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工業工程與管理學系

碩士論文

混合式啟發式解法求解多產品裝瓶產線批量與排序問題 – 以巴拿馬啤酒公司為例

A hybrid-heuristic solution approach for the Lot size and Sequencing Problem of Multi-Product Bottling Lines

A Case Study of Panama Beer Company

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摘要

本研究旨在協助巴拿馬啤酒公司之生產計畫者，於多產品裝瓶生產線之批量與排程。本研究建立一個混合整數規劃模型其符合個案公司決策分析之情境，問題旨在決定各生產計畫期間內，各產品批量與三條裝瓶生產線上之生產順序，以最小化生產計畫期間內之總成本(包含生產，存貨，整備之成本)，且能滿足各產品的需求。本研究考量該公司裝瓶生產線特性之相關因素如：生產速率限制、產能、整備時間與存貨策略。本研究提倡運用混合式啟發式演算法（又稱為 GA-LP 法）其 結合基因演算法(Genetic algorithm)及線性規劃(Linear programming)，基因演算法是著眼於解決排序問題，而線性規劃則是處理批量決策。本研究運用該公司二十週的實際數據，比較 GA-LP 法與該公司原先的生產規劃進行效益評比， 結果顯示不僅可以在更短的時間完成生產規劃，且可降低總成本達 21%；故本研究提出之 GA-LP 法，可以作為多產品裝瓶生產系統之生產規劃者在批量與排程有效的決策輔助工具。

關鍵字：啤酒工業，批量，排程，混合整數規劃，基因演算法

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Abstract
摘要

This study was motivated to support the production planners in the lot sizing and sequencing of multiple products on the packaging lines of the Panama Beer Company. We formulate a mixed integer programming model that matches with the decision-making scenarios in the company. The problem aims at the determination of the lot size of each product, and the sequence of production in the three packaging lines for each period, so as to minimize the total costs (including the production, inventory and setup costs) in the planning horizon, while meeting the demand of each product. We took into account the limitations on the production rate, capacity, setup times, and inventory policies to fit the characteristics of the packaging lines in the Panama Beer Company. In order to solve the problem, we propose a hybrid-heuristic (called GA-LP) that combines Genetic Algorithm (GA) and Linear Programming (LP) in which GA is used to solve the sequencing problem, and LP aims to solve the lot sizing problem. We evaluated the effectiveness of the proposed hybrid-heuristic by comparing the obtained solutions with the historical production plans. We conduct our experiments with the real-world data for a planning period of twenty weeks, and our results showed that the proposed GA-LP approach not only solved the production plan efficiently in a much shorter run time, but also led to an improvement of 21% in the total cost. Therefore, the proposed GA-LP approach may serve as an effective tool that supports the production planner in the lot sizing and sequencing of bottling production systems.

Keywords: Beer industry, lot sizing, scheduling, mixed-integer programming, genetic algorithm

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Thank you dear Taiwan, you've become a huge part of my life story. You will be always in my heart. *¡Hasta Pronto!*

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1. Introduction

1.1 Beverage Industry

The beer and carbonated soft drinks (CSD) industry is one of the biggest industries around the world, and as every other industry, is passing through many evolutions based on consumers' preferences. In Panama, the carbonated soft drinks industry is dominated by two large producers that own the most recognized brands worldwide. The overall quality of product depends directly on the relationship between the concentrate producer which owns the brand, and its bottlers (Ferreira, Morabito, & Rangel, 2008). In the case of Panama, the factories established in the country are mainly for the bottling and distribution of the final products.

On the other hand, the Panamanian beer industry generates more than US$ 390 million per year, and is also controlled by two major companies. In 2011, the industry present a growth of 5.1% compared to the previous year (Capital Financiero, 2012). These companies have their own brands and also distribute international brands. For those company-owned products, the manufacturing process starts when the malt grain is received, then raw materials pass through all production processes, and finally delivered to the distribution centers.

In such environment of intense competition and changes in customer's preferences, companies have a big challenge in maintaining the brand strength and keeping market share, and at the same time, to improve their operations.

To improve efficiency of the production system, one of the key factors is to use more efficient production plans. It is necessary to adopt optimization-based programs to generate efficient production plans due to the diversity in the portfolio of products and the constant changes in their demand (Ferreira, Morabito, & Rangel, 2008).

1.2 Industrial Setting

This research focuses on a Panamanian beverage manufacturing plant that produces, pack and delivers 13 different stock keeping units (SKUs) in returnable bottles. The manufacturing process starts with the reception of raw material from suppliers. The planning department receives weekly the customer's orders and demand forecasts for the next 12 months. Based on this information the senior planners generate the production plan for the next two months, weekly production scheduling and material requirement orders. The Company mandates inventory policies that the production system must maintain a specific amount of material and finished products in the warehouses, so as to meet customers' demand with a high service level.

Once the production plan is done, the brew house, which is one of the major areas of manufacturing process, starts the brewing process that consists in many steps including malting, milling, mashing, lautering, boiling, fermenting, conditioning, and finally the filtering process (Microbrewery, 2008). Appendix A depicts the typical brewing process. Once the beer is filtered it is stored in huge tanks called bright beer tank (BBT) and it is ready to be transferred to the packaging lines. These lines can pack several beers brands in different sizes and containers. All BBT are connected with all packaging lines, this means that production process can be run smoothly with one or more tanks. However, since not every packaging line has the same throughput rates, packing capabilities, production capacity or setup times, it makes the lot sizing and sequencing a complex problem.

Carbonated soft drinks (CSD) are enormously popular beverages consisting primarily of carbonated water, sugar, and flavorings. The production process of CSD may be divided into two major areas: the mixing area and packaging area. The former prepares the concentrate or syrup in tanks of different capacities. Two different liquid flavors cannot be prepared in the same tank at the same time, and by quality standards any tank must be completely empty and sterilized before a new lot can be prepared in that tank. Once ready this syrup is sent to packaging line where is mixed with carbonated water and then bottled in returnable bottles or pet containers. The difference with beer area is that CSD filling lines can receive liquid flavor from only one tank during the production, so generally tanks are prepared in the exact quantity required. However, if another line is going to produce the same flavor, this tank can provide the liquid flavor to it.

The production planning is based on different factors such as, demand, product preparation capacity, packaging lines rates, changeovers, inventory policies, quality constraints, the demand based run strategy, and working hour's availability. Packaging lines can be treated as single unit because it is a continuous flow and generally its packaging rate is defined by the filling machine, so the highest throughput rate that the line can achieve is equal to the filler rate (Toledo, Franca, & Morabito, 2002). This study solves the lot sizing and sequencing problem in the packaging lines, while meeting the demand of all products.

The production lot sizing and sequencing/scheduling problem has been studied in different industries such as the milk production (Javanmard & Kianehkandi, 2011), plastics compounding plant (Leung, 2009), wine bottling (Berruto, Tortia, & Gay, 2006) or the petroleum industry (Hagem & Torgnes, 2009). These studies reflect that mathematical models are studied and applied to improve their planning processes when facing lot sizing and sequencing problems in the real world.

1.3 Panama Beer Company

Panama Beer Company (PBC), which is a subsidiary of a multinational organization, has been in beer business for over 100 years and currently is the biggest brewery in the country. It manufactures six worldwide recognized brands of soft drinks, three brands of beers, and one brand of malt and water. Additionally, distributes two international beer brands, two milk brands, and juices. Its market share was 68% in the beer segment, 33% in soft drinks segment and 89% in malt segment in 2012 (Cerveceria Nacional S.A., 2012).

PBC has a Vision of being the leaders in the beverage market by having the highest growth potential and profitability brand portfolio, working with the best talent and always being a market-oriented organization. Its Mission is to own and promote the local and international brands preferred by the consumers.

PBC's manufacturing plant is located in Panama City, and it has an annual capacity of 2,295,412 hectoliters for beer products and of 1,223,722 hectoliters for carbonated soft drinks (CSD). It consists of three critical departments: brewing, packaging and utilities.

Brewing Department consists of a "kitchen" area, fermentation tanks, conditioning tanks and the filtering process. All these areas are managed by Brew House Director, and reports directly to Plant Director.

Utilities Department is in charge of supply indispensable utilities to brew house and packaging lines such as treated water, steam, pressure, electricity, etc. The head of this department is the Utilities Director, who also reports directly to Plant Director.

PBC Packaging Department is the largest beer bottling plant in Panama. This area packs beer products and soft drinks products, in different types of containers such as returnable bottle, cans, kegs and pet. These production lines are under Packaging Director's supervision. Since this project is focus on Packaging Department the structure of it is briefly described.

It consists of six production lines divided into two areas: beer and CSD. Both areas together have one director, two managers, six shifts' team leaders and around seventy two operators.

The beer packaging area is formed by four production lines, each having different capabilities. Below is a brief description of each:

- Line 1: bottles 2 SKUs from the beer segment and 1 from the malt segment in returnable bottle. This line has the highest throughput rate.
- Line 2: bottles 5 SKUs from the beer segment and 1 from the malt segment in returnable bottle. This line has the greatest flexibility for beer packaging.
- Line 3: packs 8 SKUs from the beer segment, 17 SKU from the CSD segment and 2 from the malt segment in aluminum cans. This is the only production line for cans.
- Line 4: packs 2 SKUs from the beer segment in kegs. This line is operated mainly by hand. It is also the smallest and simplest of the factory.

CSD packaging area consists of two lines:

- Line 5: bottles 7 SKUs from the CSD segment in returnable bottle.
- Line 6: bottles 33 SKUs from the CSD segment in PET, 3 from the malt segment and 3 from the water segment. Currently this line works at full capacity, 7 days per week, 24 hours per day.

In the last two years sales volume of beer and soft drinks packed in returnable bottles (RB) started to go down; presenting a decrease of 18% in sales in the first quarter of the last fiscal year (April '13 ~ July '13) compared to the same period of previous year (April '12 ~ July '12), also referring to Figure 1. Until the end of August 2013, the total demand had been covered using seven full dedicated teams divided between the three RB lines, working together seven shifts per day and six days per week. The change in demand from RB to cans and PET packages resulted in low utilization of the three RB lines, causing an increment of idle time in lines and personnel.

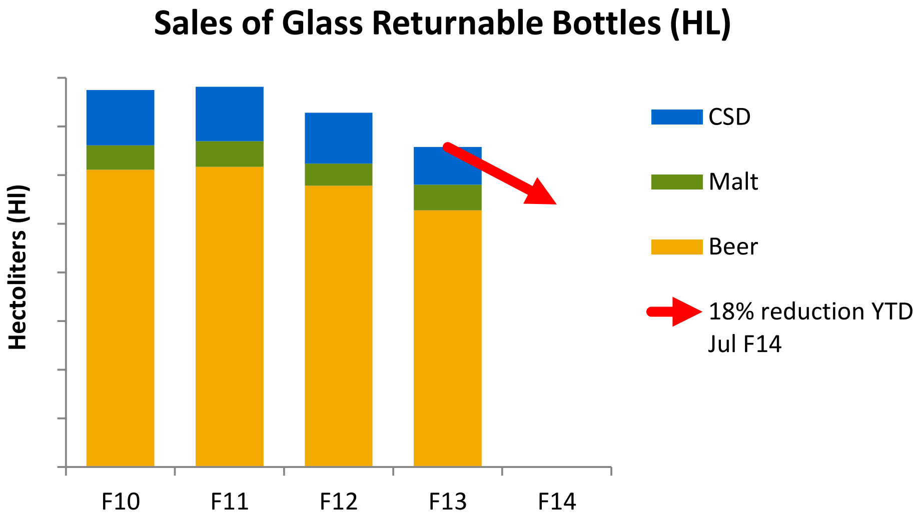

Figure 1 - Sales of Glass Returnable Bottles
(Hl are not shown due to confidentiality issues)

Plant managers decided to make a radical change in the production plans of the three RB lines and a head count reorganization. Through a capacity vs. demand analysis, PBC estimated that six shifts per day (six days per week) were enough to meet RB products' demand. Due to reduction in production requirement, managers calculate that six teams and one special team for line cleaning and changeover periods, are capable to cover the changes. With this new scheme some teams are required to work alternately between the lines.

Currently the plant is working with three crews assigned full time to line 1, and three teams working alternately between lines 2 and 5. Planning Department had to re-define the planning parameters and proposed new approaches to schedule production lines. The planners usually employ spreadsheet-based tools (e.g., MS-Excel) to generate production plans with mostly manual adjustments from their subjective judgment. So, following their intuition and experience, they have decided that Line 1 will bottle all demand requirements of three SKUs from beer and malt segment, and Line 2 will fulfil the other three SKUs from beer segment. In

Appendix B shows a flow diagram indicating the information flow of the detailed scheduling planning process currently used in PBC.

This thesis is mainly concerned about the lot sizing and production scheduling encountered in PBC's packaging lines for returnable bottles. These are Line 1, Line 2 and Line 5, which are in charge of bottled 13 different SKUs. For practical purposes, we name Line 5 as named Line 3 for our following presentation.

1.4 Purpose of Study

Generally, beverage plants have several lines that pack different products, in different containers, at different rates and with different capacities. Due to variety in products portfolio, managers pursue for the highest possible flexibility to meet market preferences, with the highest possible customer service level and the minimal associated costs. PBC has stated that the objective of their weekly production scheduling is to minimize the production costs, inventory holding costs, idle time costs and setups costs incurred.

However, the planners made their decision usually relying on subjective opinions from their experience and spreadsheet-based tools rather than an integrated and systematic approach/software. This practice is not the ideal way to solve planning problems, especially in the presence of strong fluctuations of demand between seasons (Christou, Lagodimos, & Lycopoulou, 2007). Also, the planners need to assign teams between Lines 2 and 3 since the labor capacity (i.e., the number of headcounts) was reduced due to the re-organization. The planners usually derived production plans for different packaging lines separately and conducted team assignment with subjective judgment. Obviously, there exists significant room for improving the efficiency of production plans in PBC.

Therefore, this study is motivated to propose a mathematical model and an effective solution approach for solving the (weekly) production planning and scheduling problem for PBC's packaging lines. The proposed model shall take into account the constraints from production capacity and inventory policies, as well as the issue of team assignment between Lines 2 and 3. We also use the historical data from PBC to develop our case study, in which we will evaluate the effectiveness of our solution approach by comparing the obtained solution with the historical production plans.

We hope that the proposed solution approach will assist the planners in the optimal the optimization of scheduling and lot size decisions with a shorter planning process time. Also, the proposed solution approach shall allow the planners to conduct sensitivity analysis by simulating different scenarios (demand changes, capacity limitations, etc.) and evaluating impact from different inputs/parameters.

1.5 Thesis Structure

The rest of the thesis is organized as follows: Chapter 2 presents literature review; Chapter 3 describes the decision-making scenario, the assumptions and the proposed mathematical model; Chapter 4 introduces the proposed solution approach; Chapter 5 presents our case study, which is based on PBC's real and historical data. We have further discussion on the results from the case study in Chapter 6. Chapter 7 addresses our conclusions and the directions for future works.

2. Literature Review

2.1 Lot Sizing and Scheduling for Packaging Companies

The aim of production planning is to generate a plan based on demand forecasts, that include the products that need to be produced, the inventory levels that need to be met, and the resources available to complete all tasks for a specific planning horizon (for several days, weeks or months). For operational level, Planning Department delivers a production schedule that is detailed by hours, shifts or days, and shows which product need to be produced, in which machines and its sequence (Krajewski, Ritzman, & Malhotra, 2010).

In this study, we are interested in solving the lot sizing, machine assignment and sequencing/scheduling problem in bottling production system in beverage industry. Many studies have been developed by considering similar scenarios, in which some are focus on only one decision, and others propose models and algorithms to solve simultaneously two or more decisions. Table 1 summarizes the reviewed studies in the literature.

Learning from the literature, one may know that the production system of each industry has its own characteristics (including the operational restrictions, the implementation of production processes, and the special feature of facilities), and the constraints accommodating the characteristics must be included to ensure feasibility of the production plan/schedule obtained from the mathematical model. Christou et al. (2007) derived a model for solving the production planning problem for a multi-product production system with packaging lines for juice industry. Their approach was done by decomposing the production planning problem in a hierarchical way. They divided it in 3 levels, the first one is an aggregate planning taking in consideration monthly schedule, the second level is weekly production planning, and the third one is the daily production planning. In this paper, the attention is focus on the first level of the problem, which they called multi-commodity aggregate production planning (MCAP). The constraints considered in this model are capacity constraints and product expiration date. However, the authors made strong assumptions such as, all production lines have the same throughput rate for any type of product.

Table 1 - Research done for various type of beverage industry

	Paper	Year	Product	Topic Covered	
				Lot Sizing	Scheduling
1	Proposta de um Modelo conjunto de Programacao e Dimensionamento de Lotes Aplicado a uma Industria de Bebidas. Toledo, C.F.M., Franca, P.M, Morabito, R.	2002	Soft Drinks	X	X
2	Wine Bottling Scheduling Optimization Berruto, R., Tortia, C., Gay, P.	2006	Wine		X
3	Hierarchical Production planning for multi-product lines in the beverage industry. Christou, I.T., Lagodimos, A.G., Lycopoulous, D.	2007	Bottled drinks Juices	X	
4	Solution Approaches for the Soft-Drink integrated production lot sizing and scheduling problem. Ferreira, D., Morabito, R., Rangel S.	2008	Soft Drinks	X	X
5	Optimum Production Scheduling for a Beverage Firm Based in Accra. Amponsah, S.K., Ofosu, J.B., Opoku-Sarkodie, R.	2011	Beverage	X	
6	Optimal Scheduling in a Milk Production Line Based on Mixed Integer Programming Javanmard, H., Kianehkandi.	2011	Milk	X	X
7	A genetic algorithm/mathematical programming approach to solve a two-level soft drink production problem. Toledo, C.F.M	2014	Soft Drinks	X	X

Berruto et al. (2006) studied the scheduling optimization problem for a wine bottling company in Italy. They considered the scheduling process divided in two decisions; first one is to decide the lot sizes per week of every product and it is done by solving mathematical model. The second one is regarding the sequence of production; this decision is made by bottling manager.. He focused on the first one and considered that the bottling plant has a single machine, with the constraints from warehouse capacity, manpower costs, and others. He used one month as the planning horizon, but divided in 4 weeks.

Amponsah et al. (2011) brought a case study based on a beverage company located in Ghana. For this study, the authors consider a production facility that produces a single product that has a given capacity and covers warehouses demands. The objective function looks for minimizing the production costs while meeting all demands and satisfying production capacity constraints. They point out that the production cost includes the storage cost and the manufacturing cost of the product in their model. The problem is formulated as a balanced transportation problem where the time periods when production takes place is considered as sources and the time periods in which units will be shipped as destinations. The planning horizon in their production is one year, where each period is a month.

Javanmard et al. (2011) formulated a mixed integer linear programming (MILP) model for solving the scheduling and lot sizing problem in a single milk production line of a plant located in Iran. This case is similar to PBC's case because it includes all typical constraints encountered in the production scheduling such as inventory limitations, machine capacity, and shifts restrictions, but also considers the sequence-dependent setup times and costs. The objective function of their model is to minimize all major sources of variable costs that depend on the production schedule, namely, changeover cost, inventory cost and labor cost. Unfortunately, the authors did not present their mathematical model for the problem in this paper.

Toledo et al. (2002) investigated a problem which is very similar to the one concerned in this thesis. Their paper, written in Portuguese, studies the lot sizing and scheduling problem for a production system with parallel machines that are constrained by their capacity and the setup times and costs being sequence-dependent. They took three Brazilian soft drink companies as reference cases and formulated a model that synchronized decisions between the Preparation Room and Bottling Department. Therefore this is considered as a two-level problem. Both stages are formulated based on (Fleishmann & Meyr, 1997) and (Meyr, 2002) models. The two constraints that connect between Stage 1 and Stage 2 play important roles there. They showed preliminary computational results using GAMS/CPLEX solver, however pointing out that the solver could be inefficient in finding optimal solution via or unable to solve in short time period if the number of items and/or periods increase. Their study has been extended by various researchers. Kimms et al. (2005) presented an extension of Toledo et al.'s (2002) model to solve the same problem using the same software, however concluded that they still have difficulties in obtaining good solutions for large-size instances. Ferreira et al. (2008) proposed a model similar to the one presented by Toledo et al. (2002). They presented two strategies for solving the problem, namely, a relaxation approach and a relax-and-fix heuristic with the assistance of CPLEX solver.

All models presented by these authors are based on the *General Lotsizing and Scheduling Problem* (GLSP) proposed in (Fleishmann & Meyr, 1997) for single machine and its extension for parallel machines presented by Meyr (2002).

Fleishmann et al. (1997) formulated a mixed integer programming model (MIP) that addressed to the integration of the lot-sizing and scheduling decisions in production planning subject to capacity constraints. The demand is deterministic and given over a finite time planning horizon. This model is to minimize inventory holding and sequence-dependent setup costs with all demand being met without backlogging.

Fleishmann (1997) proposed a two-level planning framework, where the planning horizon is divided in macro-periods, which in turn are further divided into micro-periods. Macro-periods are fixed time duration defined by users. Demand and holding costs are given in these periods. Micro-periods are within the macro-periods, and define the changes of the system state (Figure 2). The amount of micro-periods is predefined by user, and represents the number of lots that can be produced inside a macro-period. A pre-defined set indicates to which macro-period these macro-periods belong. These small periods have variable length and are controlled by decisions. Only one item can be produced in every micro-period. The size of the micro-period is given by the amount of items produced in that period, been possible to have zero production in some micro-periods due to capacity availability.

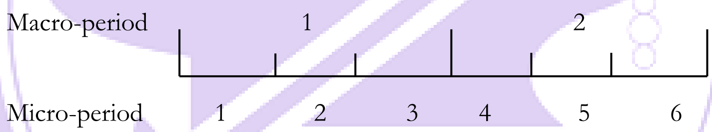

Figure 2 – Macro-periods vs. micro-periods

This model was extended by Meyr (2002) to deal with parallel machines problem and is called *General Lotsizing and Scheduling Problem for Parallel Production Lines (GLSPPL)*. The formulation presents that the limited capacity of the production lines may be further reduced by sequence-dependent setup times. For example, if there is a case where one macro-period is composed by three micro-periods, in the first micro-period can be produced a lot with 500 units and in the second 200 units. The setup time between lots also needs to be considered and it depends on the product needed to make the changeover. The sum of production times of all lots and the setup times must be less than total capacity of the respective macro-period.

Toledo et al. (2002) developed their model by adding two constraints that connect first stage (syrup room) with the second stage (packaging), however the formulations of both stages are almost the same as Meyr's (2002), but including some adjustments to fit their problem definition. Ferreira et al. (2008) also made some changes to the model based on their solution approach; their objective function only considered inventory holding costs and setup costs. We note that the work in this thesis is based on Meyr's (2002) idea, and section 3.3 presents further discussion on the mathematical formulation of the proposed model.

One can find plenty of literature about the application of Genetic Algorithm (GA) for solving the lot-sizing and scheduling problems. GA is a very popular search methodology inspired by biological evolution process (Sivanandam & Deepa, 2008). Boukef et al. (2007) presented a particular data structure (i.e., a kind of encoding) to solve flow-shop scheduling problems for the agro-food and pharmaceutical industries. Their solution approach aimed to minimize total costs related to each specific industry, such as manufacturing costs, delays costs, expired products' costs, or distribution discount costs. They employed a multi-objective optimization solution approach to deal with many criteria at the same time. Their individual representation contains information about the number of machines, the beginning time of production, the ending time of production and the product to be manufactured. They conclude that GA has a good capacity to find global optimal solution. Sikora (1996) presented an approach to solve lot-sizing and scheduling with sequence-dependent setup times. The individual representation is a string of paired values; one is the type of product and the other lot size for each (basic planning) period. He claimed to obtain better results compared to other heuristics.

Recently, Toledo et al. (2014) published a recent paper, in which the framework of their solution approach is similar to the one proposed in this thesis. They used C++ for the coding their genetic algorithm in which they called a solver in CPLEX library for solving a Linear Programming (LP) problem for the evaluation of individuals. Their approach is similar to ours in two aspects: (1) using GA to take care of the optimization of the sequencing of production lots for multiple products and (2) employing a LP solver for solving the lot sizing problem. However, the way of modeling and the implementation of the solution approach in Toledo et al. (2014) is considerably different from ours presented in this paper. First, they significantly simplified the LP model by eliminating the micro-periods. They re-defined the LP model using the following outlines:

- The objective function only considers inventory holding and stock out costs.
- They eliminate first-stage (syrup room) constraints.
- The constraints that deal with sequencing decisions are eliminated.
- The number of variables that represent lot size decision is reduced, by replacing it with a variable that represents the total lot size of product to be produced in one macro-period. If the GA defines one product to be produced twice or more in the same macro-period, the final lot size is divided evenly among the number of occurrences.

Also, Toledo et al. (2014) designed their GA according to their new encodings for the solutions. Every individual is represented by 2-D matrix M x T, where M represents the number of machines and T the number of periods. Each matrix entry (gene) contains a possible production sequence. Figure 3 illustrates an example where M and T equals 2.

	Period 1	Period 2
Machine 1	P1 → P3 → P4	P3 → P2
Machine 2	P2 → P2	P1 → P1 → P4

Figure 3 - Individual Representation in Toledo et al.'s (2014) GA

Once a sequence is given, the setup costs and setup time's information can be obtained. With the sequence and setup information they generate a LP problem by decoding two categories of input parameters: the number of times a product is produced in one period and the total time spent for changeovers. The LP model is formulated for the decision-making only in the packaging stage, but based on the sequence of tanks preparation in the syrup room.

Toledo et al.'s (2014) GA used the data structure of binary tree to store the individuals in a population hierarchically. Figure 4 depicts a population of 7 individuals, where the top individual is the best one, with the minimum cost, and a leader is located below the best individual and on the top of the corresponding cluster.

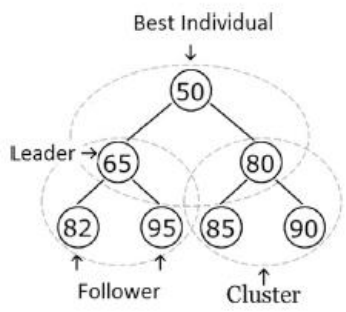

Figure 4 - Individuals in a population are stored in a binary-tree structure.

The crossover operator randomly selects individuals from each cluster to undergo "uniform crossover" using the following way: The cluster leader is always chosen for reproduction and one of its followers is randomly chosen. Mutation is applied to the new children according to some mutation rate. They used seven different mutations operators, where the one to be executed is randomly chosen at every iteration. Replacement takes place as the fitness of a child is better than the fitness of its parents. Also they execute a repair algorithm to arrange the new tree. Toledo et al.'s (2014) GA set the total time elapsed (at one hour in their study) as the stopping criterion. They made comparisons with the other two solution approaches proposed by them previously, and the new approach gained improvement in total cost and computational performance in most cases.

2.2 Summary

Following the review in section 2.1, we recommend Meyr's (2002) should be one of the most classical models since it catches well the characteristics of the production systems in consumer goods industries. Because it considers several production lines that partially offer same services, they can be used alternatively. The objective function considers inventory holding costs, production costs and setup costs. The production capacity is limited, and the setup times and costs are sequence-dependent. Since the scenario described above is similar to the one in Panama Beer Company problem, we decided to formulate our mathematical model in this thesis base on their GLSPPL model.

Note that the formulation of our model will be adjusted to fit the special characteristics and limitations in PBC's case. First, one of the key differences shows in the objective function since the production cost and setup costs are defined differently and, and the cost for idle time is included. Also, the issue of capacity-sharing between Lines 2 and 3 need to be taken into accounts, by (virtually) treating Lines 2 and 3 as a single machine being capable of producing all the products assigned to Line 2 and 3. Changeovers between products packed in Line 2 and Line 3 are set as the sum of the amount of hours required to finish production in one line plus the amount of hours required to set up the other line. We also take the average time of breakdowns per period as a parameter to include the idle time due to unexpected failures in our model since theses breakdowns may reduce available capacity of the packaging line. PBC's regulations mandates minimum production lot size and inventory policies so that inventory level at the end of every period will not drop to zero. In fact, PBC always keeps products at warehouses to face possible plant disruptions or unexpected changes in demand – one may refer to Chapter 3 for details.

The proposed solution approach in this study will be different from those presented by Toledo et al. (2002) and Ferreira et al. (2008). As mention in the previous section, Toledo et al. (2002) encountered problems when trying to solve their model with GAMS/CPLEX because the computational time increases very fast when the number of products and periods increase. Ferreira et al. (2008) presented two approaches. The first approach is called "relaxation approach" (RA) that solves just one-stage at a time, and the second "relax-and-fix" (RF), where integer variables are partitioned in subsets, and the variables of only one subset are defined as integers and the others are defined as continuous for each iteration. After the sub-model is solved, they verify its feasibility -- if it feasible, they fix those integer variables and repeat the process for the other subsets until solving all subsets. Their model and algorithms were coded in the AMPL modelling language and CPLEX was employed to solve the sub-models needed in the RA and the RF algorithms. Their RA approach outperformed Toledo's et al. (2002) using the real-world data from a company.

In order to solve the problem, we propose a hybrid-heuristic that combines genetic algorithm and Linear Programming, which is similar to Toledo's et al. (2014) approach. However, the problem definition and the proposed solution approach in our study are significantly different. The data structure of our GA is completely different, thus the implementation of GA totally changes. We solve the lot sizes of all products precisely for every micro-period in the planning horizon using the LP solver. We will explain all the details in Chapter 4. We will verify the effectiveness of the proposed solution approach by comparing it with the PBC's historical data. Chapter 6 presents our experiments, analyses and discussion and suggestions for improvement.

3. Decision-Making Scenario and Mathematical Model

3.1 Beer Packaging Process & CSD Packaging Process

At the end of every week, the Planning Department releases the next week's schedule to the packaging lines and the brew house. The packaging process starts when all materials, machines and brew house are set to run. The team leader constantly communicates with the warehouse supervisors to ensure the delivering of the required amount of crates with empty bottles during the production.

The packaging process of beers is made by continuous flow production lines. Generally, beer factories offer their products in different types of containers. The most common containers are returnable glass bottles, non-returnable glass bottles, cans, and kegs. As mention before, this thesis focuses on the Returnable Bottle (RB) production lines. Since Panama's factory uses RB, they have set a previous process that is done in their warehouses. Before crates are sent to manufacturing plant, these crates need to be checked and cleaned as much as possible because usually there are crates and bottles that are out of specification, e.g., cracked or chipped ones, as well as the ones that comes with material difficult to remove, such as cement.

The bottles come in crates which in turn are grouped in pallets. They are delivered to the depalletizer by hoists. The empty crates move through conveyors until reaching the unpacker, which is in charge of separating the empty bottles from the crates. The empty crates are sent through the conveyors to the crates washer and the bottles are sent to the washer. Inside the washer, the first step is the pre-rinse; follow by the immersion of bottles in caustic soda to sterilize. Immediately, they pass through water jets of high pressure to remove any residue of label, caustic soda or any other foreign object. Once the bottles are out of the washer, they start to accumulate in a buffer and are continuously moving to the electronic inspector. This machine assures that every bottle fulfills all quality requirements. Since the electronic inspector is considered as a critical machine to maintain the product safety, every two hours the operator need to put “fake bottles” to make sure that it is properly rejecting out-of-specification bottles, namely those being chipped, broken, having objects within, sediments or caustic soda residues.

After this inspection, the bottles passed directly to the filler, which is ready with the final product to be filled in and sealed with steel crowns with corrugated edges, twist offs, or pull tabs. The filler is the key machine of the whole packaging line and the performance of the line. The quality of the final products depends directly of the filling operation. The machines before the filler are designed in order to provide a continuous supply of bottles, and the machines after the filler are designed to allow the interrupted discharged of filled and sealed bottles. The optimal efficiency of the line is considered when the filler runs without stops during the production period and the bottles satisfy all quality specifications. Once the bottles are filled and sealed, they need to pass through codification and level inspection to assure the right quantity of liquid (Cerveceria Nacional S.A., 2008). Next is pasteurization, which is considered one of the most critical processes for quality assurance. PBC uses tunnel pasteurization. Bottles run into a tunnel where hot water is sprayed on the product. The temperature of product is carefully controlled, so the bottles are heated until the center of the package reaches a specific temperature. The bottles are held at this temperature for around 15~20 minutes and then starts to move into the cooling zone of the tunnel. This process is critical because if the temperature is not well controlled, the beer can be over heated, which jeopardizes the flavor of the beer. The bottles then are transported through conveyors to the labeler. Finally, the bottles are packed together into the crates and full crates are sent to palletizer. Hoists pick up the finish pallets and transport them to the warehouse. Figure 5 shows a simple description of the packaging process for beer products.

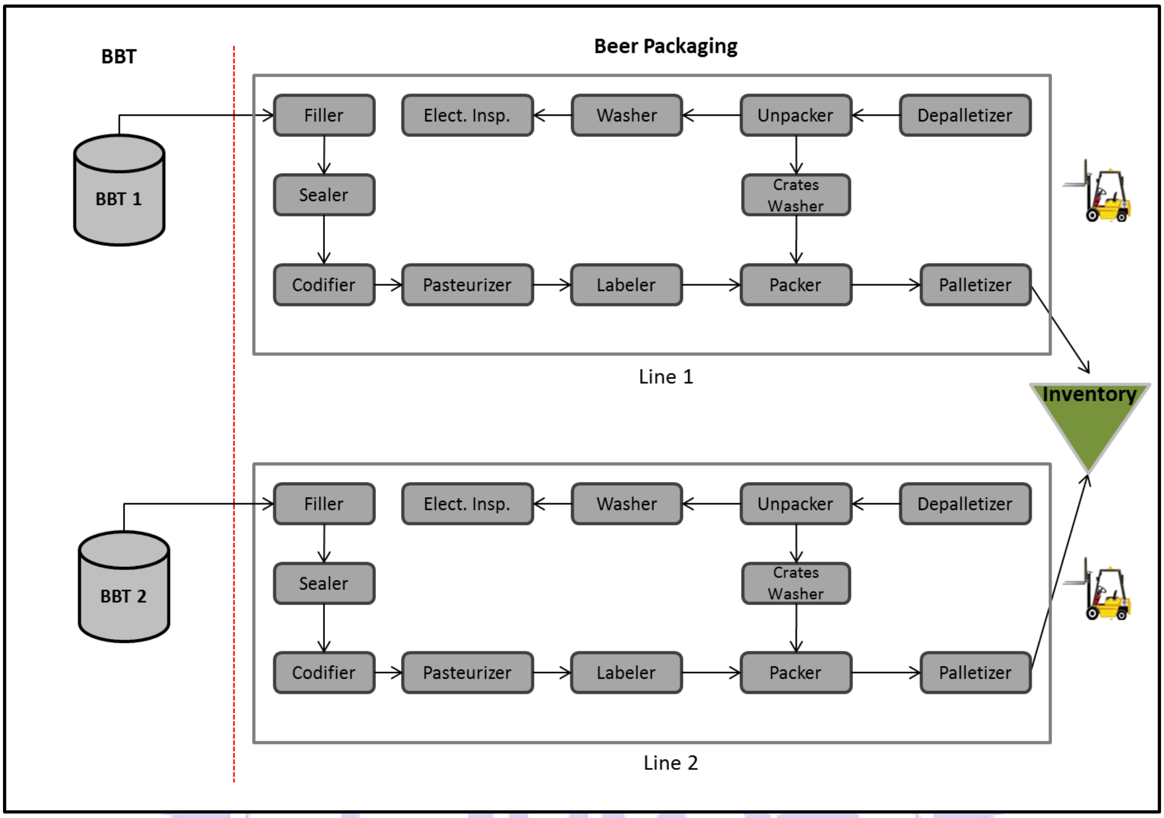

Figure 5 – Beer Packaging Process

The packaging process of soft drinks is made also by production lines. Some processes can differ depending on type of container. If the products are packed in pet containers, the process highly differs from beer packaging lines. However, in this study, we consider PBC's RB line for CSD; this process is very similar to the previous description. The main difference is that the liquid is prepared in the blenders prior to the filling process. This machine mixes the syrup concentrate and treated water. Also soft drinks do not need to pass through pasteurization process; therefore bottles are transported directly to the packing machine after the codification is done. Finally, the crates are palletized and transported to the warehouse for distribution. Figure 6 displays the packaging process of carbonated soft drinks.

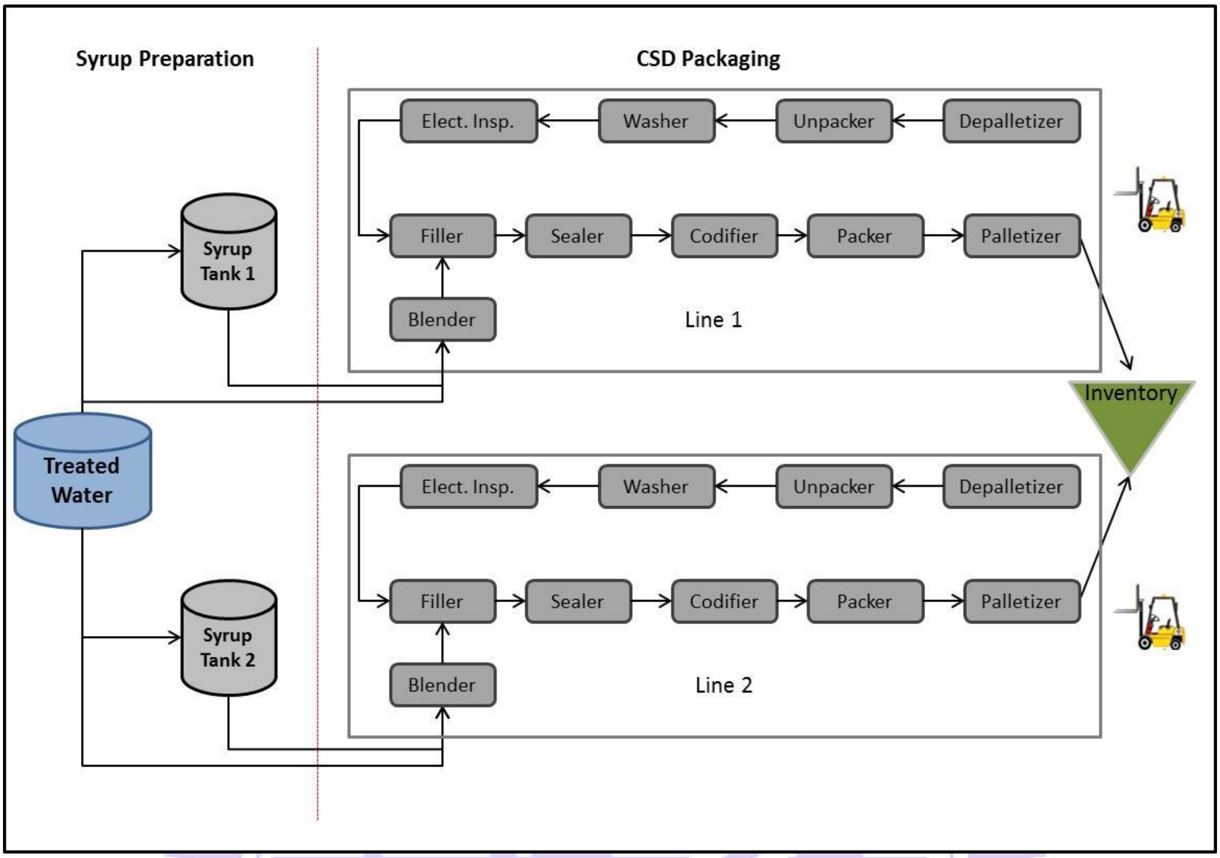

Figure 6 - Carbonated Soft Drinks Packaging Process

As mention before, packaging production lines can be treated as single unit because it is a continuous flow and its velocity is defined by the filling machine, so the highest throughput rate that the line can achieve is equal to the filler rate (Toledo, Franca, & Morabito, 2002). However, not necessarily all lines have the same processing rates for every product because it directly depends on the type of container to be filled. In the next section, PBC's main characteristics that need to be considered for the mathematical model are presented.

3.2 Decision-Making Scenario

3.2.1 PBC Characteristics

Production scheduling is not an easy task for the planners because they need to consider many factors, which make this task more difficult when they are not equipped with a computational tool to assist them. These factors can vary depending on the industry. Beverage industry involves the production of large batches using repetitive process. Production lines are shared among different products and factories usually work according to a make-to-stock policy.

PBC sales department sends the planners the sales numbers for the next week every Monday morning and the projected forecast for the next two months. These Excel files are updated daily, however for planning purposes the information updated until Wednesday is the one used for production scheduling of the brew house and the packaging department. Sales are expressed in terms of hectoliters (Hl) for each SKU. This is the unit of measure that is going to be used throughout this thesis to express production quantity. The material requirement plan and distribution plan also is generated from this data.

As described in the previous section, packaging lines are arranged in a specific sequence of operations. This sequence depends on the type of products that are going to be manufactured in every line. There is no difference in sequence for products that belongs to the same family. All types of beers and malta pass through the same stages in a returnable bottle line and all CSD pass through the same stages in its production line. Therefore it can be said that the flow pattern is a “flow shop”.

PBC has three lines dedicated to returnable bottle products. Every line has different capability to produce a set of products. In this case are considered 13 different SKUs which are listed in Table 2.

Table 2 - List of Products bottled in Returnable Bottles

SKU	Product Description	Type
1	Atlas 24 x 330 ml	Beer
2	Balboa 24 x 330 ml	Beer
3	Malta 24 x 250 ml	Malta
4	Balboa 24 x 590 ml	Beer
5	Atlas 24 x 590 ml	Beer
6	Miller Lite 24 x 300 ml	Beer
7	7UP 24 x 355 ml	CSD
8	Pepsi 24 x 355 ml	CSD
9	Ginger Ale 24 x 284 ml	CSD
10	Mirinda Manzana 24 x 355 ml	CSD
11	Squirt 24 x 355 ml	CSD
12	Mirinda Fresa 24 x 355 ml	CSD
13	Orange Crush 24 x 355 ml	CSD

Line 1 is the largest packaging line in the plant. However, it is capable to produce only three types of SKU. Although Line 2 has a lower production rate compared to Line 1, it has greater flexibility because it can produce all products from the beer and malt segment. Line 3 is exclusively designed to bottle CSD products; this last process is different from beer process, however it uses almost the same types of machines. Table 3 summarizes the packaging capabilities of each line where the "X" mark means that a line is capable to bottle the respective product.

Table 3 - Production Lines' Capabilities

SKU	Product Description	L1	L2	L3
1	Atlas 24 x 330 ml	X	X	
2	Balboa 24 x 330 ml	X	X	
3	Malta 24 x 250 ml	X	X	
4	Balboa 24 x 590 ml		X	
5	Atlas 24 x 590 ml		X	
6	Miller Lite 24 x 300 ml		X	
7	7UP 24 x 355 ml			X
8	Pepsi 24 x 355 ml			X
9	Ginger Ale 24 x 284 ml			X
10	Mirinda Manzana 24 x 355 ml			X
11	Squirt 24 x 355 ml			X
12	Mirinda Fresa 24 x 355 ml			X
13	Orange Crush 24 x 355 ml			X

In this factory, production lines possess different production rates, even for the same type of products. For example, the production rate of Line 1 for SKU number 1 is almost twice the rate of Line 2. This is an important factor for the assignment of production every week. Packaging production lines are treated as single unit because it is a continuous flow and its velocity is defined by the filling machine.

Another difference is the production cost of each line. Based on the meetings with the Packaging Director, the costs that are directly impacted by the lot sizing and scheduling decisions for packaging production lines are: electricity consumption, steam consumption, material inputs such as caustic soda, additives, and lubricants, and water consumption. These values are calculated every two years according the variance of cost and the consumption in lines. For practical purposes PBC has established a fix cost for every production line; one may refer to the details of which costs are considered in production costs in Appendix C. Commonly in packaging lines there is an amount of waste that is loss during the process. This waste is caused by different reasons such as, unexpected breakdowns in any machine, wrong adjustment in conveyors that caused bottles to fall down, handling issues, etc. Every line has different percentages of product loss, therefore managers calculate the total production cost of each line by adding the production fix cost and the amount of product waste during production. The percentage of product loss used is the average of the past 6 months. The total production costs can be calculated as follow:

Total Production Cost = (Fix Production cost of Line L ($)/Hl) * (Amount of Bottled Product j in Line L (Hl)) + (Cost of product J ($/Hl)) * (Amount of Bottled Product (Hl) * fix % of product loss of Line L)

The setup times include the cleaning time and the time for machines adjustments. It is a factor that strongly influences the production sequence, because the setup time is sequence-dependent, that is, the time length of the setup depends on which product was produced previously. In PBC's case, the setup time varies from half hour to 5 hours, depending on the line and the production sequence. These changeovers also imply a loss of the previous packaged product, where every line has a different (fix) amount of hectoliters that are loss every time a changeover is done. Thus the total setup cost can be calculated with the following equation:

Total Setup Cost = (Fix Changeover Cost of Line L ($/hour)) * Setup hours (hour) + (Cost of Previous Product ($/Hl)) * (Fix Amount of Product Loss per Changeover (Hl))

As mention in Chapter 1, PBC recently made a restructuration of headcount and working hours. With this new scheme factory is working with a schedule where Line 1 fills all demand requirements of three SKUs from beer and malt segment, and Line 2 fulfils the other three SKUs from beer segment. **Table 4** shows specifically which beer products are currently being processed in Line 1 and Line 2.

Table 4 - Current production assignment of beer products.

SKU	Product Description	L1	L2
1	Atlas 24 x 330 ml	X	-
2	Balboa 24 x 330 ml	X	-
3	Malta 24 x 250 ml	X	-
4	Balboa 24 x 590 ml		X
5	Atlas 24 x 590 ml		X
6	Miller Lite 24 x 300 ml		X

Due to the change in demand, managers calculated that six teams and one "special" team for line cleaning and changeover periods, are capable to cover these shifts. However, some teams are required to work alternately between the lines. Their work assignments and scheduling used the following rules based on teams' abilities:

Team 1, Team 2 and Team 3:

- These teams are fully dedicated to operate Line 1.
- One team covers one shift.
- There are 3 shifts per day. Every shift has duration of 8 hours. Line 1 works 24 hours per day.
- All teams are available 6 days per week.

Team 4, Team 5 and Team 6:

- These teams need to operate Line 2 and Line 3.
- One team covers one shift. This means that Line 2 and Line 3 cannot run at the same time.
- There are 3 shifts per day. Every shift has duration of 8 hours. The three teams cover 24

hours per day.

- All teams are available 6 days per week.

The six teams have the same costs; therefore can be assigned indifferently to the shifts. This constraint is important because the production of beer and malta can be divided between Line 1 and Line 2. On the other hand, the availability of Line 2 directly depends on the production schedule of Team 4, Team 5 and Team 6, which in turn also need to cover shifts of Line 3. The managers decide (usually by experienced) that teams need to work in the sequence shown in Table 5. However, it is flexible to changes.

Table 5 - Current team assignment sequence for production

Line	Team	Shift	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Line 1	Team 1	Shift 1	L1	L1	L1	L1	L1	L1
	Team 2	Shift 2	L1	L1	L1	L1	L1	L1
	Team 3	Shift 3	L1	L1	L1	L1	L1	Maintenance L1 (12 hrs)
Line 2 & Line 3	Team 4	Shift 1	L2	*L3*	*L3*	Maintenance L3 (8 hrs)	L2	L2
	Team 5	Shift 2	L2	*L3*	*L3*	L2	L2	L2
	Team 5	Shift 2	L2	*L3*	*L3*	L2	L2	Maintenance L2 (8 hrs)

Although all teams work 6 days per week, it is necessary to consider the number of hours dedicated to the weekly maintenance of production lines, because they reduced the available time for production. The data of available hours for teams is shown in Table 6.

Table 6 - PBC teams Capacity per week (hours)

Line 1	Daily	Weekly	Maintenance	Productive Available Time
Teams (1, 2, 3) Available Hours	24	144	12	132
Line 2 & Line 5	Daily	Weekly	Maintenance	Productive Available Time
Teams (4, 5, 6) Available Hours	24	144	16	128

Since the setup and production costs are high, the company defined a Minimum Lot Size policy that mandates the minimum lot size to be produced every time a line starts up a production lot. Table 7 presents the real values of the company. Currently, these values are being revised by the managers due to reduction in demand of RB products. However, the author will use these values until the new ones are approved.

Table 7 - Minimum Lot Size defined for every product in every line

Minimum Lot Size		Qmin L1 Hl	Qmin L2 Hl	Qmin L3 Hl
1	Atlas 24 x 330 ml	7128	3168	
2	Balboa 24 x 330 ml	7128	3168	
3	Malta 24 x 250 ml	2508	1680	
4	Balboa 24 x 590 ml		708	
5	Atlas 24 x 590 ml		1699.2	
6	Miller Lite 24 x 300 ml		3888	
7	7UP 24 x 355 ml			203.3
8	Pepsi 24 x 355 ml			508.1
9	Ginger Ale 24 x 284 ml			229.9
10	Mirinda Manzana 24 x 355 ml			304.8
11	Squirt 24 x 355 ml			397.4
12	Mirinda Fresa 24 x 355 ml			304.8
13	Orange Crush 24 x 355 ml			301.5

At the same time PBC has policies that regulate the maximum amount of inventory maintained in the warehouses in order to control the inventory holding costs. This measurement is called “days of coverage” and the unit is days. It indicates the number of days that current inventory and production is able to respond to future demand. They set a minimum “days of coverage” which can be considered as the replenishment point and a maximum “days of coverage” which can be considered as the maximum amount of items that can be stored in the warehouses. The planners try to maintain the “coverage” between these two values by trial-and-error, however most of the time they prefer to keep the maximum coverage to be “safe”. For example if the policy says that for product 1, a minimum amount of coverage that need to be cover is 6 days (1 week), this means that inventory at the end of the planning horizon at least need to have enough products to cover next week’s demand.

The inventory policy is maintained due to the reliability of production lines or unexpected fluctuations in demand. Normally, lines are interrupted by unexpected breakdowns, which reduce the capacity of production. Therefore the average breakdown time is another important parameter that needs to be considered in the mathematical formulation.

According to the parameters of Planning Department and demand analyses, PBC’s managers consider that some products need to be produced in a weekly manner, others every two weeks, three weeks or four weeks. Table 8 shows the current frequency of production of every item. This characteristic helps the planners to determine the number of lots that need to be considered in every week. However, this schedule is not followed exactly, because the final decision depends on demand of specific periods.

Table 8 - Frequency of production of every item

SKU	Product Description	Every Week	Every 2 weeks	Every 3 weeks	Every 4 weeks
1	Atlas 24 x 330 ml	X			
2	Balboa 24 x 330 ml	X			
3	Malta 24 x 250 ml		X		
4	Balboa 24 x 590 ml		X		
5	Atlas 24 x 590 ml		X		
6	Miller Lite 24 x 300 ml	X			
7	7UP 24 x 355 ml			X	
8	Pepsi 24 x 355 ml	X			
9	Ginger Ale 24 x 284 ml				X
10	Mirinda Manzana 24 x 355 ml		X		
11	Squirt 24 x 355 ml	X			
12	Mirinda Fresa 24 x 355 ml		X		
13	Orange Crush 24 x 355 ml	X			

Quality constraints are also taken into consideration by the planners for the final scheduling. These are the requirements to keep certain international standards of beer and CSD production. For Line 1 a major sterilization need to be done if this has been running a product for more than 72 hours; this sterilization lasts 4 hours. Line 2 has the same restriction, but the sterilization lasts 3 hours. And for Line 3, a major sterilization is required after 36 hours of continuous production; this procedure lasts 3 hours. These sterilizations are in addition to those strictly required every time a changeover is done. Since demand of RB products are going down is very rare that PBC production lines has runs that last more than 36 or 72 hours. Therefore, for simplicity purpose these parameters are not considered in our mathematical model.

Besides the limitations that exist within the packaging system, the production lines are also constrained by the brewery, utilities supply and packaging material.

The brewery and the syrup room are in charge for the supply of beer and liquid concentrate respectively. Utilities department provides steam, treated water, compressed air, and refrigeration systems. Materials such as glass bottles, crates, labels, glue, caustic soda, lubricants, caps, pallets and others, are supplied by the Materials Storage Department. In this thesis all these supplies are assumed infinite, so we consider no constraint from them.

3.2.2 Statement of Problem

Since the aim of this thesis is to solve PBC's lot sizing and scheduling problem, the principal characteristics considered for the formulation of our mathematical are summarized in this section.

We had made some considerations about the capacity-sharing issue between Lines 2 and 3. Based on Meyr's (2002) formulation, the lot sizing and scheduling problem can be solved for the PBC problem by changing or adding some constraints to represent the company's characteristics and restrictions. We must consider the fact that Lines 2 and 3 cannot operate simultaneously. Therefore to simulate PBC's problem, it's been established that for modeling purposes a (virtual) Line 2 will represent a line which has the capability to bottle all products produced in Lines 2 and 3. Thus its production capacity will be the sum of teams' availability. The lot size and the number of changeovers in every period will be constrained by the production capacity.

The simulation of changeovers between products packed in Lines 2 and 3 is done by adding the amount of hours required to complete the production in one line and the amount of hours required to start up the other line. With this parameter the real situation can be simulated due to necessity of moving a team from one line to the other. Teams will shift from one line to the other when the sequence in production goes from a beer product to a CSD product, and vice versa.

The setup times are sequence-dependent. Product sharing between Lines 1 and 2 is also a characteristic of this problem. The solution approach will help to decide in which production line is less expensive to assign the lot of a specific product. The setup costs are included as part of the objective function.

The proposed model also follows the characteristics of the packaging lines, which usually suffer from reliability issues (viz. by adding downtime due to breakdowns). This reduces capacity availability.

Since the setup and production costs are high, the company defines a Minimum Lot Size policy that the minimum quantity needs to be produced every time the line starts up a production lot of a specific product. Following this, designated constraints for this issue will be included in the mathematical model.

A very particular characteristic of this company is that they do not expect to reduce the total inventory level to zero. This company have inventory policies, that set a minimum amount of inventory that need to be at the end of every week is the warehouse. Usually these amount need to cover from 1 to 3 weeks of future demand. This type of policies is established due to the reliability of production lines or unexpected fluctuation in demand, since these are fast-moving goods. The objective function also includes the inventory holding costs associated with the amount of inventory at the end of every week.

The output of our solution approach will be the lot sizes for every product and the scheduling in each line that minimizes the total costs. We will verify the effectiveness of the proposed solution approach by comparing it with the AS-IS approach using PBC's historical data.

3.2.3 Assumptions

We make the following assumptions for our mathematical formulation.

- The line runs to a specific throughput rate that is defined by the filler rate.
- The planners define the total number of lots that can be produced per macro-period.
- It is assumed that packing material such as bottles, caps, labels, glue, caustic soda, lubricants and pallets are infinite.
- Liquid products (beer and syrup) are always available by the time of packaging process.
- Utilities Department supplies steam, electricity, treated water, compressed air and refrigeration as needed.
- Line 2 will represent the packaging Lines 2 and 3. The total capacity per period will be defined by Teams 4, 5 and 6's time availability.
- Line 2 will be set with the capability to bottle the products of Lines 2 and 3.
- The time for the changeovers between products packed in Lines 2 and 3 are calculated by the sum of the amount of hours required to finish production in one line and the amount of hours required to start up the other line.

3.3 Mathematical Model

This section presents a mathematical model for the production planning and scheduling problem in Panama Beer Company (PBC). The proposed model is based on Meyr's (2002) called the *General Lot-sizing and Scheduling Problem on Parallel Machines*, and it assists the planners in the decisions of the lot-size for each product, the assigned packaging line and the production sequence of products, to meet demand in a finite planning horizon, considering the capacity availability, the characteristics of the packaging lines in the production system and PBC's policies on inventory and production.

The following characteristics have been considered for the proposed model:

- Demand need to be met in every period;
- L number of lines available to produce;
- T represents the length of the production planning horizon (in number of weeks);
- A lot can be started if and only if machine is ready for production;
- Setup times between products depends on the sequence of production;
- Cost of changeover will depend on the total amount of time spent on setups;
- Minimum days of coverage according to PBC's Inventory policy;
- Minimum Lot Size according to PBC's Production policy;
- Teams' availability represents the total capacity of each line per period.

The problem-size of the model is defined by the number of products (beer and soft drinks), the number of packaging lines and the total number of micro-periods. All these parameters are defined by users as follows.

J = number of products

L = number of lines

T = macro-period (planning horizon)

N = number of micro-periods in every macro-period. (It serves as a restriction on the number of lots per period.)

Consider the following indices used in the mathematical formulation:

Indices Definition

$i, j = 1,\ldots, J$ represents all products

$t = 1,\ldots,T$ represents macro-periods

$l = 1,\ldots, L$ represents the lines of the system

$n = 1,\ldots,N$ represents the micro-periods that are part of a macro-period.

Known Sets

M_t set of micro-periods in each macro-period t.

λ_j set of lines l that produce product j.

α_l set of products that can be produced in line l.

F_t set of first micro-period of every macro-period t.

LP_t set of last micro-period of every macro-period t.

Known Data

d_{jt} demand of product j in period t (Hl);

h_j inventory holding cost for one unit of product j (\$/Hl);

I_{j0} initial inventory of product j at the beginning of horizon (Hl);

s_l fixed cost if a changeover is made in line l (\$/hour);

st_{ijl} changeover time from product *i* to product *j* in line *l* (hours);

sp_l default amount of product that is lost during a changeover in line *l* (Hl);

y_{jl0} $\begin{cases} 1 & \text{if line } l \text{ is set at the beginning of period to produce product j} \\ 0 & \text{otherwise} \end{cases}$

m_l fix % of product loss while running in line *l* (%);

p_{jl} fixed production cost for produce one unit (Hl) of product *j* in line *l* ($/Hl);

pc_j cost of one unit of product *j* ($/Hl);

r_{jl} production rate of product *j* in line *l* (Hl/hour);

δ_{lt} average downtime in line *l* per period *t* (hours);

idc_l fix cost of idle time in line *l* per hour ($/hour);

K_{lt} total capacity of line *l* in period *t* (hours);

$Qmin_{jl}$ minimal amount of product *j* that can be produced in line *l* (Hl);

$cobmin_{jt}$ minimum amount of "coverage" (inventory) of product *j* (Hl) in time *t*. It varies depending on planning date.

Variables

Q_{jnl} production quantity of product *j* in line *l* in micro-period *n* (Hl);

I_{jt} inventory of product *j* at the end of macro-period *t* (Hl);

idt_{lt} idle time in line *l* at the end of macro-period *t* (hours);

y_{jnl} $\begin{cases} 1 & \text{if line } l \text{ is setup for product } j \text{ in micro-period } n \\ 0 & \text{Otherwise;} \end{cases}$

z_{ijnl} $\begin{cases} 1 & \text{if a changeover from product } i \text{ to product } j \text{ takes place on line } l \text{ in micro-period } n. \\ 0 & \text{Otherwise} \end{cases}$

We present the mathematical model for the production planning and scheduling problem in PBC as follows.

Objective Function

The objective function of the proposed model addresses to the managers' key concern, namely, the minimization of the total costs. The expression for the total costs in equation (3.1) is similar to (Meyr, 2002), but with some modifications to fit PBC's decision-making scenario.

$$Min\ Z = \sum_{j=1}^{J}\sum_{t=1}^{T}(h_j\, I_{jt}) + \sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{i\in\alpha_l}\sum_{j\in\alpha_l}\Big(z_{\,ijnl}\big(s_l st_{ijl} + pc_i sp_l\big)\Big) + \sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{j\in\alpha_l}(Q_{jnl}\big(p_{jl} + pc_j m_l\big)) + \sum_{l=1}^{L}\sum_{t=1}^{T}(idt_{lt} * idc_l) \qquad (3.1)$$

The first term in (3.1) computes the inventory holding cost associated with the amount of inventory after meeting demand of the week. The second term represents the changeover costs as described in Section 3.2.1. The third term is regarding to the production cost incurred, which also follows the definition given by the managers in PBC. The last term is for the idle time costs that penalize the time that production lines are not set for production.

Subject to the following constraints:

Production Quantity-Demand Balance Constraint

The total production quantity for every product *j* needs to be greater or equal than the minimum amount of coverage minus the difference between the closing stock in the previous period and the demand in the current planning period. We use this constraint, expressed in (3.2), to follow the Minimum Safety-Stock policy that requires the minimum amount of inventory that must be at stock at the end of each macro-period.

$$\sum_{l\in\lambda_j}\sum_{n\in M_t} Q_{jnl} \quad \geq \ cobmin_{jt} - \ (I_{j(t-1)} - \ d_{jt}) \qquad j = 1, \dots, J \quad t = 1, \dots, T \qquad (3.2)$$

Capacity Constraint

The constraints in (3.3) guarantee that the production time plus the time needed to make all changeovers do not exceed the available capacity of each packaging line in every macro-period *t* which is also reduced by the average downtime of line *l* in period *t*.

$$\sum_{j\in\alpha_l}\sum_{n\in M_t}\frac{Q_{jnl}}{r_{jl}} + \ \sum_{i\in\alpha_l}\sum_{j\in\alpha_l}\sum_{n\in M_t}\left(st_{ijl}z_{ijnl}\right) \leq \ K_{lt} \ - \delta_{lt}$$

$$l = 1, \dots, L \quad t = 1, \dots, T \qquad (3.3)$$

The quantity produced in every micro-period is subject to the setup state variable y_{ljn} and the total capacity of one line to produce this product. No line can produce without the setup ready for any product *j*. Therefore, we have the inequality for the capacity constraint as (3.4) as follows.

$$Q_{jnl} \leq \left(K_{lt} * \ r_{jl}\right)\left(y_{jnl}\right) \qquad l = 1, \dots, L \quad t = 1, \dots, T \quad j \in \alpha_l \quad n \ \in M_t \qquad (3.4)$$

Idle Time

The idle time in period *t* in line *l*, expressed in equation (3.5), is equal to the amount of hours that were not assigned for production in every line *l*. Recall that we penalized idle time in the objective function.

$$idt_{lt} = K_{lt} - \delta_{lt} - \sum_{j\in\alpha_l}\sum_{n\in M_t}\frac{Q_{jnl}}{r_{jl}} - \sum_{i\in\alpha_l}\sum_{j\in\alpha_l}\sum_{n\in M_t}(st_{ijl}z_{ijnl})$$

$$l = 1, \dots, L \quad t = 1, \dots, T \qquad (3.5)$$

Minimum Lot Size Constraint

The managers in PBC mandate a Minimum Lot Size policy for every product in every line. The lot size of any product must be larger than a minimum threshold once it is determined to be produced. This constraint is defined in (3.6).

$$Q_{jnl} \geq Qmin_{jl}(y_{jnl}) \qquad l = 1, \dots, L \quad j = 1, \dots, J \quad n = 1, \dots, N \tag{3.6}$$

Inventory level at the end of period

The inventory of every product at the end of period is the remaining quantity after the sum of the amount at the end of the last period and the production quantity on all lines meets the demand in the current period. Usually, we would like to minimize the inventory holding at the end of every period by deciding the optimal production quantities and the best line to be produced.

$$I_{jt} = I_{j(t-1)} + \sum_{l \in \lambda_j} \sum_{n \in M_t} Q_{jnl} - d_{jt} \qquad j = 1, \dots, J \quad t = 1, \dots, T \tag{3.7}$$

Changeover Constraints

Equation (3.8) ensures that only one product is produced in a micro-period n and guarantees that every line is prepared to produce only one product in micro-period n.

$$\sum_{j=1}^{J} y_{jnl} = 1 \qquad l = 1, \dots, L \quad n = 1, \dots, N \tag{3.8}$$

The connection between the changeover indicator and the setup state indicators is established by equation (3.9). Taking this equation and (3.10) together ensures that z_{lijn} is only set to 1 if line l was set up for product i in $n-1$ and for j in n. It is important to mention that since a setup for the same product j in two consecutive micro-period $n-1$ and n is possible, and since $st_{jjl} = 0$ holds for all lines l and products j, the corresponding variables z_{ljjn} directly allow a setup for the next micro-period.

$$y_{i(n-1)l} + y_{jnl} - 1 \leq z_{ijnl} \qquad n = 1, \dots, N \qquad l = 1, \dots, L \qquad i, j \in \alpha_l \tag{3.9}$$

The following equation ensures that there is no more than one changeover from product i to product j in line l per micro-period n.

$$\sum_{i \in \alpha_l} \sum_{j \in \alpha_l} z_{ijnl} \leq 1 \qquad l = 1, \dots, L \qquad n = 1, \dots, N \tag{3.10}$$

Variable Domain

$$I_{jt} \geq 0 \qquad z_{ijnl} \geq 0 \qquad idt_{lt} \geq 0 \qquad y_{jnl} \in \{0,1\}$$

$$j = 1, \dots, J \qquad t = 1, \dots, T \qquad l = 1, \dots, L \qquad i, j \in \alpha_l \qquad n \in M_t \tag{3.11}$$

Observe that inequality (3.2) is included to control the minimum amount of products that need to be produced in every period, which is defined by the closing stock, the demand in the period and the minimum coverage to be fulfilled. This follows PBC's Minimum Safety Stock policy requiring a minimum amount of inventory must be stocked in the warehouse to respond to abrupt changes in demand, or to prevent stock out if a problem appears in the manufacturing plant. Inequality (3.3) shows that the capacity is reduced by the average downtime per period to match with real life situations as possible. Equation (3.5) expresses the time that production lines remain idle, and the idle time varies according to the final amount of hours dedicated to production. Constraint (3.7) represents the inventory level at the end of a period. Equations (3.4), (3.6), (3.7), (3.8), and (3.9) are taken from (Meyr, 2002) and equation (3.10) is taken from Ferreira et al. (2008).

For PBC's case, Line 1 works 24 hours for 6 days a week with fully dedicated teams. Therefore, the representation of the final schedule reflects the changes that teams need to make in Line 1. On the other hand, the capacity of Teams 4, 5 and 6 need to be shared between Lines 2 and 3. To simplify the situation, we represent the problem by treating Lines 2 and 3 as a (virtual) single packaging line and the position of teams will depend on the sequence of production between beer products and soft drinks products. The sequence will indicated when teams need to shift from one line to the other.

4. Proposed Solution Approach

4.1 Overview of Methodology

Charles Darwin stated the theory of natural evolution in the origin of species, that explains how biological organisms evolve based on the principle of natural selection “survival of the fittest” to reach certain remarkable characteristics. In 1975, Holland developed the idea of how this principle can be applied to optimization problems in his book “Adaptation in natural and artificial systems” (Sivanandam & Deepa, 2008). Genetic Algorithm (GA) can be defined as a stochastic heuristic search method whose mechanisms are based upon simplifications of evolutionary processes observed in Nature (Wall, 1996). This method is considered a powerful tool because its capability in exploitation and exploration, since a population of individuals search in parallel in the solution space.

Figure 7 illustrates the flowchart of GA. It starts with creating an initial population of possible solutions for the concerned problem. The fitness of every individual is evaluated by the objective function. The best solution is temporarily stored as the optimal one. Individuals are selected from the current population according their fitness, to mate and create new individuals in the population of the next generation. The process of combining two individuals is known as crossover and it consists of choosing genetic material from both parents to create a pair of new individuals. The individuals of the created pair replace their parents if they are feasible. After replacement, some individuals mutate according a pre-defined rate, this aims to maintain diversity in the population. Mutated individuals replace previous, and the new population passes through the evolutionary process again.

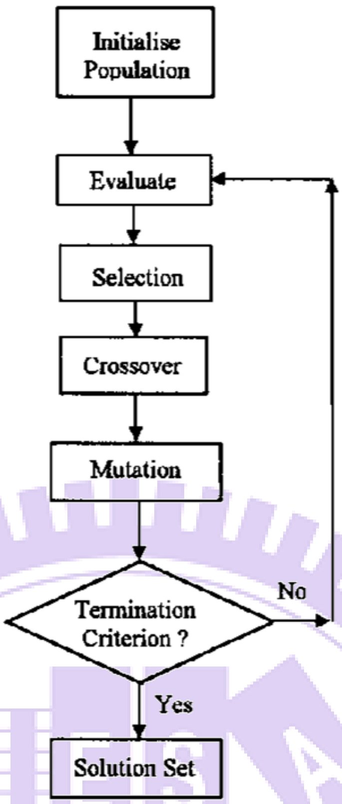

Figure 7 – The flowchart of the proposed Genetic Algorithm.

Encoding is a way of representing individuals; it may be using bits, numbers, arrays, trees or others. Usually this decision depends on the problem to be solved. This representation should not be able to represent infeasible solutions. This is useful, because the GA will work only to find optimality and but not wasting of time in finding infeasible solutions.

The most common representation is binary string, where each bit or the entire string represents some characteristic of the solution or the solution itself. Octal encoding is the one that uses string made up of octal numbers (0-7). Permutation Encoding is the one that every chromosome string represents the number in sequence. In this kind of encoding every chromosome is a string of integer/real values, which represents number in a sequence (Sivanandam & Deepa, 2008).

Our solution can be represented in one 3-D array filled with ones and zero, therefore in this thesis, every chromosome is an exact representation of the solution of the binary variable of the original mathematical model, which represents the sequencing of production; we will present details in section 4.3.1. For the evaluation step, Linear Programming is executed to solve the lot sizing problem; we will have further discussion in the next section.

4.2 Sub-problem in Genetic Algorithm

We apply Genetic Algorithm to find the optimal production sequence by generating possible solutions resulting from sets of the binary variables (y_{jnl}). Once a possible solution is obtained, the set of changeover indicator variables (z_{ijnl}) can be solved. Both sets of (y_{jnl}) and z_{ijnl} are taken by LP-solver as input parameters. The updated mathematical model, namely Problem ZZ (introduced later), will be turned into a Linear Programming model and this will be used to obtain the optimal lot sizes, the final inventory levels and the values of idle time.

Problem ZZ

New input parameters:

y_{jnl} = sequence of production for product *j* in micro-period *n* and line *l*, given by GA.

z_{ijnl} = sequence of changeover from product *i* to product *j* in micro-period *n* in line *l*. It can be calculated as the values of y_{jnl} are given by the GA.

Variables

Q_{jnl} production quantity of product *j* in micro-period *n* in line *l* (Hl);

I_{jt} inventory level of product *j* at the end of macro-period *t* (Hl);

idt_{lt} idle time in line *l* at the end of macro-period *t* (hours);

Objective Function

The objective function of the updated LP mode considers the inventory holding costs, the production costs and the idle time costs. The changeover cost expressions are eliminated from the objective function since they become constants as both sets of y_{jnl} and z_{ijnl} are given. However, after the optimal solution is found by LP, the changeover costs are added back to the objective function, and such a value of total cost is the one considered as the base for the *ranking selection* process.

$$Min\ ZZ = \sum_{j=1}^{J}\sum_{t=1}^{T}(h_j\, I_{jt}) \quad + \quad \sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{j\in\alpha_l}(Q_{jnl}(p_{jl}+pc_j m_l)) \quad + \quad \sum_{l=1}^{L}\sum_{t=1}^{T}(idt_{lt} * idc_l) \qquad (4.1)$$

Subject to the following constraints:

Inequalities

$$\sum_{l\in\lambda_j}\sum_{n\in M_t} Q_{jnl} \quad \geq \ cobmin_{\boldsymbol{jt}} - \ (I_{j(t-1)} - \ d_{jt}) \qquad j=1,\dots,J \quad t=1,\dots,T \qquad (4.2)$$

$$\sum_{j\in\alpha_l}\sum_{n\in M_t}\frac{Q_{jnl}}{r_{jl}} \leq \ K_{lt} \ -\delta_{lt} - \sum_{i\in\alpha_l}\sum_{j\in\alpha_l}\sum_{n\in M_t}(\ st_{ijl}z_{ijnl})$$

$$l=1,\dots,L \quad t=1,\dots,T \qquad (4.3)$$

$$Q_{jnl} \leq (K_{lt} * r_{jl})(y_{jnl}) \qquad l=1,\dots,L \qquad t=1,\dots,T \qquad j\in\alpha_l \qquad n\in M_t \qquad (4.4)$$

$$Q_{jnl} \geq Qmin_{jl}(y_{jnl}) \qquad l = 1, \dots, L \quad j = 1, \dots, J \quad n = 1, \dots, N \tag{4.5}$$

Equalities

$$idt_{lt} + \sum_{j \in \alpha_l} \sum_{n \in M_t} \frac{Q_{jnl}}{r_{jl}} = K_{lt} - \delta_{lt} - \sum_{i \in \alpha_l} \sum_{j \in \alpha_l} \sum_{n \in M_t} (st_{ijl} z_{ijnl})$$

$$l = 1, \dots, L \quad t = 1, \dots, T \tag{4.6}$$

$$I_{jt} = I_{j(t-1)} + \sum_{l \in \lambda_j} \sum_{n \in M_t} Q_{jnl} - d_{jt} \qquad j = 1, \dots, J \quad t = 1, \dots, T \tag{4.7}$$

Variable Domain

$$I_{jt} \geq 0, \qquad idt_{lt} \geq 0 \qquad j = 1, \dots, J \quad t = 1, \dots, T \quad l = 1, \dots, L \tag{4.8}$$

Equations (4.2) and (4.3) corresponds to the constraints (3.2) and (3.3), respectively, as previously defined in section 3.3 though the variables z_{ijnl} are treated as given parameters in the updated model. Equations (4.4) and (4.5) are corresponding to the constraints (3.4) and (3.6) respectively; for these constraints the binary variables y_{jnl} are taken as given parameters. Equalities constraints (4.6) and (4.7) are analogous to constraints (3.5) and (3.7). Constraints (3.8), (3.9) and (3.10) are not included in this model because they shall be handled by the GA. All the other variables and indices remains as the original model. For the *Problem ZZ*, all variables are continuous, and three sets of constraints, corresponding to (3.8), (3.9) and (3.10), are removed.

4.3 Implementation of Genetic Algorithm

In this section we present the implementation of the GA for solving our problem in detail. Section 4.3.1 explains how we design the encoding of an individual to represent a possible production sequence corresponding to a solution of the y_{jnl} variables. Section 4.3.2 describes the way of generating an initial population, the infeasibility prevention mechanism checking individuals before they join the population and the data structure for the population. Section 4.3.3 explains the evaluation of individuals and the selection mechanism for mating. Section 4.3.4 discusses the genetic operators and the stopping condition employed in the proposed GA. Finally, we present the pseudo-code corresponding to our approach.

4.3.1 Representation of Individuals

Each individual, that corresponds to a possible solution of the production sequence, is represented by three-dimension matrix $J \times N \times L$, where J is the number of products, N is the number of micro-periods and L is the number of lines. Figure 8 shows an example individual that is composed by 12 micro-periods, which represents the total number of lots that can be produced for the 13 products on 2 bottling lines in the planning horizon. As mention before, only one product can be produced in each micro-period. A bit "1" at the position (j,n) indicates a production lot is assigned to product j in micro-period n, or "0", otherwise.

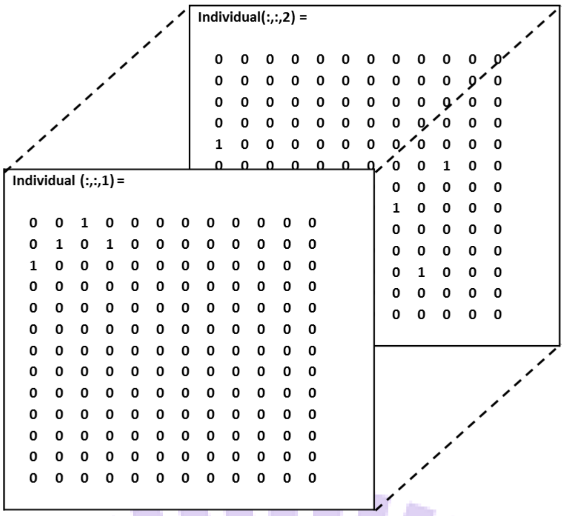

Figure 8 – An example of an individual.
Production sequence for Line 1 (front) and Line 2 (back).

Per the PBC manager's requirement, the first micro-period is not allowed being idled, and must have some production lot assigned. Given a production sequence resulting from our GA, we do pre-processing calculation, e.g., the corresponding setup costs and times, etc. These parameters from pre-processing are used as the inputs of the Linear Programming model, i.e., Problem ZZ in Section 4.2. Then, we employ LP-solver to determine the production lot size of each product, the inventory levels and the values of idle time for each individual. To get a correct and complete the objective function value for an individual, we add the changeover costs (corresponding to the production sequence from GA) to the objective function value of the optimal solution from the linear programming model. We will evaluate the fitness of the interested individual using the complete objective function value.

We employ the "linprog" optimization tool in MATLAB R2013a for solving the LP model. The Simplex Algorithm in "linprog" is a two-phase method in which Phase 1 computes an initial basic feasible point, and Phase 2 seeks for the optimal solution. This tool is very efficient not only in determining the optimal solution (of continuous variables) and but also in checking the feasibility of those production sequences from the GA. We will present further discussion in Chapter 6.

4.3.2 Initialization

In the initialization of GA, we randomly generate individuals (corresponding to production sequences) to join an initial population. It is possible that there exists no solution for some individuals. Tough LP solver helps in detecting infeasible solutions, it could be too time-consuming so as to significantly deteriorate the efficiency of GA. Therefore, we are motivated to propose an "infeasibility prevention mechanism" that may easily and effectively detect production sequences not being able to generate feasible LP solutions. The infeasibility prevention mechanism is composed by two rules as follows.

Rule 1: Does the inequality always hold?

$$cobmin_{jt} - \left(I_{j(t-1)} - d_{jt}\right) \leq \sum_{l\in\lambda_j}\sum_{n\in M_t}\left(K_{lt} * r_{jl}\right)\left(y_{jnl}\right) \tag{4.9}$$

This rule measures if the minimum amount of products that need to be produced is less than the available capacity for the assigned products in the assigned productions lines.

Rule 2: Does the inequality always hold?

$$\sum_{j\in\alpha_l}\sum_{n\in M_t}\frac{Qmin_{jl}(y_{jnl})}{r_{jl}} \leq K_{lt} - \delta_{lt} - \sum_{i\in\alpha_l}\sum_{j\in\alpha_l}\sum_{n\in M_t}\left(st_{ijl}z_{ijnl}\right) \tag{4.10}$$

This rule measures if the minimum lot size that needs to be produced in each line is less than the available capacity, taking into consideration the downtime and setup times required.

These inequalities can be easily checked because all parameters are known as one decodes the representation of y_{jnl} variables for each individual (and also they can be used to compute the z_{ijnl} variables, too). These two rules may let some (but, only few) infeasible solutions pass to the LP solver for evaluation; however they are very helpful in reducing the computing time by avoiding checking solutions that are obviously infeasible.

Once an individual passed the feasibility test, the LP solver takes the production sequence as (part of) the input parameters and determine if it is feasible or not. If a production sequence results in an infeasible solution, we generate another new sequence. We repeat these steps until completing with an initial population with all the corresponding solutions being feasible.

Note that the population is represented by a 4-dimension matrix $J \times N \times L \times P$, where J are the products, N the micro-periods, L the production lines and P the number of individuals. Figure 9 depicts an example of a population that has J=13, N=12, L=2 and P=2. The parameters of GA, such as population size (*pop_size*), crossover rate, mutation rate and maximum number of generations, are user specified.

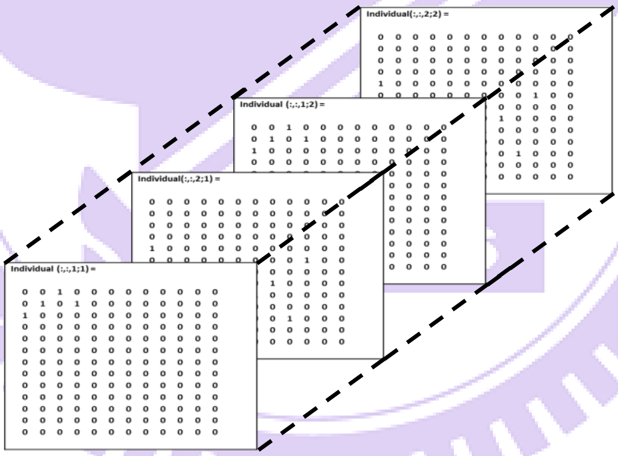

Figure 9 – An example of a population of 2 individuals

4.3.3 Fitness Evaluation and Selection Process

We need to evaluate the fitness of each individual in the population using the objective function value that is the sum of the optimal objective function value of the LP model and the total setup cost from the changeover sequence. For this case study, a feasible solution with the minimum cost represents the best solution. After all individuals are evaluated, we update the "best on hand" solution as locating a better solution.

Selection Process

We employ "linear ranking" for our selection process that selects individuals and passes to the next generation to undergo evolutions of genetic operators. We pick the linear ranking method since it usually gave satisfactory performance in minimization problems, and it resulted in slow convergence but prevents too quick convergence. It also keeps up selection pressure when the fitness variance is low (Sivanandam & Deepa, 2008).

The linear ranking method first ranks the individuals in the population using their objective function values and then each individual receives a probability based on its ranking. The selection pressure (SP) can be controlled by varying it between $1/$*pop_size* and $2/$*pop_size*. The probability of each individual to be selected is calculated as follow:

$$Probability\ of\ Selection\ (rank) = SP - (rank - 1) * \frac{SP}{pop\ size - 1} \qquad (4.11)$$

The probabilities are sorted in descend order, and the values of the cumulative probability are calculated for the roulette wheel selection. A random number (*rand_num*) is generated to select the parents to mate. If *rand_num* is located between the cumulative probabilities of the i^{th} and $(i+1)^{th}$ individuals, then we pick the i^{th} individual to join the next generation. We repeat the selection process until the number of the individuals reaches the required size of the population.

4.3.4 Genetic Operators

We propose the crossover and mutation operators according to the proposed data structure (i.e., the representation of solution) as follows.

Crossover

The method of crossover used is the One-Point Matrix Crossover. The idea is based on Homaifar et al. (1991) approach. Two individuals undergo the One-Point Matrix Crossover, where each individual was represented by a matrix. This operator exchanges all entries of the two parent's matrices, either after the cut-point. Figures 10 and 11 illustrate this method. In Figure 10, the matrix on the top represents the first parent and the matrix at the bottom represents the second parent.

parents(:,:,1,1) =

0	0	1	0	0	0	0	0	0	0	0	0
0	1	0	1	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	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	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	0	0

(:,:,2,1) =

0	0	0	0	0	0	0	0	0	0	0	0
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	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	1	0	0	0
0	1	0	0	0	0	0	0	0	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	0	1	0	0	0	0	0	0
0	0	0	1	0	0	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

parents(:,:,1,2) =

0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	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	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	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	0

(:,:,2,2) =

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	1	0	0	0	0	0	0	0	0
0	0	0	0	0	1	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	1	0	0	0
0	0	1	0	0	0	0	0	0	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	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	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

Figure 10 - Parent 1 (top) and Parent 2 (bottom)

In this process one cutting point is randomly generated; in the illustration, the point is between column 6 and column 7. Two offspring are obtained after the mating (Figure 11), where the first child receives the head from parent 2 and the tail from parent 1. The second child receives the head from parent 1 and the tail from parent 2.

```
child(:,:,1,1) =
 0 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 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 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 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 0
```

```
(:,:,2,1) =
 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 1 0
 0 0 0 1 0 0 0 0 0 1 0 0
 0 0 0 0 0 1 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 1 0 0 0
 0 0 1 0 0 0 0 0 0 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 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 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
```

```
child(:,:,1,2) =

 0 0 1 0 0 0 0 0 0 0 0 0
 0 1 0 1 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 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 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 0 0
```

```
(:,:,2,2) =

 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 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 1 0 0 0
 0 1 0 0 0 0 0 0 0 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 0 1 0 0 0 0 0 0
 0 0 0 1 0 0 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
```

Figure 11 - Child 1 (top) and child 2 (bottom)

Repair Procedure

Every (infeasible) child needs to pass through a repair procedure after crossover operations since some child can have "idle micro-periods" between two assignments – that are not allowed in the real life scenario following the PBC managers' opinions. So the repair procedure assures that all "idle micro-periods" remain at the end of every production sequence.

Replacement

Replacement method is the process to decide which parents and which child survive for the next generation. In this case, the Weak Parent Replacement method is used. A child can replace any parent if it is feasible and stronger (Sivanandam & Deepa, 2008). It does not matter if the child is not an offspring of that parent. This replacement method prevents weaker individuals entering the population and keeps the best individuals in it. The children representing infeasible solutions are eliminated immediately.

Mutation

The swap mutation operator is used in the proposed GA. It selects randomly individuals from the population according a specified mutation rate. When an individual is selected to mutate, the process selects randomly the column to be swap with its adjacent right column. This process tries to change the sequence of production of lines and helps to create new individuals. A feasibility test is always done after mutation to prevent generating undesired solutions after mutation. This new individual replaces entirely the original one. Figure 12 illustrates the behavior of this process. The repair procedure also applies to individuals because after mutation some individual can contain "idle micro-periods" between assignments. Mutation helps to keep diversity inside the population by including some stronger or weaker individuals with different information.

Individual (:,:,1,1) =

0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	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	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	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	0

(:,:,2,1) =

0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	1	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	1	0	0	0
0	0	1	0	0	0	0	0	0	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	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	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

New Individual (:,:,1,1) =

0	0	0	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	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	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
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

(:,:,2,1) =

0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	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	1	0	0	0
0	0	1	0	0	0	0	0	0	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
1	0	0	0	0	0	0	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

Figure 12 - Original Individual (top) and Mutated individual (bottom)

Stopping Condition

The stop criterion in the proposed GA is the maximum number of generations evolved.

Pseudo Code

The following pseudo-code summarizes the procedures presented above. Note that LP-Solver evaluates all individuals that pass the infeasibility prevention mechanism in each generation. A flow chart is also presented in Appendix F.

```
Begin function Genetic Algorithm

Load Input parameters

For all population size do
     While individual is not feasible do
              Generate Individual
              Infeasibility Prevention Mechanism
     end while
    Insert individual in population matrix
end for

While number of generations < maximum number of generations do

      for all individual in the population do
           Calculate setup costs and setup times
           Fitness Evaluation (Call LP solver)
      end for

       Update best on hand solution (All Optimal Value and All Optimal Individual)

       [parents] = Ranking Selection

       Execute Crossover Operator
       Repair children

      for all children do
            Fitness Evaluation of child
            Feasibility Evaluation of child

            if child is feasible and Child Fitness>=Parent Fitness then
                   replace parent by child
            else
                   keep parent
            end if
      end for

      for all individual in the population do
           if Mutation Rate is satisfied then
             Execute Mutation Operator
             Repair Individual
             Evaluate Feasibility
             Insert new individual to population
           end if
      end for

     number of generation + 1

End while

All Optimal Value
All Optimal Individual
All Optimal Solution

End
```

5. Case Study

As mention in previous chapters, the goal of this thesis is to propose a mathematical model and a solution approach that supports the planning decisions of short-term production scheduling problem (weekly) of a bottling company that fits the characteristics of Panama Beer Company. The model considers demand, production constraints, setup times, inventory and production policies, average downtime and working time availability, which are important factors in the planning process for any company that faces the same type of problems.

5.1 Data Collection

The data collection started with the compiling of different kind of information relevant to the production planning process. This was accomplished by having regular semi-structured meetings with Senior Production Planners, Plant Director, Planning Managers and Team Leaders. These meetings have the objective to answer specific questions about the processes and to understand the relevant parameters that need to be considered to construct a weekly schedule for packaging lines. Also meeting with operators were carried, to fully understand the operational process of each machine in the packaging area. A Gantt chart is presented with the Data Collection Plan in Appendix D.

Data was collected in different tables and documents. This was extracted from different sources, such as internal company data, meeting notes, company's process manuals, articles, and the Internet. Because the information comes from different users and departments, it was necessary to sort the data for better handling. Data used in our experiments corresponds to the period from January 6th to May 24th of 2014; calendar week number is used through this study.

Company provided sensitive data, which is going to be used to compare the improvement of results of the presented solution approach. However, information such as demand, specific costs and others cannot be published due to confidentiality issues.

5.2 Current Decision-Making Process

The results obtained by our solution approach will be compared with the results obtained by current PBC's production planning processes.

As mention in Section 3.1, currently PBC's planners assign the total production of Products 1, 2 and 3 entirely to Line 1 and the others are produced by Line 2. This is because Line 1 has higher production rates and let the Line 2 change dynamically between the other products. Our results showed that in some cases it is cheaper to produce products in Line 2 and assume idle time of Line 1, depending on demand needs.

In terms of costs, the AS-IS process usually does not consider the costs associated with the allocation of production and the optimal lot size. Basically, they try to avoid as much as possible the idle time and at the same time maintain the inventory level at the maximum coverage possible. This means that PBC's safety stock usually represents demand of 3 or more weeks. With the objective of reducing idle time of personnel, the planners assign productions even if they will not be used for demand immediately (and, of course accumulate unnecessary inventory). It indicates that PBC could reduce a significant amount of cost by adjusting their policies. For this research we kept the inventory policy, but we set the policy at the minimum level established by the managers to prove that is possible to maintain safety stock and meet demand without overtime or high inventory holding costs.

Currently, the Planners need to spend at least half-day to prepare the schedule of the next two weeks. In addition, they changed it every day according to the closing status of previous day. Usually they "freeze" the schedule by the end of the week and pass it to the Packaging Department as the official schedule for next week.

According to PBC's production policy, they need to produce a minimum lot size of every product. However, this amount can be change according the needs. Currently PBC do not follow exactly this parameter, we assumed that other external factors affect these decisions. For purposes of this study, we consider the policy established by the company, because we are not able to predict the possible causes of reducing the value set.

Recall that (virtual) Line 2 represents the capabilities of PBC's Line 2 and Line 3 in the real world, thus they work independently. For this motive, if there is the case that Line 1 personnel are idle, they can be assigned to operate Line 2, because both lines has similar processes. In this scenario, Line 2 and Line 3 are able to run simultaneously. Our tool gives users the option of reducing capacity of Line 1 and adding it to Line 2; and if needed, it also has the option of reducing capacity because of national holidays. For experimental purposes, standard capacity is set for each line and reduced capacity is applied to national holidays in two specific weeks.

5.3 Computational Study

PBC's packaging plant is divided into two major areas, namely, Beer packaging and CSD packaging. We collected data such as demand, current changeover times, inventory policies, costs, production rates, and plant capacity, corresponding to returnable bottle lines from the PBC and use them as the base scenario to test the proposed solution approach.

Description

The GA and LP model will solve scenarios that have the following characteristics:

- 2 production lines.
- 13 products. Line 1 only can produce 3 items. Line 2 can produce all items.
- 1 macro-period. Represent one week of production.
- 10 micro-periods.

The data for the base-scenarios includes: minimum and maximum number of weeks of inventory coverage, holding cost per every unit of product, production rates, changeover times, setup cost per hour, minimum lot size, product loss caused by changeover, fix percentage of product loss when line is running, item costs, average downtime per period per line and specific sets that specify capabilities of production. These are summarized in details in Appendix E.

Twenty consecutive weeks are analyzed, by comparing the results obtained by the AS-IS planning methods (currently used by the planners) and the proposed solution approach. The Data in our experiments corresponds to a period of 5 months, where the capacity of each line was 6 days per week, 24 hours each day. However for some weeks a reduction of capacity is considered due to country's holidays. We use the same set of data as the platform to conduct a fair comparison between the results from both approaches.

Prerequisites

Some data is given depending on the scenario to be analyzed. The following information need to be input for every run:

- Demand of every product for three weeks in hectoliters.
- Initial inventory level of every product at the beginning of period.

- Initial setup state of each production line.
- Available capacity for every line.

For the genetic algorithm the following parameters need to be set:

- Maximum number of generations.
- Population Size.
- Crossover Rate.
- Mutation Rate.

A further discussion on how the parameters for the GA were set is presented in Chapter 6.

Test Execution

- The computational results presented were executed using a processor Intel Core i5, 3.10 GHz, 4.0 GB RAM, 64-bit Operating System.
- Genetic Algorithm and LP model were coded using MATLAB R2013a.
- The input parameters are stored in Excel files.
- Running time depends on the number of generations that GA needs to stop, crossover rate and mutation rate set. For our experiments, we set 500 generations as the maximum number of generations, crossover rate equal 0.30 and mutation rate 0.10.

Expected results

The following results will be output and analyzed in our experiments:

- Optimal Lot Size for every micro-period.
- Total Cost, that includes inventory, setup, production and idle time costs.

- Optimal Sequence of Production for every line in every period.
- Final inventory levels at the end of every period.
- Setup time incurred.
- Idle time in every period.
- Running time of code.
- Comparison with historical plans of Panama Beer Company.
- T-test between original data and results obtained. A paired sample t-test was executed to determine if there exist statically difference between the current process and the solution approach presented in this study.

6. Results and Discussions

In this chapter we will present and discuss the results of our numerical experiments, and conduct comparison analyses with the real production plans in PBC.

The proposed solution approach solves a weekly production plan one at a time in a sequential fashion. The results from the last weekly production plan, including the inventory level at the end, become input parameters for the next week. We use the real-world data in PBC as inputs for comparison; one may refer to Appendix E for details. A total of 20 weeks are solved, each week has 132 available hours for Line 1 and 128 hours for Line 2; except those weeks that have national holidays. Since Line 1 has the capability to bottle three products and Line 2 is capable to bottle 13 products, we have set the number of micro-periods as 10, giving the possibility to Line 2 to bottle up to 10 lots per week. This forces Line 1 to always have production so teams do not remain idle.

Table 9 summarized the information on the size of the problem with the number of lines, the number of products, the number of macro-periods and the number of micro-periods.

Table 9 – Parameters used for the GA and LP tests

number of lines	number of products	number of macro-periods	number of micro-periods
2	13	1	10

We further present the number of the continuous variables, the binary variables and the constraints presented in our problem in Table 10.

Table 10 – The numbers of the variables and constraints in our model

Continuous Variables	Binary Variables	Constraints
3655	260	7580

Recall that the encoding of GA takes the binary variables to represent a production sequence for each individual. In the Problem ZZ, the size of the LP model is significantly reduced to 275 continuous variables and 560 constraints.

No specific procedure was made to tune the genetic algorithm; however we try to determine, according results and running time, which parameters were the best among the options. GA-LP code was run for a fixed number of generations and population size using different crossover and mutation rates.

6.1 Parameter Setting in Genetic Algorithm

6.1.1 Number of Generations

To determine the best number of generations, we run our GA-LP for 10 runs using a stopping criterion of 1,000 generations. We recorded the generation in which the best on hand solution was found were recorded and observed the outcomes of our experiments illustrated in Figure 13. For the 8^{th} run, the best solution was obtained at the 419^{th} generation. But, for all other runs, the best solution was obtained before 200 generations. Following our observations from this experiment, we set a maximum of 500 generations as the termination condition for all of our experiments.

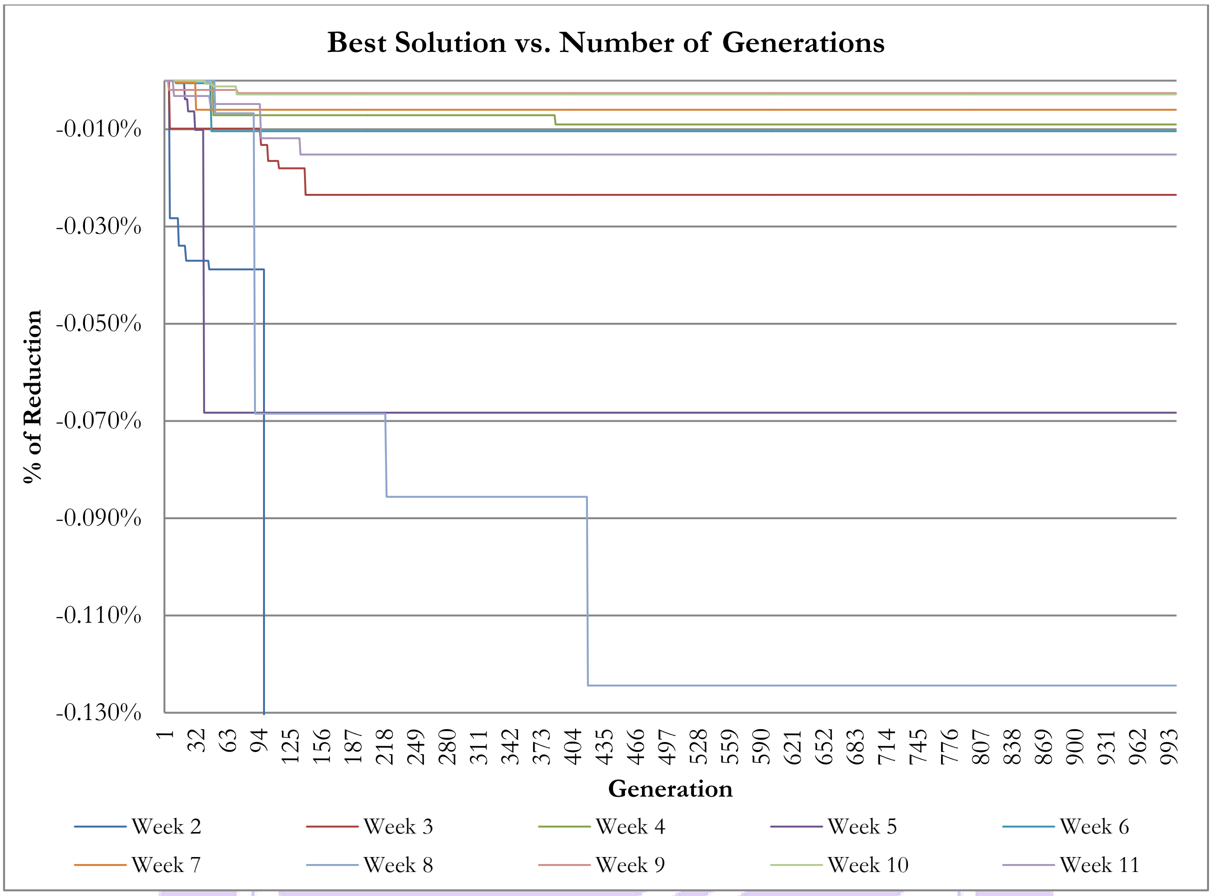

Figure 13 – The best on hand solution vs. the number of generation where it was found

6.1.2 Crossover Rate Tuning

To determine which crossover rate is the most appropriate for solving the production planning and scheduling problem in PBC, we ran several tests using different rates. For each week, the code was run once using 3 different rates and fixing the mutation rate at 0.10. A population of 20 individuals was used and the maximum number of generations was 500. Table 11 summarizes the crossover rates tested for the genetic algorithm and linear programming runs.

Table 11 – Crossover rates used for Genetic Algorithm and Linear Programming

Crossover Rate			
0.1	0.2	0.3	0.4

Table 12 and Figure 14 summarize the average costs obtained for each instance. The best result is presented in the last column of the table and corresponds to the yellow colored cell. The rate of 0.40 is not recorded because of an extremely high running time. Using a crossover rate of 0.40 took more than 3 hours of running time to create 33 generations and until that point solution was not better than the one obtained by smaller rates. Due to slow performance, we decide to use different strategies to deal with higher crossover rates, which is explained in the Section 6.1.2.1.

Table 12 – The impact of crossover rate (CR) on the total cost.

Week	CR= 0.10	CR= 0.20	CR= 0.30	Minimum
2	$ 322,813.74	$ 322,815.84	$ 321,099.23	$ 321,099.23
3	$ 334,562.82	$ 334,570.88	$ 334,555.89	$ 334,555.89
4	$ 296,612.35	$ 291,963.73	$ 291,947.04	$ 291,947.04
5	$ 312,827.18	$ 312,821.75	$ 287,748.48	$ 287,748.48
6	$ 232,679.48	$ 232,679.49	$ 233,708.25	$ 232,679.48
7	$ 293,529.04	$ 293,533.51	$ 292,326.32	$ 292,326.32
8	$ 293,790.98	$ 293,785.28	$ 291,490.19	$ 291,490.19
9	$ 190,750.74	$ 190,654.92	$ 188,546.58	$ 188,546.58
10	$ 311,410.49	$ 311,401.35	$ 309,178.62	$ 309,178.62
11	$ 330,209.12	$ 331,556.85	$ 329,325.72	$ 329,325.72
12	$ 320,582.61	$ 320,281.61	$ 319,504.89	$ 319,504.89
13	$ 283,233.86	$ 281,524.75	$ 283,374.89	$ 281,524.75
14	$ 368,499.30	$ 368,743.18	$ 368,563.63	$ 368,499.30
15	$ 268,590.02	$ 268,588.88	$ 269,011.56	$ 268,588.88
16	$ 254,396.83	$ 254,394.64	$ 254,307.41	$ 254,307.41
17	$ 281,041.64	$ 281,391.36	$ 281,205.55	$ 281,041.64
18	$ 270,977.63	$ 270,976.44	$ 270,991.17	$ 270,976.44
19	$ 279,197.67	$ 279,370.83	$ 279,211.77	$ 279,197.67
20	$ 326,377.03	$ 326,375.92	$ 326,372.10	$ 326,372.10
21	$ 325,372.24	$ 325,401.65	$ 325,380.52	$ 325,372.24

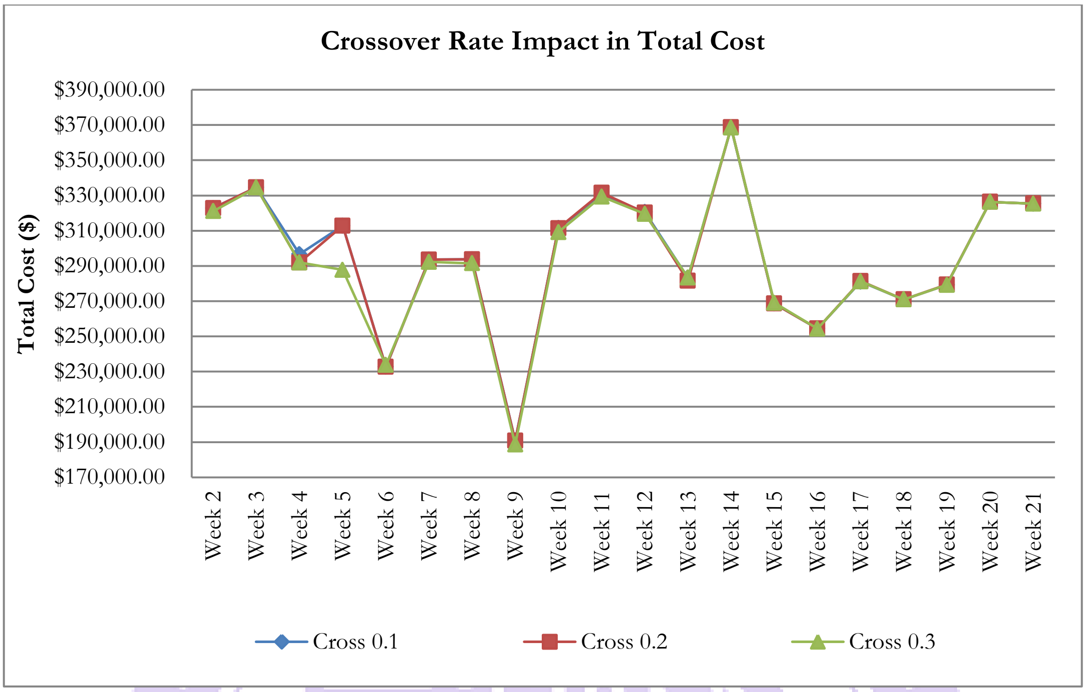

Figure 14 – The impact of crossover rate on the total cost

Table 13 presents the variation between the total costs obtained using each crossover rate and the minimum cost obtained. The percentage of variation was calculated using eq. (6.1).

$$\% \text{ of variation} = \frac{(Min\ Total\ Cost - Total\ Cost)}{Total\ Cost} \cdot 100\% \tag{6.1}$$

The GA-LP using a rate of 0.30 outperforms the results from a rate of 0.10 in 12 weeks and also a rate of 0.20 in 16 weeks. The highest difference between rates was obtained in week 5, where the minimum total cost obtained with crossover 0.30 was 8% better than the others. The smallest variations were obtained after week 5.

Table 13 - Variation between crossover rates.

Week	Minimum	Pc = 0.10	Pc = 0.20	Pc = 0.30
2	$ 321,099.23	-0.53%	-0.53%	0.00%
3	$ 334,555.89	-0.002%	-0.004%	0.00%
4	$ 291,947.04	-1.57%	-0.01%	0.00%
5	$ 287,748.48	-8.02%	-8.02%	0.00%
6	$ 232,679.48	0.00%	-0.000001%	-0.44%
7	$ 292,326.32	-0.41%	-0.41%	0.00%
8	$ 291,490.19	-0.78%	-0.78%	0.00%
9	$ 188,546.58	-1.16%	-1.11%	0.00%
10	$ 309,178.62	-0.72%	-0.71%	0.00%
11	$ 329,325.72	-0.27%	-0.67%	0.00%
12	$ 319,504.89	-0.34%	-0.24%	0.00%
13	$ 281,524.75	-0.60%	0.00%	-0.65%
14	$ 368,499.30	0.00%	-0.07%	-0.02%
15	$ 268,588.88	-0.0004%	0.00%	-0.16%
16	$ 254,307.41	-0.04%	-0.03%	0.00%
17	$ 281,041.64	0.00%	-0.12%	-0.06%
18	$ 270,976.44	-0.0004%	0.00%	-0.01%
19	$ 279,197.67	0.00%	-0.06%	-0.01%
20	$ 326,372.10	-0.002%	-0.001%	0.00%
21	$ 325,372.24	0.00%	-0.01%	-0.003%

Figure 15 presents the execution time according to different crossover rates. The results show that the minimum time is obtained with the crossover rate being 0.1, and it remains almost the same with 0.2. In this case the *Linear Programming* function costs more than 90% of its run time. As mention in previous chapter, the LP solver in MATLAB solves the LP model within 2 seconds in our experiments.

The run time for the crossover rate of 0.30 results in a run time almost five times higher than others. In this case, *ranking selection* process represents around 70% of its run time. This is caused by the setting, that all individual to be mate need to be "unique", making more difficult to obtain individuals if the number of parents to be selected increased.

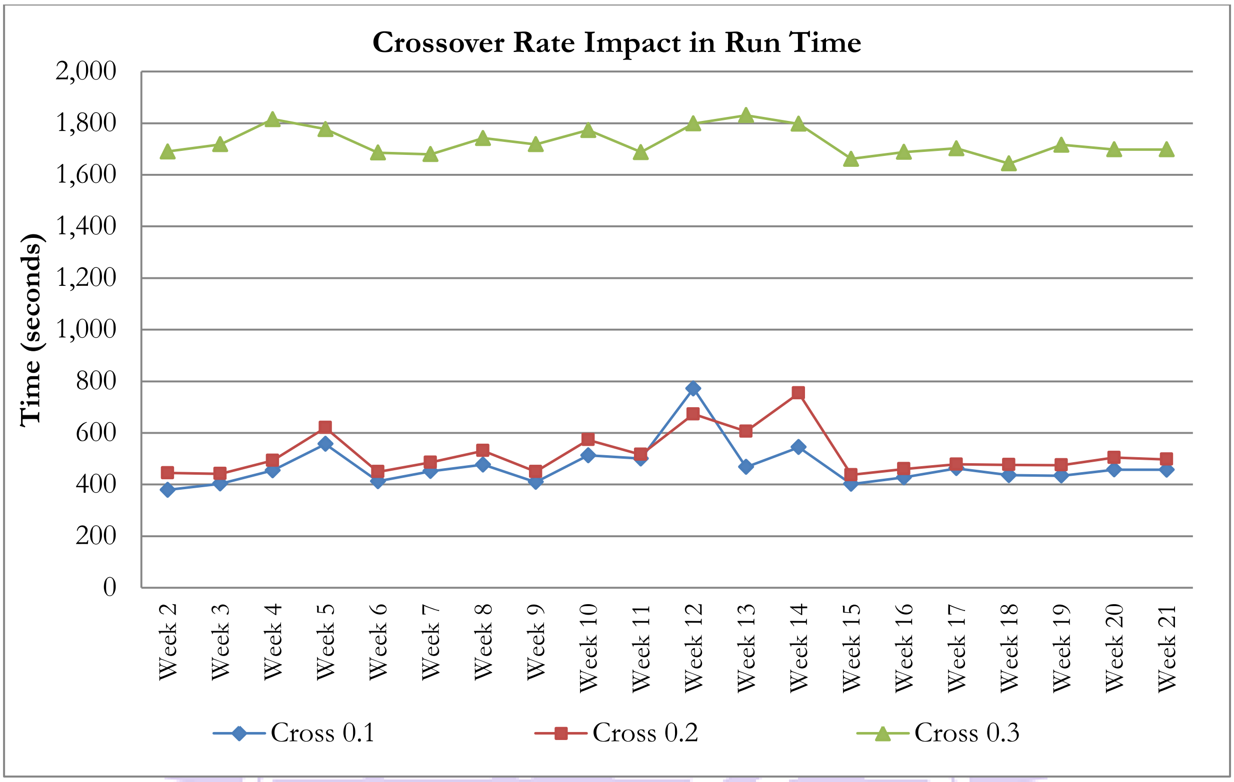

Figure 15 - Execution time to find best solution with different crossover rates.

6.1.2.1 Modified Selection Process

In order to improve the execution time of the GA-LP, the *selection process* was slightly changed. Originally was set that all individuals in the parents' matrix need to be "unique", however this caused an abrupt increase in running time when the number of parents to be selected increases. For this reason, it was decided to modify the algorithm by requiring the selection of individuals to form "unique couples". This means that one individual can be in more than one couple as long as the mating is different.

After this modification, two crossover rates were tested, 0.30 and 0.40, to detect if any improvement can be obtained in running time and total cost. All weeks were run one time and with 500 maximum generations. Table 14 summarizes the parameters used for these tests.

Table 14 - Parameters used for GA-LP with modified Selection Process.

Crossover Rate	Mutation Rate
0.30	0.10
0.40	0.10

Table 15 – The impact of crossover rate on the total cost.

Week	CR = 0.10	CR =0.20	CR =0.30	CR = 0.40	Minimum
2	$ 322,813.74	$ 322,815.84	$ 322,814.44	$ 314,212.34	$ 314,212.34
3	$ 334,562.82	$ 334,570.88	$ 334,555.89	$ 341,894.18	$ 334,555.89
4	$ 296,612.35	$ 291,963.73	$ 298,169.08	$ 312,707.88	$ 291,963.73
5	$ 312,827.18	$ 312,821.75	$ 287,556.02	$ 313,117.07	$ 287,556.02
6	$ 232,679.48	$ 232,679.49	$ 233,696.10	$ 232,880.47	$ 232,679.48
7	$ 293,529.04	$ 293,533.51	$ 292,493.41	$ 293,528.85	$ 292,493.41
8	$ 293,790.98	$ 293,785.28	$ 291,487.00	$ 293,792.01	$ 291,487.00
9	$ 190,750.74	$ 190,654.92	$ 188,546.58	$ 190,776.99	$ 188,546.58
10	$ 311,410.49	$ 311,401.35	$ 309,175.38	$ 311,411.46	$ 309,175.38
11	$ 330,209.12	$ 331,556.85	$ 329,307.71	$ 331,539.98	$ 329,307.71
12	$ 320,582.61	$ 320,281.61	$ 319,547.14	$ 319,149.02	$ 319,149.02
13	$ 283,233.86	$ 281,524.75	$ 283,301.97	$ 283,395.13	$ 281,524.75
14	$ 368,499.30	$ 368,743.18	$ 368,564.83	$ 368,546.99	$ 368,499.30
15	$ 268,590.02	$ 268,588.88	$ 269,016.94	$ 269,022.20	$ 268,588.88
16	$ 254,396.83	$ 254,394.64	$ 254,265.76	$ 254,398.75	$ 254,265.76
17	$ 281,041.64	$ 281,391.36	$ 281,200.61	$ 281,389.21	$ 281,041.64
18	$ 270,977.63	$ 270,976.44	$ 270,976.27	$ 270,971.02	$ 270,971.02
19	$ 279,197.67	$ 279,370.83	$ 279,370.90	$ 279,225.95	$ 279,197.67
20	$ 326,377.03	$ 326,375.92	$ 326,357.91	$ 326,370.50	$ 326,357.91
21	$ 325,372.24	$ 325,401.65	$ 325,385.33	$ 325,361.08	$ 325,361.08

We compare the results were for different crossover rates and summarize them in Table 15. The GA-LP approach using a crossover rate of 0.30 in general outperforms 9 weeks. Comparing with each rate it outperforms the rate of 0.10 in 11 weeks, 15 weeks for the rate of 0.20 and 13 weeks for the rate of 0.40. Again the highest improvement was 8% in week 5. Very small changes in the total cost were obtained after the week 5. Also the variations in the total costs obtained using each crossover rate and the minimum cost obtain were calculated; the results are summarized in Table 16.

Table 16 – The variation between the crossover rates

Week	Pc = 0.10	Pc = 0.20	Pc = 0.30	Pc = 0.40
2	-2.66%	-2.67%	-2.66%	0.00%
3	-0.002%	-0.004%	0.00%	-2.15%
4	-1.57%	0.00%	-2.08%	-6.63%
5	-8.08%	-8.08%	0.00%	-8.16%
6	0.00%	-0.000001%	-0.44%	-0.09%
7	-0.35%	-0.35%	0.00%	-0.35%
8	-0.78%	-0.78%	0.00%	-0.78%
9	-1.16%	-1.11%	0.00%	-1.17%
10	-0.72%	-0.71%	0.00%	-0.72%
11	-0.27%	-0.68%	0.00%	-0.67%
12	-0.45%	-0.35%	-0.12%	0.00%
13	-0.60%	0.00%	-0.63%	-0.66%
14	0.00%	-0.07%	-0.02%	-0.01%
15	-0.0004%	0.00%	-0.16%	-0.16%
16	-0.05%	-0.05%	0.00%	-0.05%
17	0.00%	-0.12%	-0.06%	-0.12%
18	-0.0002%	-0.0002%	-0.0002%	0.00%
19	0.00%	-0.06%	-0.06%	-0.01%
20	-0.01%	-0.01%	0.00%	-0.0004%
21	-0.0003%	-0.01%	-0.01%	0.00%

Total running time was greatly improved with the new selection process. Figure 16 depicts the total time for each week. We were satisfied with the situation that we reduce the running time for higher crossover rates without sacrificing the solution quality.

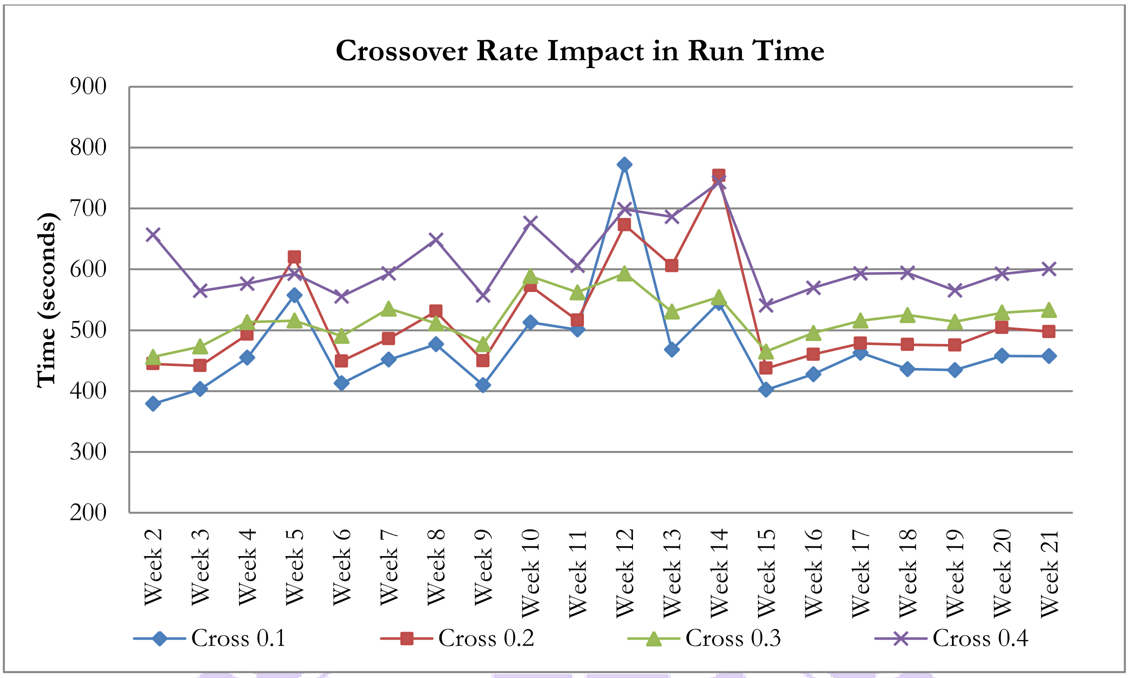

Figure 16 – The impact of crossover rates on the total run time.

The sum of all instances also helps us to verify which crossover rate perform better in overall. Figure 17 show that the crossover rate of 0.30 performs better. Therefore this is picked as the best crossover rate, which is going to be tested with different mutation rates.

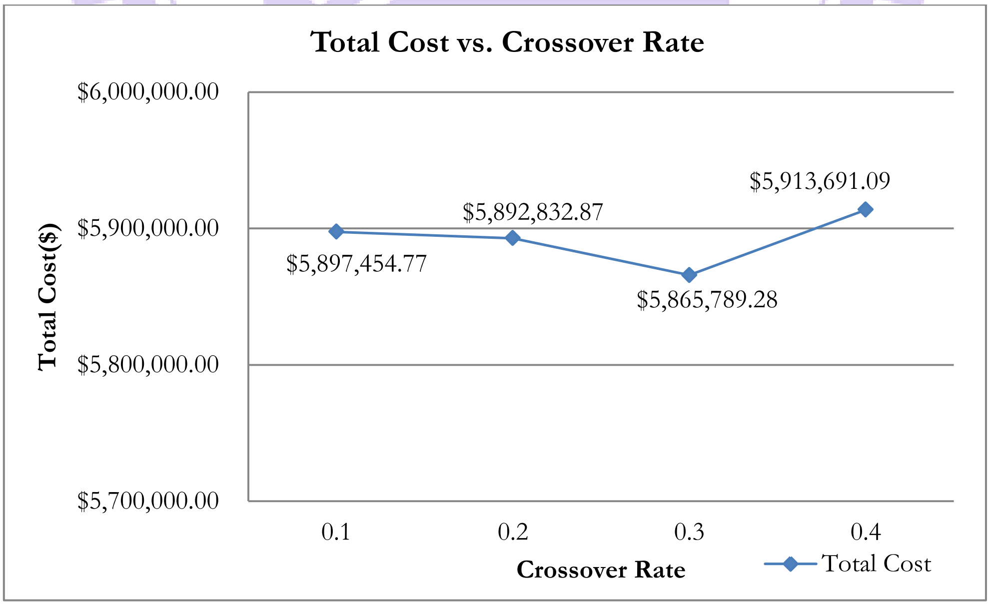

Figure 17 - Total Cost vs. Crossover Rate.

6.1.3 Mutation Rate Tuning

We use similar steps to choose the mutation rate in GA. Recall that we pick 0.30 as the crossover rates since it outperformed the other settings. Here, we fixed this crossover rate and vary different settings of mutation rate. Table 17 summarizes the different mutation rates for test.

Table 17 – The tested mutation rates for tuning

Mutation Rate		
0.05	0.1	0.15

Figure 18 depicts the impact of the mutation rate on the total cost per week. The mutation rate of 0.10 obtains better results than the rate of 0.05 and the rate of 0.15 for 16 and 11 weeks, respectively. The largest advantage was approximately 7%. The total running time did not show significant difference.

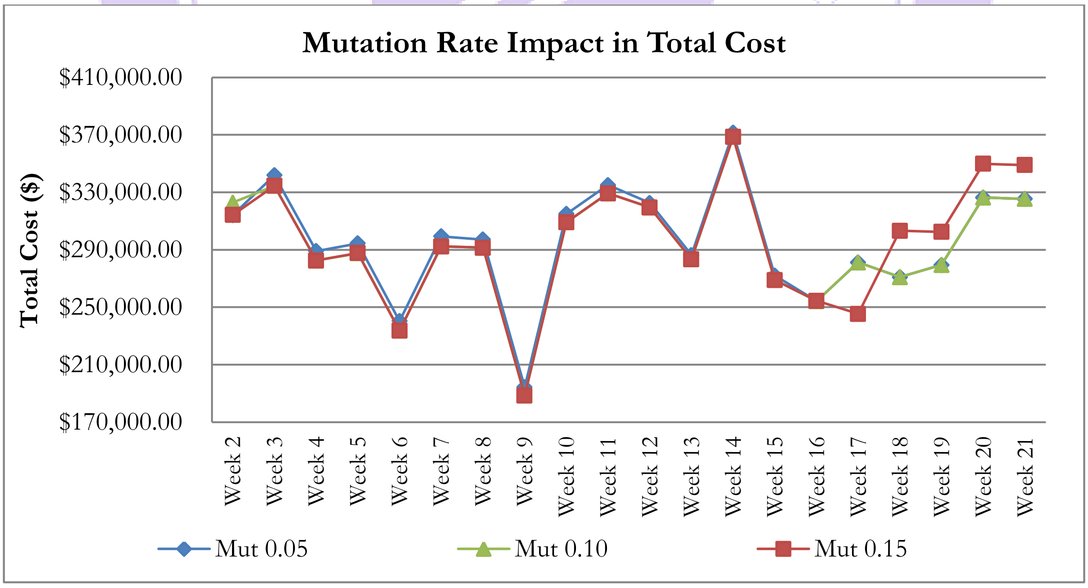

Figure 18 - Mutation Rate impact in Total Cost per week.

The sum of the total cost among all instances also assists us to verify the mutation rate of 0.10 performs better than the others, and Figure 19 shows our experiment results. Therefore we pick the mutation rate of 0.10 as the setting for our GA.

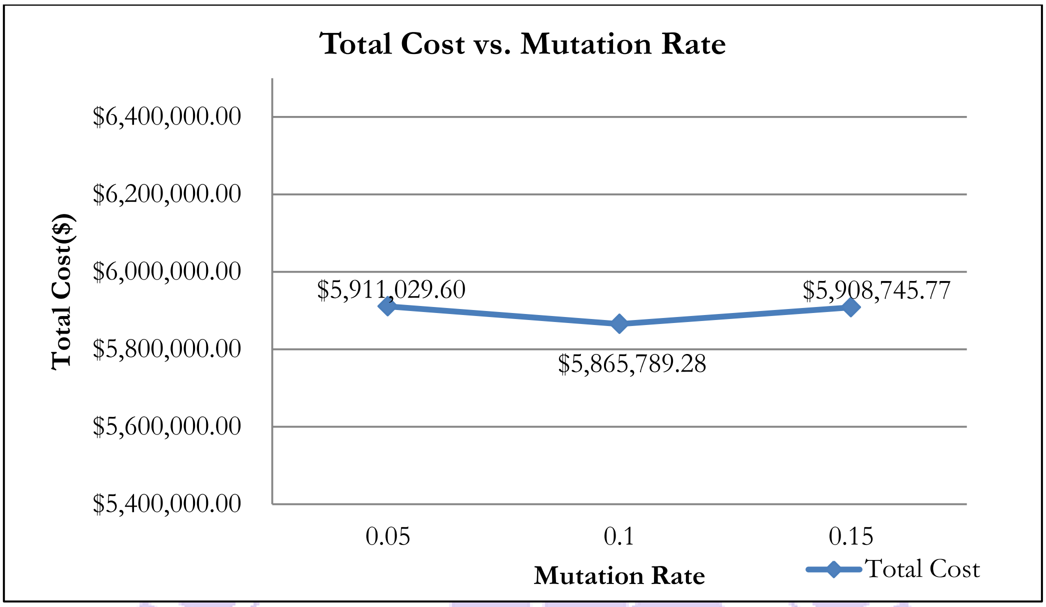

Figure 19 - Total Cost vs. Mutation Rate.

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6.2 Comparison and Analysis of Results

6.2.1 Results

Panama Beer Company currently uses Excel based templates and planners' experience as the main tool to decide production sequence and lot sizes. The Planners usually spend at least half of a day to prepare the schedule of the next two weeks. In addition, they changed it every day according the closing status of previous day. Usually they "freeze" the schedule by the end of the week and pass it to the Packaging Department as the official schedule for next week. Usually the managers made only minor changes due to external factors after the schedule is delivered.

Table 18 summarized the values of the total costs, calculated based on the historical data, for 20 weeks. (Appendix G presents the results obtained per week.) It shows that the inventory holding cost takes the largest share of the total cost, following by the production costs. The idle time and setup costs take only around 1% of the total cost.

Table 18 – The cost profile of Panama Beer Company for 20 weeks.

Costs	$USD	% of Total
Inventory Holding Costs	$ 6,505,805.04	87.8%
Production Costs	$ 751,849.49	10.1%
Idle Time Costs	$ 79,332.73	1.1%
Setup Costs	$ 73,041.81	1.0%
Total Costs	**$ 7,413,456.27**	**100%**

We conduct the comparison analysis between the GA-LP approach and the AS-IS approach after determining the settings of the crossover rate and the mutation rate. We also use the input parameters following the company's data and policies. Table 19 presents the parameters used for these tests.

Table 19 – The best combination of parameters for the GA-LP approach.

Number of Generations	Crossover Rate	Mutation Rate	Population Size	Number of Weeks	Number of runs per week
500	0.30	0.10	20	20	5

After running five times for each instance, we calculate the average of the total costs for each week and compared it with the company's historical results. Figure 20 displays that the GA-LP approach outperforms the AS-IS approach in 16 weeks. The largest reduction obtained was 50% for week 6.

The company's results were better in 4 weeks, specifically in Week 11, 12, 13 and 14. We detect that PBC's results were better because their plans violate the Minimum Lot Size policy and the Safety Stock policy. For fair comparison we modified these two policies according their violations during these weeks and run test from Week 11 onwards. We present further discussion in Section 6.2.2.

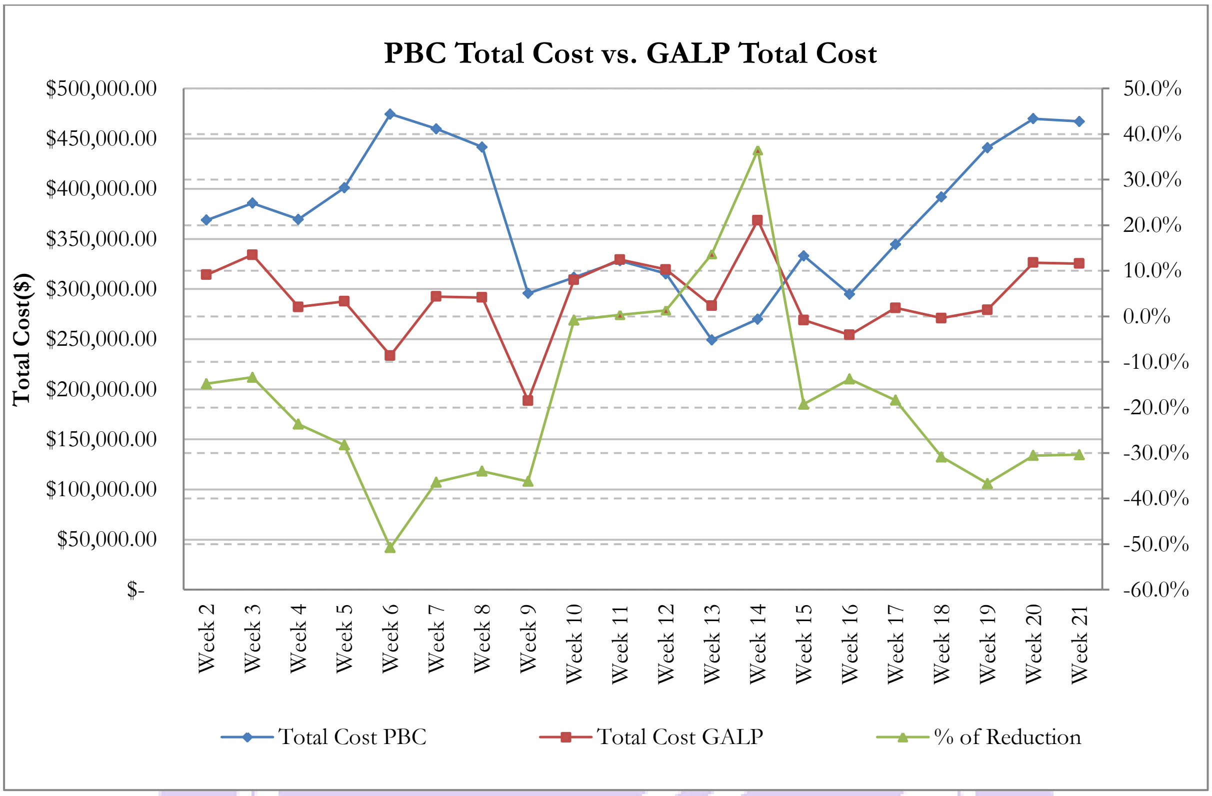

Figure 20 – The total cost of the AS-IS approach and the GA-LP approach

Figure 21 shows the average running time taking from 5 runs the GA-LP approach for each instance. It also shows the minimum and maximum values of run time. The average running time for each week was 532 seconds (approx. 9 minutes). Currently PBC's planners spend around half-day (approx. 4 hours) to plan 2 weeks for all production lines.

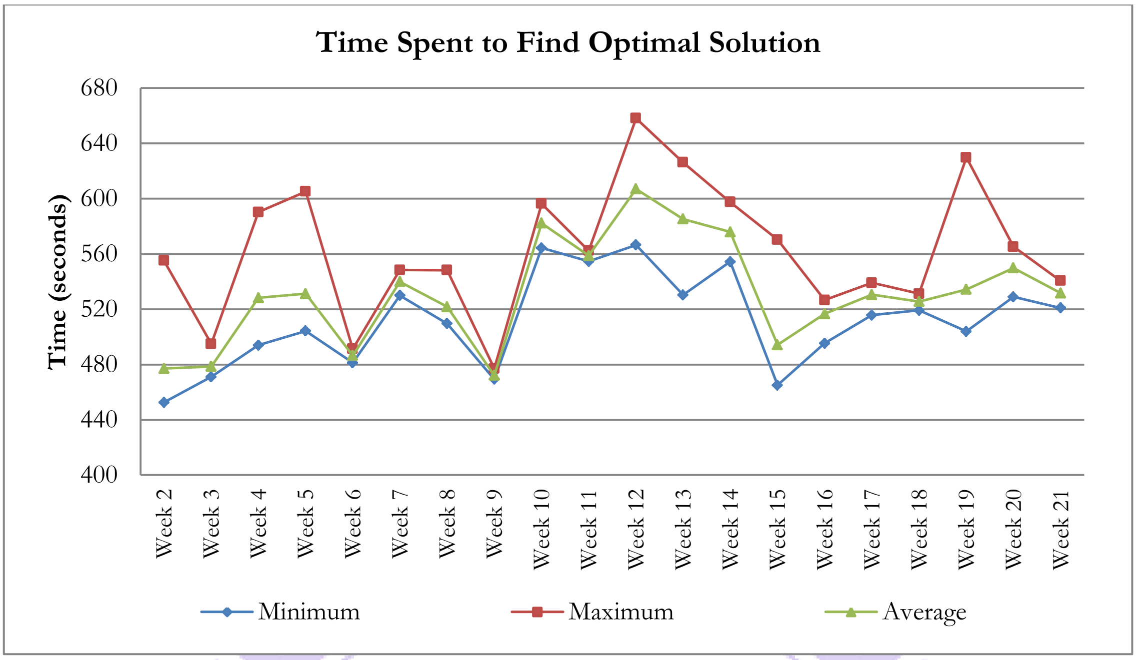

Figure 21 – The run time spent of the GA-LP approach for solving each instance.

Table 20, summarizes the cost profile for the "best" solution obtained for 20 weeks. Similar to PBC's historical data, the inventory holding costs takes more than 85% of the total cost, followed by the production costs. We present the complete details for the solution for each instance in Appendix H. Table 21 compares the results of the AS-IS approach in PBC and the GA-LP approach. The sum of the total cost of 20 weeks could be reduced up to 21%.

Table 20 – The cost profile for the best solution obtained from the GA-LP approach.

Costs	$USD	% of Total
Inventory Holding Costs	$5,009,668.54	85.77%
Production Costs	$674,463.79	11.55%
Idle Time Costs	$92,824.76	1.59%
Setup Costs	$63,904.22	1.09%
Total Costs	**$5,840,711.74**	**100%**

Table 21 - The results of the AS-IS approach in PBC and the GA-LP approach

Costs	PBC	GA-LP	Reduction	
	$USD	$USD	$USD	%
Inventory Holding Costs	$6,505,805.04	$5,009,668.54	$1,496,136.50	-23%
Production Costs	$751,849.49	$674,463.79	$77,385.69	-10%
Idle Time Costs	$79,332.73	$92,824.76	($13,492.03)	17%
Setup Costs	$73,041.81	$63,904.22	$9,137.59	-13%
Total Costs	**$7,413,456.27**	**$5,840,711.74**	**$1,572,744.53**	**-21%**

Figures 22 to 25 present the comparisons between the AS-IS approach and the GA-LP approach for each type of cost. The GA-LP approach outperformed in 16 weeks for the inventory holding costs, in 12 weeks for the production costs, 11 weeks for the idle time cost and 12 weeks for the setup cost.

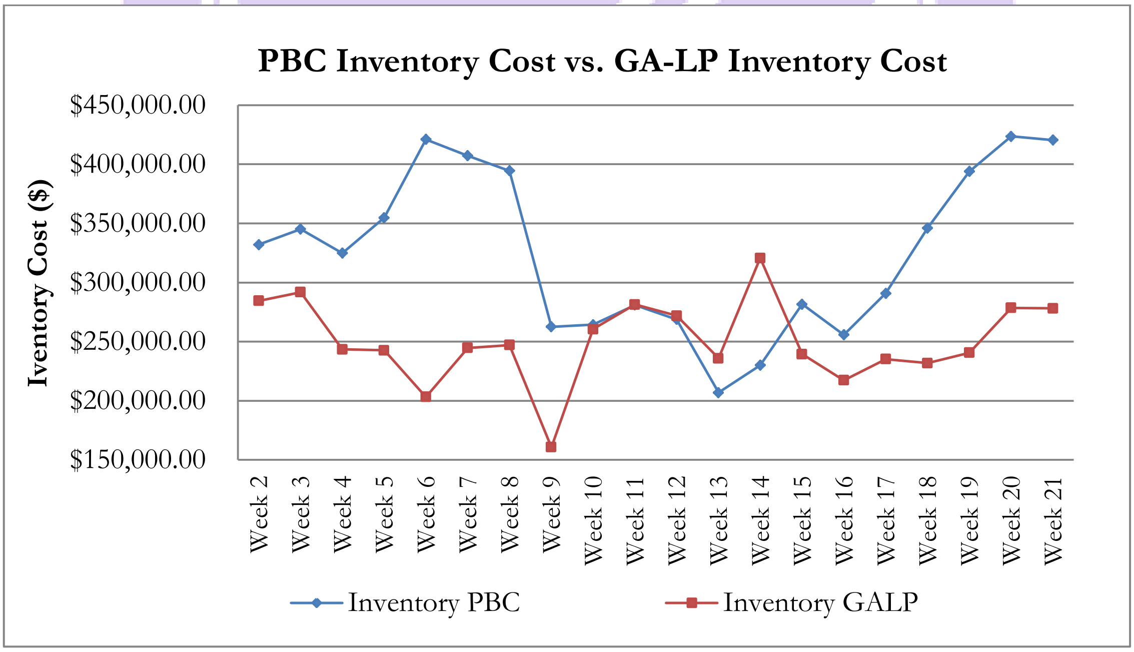

Figure 22 – The comparison of the inventory holding costs

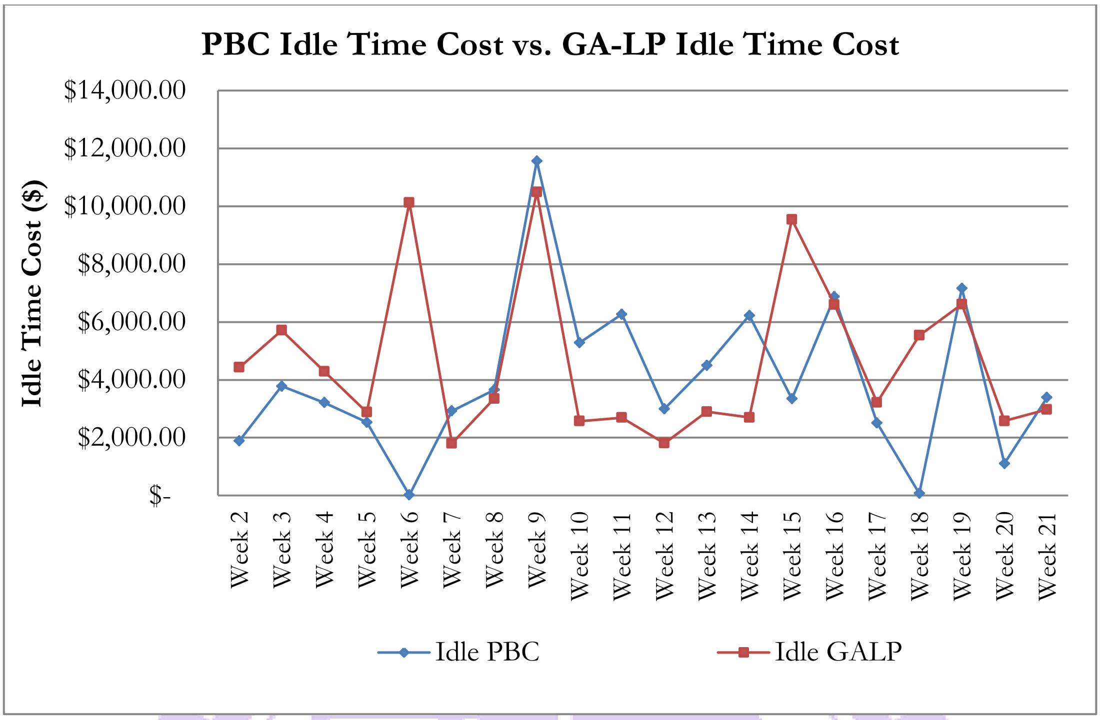

Figure 23 - The comparison of the idle time costs

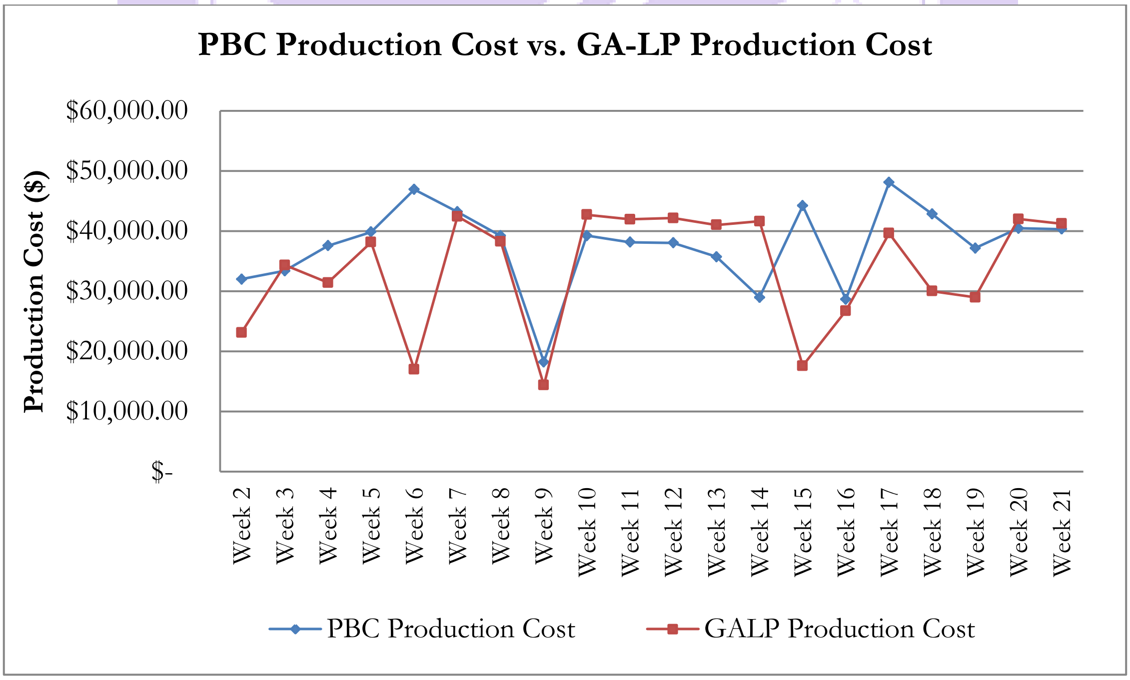

Figure 24 - The comparison of the production costs

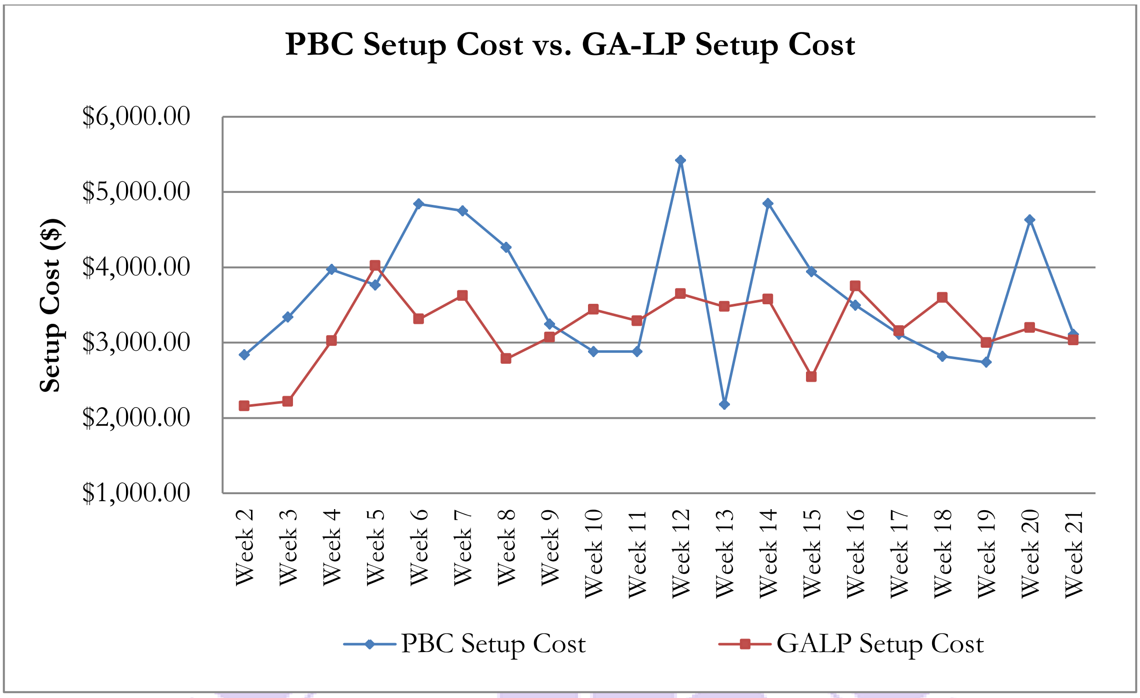

Figure 25 - The comparison of the set up costs

6.2.2 Case with modified parameters

As mention in section 6.2.1, the GA-LP approach did not obtain better results for Weeks 11, 12, 13 and 14. The historical data shows that the two constraints regarding Minimum Lot Size and Inventory Policy were violated for almost all the weeks; see Table 22. To make a fair comparison for these weeks, we modify the parameters the Minimum Lot Size according to the values used by the company. The inventory policy was not modified, since in our studies the minimum safety stock policy is preserved. Table 23 summarizes the parameters of the Minimum Lot Size according to the values used by PBC's planners.

Table 22 – The violation of the Minimum Lot Size and Safety Stock policies

	Min. Safety Stock	Details	Minimum Lot size	Details
Week 2	X	P3	X	L1 , L2
Week 3	X	P4, P5	-	-
Week 4	X	P4	X	L1, L2
Week 5	X	P2, P5	X	L1, L2
Week 6	X	P3, P5, P7, P11	X	L1
Week 7	X	P3, P5	X	L1, L2
Week 8	X	P3, P4	X	L1, L2
Week 9	X	P3, P5, P7	X	L1
Week 10	X	P1, P4, P5, P7	X	L1, L2
Week 11	X	P3, P4, P5, P7	X	L1, L2
Week 12	X	P1, P6	X	L1,L2
Week 13	X	P3, P4, P5, P7, P12	X	L2
Week 14	X	P4, P5, P6	X	L1, L2
Week 15	X	P3, P4, P5, P6, P12	X	L1, L2
Week 16	X	P4, P5, P6, P7, P9, P10, P12	X	L1, L2
Week 17	X	P3, P4, P5, P6	X	L1, L2
Week 18	-	-	X	L1
Week 19	X	P6	X	L1, L2
Week 20	X	P5, P6	X	L1, L2
Week 21	X	P5	X	L1

Table 23 – The modified parameters for the Minimum Lot Size policy

	Product	Line	Min. Lot Size (Hl)	Modified Min. Lot Size (Hl)
Week 11	2	1	7128	6574
	6	2	3888	2116
	10	2	305	203
Week 12	1	1	7128	2940
	6	2	3888	1067
	12	2	305	202
Week 13	1	1	7128	6881
	2	1	7128	6983
	10	2	305	199
Week 14	1	1	7128	5814
	2	1	7128	3223
	6	2	3888	1000
	12	2	305	270

The GA-LP approach was run one time per week using a crossover rate of 0.30 and mutation rate of 0.10. Figure 26 depicts the results obtained for each week, and the GA-LP approach outperformed in Weeks 11 and 12. We observe that two categories of costs, namely, the inventory holding costs and the production costs, decreased significantly after changing the parameters. For Weeks 13 and 14, the costs were reduced but still not better than the total cost of the AS-IS approach in PBC. After carefully examining the historical data, PBC not only violate the Minimum Lot Size policy, but also the Minimum Safety Stock in these weeks. The total cost of the GA-LP approach was also slightly larger than the AS-IS approach for Week 16, primarily because the production cost was larger due to the Minimum Lot Size policy that was not changed for this week, and therefore the inventory holding costs increased. We will present further observations in Section 6.4.

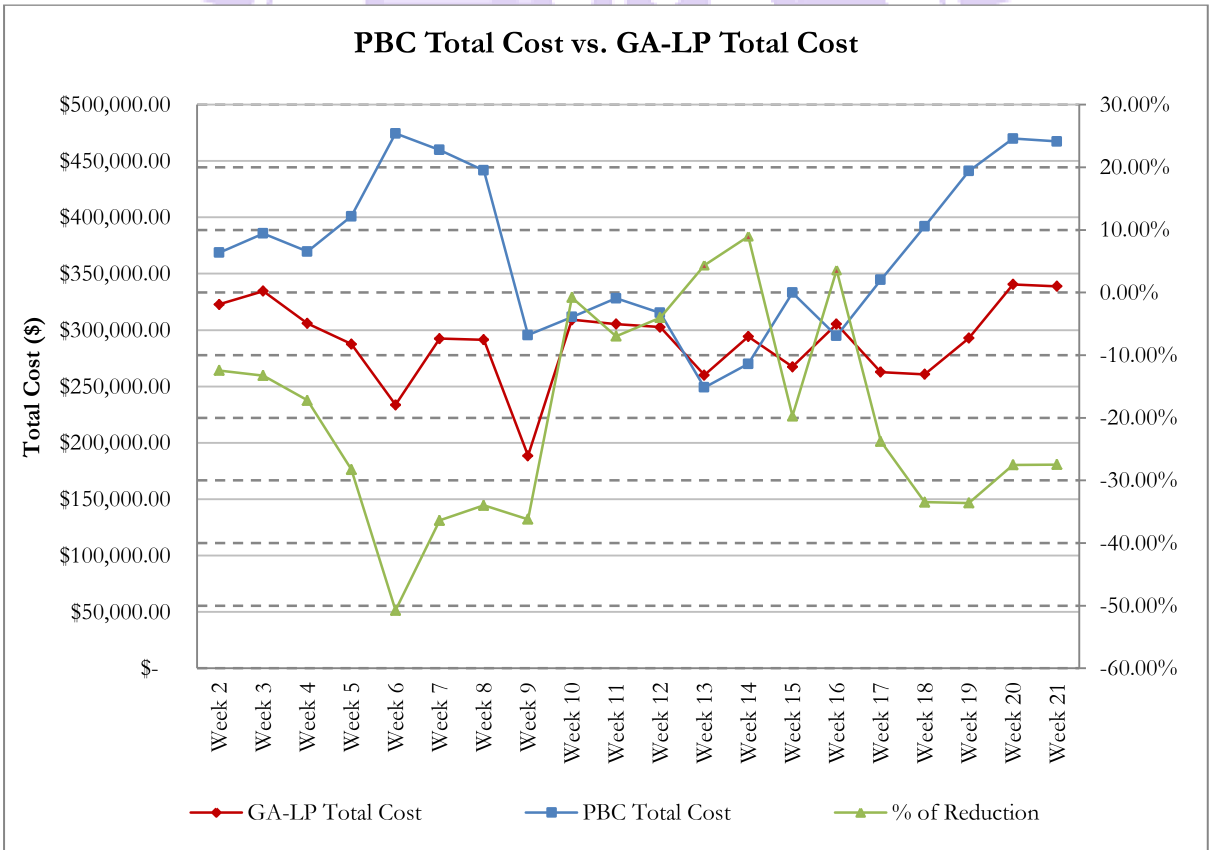

Figure 26 - The comparison between the AS-IS approach and the GA-LP approach with modified parameters.

6.3 T-test

The t-test assesses whether the means of two groups are statistically different from each other. This analysis is appropriate whenever one would compare the means of two groups (Trochim, 2014).

For this study we compare the results obtained by the GA-LP approach and the AS-IS approach in PBC based on the twenty weeks used in Section 6.2. Let X represent the results obtained by GA-LP approach and Y the results from the AS-IS approach.

- Null hypothesis H_0: X will always be less than Y, even if we increased it by *m*%.
    - H_0: $X(1 + m\%) \leq Y$

For our experiments, we started the test with $m = 0$. Then we kept increasing the value of *m* until it did not pass the test; at that point we shall know the maximum value of *m*.

Results for non-modified parameters case

Table 24 summarizes the results obtained from both approaches. After finishing the t-test we could observe that the *t* value is greater than the *t-critical*. It means that the difference between the tested pair of means is significant with a confidence level of 95%. The value of *p* (0.00054) < 0.05 indicates that the probability of rejecting the null hypothesis is very small.

Table 24 – The results of t-test for comparing the GA-LP and AS-IS approaches

	(GA-LP - PBC)/ PBC*100%
Mean	-18.3%
Variance	4.20%
Observations	19
Degree of Freedom	18
t Stat	4.197
p	0.00054
t Critical	2.101

We kept increasing the value of *m* until the value of *p* exceeds the significance level of the null hypothesis, which is set at 0.05. According to our experimental results, we will not reject the null hypothesis with a confidence level of 95% that the GA-LP obtained better solutions than the AS-IS approach by 12.6%.

Results for modified parameters case

Table 25 summarizes the results obtained from both approaches after the parameters were modified according to PBC's violation. In this case the *t* value of the null hypothesis is also greater than the *t-critical*. The value of *p* (0.00009) is less than the significance level of 0.05, and it indicates the probability of rejecting the null hypothesis is very small.

Table 25 – The results of t-test for comparing the GA-LP and AS-IS approaches using modified parameters

	(GA-LP-PBC)/ PBC*100%
Mean	-19.5%
Variance	2.69%
Observations	19
Degree of Freedom	18
t Stat	4.971
p	0.00009
t Critical	2.101

Similarly, we increase the value of $m=1$ until the t-test failed. According to our experimental results, we will not reject the null hypothesis with a confidence level of 95% that the GA-LP obtained better solutions than the AS-IS approach by 13.5%.

6.4 Observations and Discussions

We may conclude that the proposed GA-LP approach may serve as an effective tool for supporting the planners in the decision-making of the lot sizing and scheduling problems. We have further observations and discussions as follows.

- The proposed GA-LP approach was able to obtained solutions with excellent solution quality for weekly production planning in approximately 9 minutes. This represents a great improvement compared to the time spent in production planning by the planners.
- The infeasibility prevention mechanism was able to reduce 89% of the infeasible individuals before sending them to the LP-solver for testing feasibility, and thus the total run time was also significantly reduced.
- We use a modified way of selecting individual for crossover to improve the run time for without affecting the final results. We may feel free to analyze higher values of crossover rate on their impacts on the final results.
- According our experiments in section 6.2.2, the GA-LP approach did not outperform the results from the AS-IS approach for Weeks 13, 14 and 16. After carefully examining the historical data, we learn that PBC experienced the problems of shortages in the weeks as summarized in Table 26. Taking this factor into account, the proposed GA-LP approach can never outperform the AS-IS approach in these weeks because we do not allow shortage. The proposed GA-LP approach shall obtain better solutions than the AS-IS approach if the

comparison is done without violating the Minimum Safety-Stock Policy and the assumption of no shortage.

Table 26 – The shortage of products in Weeks 13, 14 and 16

Week	Products
13	1 (Figure H.2) 6 (Figure H.7)
14	3 (Figure H.4) 5 (Figure H.6) 12 (Figure H.13)
16	3 (Figure H.4) 12 (Figure H.13)

- According to the results obtained from the GA-LP approach, the Inventory Holding Costs can be reduced up to 23%, and as mention in our analysis, it takes almost 86% of the total cost. Currently PBC is carrying very high levels of inventory, mainly because they stick to their safety stock policies. According to the planners, they try to maintain inventory at the highest safety stock because they are so afraid of out-of-stock accidents due to a sudden rise of demand caused by marketing promotions or special holiday sales at the demand side. However, we still see shortage problems incurred for some products for three weeks among the 20 weeks of historical data.
- Following our analysis on the obtained solution from the GA-LP approach, we conclude that the managers in PBC should revise the current inventory policy of some products. (One may refer to Figures H.2 to H.14 in Appendix H for the demands versus the inventory levels maintained by PBC and those obtained from the GA-LP approach.) For example, Product 5 has a minimal safety stock equal the demand of 2 weeks ahead, which leads to the inventory holding costs of more than USD$ 517,000.00 for this study. In fact, the real plan did not follow it strictly. If the managers decided to lower the threshold down to 1.5 weeks, the inventory holding costs for this product in these 20 weeks could be reduced to $388,370.00;

which represents a reduction of 2.2% in the total cost. (One may refer to Figure H.15 in Appendix H for this example.)

- The production costs are also of opportunities for significant cost reduction. From our analysis, we observe that the improvements result primarily from the optimal lot sizes and the lot-assignments of shared products. The solutions from the GA-LP approach show that in some weeks it was more economical to assign the production lot of one product to Line 1 and keep the rest of the week maintain idle, and assign the production lot of the rest of shared products in Line 2.
- Usually, the planners in PBC paid more attention to minimize the idle time of packaging lines. The results of the GA-LP approach show that keeping the personnel idle leads to less costs than the inventory holding costs from the inventory that will not be used immediately. The production plans from the AS-IS approach showed that PBC needs to use overtime to cover demand for Weeks 6 and 7. It is assumed that this happened because major holiday was expected for Weeks 9 and 10. However, according to the results obtained from the GA-LP approach, demand could have been satisfactorily covered using normal parameters (capacity, minimum lot size, inventory policies) and even have some idle time remaining in the packaging lines. Table 27 shows that the results from the GA-LP approach achieved more than 50% reduction in the total cost for Week 6 and 36% for Week 7. The managers should check if PBC really requires the teams working six days a week, or if it is more economical to reduce capacity to five days a week for RB packaging lines.

Table 27 – The total costs for Weeks 6 and 7

Week #	PBC	GA-LP	% of Reduction
Week 6	$ 474,478.86	$ 233,696.10	-51%
Week 7	$ 459,834.66	$ 292,493.41	-36%

- The results show that the GA-LP approach was able to reduce the setup costs by 13%. However, we must notice that in real life the decisions of production sequences and lot assignments are subjected to external factors such as: the other production lines, the capacity of the syrup room and the brewing house, the utilities supply, among others that were not considered in this study.
- From the historical data, the AS-IS approach assigned some unnecessary production lots for some products in some weeks. (One may refer to Figures H.16 and H.17 that show the production sequence of each production line for Week 2 according to PBC's data and the results of the GA-LP approach. To cover demand and safety stock, it was not necessary to produce Products 1, 10, 12, 8 and 11. Also the production lot of Product 3 was shifted to Line 2 shown in the results of the GA-LP approach, representing that it is cheaper to bottle the lot in Line 2 than in Line 1.)

7. Conclusions and Future Works

7.1 Conclusions

The goal of this thesis is to propose a mathematical model and a solution approach that supports the planning decisions of a short-term production scheduling problem (weekly). The model takes into accounts the product-assignment constraints, inventory policies, time due to breakdowns, setup sequence times and working time availability, which are important factors in the production planning process for any company that faces the same type of problems.

Panama Beer Company is the case study of this study. Its Packaging Department is the largest beer bottling plant in Panama, where beer products and soft drinks products are packed in different types of containers such as returnable bottle (RB), cans, kegs and pets.

Packaging Department consists of six production lines divided in two areas: beer and CSD. The beer packaging area is formed by four production lines, each having different capabilities and CSD packaging area consists of two lines, one for returnable bottle products and one for PET containers products. In total, the factory has three RB lines; two for beer and one for soft drinks, and these are the ones that were considered. In this study, we focused on the scheduling and lot sizing problem of the RB packaging lines of beer and soft drinks.

The proposed model was based on the GLSP-PL model presented by Meyr (2002). However, changes need to be done to fit our decision-making scenario. For the mathematical model formulation we considered characteristics such as capacity-sharing issue between Lines 2 and 3, since they cannot operate simultaneously. Sequence-dependent setup times are also considered, and the aim was to obtain the optimal sequence that minimizes the setup times and costs. Product-sharing between Lines 1 and 2 is another important characteristic of this problem.

The proposed model also includes reliability issue, which is another significant characteristic of packaging lines. Average breakdown time is a user defined parameter, and it reduces the capacity availability. Since the setup and production costs are high, the bottling companies usually pre-defined a Minimum Lot Size that need to be produced every time the line starts up a production lot of a specific product. This company has an inventory policy, which set a minimum amount of inventory that needs to be at the end of every week in the warehouse. Such inventory policy is established to accommodate the reliability of production lines and/or the fluctuation in demand, since the products are fast-moving goods.

To solve the concerned problem, we proposed a hybrid-heuristic that combines a genetic algorithm and linear programming. Genetic algorithm was used to find production sequences. Once a possible sequence was obtained, the indicator variables for changeover could be solved. Then, we employ an LP-solver to solve the production quantity of each product by taking the (given) values of binary variables input parameters. We calculate the objective function of each solution to evaluate its fitness value. Each individual is represented as a 3-D matrix (and consequently, a population as a 4-D matrix). No decoding procedure was necessary, because each individual represented the binary variables in our mathematical model. We use MATLAB R2013a to code the proposed solution approach, abbreviated as the GA-LP.

We applied the GA-LP to solve the real problems from Panama Beer Company. Twenty consecutive weeks were analyzed, by comparing the results obtained by the AS-IS planning methods and the proposed solution approach. The data set for our experiments corresponds to a period of 5 months from 2014, where the capacity of each line was 6 days per week, 24 hours each day. However for some weeks a reduction of capacity was considered due to country's holidays.

Our results are encouraging, since they show a possible reduction of 21% in the total cost for the 20 weeks in our experiments. Impressively, it leads to a total cost saving of more than one million US dollars. The GA-LP was able to outperform the AS-IS approach for 16 weeks without any constraint violation. The execution time of the GA-LP was in an average of 9 minutes; this represents a great improvement compared to the time spent by the planners every day. (They usually spent around half-day, about 4 hours for the production planning of 2 weeks.) The infeasibility prevention mechanism significantly helped in improving the efficiency of the GA-LP, by reducing 89% of infeasible individuals to be passed to the LP-solver so that the running time is significantly decreased.

We observed that currently PBC carrying very high levels of inventory, mainly because the managers stick to their safety-stock policies. As suggested, the managers should revise the safety-stock policies for some products, since the inventory holding cost takes more than 80% of the total costs. Our results also showed that in some cases it is less expensive to maintain personnel idle than increase inventory levels.

According to the results from the GA-LP approach, the current capacity is enough to cover all demand, and on an average 2 days remain idle per week. The managers also should check if the company really requires teams working six days a week, or if it is more economical to reduce capacity to five days a week for RB packaging lines.

7.2 Future Works

The GA-LP approach may serve as an effective tool to support the planners in their daily tasks. However, for future implementation in Panama Beer Company the code should be extended to cover all packaging lines, because the produced products that are supplied by syrup room and brewing house. It is also recommended to extend the solution approach to be able to solve at least two weeks of production at the same time, and take into account the capacity of syrup room because it is a bottleneck for the CSD packaging department at present. This means that the production scheduling of the syrup room leads possible changes in the lot sizes and weekly production sequence of the soft-drink products.

This study may be extended in the aspects of the model formulation and the proposed solution approach. We suggest exploring the following issues in the future:

- The proposed solution approach can be extended to solve for two weeks or more. It is possible to compare more production sequences so as to obtain better solutions.
- This proposed solution approach may compare with other approaches in the literature. We are interested in the one presented in Toledo et al. (2014), where they proposed a similar, but more restricted, solution approach.
- Have more time available, we shall be able to do more tests. We may test the proposed solution approach for more crossover rates to observe their impact on the quality and the run time of the obtained solution. Similarly, we may try more combinations of parameters, e.g., increasing the population size or the mutation rate.
- One may design different data structures and other corresponding genetic operators to improve the quality of the obtained solution. It may lead to possible change in the number of generations for evolution before termination.
- To be more practical to the planners in Panama Beer Company, the proposed approach should be adjusted to deal with more production lines and products. It will be good to have a planning horizon covering for 3 weeks, because a beer company usually schedules the production of beer liquid at least 2 weeks prior to packaging. Also, the proposed approach integrates the scheduling in the brewing house and the syrup room.
- One may conduct more sensitivity analysis by testing different situations, for example reducing capacity, increasing idle time cost, or eliminating the inventory or minimum lot size policy.

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Appendix

A. General Description of Brewing Process

Figure A.1 - General Description of Brewing Process

(Ranjan, 2007)

B. Panama Beer Company Planning Process

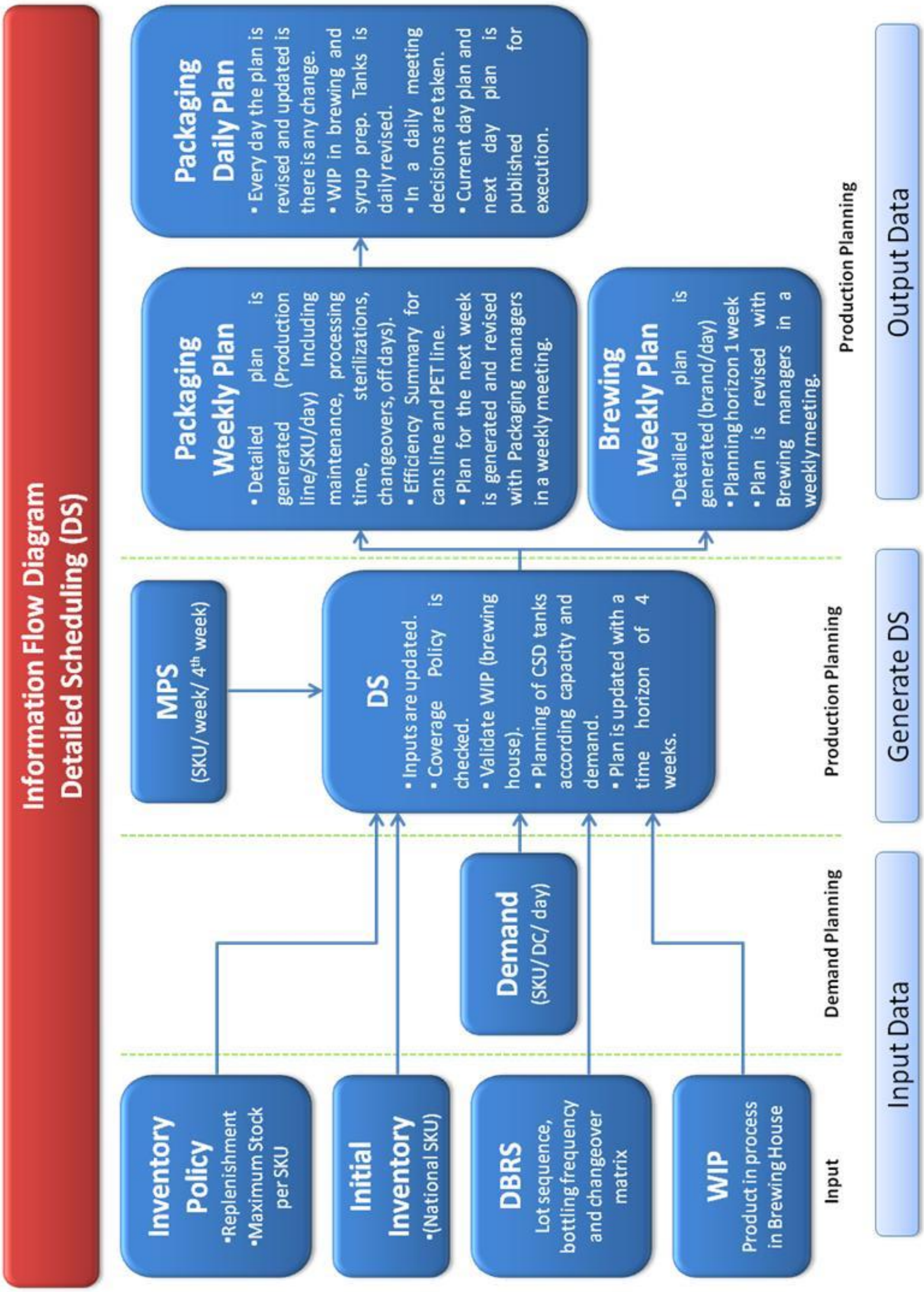


Figure B.1 - PBC Information Flow Diagram used in Planning Department

(Cerveceria Nacional S.A., 2013)

C. PBC production cost, idle time cost and changeover cost description

The costs that are directly impacted by the lot sizing and scheduling decisions for packaging production lines are: electricity consumption, steam consumption, material inputs such as caustic soda, additives, and lubricants, and water consumption. These values are calculated every two years according the variance of cost and the consumption in lines. For practical purposes PBC has established a fix cost for every production line.

Table C.1 – Production Costs that are directly associated with production schedule

Production Cost ($/Hl)
Electricity
Line consumption
Compressed Air
Refrigeration
Steam
Washing machine
Pasteurizer
Material Inputs
Conveyor Lubricant
Washer's additives
Caustic Soda
Other Lubricants
Waste
Product Loss(%)
Water
Hl of water/Hl of beer
Idle Time Cost ($/Hour)
Human Resource
Change Over Cost ($/Hour)
Idle Time Cost
Team Cost
Cleaning Material Cost
Product Loss

D. Data Collection Gantt chart

			July																	August															
Collection of Data	Source of Info	Due Date	15	16	17	18	19	20	21	22	23	24	25	26	20	21	29	30	31	1	2	20	21	5	6	7	8	9	20	21	12	13	14	15	16
Overview of Current Planning Process	Victor B.	24-Jul																																	
Download Demand historical data (past 3 years)	Victor B.	23-Jul																																	
Working hours in different months	Victor B.	23-Jul																																	
List of products packed by KHS, SAS, HKB	Victor B.	18-Jul																																	
Define Workforce size of Line 1 KHS	Luis M.	2-Aug																																	
Operational Costs of line for each product	Luis M.	9-Aug																																	
Operations Process Chart	Luis M.	25-Jul																																	
Machine rates	Luis M.	16-Aug																																	
Setup times	Victor B.	2-Aug																																	
Sequence dependency of the products	Victor B.	16-Aug																																	
Special production constraints.	Victor B./ Luis M.	30-Jul																																	
Hourly rate for different teams	Luis M.	31-Jul																																	
Idle cost of a team	Luis M.	7-Aug																																	
Inventory holding cost	Victor B./ Luis M.	14-Aug																																	
Stock Out Cost	Victor B./ Luis M.	14-Aug																																	

E. Data of Panama Beer Company for Base Scenario

Base data for scenarios includes: minimum and maximum number of weeks of inventory coverage, holding cost per every unit of product, production rates, changeover times, setup cost per hour, minimum lot size, product loss caused by changeover, fix % of product loss when line is running, item costs, average downtime per period per line and specific sets that specify capabilities of production.

Table E.1 - Data of base scenario for PBC Case

a) Number of items (J), lines (L), macro-periods (T) and micro-periods (N)

J	13
L	2
T	1
N	10

b) Initial inventory (Hl), holding costs ($/Hl), minimum and maximum coverage (weeks)

	Ij0	*hj*	*cobminj*	*cobmaxj*
j = 1	TBD	confidential	1	2
j = 2	TBD	confidential	1	2
j = 3	TBD	confidential	1	2
j = 4	TBD	confidential	2	3
j = 5	TBD	confidential	2	3
j = 6	TBD	confidential	1.5	2
j = 7	TBD	confidential	2	3
j = 8	TBD	confidential	1	2
j = 9	TBD	confidential	1	2
j = 10	TBD	confidential	1	2
j = 11	TBD	confidential	1	2
j = 12	TBD	confidential	1	2
j = 13	TBD	confidential	1	2

c) Production rates of product j in line l (Hl/hour)

rjl	j = 1	j = 2	j = 3	j = 4	j = 5	j = 6	j = 7	j = 8	j = 9	j = 10	j = 11	j = 12	j = 13
l = 1	158	158	108	0	0	0	0	0	0	0	0	0	0
l = 2	92	92	75	142	142	84	151	152	113	150	149	161	149

d) First micro-period, set of micro-periods belonging to a macro-period and last micro-period of t

	Ft	*Nt*	*LPt*
t = 1	1	{1….10}	10

e) Setup Fix Costs ($/hour)

	sl
l = 1	79.3
l = 2	76.3

f) Setup Times (hours)

stijl		j = 1	j = 2	j = 3	j = 4	j = 5	j = 6	j = 7	j = 8	j = 9	j = 10	j = 11	j = 12	j = 13
l = 1	i = 1	0	0.66	5										
	i = 2	0.66	0	5										
	i = 3	5	5	0										
l = 2	i = 1	0	0.75	4	3	3	3	3.38	3.38	3.38	3.38	3.38	3.38	3.38
	i = 2	0.75	0	4	3	3	3	3.38	3.38	3.38	3.38	3.38	3.38	3.38
	i = 3	4	4	0	4	4	3	3.38	3.38	3.38	3.38	3.38	3.38	3.38
	i = 4	3	3	4	0	0.75	3	3.38	3.38	3.38	3.38	3.38	3.38	3.38
	i = 5	3	3	4	0.75	0	3	3.38	3.38	3.38	3.38	3.38	3.38	3.38
	i = 6	3	3	3	3	3	0	3.38	3.38	3.38	3.38	3.38	3.38	3.38
	i = 7	4.83	4.83	4.83	4.83	4.83	4.83	0	0.75	1.50	0.75	0.75	0.75	0.75
	i = 8	4.83	4.83	4.83	4.83	4.83	4.83	0.75	0	1.50	0.50	0.50	0.75	0.75
	i = 9	4.83	4.83	4.83	4.83	4.83	4.83	1.50	1.50	0	1.50	1.50	1.50	1.50
	i = 10	4.83	4.83	4.83	4.83	4.83	4.83	0.75	0.50	1.50	0	0.50	0.75	0.75
	i = 11	4.83	4.83	4.83	4.83	4.83	4.83	0.75	0.50	1.50	0.50	0	0.75	0.75
	i = 12	4.83	4.83	4.83	4.83	4.83	4.83	0.75	0.75	1.50	0.75	0.75	0	0.75
	i = 13	4.83	4.83	4.83	4.83	4.83	4.83	0.75	0.75	1.50	0.75	0.75	0.75	0

g) Product loss caused by changeovers (Hl)

	spl
l = 1	7
l = 2	3

h) Fix % product loss when line is running

ml	
l = 1	0.42%
l = 2	0.68%

i) Fix production costs of line l to produce product j ($/Hl)

pjl	j = 1	j = 2	j = 3	j = 4	j = 5	j = 6	j = 7	j = 8	j = 9	j = 10	j = 11	j = 12	j = 13
l = 1	1.38	1.38	1.38	M	M	M	M	M	M	M	M	M	M
l = 2	0.98	0.98	0.98	0.98	0.98	0.98	1.56	1.56	1.56	1.56	1.56	1.56	1.56

j) Items Costs ($/Hl)	
pcj	
$j = 1$	Confidential
$j = 2$	Confidential
$j = 3$	Confidential
$j = 4$	Confidential
$j = 5$	Confidential
$j = 6$	Confidential
$j = 7$	Confidential
$j = 8$	Confidential
$j = 9$	Confidential
$j = 10$	Confidential
$j = 11$	Confidential
$j = 12$	Confidential
$j = 13$	Confidential

k) Minimum Lot Size (Hl)		
Qminjl	l = 1	l = 2
$j = 1$	7128	3168
$j = 2$	7128	3168
$j = 3$	2508	1680
$j = 4$	0	708
$j = 5$	0	1699
$j = 6$	0	3888
$j = 7$	0	203
$j = 8$	0	508
$j = 9$	0	230
$j = 10$	0	305
$j = 11$	0	397
$j = 12$	0	305
$j = 13$	0	302

l) Set of products that can be produce in line l	
α_l	
$\alpha 1$	{1,2,3}
$\alpha 2$	{1,2,3,4,5,6,7,8,9,10,11,12,13}

m) Set of lines that produce product j	
λ_j	
$\lambda 1$	{1,2}
$\lambda 2$	{1,2}
$\lambda 3$	{1,2}
$\lambda 4$	{2}
$\lambda 5$	{2}
$\lambda 6$	{2}
$\lambda 7$	{2}

$\lambda 8$	{2}
$\lambda 9$	{2}
$\lambda 10$	{2}
$\lambda 11$	{2}
$\lambda 12$	{2}
$\lambda 13$	{2}

n) Average downtime per period t of line l (hours) δ_{lt}	
δ_{1t}	2
δ_{2t}	1

o) Demand (Hl) (To be Defined)

djt	T1	T2	T3
$j = 1$	TBD	TBD	TBD
$j = 2$	TBD	TBD	TBD
$j = 3$	TBD	TBD	TBD
$j = 4$	TBD	TBD	TBD
$j = 5$	TBD	TBD	TBD
$j = 6$	TBD	TBD	TBD
$j = 7$	TBD	TBD	TBD
$j = 8$	TBD	TBD	TBD
$j = 9$	TBD	TBD	TBD
$j = 10$	TBD	TBD	TBD
$j = 11$	TBD	TBD	TBD
$j = 12$	TBD	TBD	TBD
$j = 13$	TBD	TBD	TBD

p) Initial Setup (To be Defined)

ylj0	j = 1	j = 2	j = 3	j = 4	j = 5	j = 6	j = 7	j = 8	j = 9	j = 10	j = 11	j = 12	j = 13
$l = 1$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
$l = 2$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

q) Capacity of Lines per macro-period t (hours) (To be Defined)

Klt	
$l = 1$	TBD
$l = 2$	TBD

F. Solution Approach Flow Chart

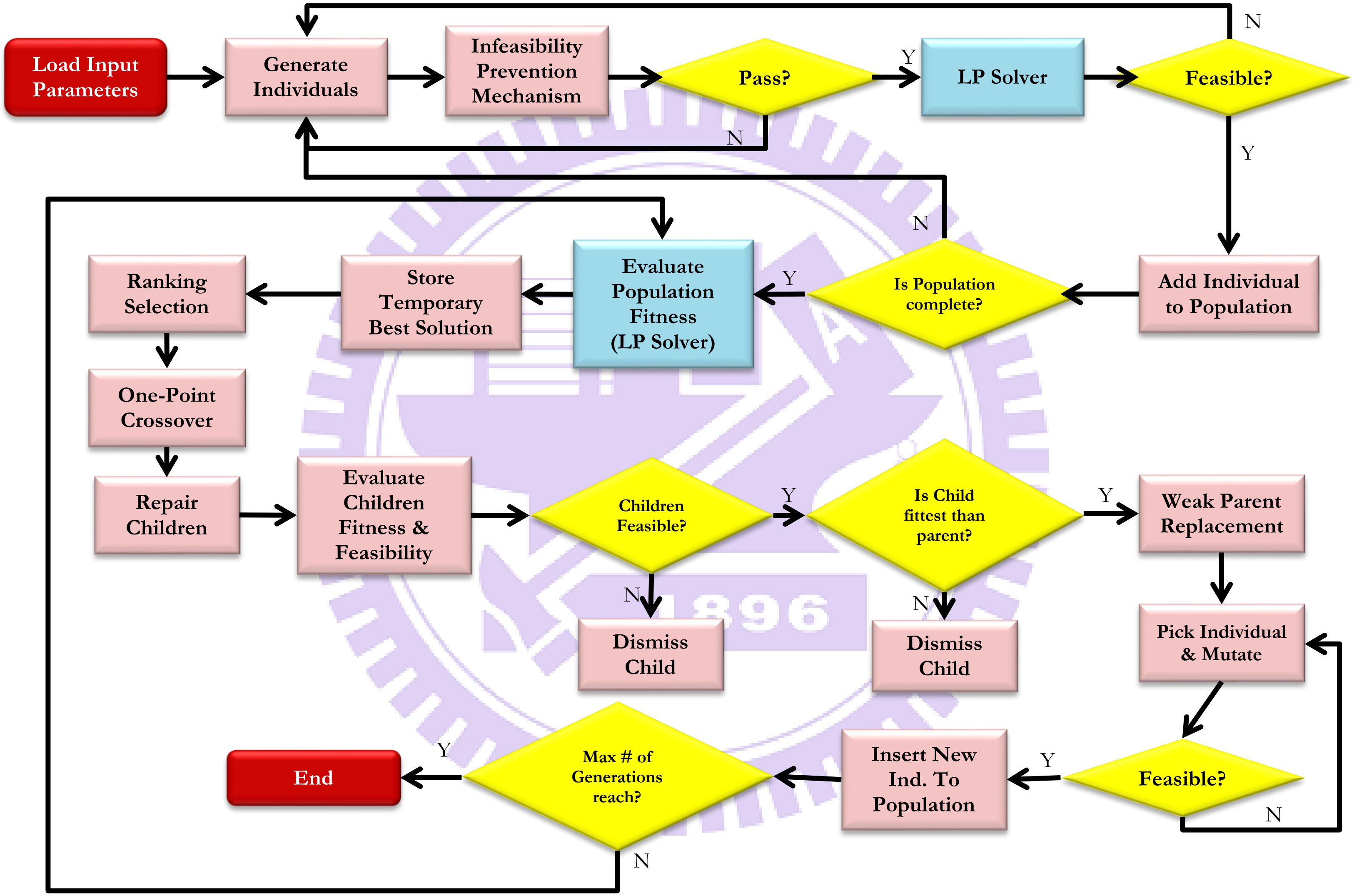


Figure F.1 - GA-LP Flow Chart

G. Panama Beer Company Total Costs

This section presents the inventory holding costs, setup costs, production costs and idle time costs according Panama Beer Company historical plans.

Table G.1 Panama Beer Company Costs

Costs	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11
	6-Jan	13-Jan	20-Jan	27-Jan	3-Feb	10-Feb	17-Feb	24-Feb	3-Mar	10-Mar
Inventory Holding Costs	$ 332,003.58	$ 345,226.60	$ 324,857.06	$ 354,797.44	$ 421,000.64	$ 407,274.12	$ 394,491.76	$ 262,601.64	$ 264,270.00	$ 280,950.32
Production Costs	$ 31,979.65	$ 33,377.02	$ 37,547.92	$ 39,833.02	$ 46,904.51	$ 43,171.43	$ 39,191.26	$ 18,194.94	$ 39,231.25	$ 38,129.26
Idle Time Costs	$ 1,892.65	$ 3,784.20	$ 3,213.00	$ 2,533.25	$ 20.71	$ 2,927.40	$ 3,657.57	$ 11,566.80	$ 5,283.60	$ 6,270.53
Setup Costs	$ 2,835.98	$ 3,336.42	$ 3,970.38	$ 3,764.21	$ 4,839.41	$ 4,748.11	$ 4,262.12	$ 3,245.54	$ 2,879.40	$ 2,879.40
Total Costs	**$ 368,711.86**	**$ 385,724.24**	**$ 369,588.36**	**$ 400,927.92**	**$ 474,478.86**	**$ 459,834.66**	**$ 441,602.71**	**$ 295,608.92**	**$ 311,664.26**	**$ 328,229.51**

Costs	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17	Week 18	Week 19	Week 20	Week 21
	17-Mar	24-Mar	31-Mar	7-Apr	14-Apr	21-Apr	28-Apr	5-May	12-May	19-May
Inventory Holding Costs	$ 268,810.03	$ 206,815.24	$ 230,008.46	$ 281,724.96	$ 255,771.81	$ 290,872.42	$ 346,200.11	$ 393,966.91	$ 423,698.82	$ 420,463.13
Production Costs	$ 38,031.39	$ 35,712.17	$ 28,961.66	$ 44,181.43	$ 28,638.27	$ 48,067.80	$ 42,816.51	$ 37,131.95	$ 40,436.55	$ 40,311.49
Idle Time Costs	$ 2,998.80	$ 4,498.20	$ 6,226.08	$ 3,343.82	$ 6,872.78	$ 2,509.01	$ 71.22	$ 7,167.23	$ 1,106.70	$ 3,389.18
Setup Costs	$ 5,419.82	$ 2,176.74	$ 4,846.39	$ 3,940.18	$ 3,495.82	$ 3,108.71	$ 2,815.69	$ 2,738.27	$ 4,630.93	$ 3,108.29
Total Costs	**$ 315,260.04**	**$ 249,202.35**	**$ 270,042.59**	**$ 333,190.39**	**$ 294,778.68**	**$ 344,557.95**	**$ 391,903.53**	**$ 441,004.37**	**$ 469,873.00**	**$ 467,272.09**

H. GA-LP Results

H.1 Total Costs

This section presents the inventory holding costs, setup costs, production costs and idle time costs according our solution approach. Figure H.1 presents results for every run in every instance. It shows that small variation is obtained between every run.

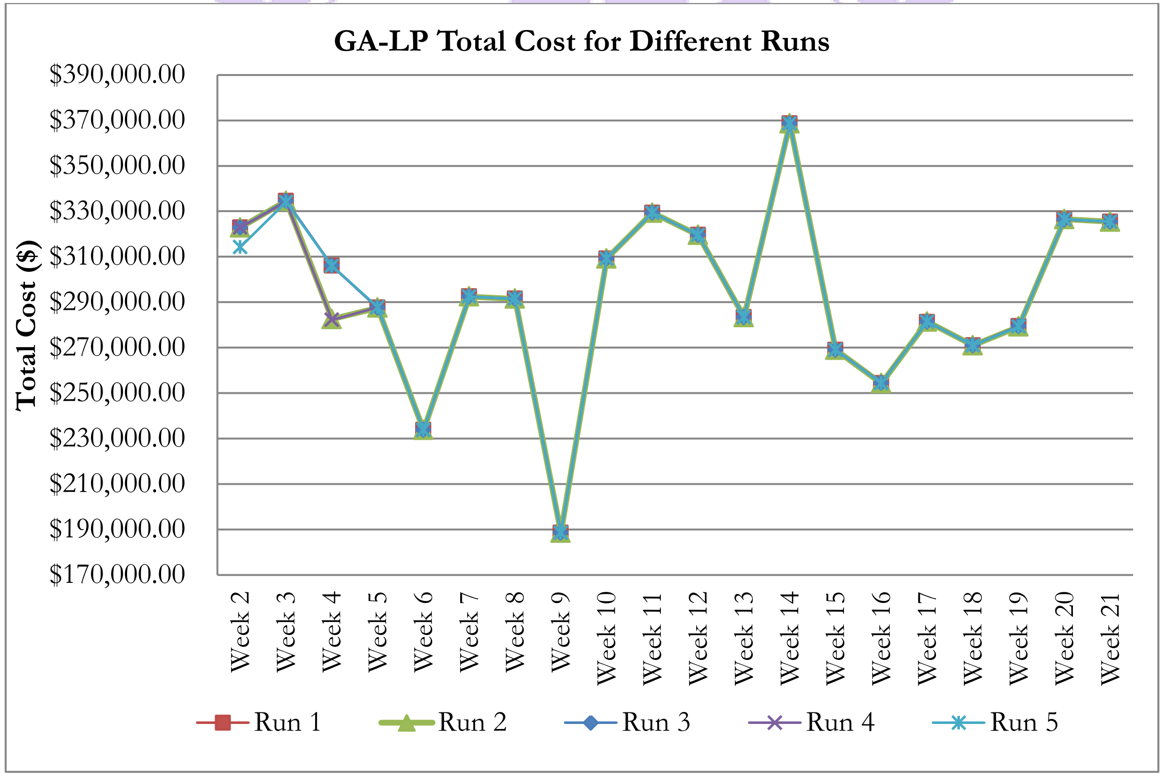


Figure H.1 – GA-LP results for all instances and repetitions.

Table H.1 - GA-LP Costs

Costs	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11
	6-Jan	13-Jan	20-Jan	27-Jan	3-Feb	10-Feb	17-Feb	24-Feb	3-Mar	10-Mar
Inventory Holding Costs	$ 284,559.07	$ 291,835.97	$ 243,435.98	$ 242,681.77	$ 203,260.32	$ 244,662.66	$ 247,098.60	$ 160,634.24	$ 260,471.96	$ 281,401.76
Production Costs	$ 23,096.95	$ 34,336.73	$ 31,408.28	$ 38,141.56	$ 16,996.14	$ 42,405.21	$ 38,251.16	$ 14,348.28	$ 42,694.80	$ 41,925.97
Idle Time Costs	$ 4,432.14	$ 5,709.71	$ 4,289.29	$ 2,881.30	$ 10,128.55	$ 1,802.24	$ 3,351.70	$ 10,492.48	$ 2,570.88	$ 2,691.78
Setup Costs	$ 2,157.23	$ 2,217.58	$ 3,024.92	$ 4,020.13	$ 3,311.09	$ 3,623.30	$ 2,785.54	$ 3,071.59	$ 3,437.75	$ 3,288.20
Total Costs	**$ 314,245.40**	**$ 334,100.00**	**$ 282,158.47**	**$ 287,724.76**	**$ 233,696.10**	**$ 292,493.41**	**$ 291,487.00**	**$ 188,546.58**	**$ 309,175.38**	**$ 329,307.71**

Costs	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17	Week 18	Week 19	Week 20	Week 21
	17-Mar	24-Mar	31-Mar	7-Apr	14-Apr	21-Apr	28-Apr	5-May	12-May	19-May
Inventory Holding Costs	$ 271,905.06	$ 235,912.35	$ 320,669.80	$ 239,344.77	$ 217,348.82	$ 235,223.80	$ 231,865.28	$ 240,627.73	$ 278,586.02	$ 278,142.57
Production Costs	$ 42,138.45	$ 41,013.28	$ 41,620.89	$ 17,574.48	$ 26,706.06	$ 39,628.30	$ 29,997.63	$ 28,962.58	$ 41,994.80	$ 41,222.23
Idle Time Costs	$ 1,808.87	$ 2,898.53	$ 2,700.48	$ 9,543.16	$ 6,600.89	$ 3,216.46	$ 5,534.67	$ 6,613.42	$ 2,580.14	$ 2,978.08
Setup Costs	$ 3,645.90	$ 3,477.80	$ 3,574.08	$ 2,543.81	$ 3,747.91	$ 3,154.43	$ 3,595.04	$ 3,000.19	$ 3,196.95	$ 3,030.79
Total Costs	**$ 319,498.28**	**$ 283,301.97**	**$ 368,565.25**	**$ 269,006.22**	**$ 254,254.10**	**$ 281,223.00**	**$ 270,992.62**	**$ 279,203.92**	**$ 326,357.91**	**$ 325,373.67**

H.2 Percentage of Reduction

After compare total costs obtain by GA-LP approach, the % of reduction per week were calculated. As mention in previous chapters, our approach outperforms 16 weeks. According the comparison, PBC's historical plans have better results for week 11, 12, 13 and 14.

Table H.2 – Percentage of reduction per week

	% of Reduction
Week 2	-14.8%
Week 3	-13.4%
Week 4	-23.7%
Week 5	-28.2%
Week 6	-50.7%
Week 7	-36.4%
Week 8	-34.0%
Week 9	-36.2%
Week 10	-0.8%
Week 11	0.3%
Week 12	1.3%
Week 13	13.7%
Week 14	36.5%
Week 15	-19.3%
Week 16	-13.7%
Week 17	-18.4%
Week 18	-30.9%
Week 19	-36.7%
Week 20	-30.5%
Week 21	-30.4%

H.3 Product's demand vs inventory levels

In this section the amount of demand and inventory levels according historical data and GA-LP results are presented.

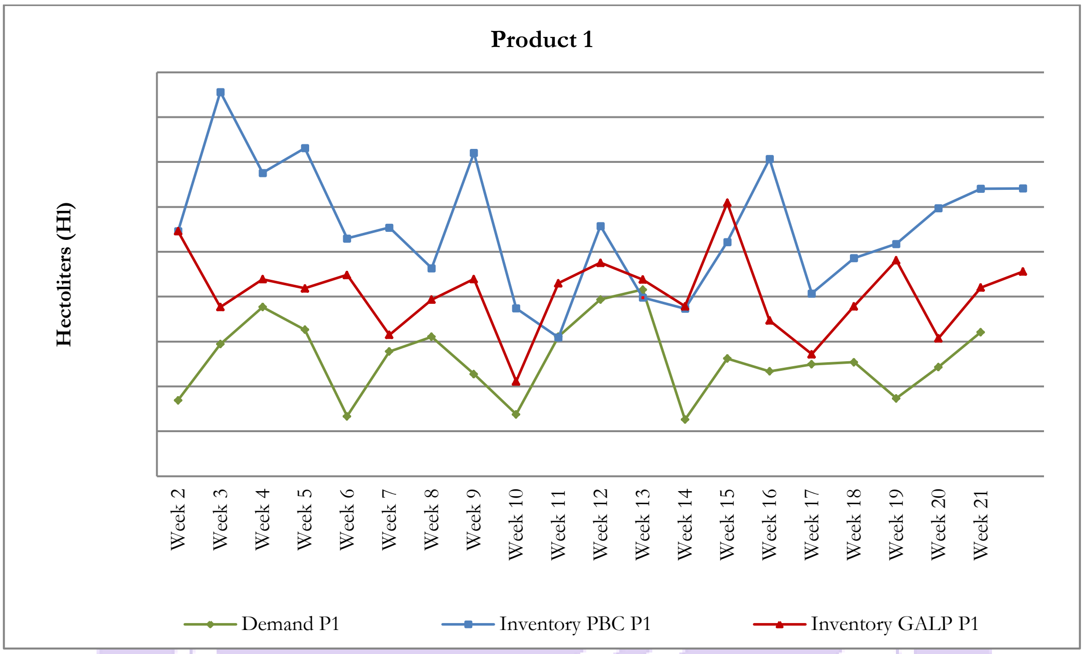


Figure H.2 – Demand of Product 1, PBC Inventory level and GA-LP Inventory level.

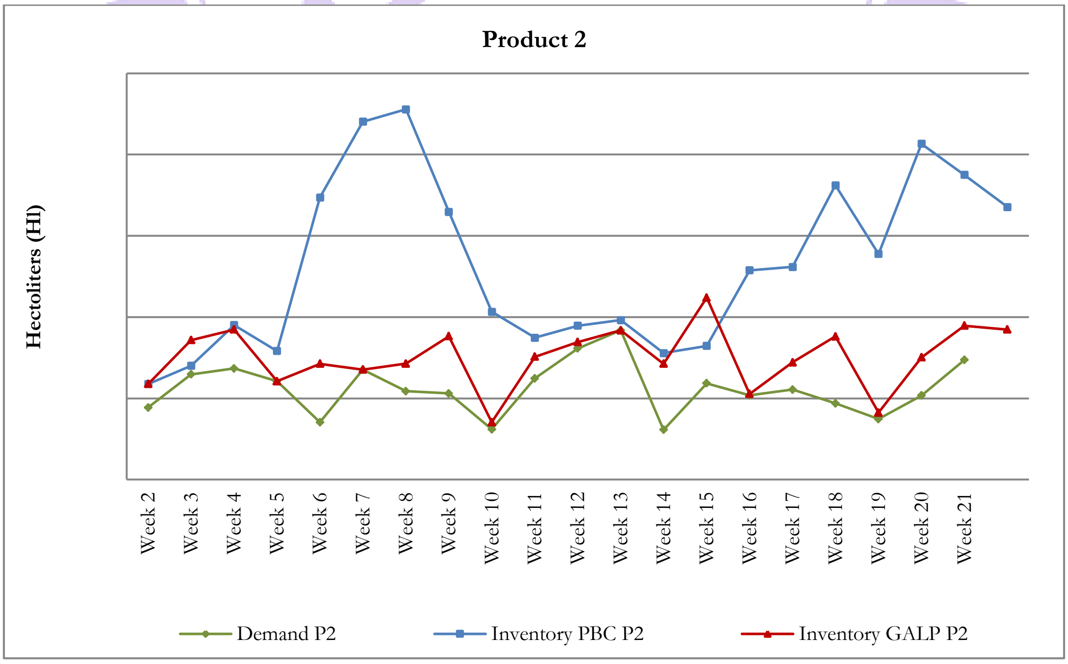


Figure H.3 – Demand of Product 2, PBC Inventory level and GA-LP Inventory level.

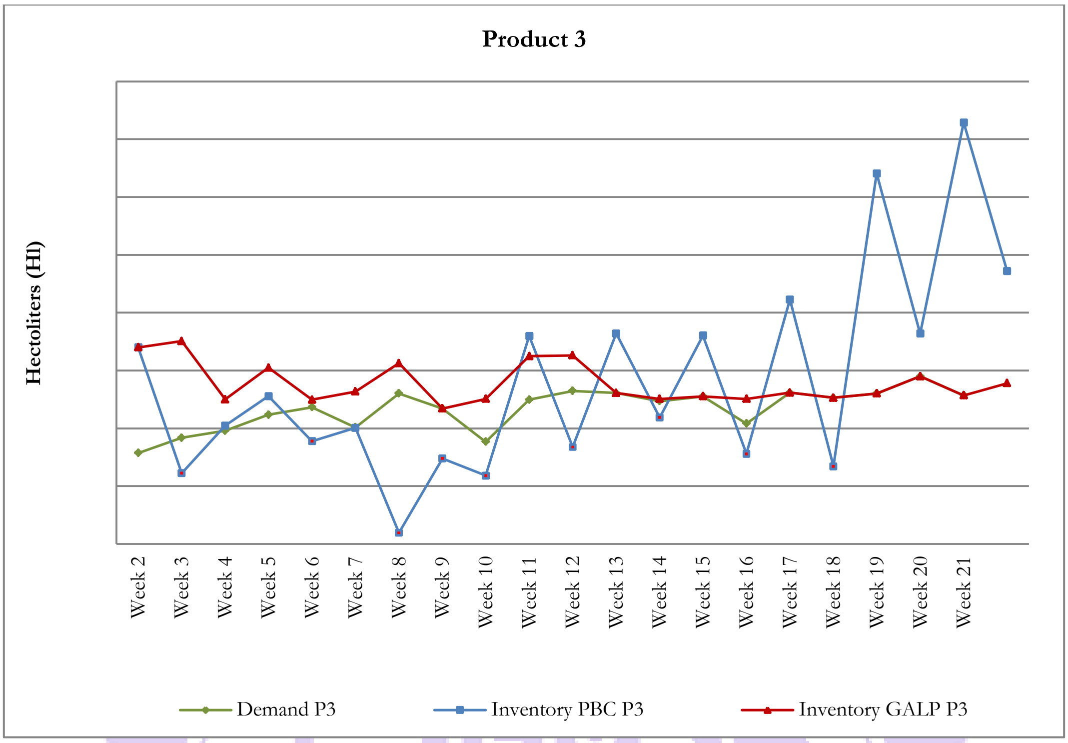


Figure H.4 – Demand of Product 3, PBC Inventory level and GA-LP Inventory level.

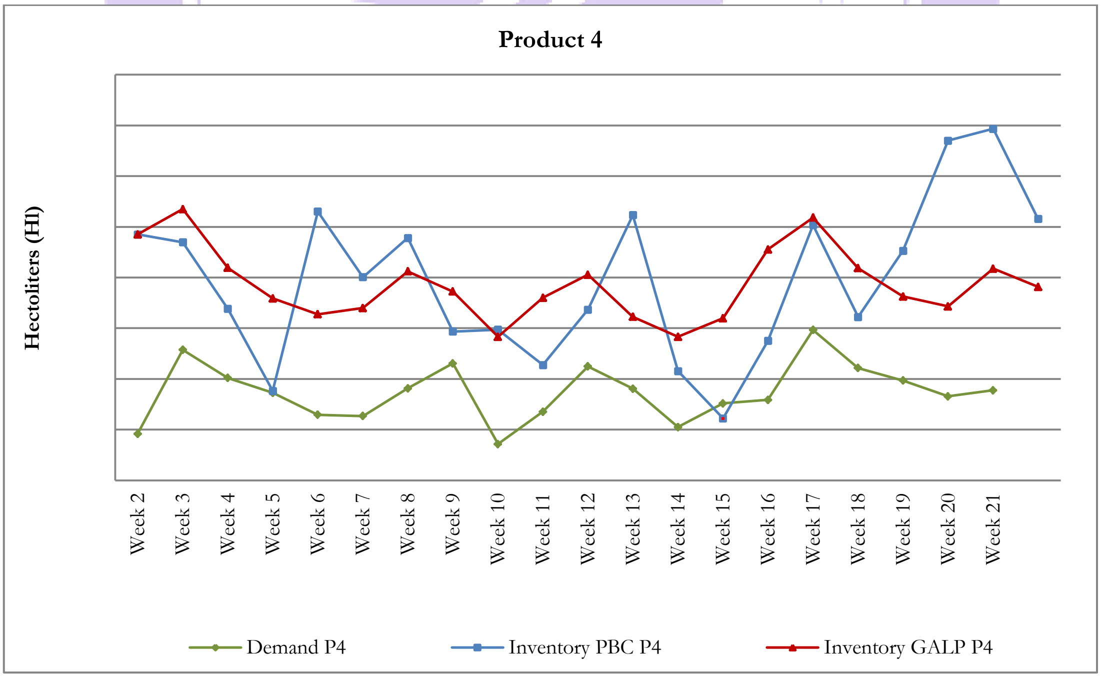


Figure H.5 – Demand of Product 4, PBC Inventory level and GA-LP Inventory level.

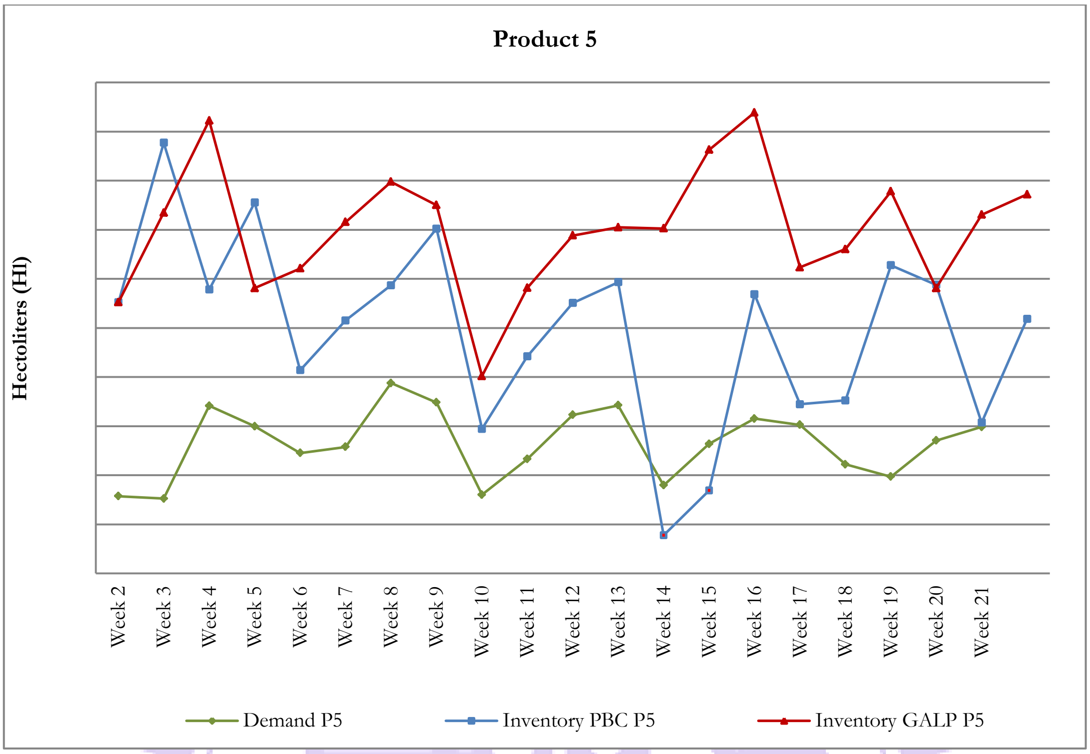


Figure H.6 – Demand of Product 5, PBC Inventory level and GA-LP Inventory level.

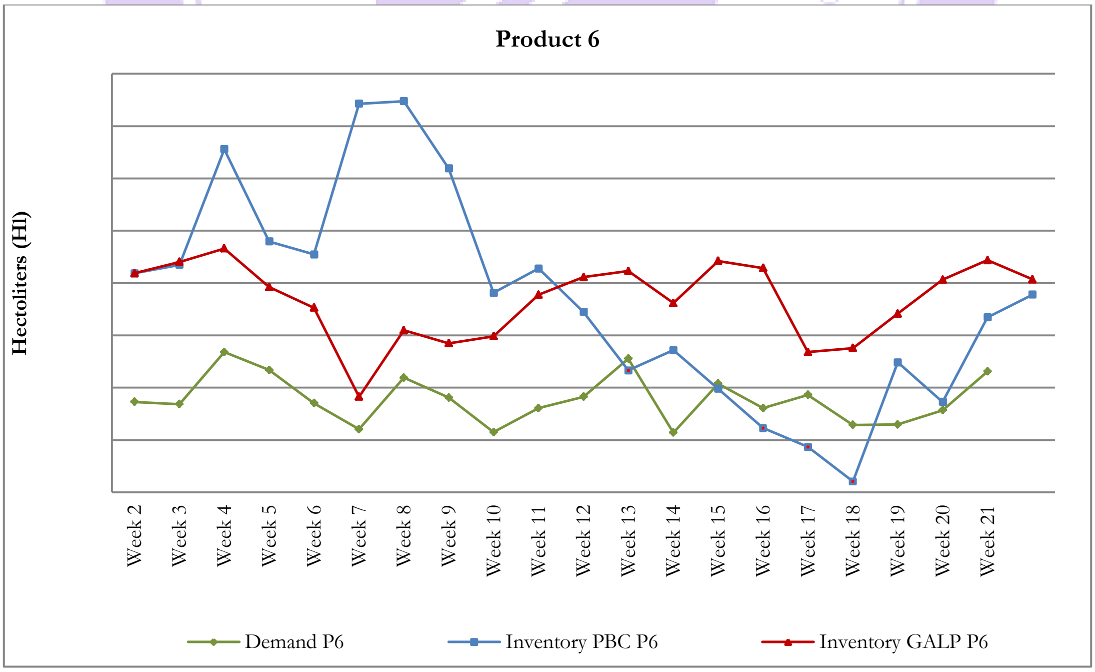


Figure H.7 – Demand of Product 6, PBC Inventory level and GA-LP Inventory level.

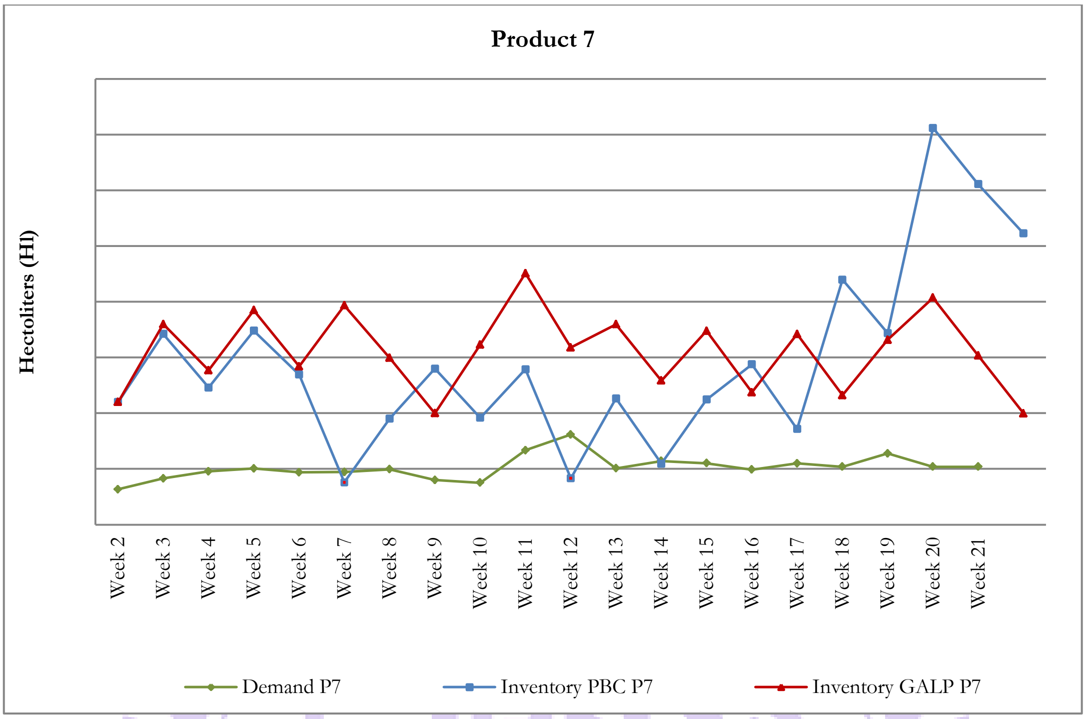


Figure H.8 – Demand of Product 7, PBC Inventory level and GA-LP Inventory level.

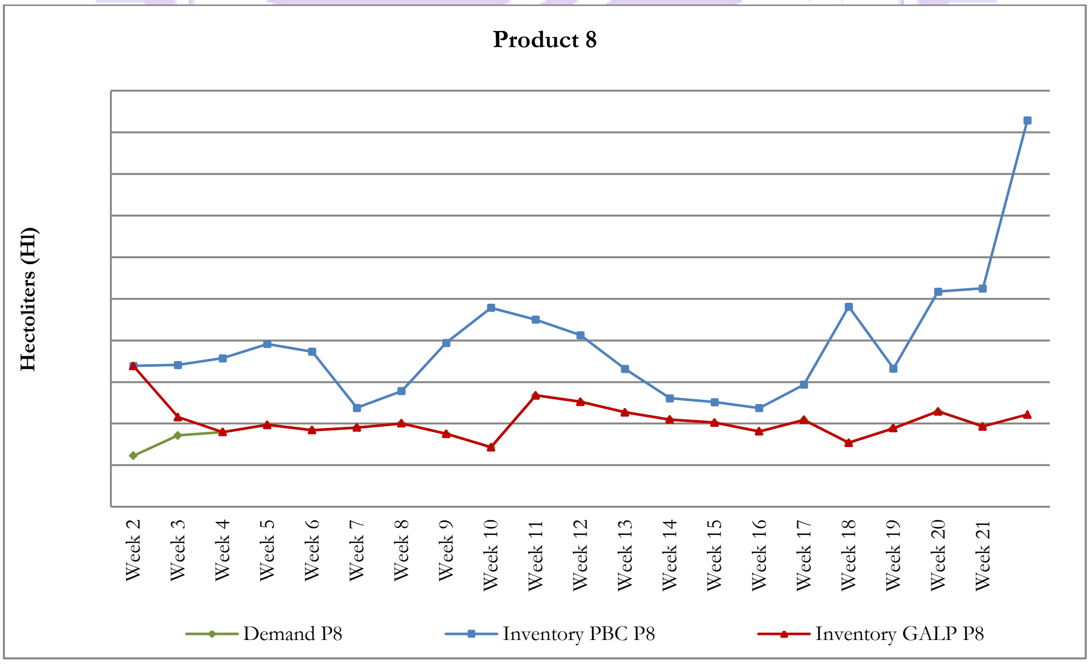


Figure H.9 – Demand of Product 8, PBC Inventory level and GA-LP Inventory level.

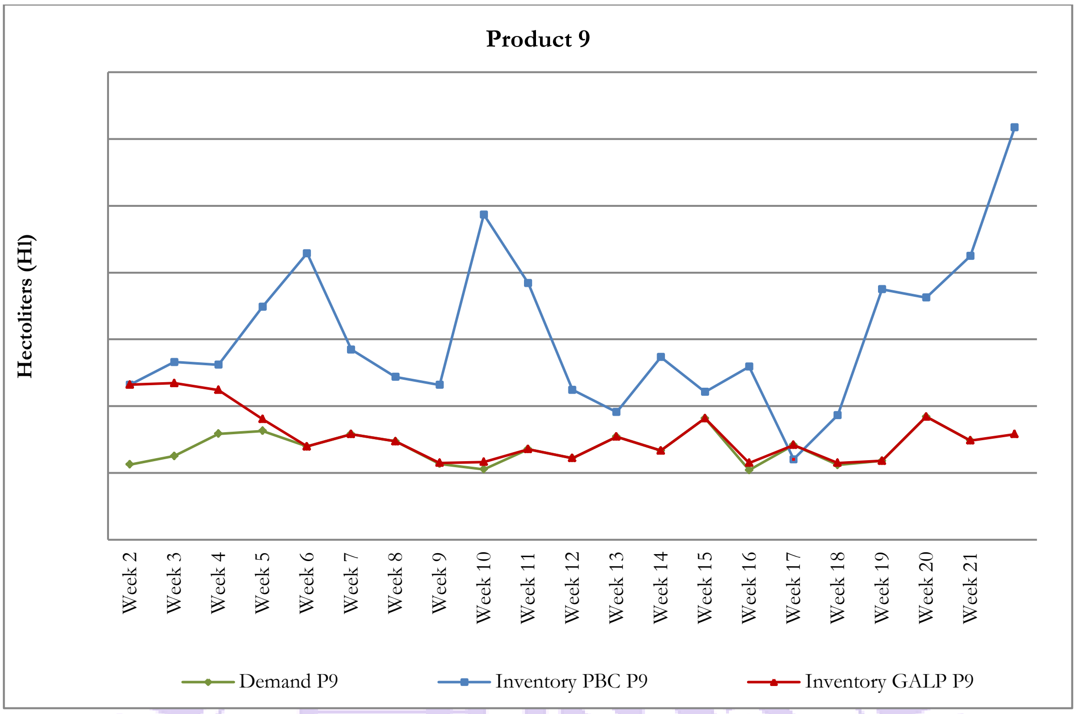


Figure H.10 – Demand of Product 9, PBC Inventory level and GA-LP Inventory level.

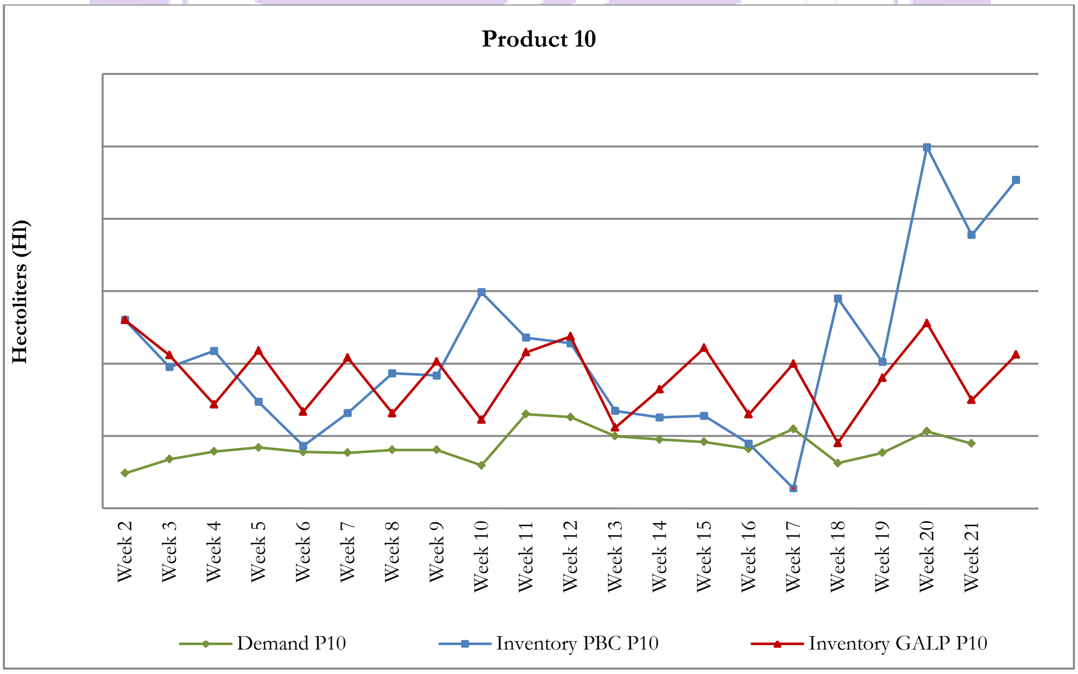


Figure H.11 – Demand of Product 10, PBC Inventory level and GA-LP Inventory level.

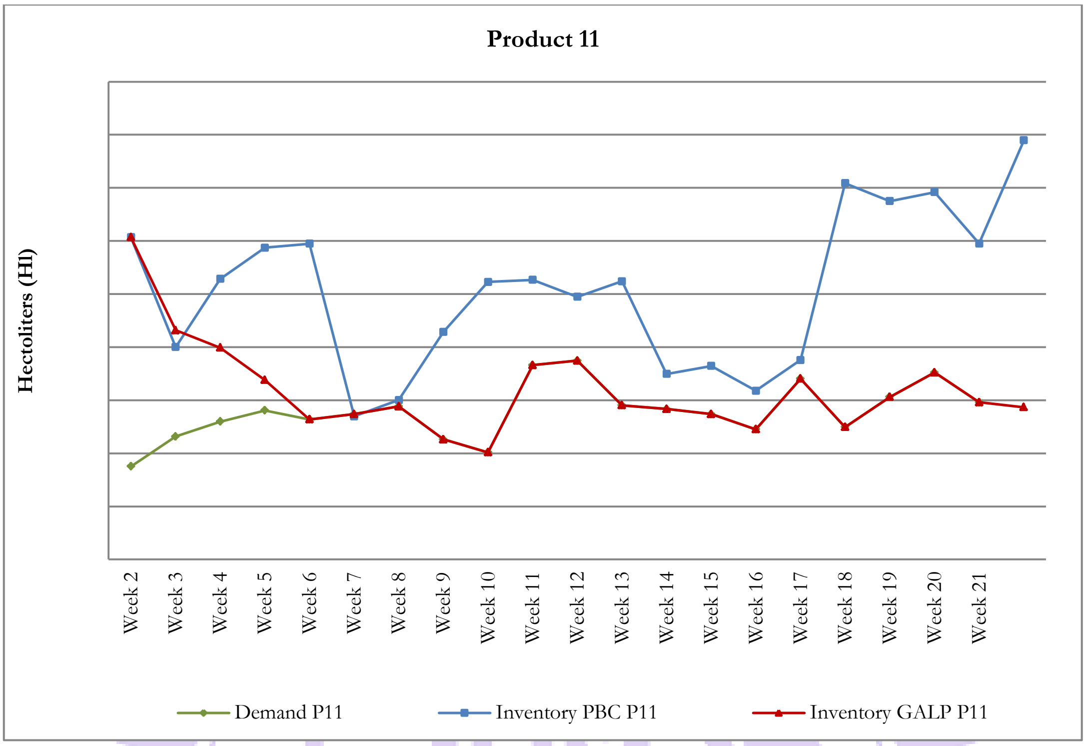


Figure H.12 – Demand of Product 11, PBC Inventory level and GA-LP Inventory level.

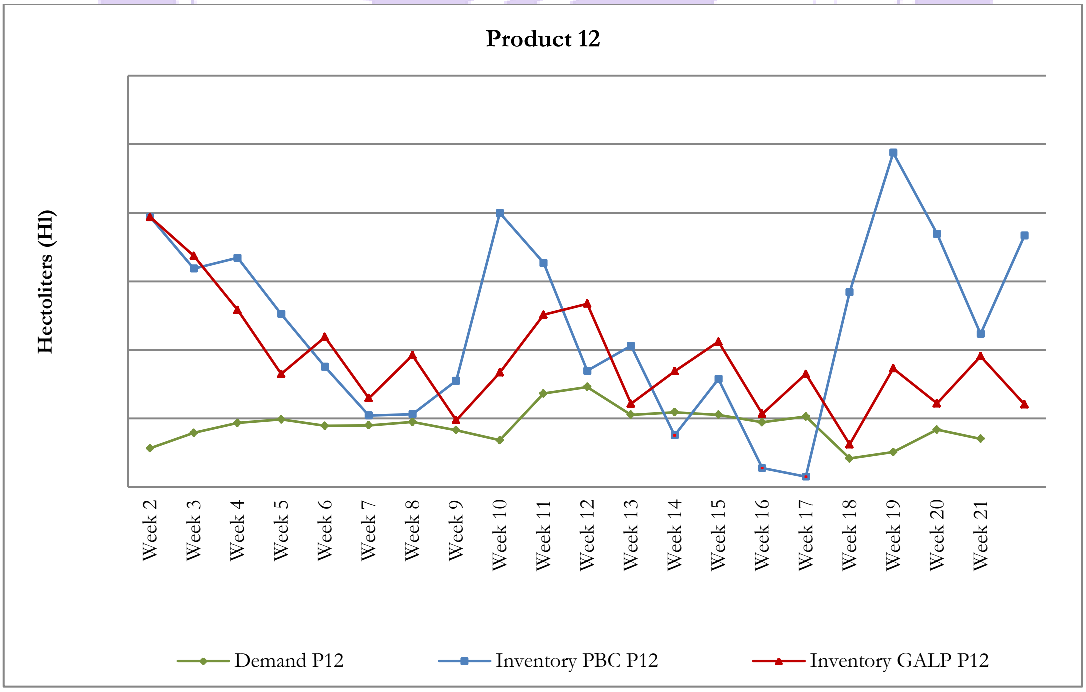


Figure H.13 – Demand of Product 12, PBC Inventory level and GA-LP Inventory level.

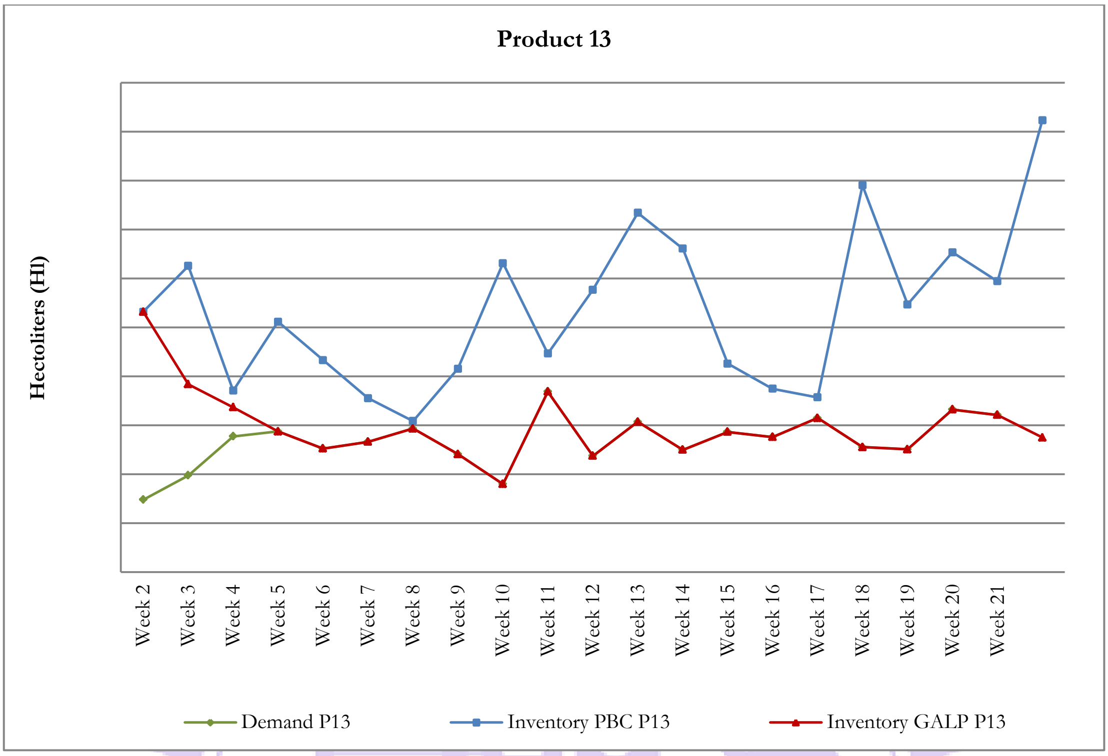


Figure H.14 – Demand of Product 13, PBC Inventory level and GA-LP Inventory level.

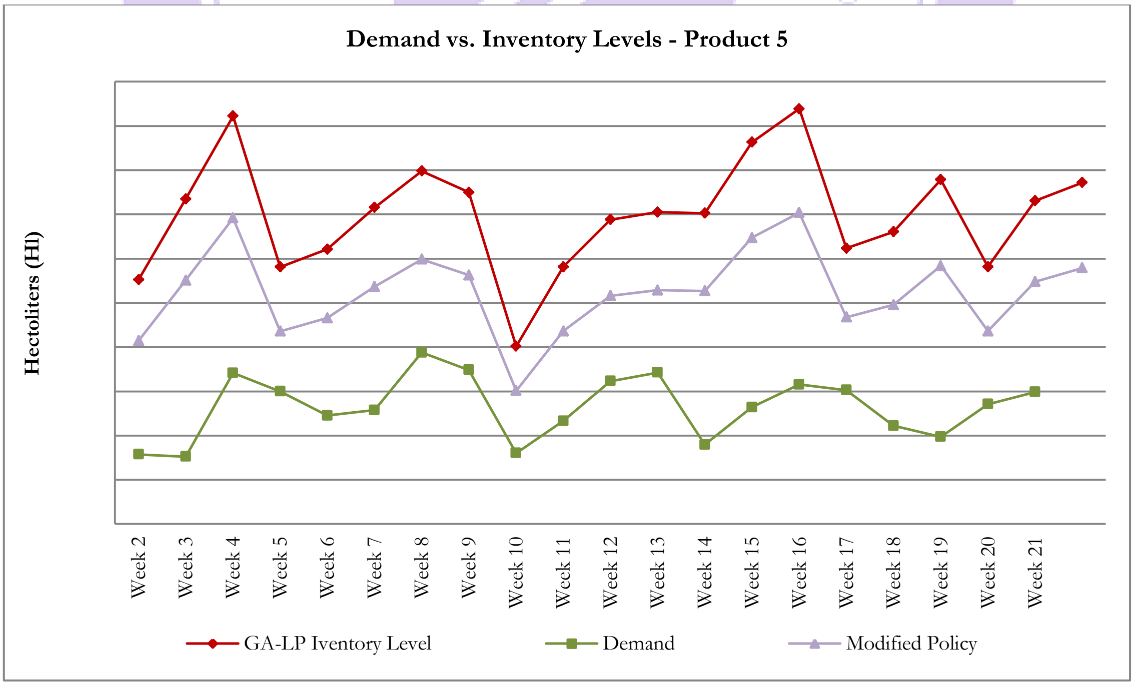
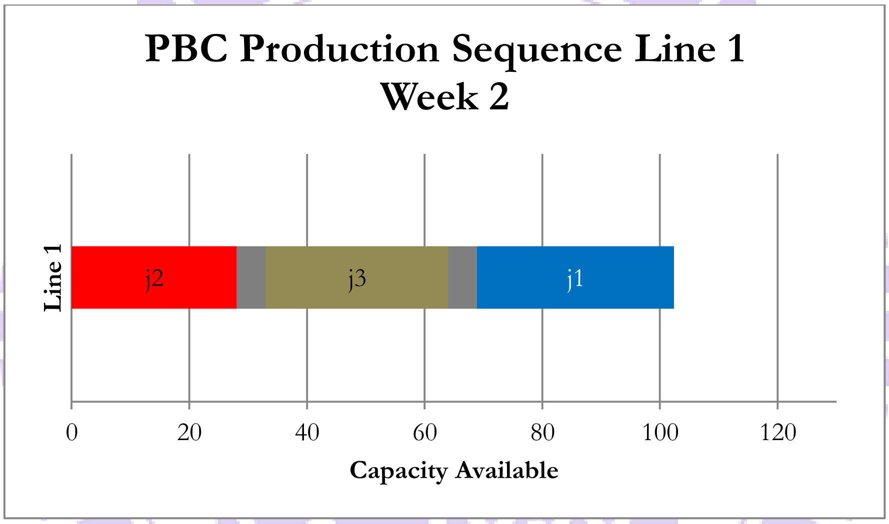


Figure H.15 – Example of reduction in Inventory Policy for product 5.

H.4 Production Sequences

Table H.3 – Costs for week 2

Costs	PBC	GA-LP	Reduction
Inventory Holding Costs	$ 332,003.58	$ 284,559.07	-14.29%
Production Costs	$ 31,979.65	$ 23,096.95	-27.78%
Idle Time Costs	$ 1,892.65	$ 4,432.14	134.18%
Setup Costs	$ 2,835.98	$ 2,157.23	-23.93%
Total Costs	**$ 368,711.86**	**$ 314,245.40**	**-14.77%**



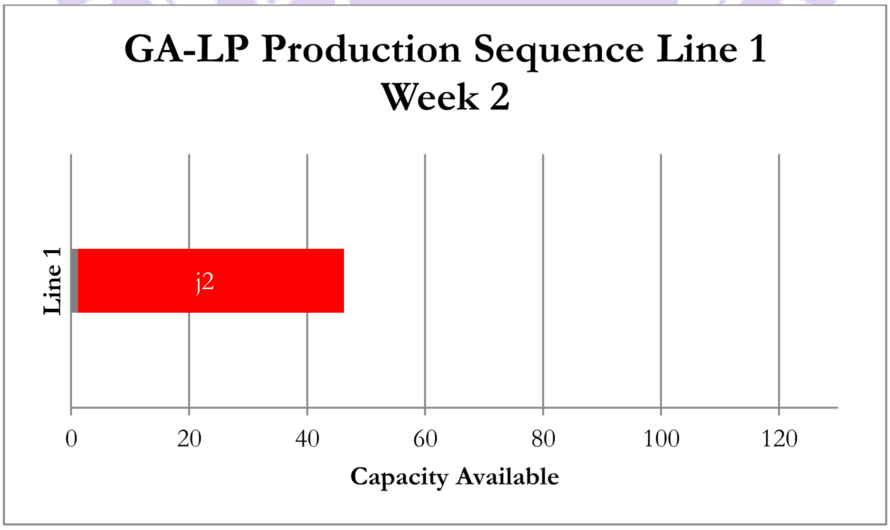
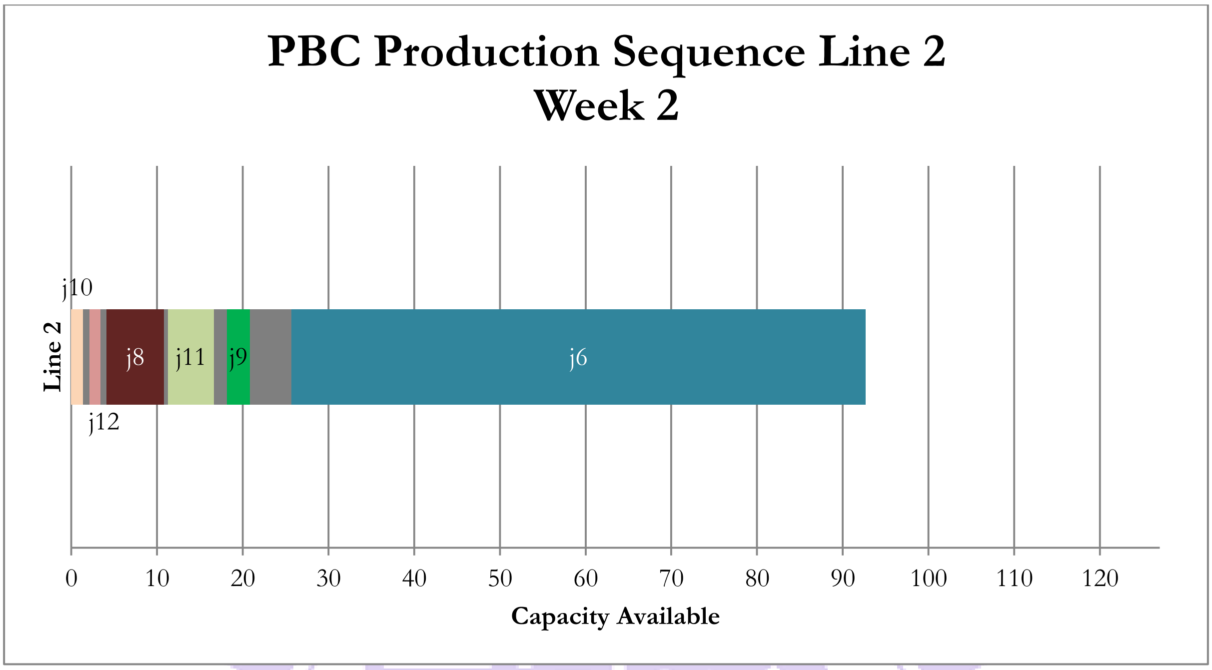


Figure H.15 – Production sequence: a) According PBC plans; b) according GA-LP results



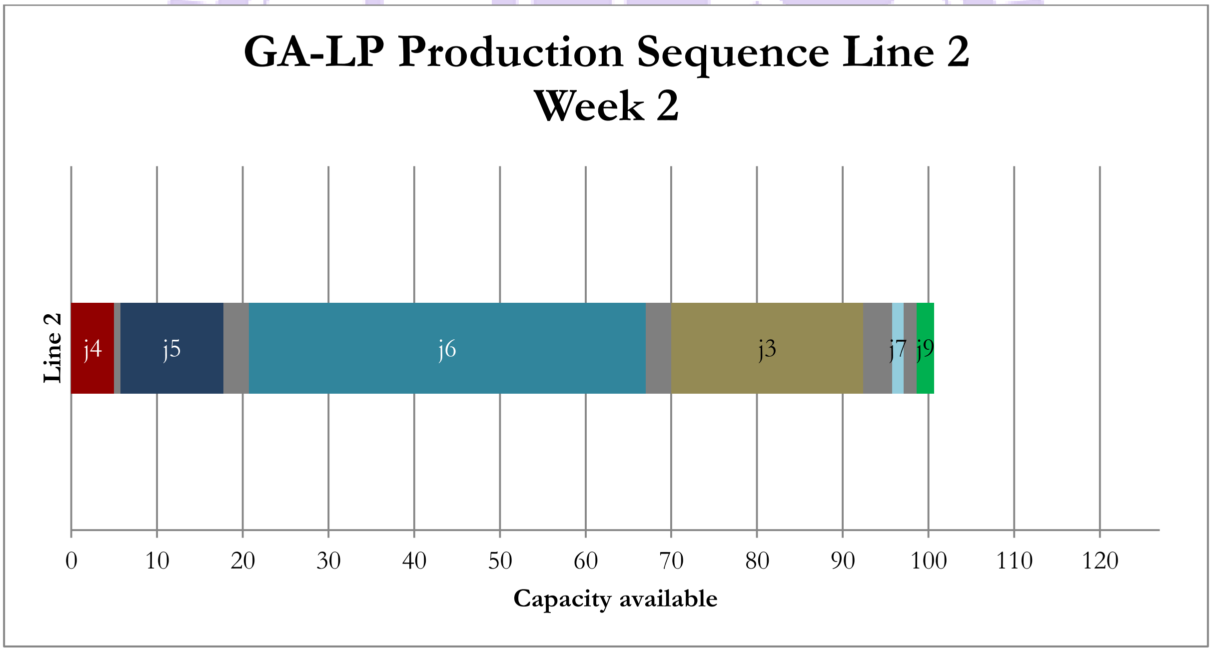


Figure H.16 – Production sequence: a) According PBC plans; b) according GA-LP results