-26 17:00	2023-01-27 13:00
$Packaging_4$	Changeover	-	2023-01-27 13:00	2023-01-27 19:00
$Packaging_4$	SKU_{44}	300.000	2023-01-28 17:00	2023-01-31 05:00
$Packaging_4$	Changeover	-	2023-01-31 05:00	2023-01-31 11:00
$Packaging_4$	SKU_{43}	500.000	2023-02-02 00:00	2023-02-06 04:00
$Packaging_4$	Changeover	-	2023-02-06 04:00	2023-02-06 10:00

Table C.22: $Packaging_4$ six weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_5$	SKU_3	600.000	2023-01-07 21:00	2023-01-12 21:00
$Packaging_5$	Changeover	-	2023-01-12 21:00	2023-01-13 03:00
$Packaging_5$	SKU_{21}	400.000	2023-01-15 00:00	2023-01-18 08:00
$Packaging_5$	Changeover	-	2023-01-18 08:00	2023-01-18 14:00
$Packaging_5$	SKU_{22}	320.000	2023-01-20 10:00	2023-01-23 02:00
$Packaging_5$	Changeover	-	2023-01-23 02:00	2023-01-23 08:00
$Packaging_5$	SKU_{23}	255.000	2023-01-23 08:00	2023-01-25 11:00
$Packaging_5$	Changeover	-	2023-01-25 11:00	2023-01-25 17:00
$Packaging_5$	SKU_{23}	105.000	2023-01-26 17:00	2023-01-27 14:00
$Packaging_5$	Changeover	-	2023-01-27 14:00	2023-01-27 20:00
$Packaging_5$	SKU_{30}	100.000	2023-01-27 20:00	2023-01-28 16:00
$Packaging_5$	Changeover	-	2023-01-28 16:00	2023-01-28 22:00
$Packaging_5$	SKU_{35}	400.000	2023-01-28 22:00	2023-02-01 06:00
$Packaging_5$	Changeover	-	2023-02-01 06:00	2023-02-01 12:00
$Packaging_5$	SKU_{48}	240.000	2023-02-02 02:00	2023-02-04 02:00
$Packaging_5$	Changeover	-	2023-02-04 02:00	2023-02-04 08:00
$Packaging_5$	SKU_{49}	360.000	2023-02-04 08:00	2023-02-07 08:00
$Packaging_5$	Changeover	-	2023-02-07 08:00	2023-02-07 14:00
$Packaging_5$	SKU_{50}	200.000	2023-02-08 07:00	2023-02-09 23:00
$Packaging_5$	Changeover	-	2023-02-09 23:00	2023-02-10 05:00
$Packaging_5$	SKU_{50}	100.000	2023-02-10 13:00	2023-02-11 09:00
$Packaging_5$	Changeover	-	2023-02-11 09:00	2023-02-11 15:00

Table C.23: $Packaging_5$ six weeks production schedule.

Resource	Activity	Output [tubes]	Start Time	End Time
$Packaging_6$	SKU_{19}	80.000	2023-01-06 06:00	2023-01-07 02:00
$Packaging_6$	Changeover	-	2023-01-07 02:00	2023-01-07 08:00
$Packaging_6$	SKU_2	300.000	2023-01-07 22:00	2023-01-11 01:00
$Packaging_6$	Changeover	-	2023-01-11 01:00	2023-01-11 07:00
$Packaging_6$	SKU_{19}	120.000	2023-01-11 17:00	2023-01-12 23:00
$Packaging_6$	Changeover	-	2023-01-12 23:00	2023-01-13 05:00
$Packaging_6$	SKU_{20}	256.000	2023-01-14 03:00	2023-01-16 19:00
$Packaging_6$	Changeover	-	2023-01-16 19:00	2023-01-17 01:00
$Packaging_6$	SKU_{18}	200.000	2023-01-17 02:00	2023-01-19 04:00
$Packaging_6$	Changeover	-	2023-01-19 04:00	2023-01-19 10:00
$Packaging_6$	SKU_{25}	200.000	2023-01-20 10:00	2023-01-22 12:00
$Packaging_6$	Changeover	-	2023-01-22 12:00	2023-01-22 18:00
$Packaging_6$	SKU_{31}	300.000	2023-01-22 18:00	2023-01-25 21:00
$Packaging_6$	Changeover	-	2023-01-25 21:00	2023-01-26 03:00
$Packaging_6$	SKU_{24}	160.000	2023-01-26 17:00	2023-01-28 09:00
$Packaging_6$	Changeover	-	2023-01-28 09:00	2023-01-28 15:00
$Packaging_6$	SKU_{34}	128.000	2023-01-30 22:00	2023-02-01 06:00
$Packaging_6$	Changeover	-	2023-02-01 06:00	2023-02-01 12:00
$Packaging_6$	SKU_{34}	234.000	2023-02-02 08:00	2023-02-04 18:00
$Packaging_6$	Changeover	-	2023-02-04 18:00	2023-02-05 00:00

Table C.24: $Packaging_6$ six weeks production schedule.

Material Paste	Total Production [lbs]	Target Demand [lbs]
$Paste_{19}$	260.000	250.000
$Paste_{20}$	180.000	180.000
$Paste_{21}$	240.000	240.000

Table C.25: Additional material pastes comparison between production and demand.

Final Product	**Total Production [tubes]**	**Target Demand [tubes]**
SKU_{42}	100.000	100.000
SKU_{43}	500.000	500.000
SKU_{44}	300.000	300.000
SKU_{45}	200.000	200.000
SKU_{46}	320.000	320.000
SKU_{47}	300.000	300.000
SKU_{48}	240.000	240.000
SKU_{49}	360.000	360.000
SKU_{50}	300.000	300.000

Table C.26: Additional SKUs comparison between production and demand.

Figure C.1: Complete six weeks Optimal Scheduling Plan.

Material Paste	**Colour**
$Paste_{19}$	Moccasin
$Paste_{20}$	Red
$Paste_{21}$	Steel blue

Table C.27: Material pastes updated legend.

Final Product	**Colour Shade**
SKU_{42}	Moccasin
SKU_{43}	Moccasin
SKU_{44}	Moccasin
SKU_{45}	Red
SKU_{46}	Red
SKU_{47}	Red
SKU_{48}	Steel blue
SKU_{49}	Steel blue
SKU_{50}	Steel blue

Table C.28: SKUs updated legend.

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