mathematics

Article

An Icon-Based Methodology for the Design of a Prototype of a Multi-Process, Multi-Product, Aggregated Production Planning Software

Erick Miranda-Meza *, Iván Derpich * and Juan M. Sepúlveda

Department of Industrial Engineering, Universidad de Santiago de Chile, Santiago 8370458, Chile; juan.sepulveda@usach.cl
* Correspondence: erick.miranda@usach.cl (E.M.-M.); ivan.derpich@usach.cl (I.D.)

Abstract: This paper proposes an icon-based methodology for the design of prototype aggregated production planning software that addresses the complexity of multi-process and multi-product production. Aggregate planning is a critical task in production management, which involves coordinating the production of multiple products in different processes to meet demand efficiently. The approach focuses on the use of visual icons to represent key elements of the production process, such as products, processes, resources, and constraints. These icons allow an intuitive representation of information and facilitate communication between production team members. In addition, this paper presents a conceptual structure that defines the relationships between the icons and how they are used to model and simulate aggregate production planning. The prototype software based on a conceptual foundation allows planners to easily create and adjust production plans in a visual environment. This method improves the ability to make informed and rapid decisions in response to changes in demand or production capacity. The prototype is based on icons and programmed in Excel spreadsheets to facilitate the planner's planning. At the end of the document, the application of a case study is shown.

Keywords: aggregate production planning; computational tool; visual modeling; operations research

MSC: 90-04

check for updates

Citation: Miranda-Meza, E.; Derpich, I.; Sepúlveda, J.M. An Icon-Based Methodology for the Design of a Prototype of a Multi-Process, Multi-Product, Aggregated Production Planning Software. *Mathematics* **2024**, *12*, 336. https://doi.org/10.3390/math12020336

Academic Editor: Xiang Li

Received: 30 October 2023
Revised: 25 December 2023
Accepted: 15 January 2024
Published: 19 January 2024

1. Introduction

1.1. Motivation and Topics

The production industry continuously faces planning challenges to avoid, among other problems, stockouts, or unfulfilled orders. The motivation behind the creation of this document is to provide productive companies with a simpler way to plan their production for decision making, without neglecting the mathematical tools that enable optimal planning. This motivation arises from the need to streamline the construction of the mathematical model and subsequent computational model essential for production planning and scheduling. This operation entails building a complex mathematical and computational model, requiring highly trained and costly personnel. Therefore, a graphic method based on icons has been conceived to allow for an intuitive and visual construction of the model. These icons form the core of this project and have been successfully incorporated into small-scale test software, demonstrating the achievement of the goal to simplify planning. Another equally important motivation is to contribute to the digital transformation of resource-constrained productive enterprises, such as small and medium-sized enterprises (SMEs), through the use of everyday tools within business practices, such as Excel spreadsheets. These motivations stem from the desire to enhance the productivity of the industrial sector as a contributing factor to the economic development of the operational region. This research proposes to address production inefficiencies through aggregated production planning from a simplified point of view. Production planning is a fundamental pillar in industry; specifically, aggregate production planning (APP) allows for the determination of production, inventory, and workforce level when demand is dynamic and for a planning horizon of up to one year [1]. By using different strategies and methodologies, the APP solution can be utilized to control and plan production activity, with the aim of achieving the minimum total cost and at the same time, the best allocation of resources such as machine capacity, available storage, and worker capacity. Classical strategies for production planning and control consider changing the size of the workforce, changing the production rate, consolidating seasonal inventories, planning and allowing back-orders, sub-contracting, and influencing demand [2]. This research uses the first three strategies.

The solution of APP has been classically achieved using tabular and graphical methods and mathematical methods; an example of this approach can be seen in [3]. In this paper, we present a conceptual framework that serves as a basis for the design of a methodology that is applied by using a computational tool to allow a user to solve APP problems in an optimal way that does not require knowledge of linear programming. Classical strategies and mathematical methods from operations research are used, reducing the complexity of the mathematical modeling of the target production system. This conceptualization is based on icons that allow representation of the plant layout, the inventories, the available resources of machine capacity, labor force level, the processes and the machines involved in the production, and the forecasted demand. In this article, icons are conceived as editable data containers where the user can emulate a target production system in an initial spreadsheet by activating and deactivating icons. Once the data are loaded into the icons, the APP mathematical model is automatically generated, and the exact solution of the mixed-integer linear programming (MIP) problem with logical decisions can be obtained by using a solver for a given time horizon.

In the literature, we can find the following classification of production systems: job shop, batch flow, operator-paced line flow, continuous flow, just-in-time, and flexible manufacturing system [4]. It is expected that the proposed tool can be adapted to the six classification types. However, and as an initial scope, a case study with a batch flow production system with multiple processes and products is presented. In addition, a solution is presented with a prototype of the proposed tool. For this purpose, a taxonomy of icons is proposed to model an APP problem, and, as a consequence, a tool that requires the input of the production system data was obtained, reducing the complexity of mathematical modeling by means of visual programming with icons and virtual figures. The authors hope that the usefulness of this tool will mainly empower small and medium-sized manufacturing enterprises (SMEs) and/or companies with low investment resources and low levels of technological development, allowing the planning and control of their production activities.

The main contributions of this work are to propose a methodology, based on an iconic conceptualization, and to build a mathematical model that supports the scheduling of activities associated with the aggregate planning of operations. The method can also be employed by users without knowledge of linear programming. This is mainly relevant in SME companies lacking the resources to invest in trained personnel or in a consulting service to generate technological development. Through the application of a computational tool, the methodology can visually represent the target production system with virtual icons. In this approach, the user does not need to know the techniques of the mathematical optimization approach, which is characterized by constraints and an objective function, and only needs to learn the visual language of the icons and pictures of the proposed tool to represent the production process as if it were a flowchart. In other words, the icons can reproduce the plant layout to build the APP model.

To validate the methodology and its conceptualization, a small-scale prototype was built within a spreadsheet, so that any company including SMEs can use it. This prototype has the basic functions to solve an APP problem. In the following, the literature review and problem definition sections are presented, then the definitions and structure of the proposed methodology section are introduced, and then we proceed to the section in which a case study is presented. Finally, the results and conclusions are presented.

1.2. Literature Review

1.2.1. Aggregate Production Planning

The literature on APP is abundant. In 1975, Eilon published an early short review demonstrating five solution approaches for APP problems [5]. More recently in 2019, Cheraghalikhani et al. published a review of the last 27 years, classifying APP models into two groups, deterministic models and uncertain models [6]. Of those falling into the uncertain model classification, Jamalnia et al. [7] reviewed the uncertainty handling methods in depth. For the deterministic model's classification, a comprehensive review of the APP problem from a circular economy and sustainability perspective was published in early 2022 by Aydin et al. [8]. The authors emphasized that in order to meet the environmental and social sustainability criteria in the planning period, the principles of the circular economy can be used; their work is the first systematic review of the last 50 years of APP research and offers a classification of the papers by the type of objective function. Table 1 shows the most recent studies and research where the criterion used for the search was the aggregate production planning problem and scheduling problem.

Table 1. Recent research on aggregate production planning.

Authors	Year	Contribution
Werner, F.	2023	A special issue that includes comparative analysis and performance evaluations of scheduling algorithms and applications of recent papers [9].
Elidrissi, A.; Benmansour, R.; Hasani, K.; Werner, F.	2023	The authors propose two MILP formulations and polynomial-time solvable cases for the scheduling problem on two identical parallel machines with a single server [10].
Yazd, S.; Salamirad, A.; Kheybari, S.; Ishizaka, A.	2023	APP for multi-line manufacturing systems based on line efficiency calculated based on pollution rate, defective product rate, production capacity, downtime, and electricity consumption [11].
Özelkan, E.; Torabzadeh, S.; Demirel, E.; Lim, C.	2023	Bi-objective APP where, in addition to cost, the stability of the plan is considered as an objective, and it is compared with other classic APP models [12].
Tirkolaee, E.B.; Aydin, N.S.; Mahdavi, I.	2022	The authors propose a hybrid multi-objective model for the APP problem that presents a continuous Markov chain for inventory [13].
Gomez-Rocha, J.E.; Hernandez-Gress, E.S.	2022	The authors propose a stochastic programming model for multi-product APP that is more efficient in terms of CPU iterations and sensitivity analysis [14].
Islam, S.R.; Novoa, C.; Jin, T.D.	2022	The authors propose an APP model that incorporates renewable energies, optimizing energy, production, and cost decisions under uncertainty conditions, with practical applications in the United States [15].
Singh, N.K.; Kuthambalayan, T.S.	2022	A planning study in a production system for perishable products with demand- and shelf-life-dependent costs. Proposal of efficient heuristics for large problems [16].
Matos, C.; Sola, A.V.H.; Matias, G.D.; Lermen, F.H.; Ribeiro, J.L.D.; Siqueira, H.V.	2022	The authors propose a model that integrates electric power demand into production planning, with positive results in cost reduction in the food industry [17].
Galankashi, M.R.; Madadi, N.; Helmi, S.A.; Rahim, A.A.; Rafiei, F.M.	2022	Integration of lean manufacturing and the APP problem. The proposed model is multi-objective and seeks to minimize cost, lead time, and waste, in addition to maximizing quality [18].
Yu, V.F.; Kao, H.C.; Chiang, F.Y.; Lin, S.W.	2022	The authors propose a technique to address multi-objective production planning problems (PPPs) as if they were bi-objectives using order preferences with the TOPSIS approach [19].
Liu, L.F.; Yang, X.F.	2022	The authors propose a method to evaluate early and late delivery losses in an APP problem [20].

Table 1. *Cont.*

Authors	Year	Contribution
Dohale, V.; Ambilkar, P.; Gunasekaran, A.; Bilolikar, V.	2022	The authors propose an integrated fuzzy analytic hierarchy process to select essential objectives for the enterprise, which are the objectives of the PPP problem [21].
Yaghin, R.G.; Darvishi, F.	2022	The authors propose a multi-objective scheduling model for integrated materials and production management in the supply chain [22].
Liu, L.F.; Yang, X.F.	2021	This study proposes an efficient genetic algorithm for APP in manufacturing, considering stability and costs [23].
Khalili, J.; Alinezhad, A.	2021	The authors propose an APP performance evaluation model, using the Grey APP method with SWARA and RED, to improve decision making in the auto parts manufacturing industry [24].
Tuang, D.H.; Chiadamrong, N.	2021	A hybrid model is developed to solve a multi-objective APP problem in a supply chain under uncertainty conditions [25].
Rehman, H.U.; Ahmad, A.; Ali, Z.; Baig, S.A.; Manzoor, U.	2021	The authors propose the inclusion of productivity loss in the aggregate production plan using linear programming to assess its impact on the hiring and firing of the labor force [26].
Krajcovic, M.; Furmannova, B.; Grznar, P.; Furmann, R.; Plinta, D.; Svitek, R.; Antoniuk, I.	2021	The article presents a data structure and planning methodology for labor utilization in production based on a parametric model and object-oriented analysis [27].
Ning, Y.F.; Pang, N.; Wang, S.; Chen, X.M.	2021	An APP model for vegetable production in volatile and uncertain markets and considering the level of service [28].
Rahmani, D.; Zandi, A.; Behdad, S.; Entezaminia, A.	2021	A multi-product, multi-period aggregate production planning model with environmental considerations and robust optimization under uncertainty conditions [29].
Torabzadeh, S.; Ozelkan, E.C.	2021	The authors propose a fuzzy aggregate production planning technique with a flexible requirements profile, which shows stability and cost effectiveness compared to traditional models [30].
Sutthibutr, N.; Chiadamrong, N.	2020	The authors propose an improved fuzzy programming approach to optimize APP in uncertain environments, with results superior to traditional defuzzification methods [31].
Darvishi, F.; Yaghin, R.G.; Sadeghi, A.	2020	The authors address inbound logistics and APP in the textile industry under uncertainty conditions. A mathematical model and an efficient algorithm for its solution are proposed [32].
Jang, J.; Chung, B.D.	2020	The authors propose a robust optimization approach for the APP problem, addressing uncertainty in employee hiring and firing [33].
Rasmi, S.A.B.; Kazan, C.; Turkay, M.	2019	A multi-objective APP model including sustainability, applied to a manufacturer of household appliances. An exact solution method for mixed multi-objective programs is provided [34].
Zaidan, A.A.; Atiya, B.; Abu Bakar, M.R.; Zaidan, B.B.	2019	The authors propose a hybrid fuzzy programming approach to solve APP problems, which is more efficient and effective than other methods [35].
Goli, A.; Tirkolaee, E.B.; Malmir, B.; Bian, G.B.; Sangaiah, A.K.	2019	The authors propose a robust multi-objective APP approach, using genetic and optimization algorithms, to address uncertain seasonal demand [1].
Jamalnia, A.; Yang, J.B.; Xu, D.L.; Feili, A.; Jamali, G.	2019	The study evaluates different APP strategies in the presence of uncertainty, using multi-objective optimization and simulation models, with validation on real data from the beverage industry [36].
Yuliastuti, G.E.; Rizki, A.M.; Mahmudy, W.F.; Tama, I.P.	2019	The authors propose a hybrid approach of a genetic algorithm and simulated annealing to improve aggregate production planning in a multi-product company [37].
Aazami, A.A.; Saidi-Mehrabad, M.	2019	A robust bi-level programming model in APP using the Stackelberg game and Bender's decomposition algorithm. It was validated with real data [38].

Table 1. *Cont.*

Authors	Year	Contribution
Ning, Y.F.; Pang, N.; Wang, X.	2019	The authors propose an APP model for vegetables that considers uncertainty and investment in preservation technology [39].
Djordjevic, I.; Petrovic, D.; Stojic, G.	2019	An APP model based on fuzzy logic is proposed to consider uncertainty in demand, production, and inventory times. Improved operational efficiency with real data is demonstrated [40].

In the literature reviewed, no methodologies were found to reduce the complexity of mathematical modeling in APP problems.

1.2.2. Computational Tools

Penlesky and Srivastava (2007) published software that solves APP problems using a spreadsheet; however, unlike the optimal solution proposed by the prototype of this research, they solved the problem with the "trial and error" method [41]. More recently, in 2021, Rehman et al. published a work on optimizing APP problems with two models: with and without productivity loss. Their work was programmed in Python, and the code can be read in the publication [26]. Regarding software testing in real cases, we will mention some cases. In 2001, Brown et al. described the application of planning software for the Kellogg's Company; according to the authors, the production and inventory costs were markedly reduced, in addition to facilitating decision making in the short and medium term [42]. In 2015, Zago and Mezquita implemented a production planning and scheduling software for a Brazilian dairy company. The results were promising; they managed to increase control over inventory levels and reduce costs associated with the process [43].

Another study published in 2015 by Jonsson and Ivert warns that, at least in the Swedish industry, only a small number of companies use a sophisticated method to plan production and concludes that the use of advanced methods allows for more feasible plans [44]. It is worth mentioning that not everything is conducive to the prototype proposed in this research, since it has been designed with Excel spreadsheets. In 2011, Vlckova and Patak examined the planning practices of four food industries using Excel spreadsheets; they concluded that effective planning can only be achieved with an integrated information system [45]. On the web, commercial software is available that offers APP among other services. Table 2 shows some examples of this software with the pages where they can be purchased.

Table 2. Some commercial production planning software examples.

Software	Description	Strengths	Weaknesses	Web Page
Solvoyo	Offers optimization of production plans in different time horizons with artificial intelligence.	Solvoyo offers an end-to-end supply chain planning and analytics platform, with AI, machine learning, and optimization technology.	Aimed at large companies such as Unilever and others, which have technical personnel who understand AI-type tools.	https://www.solvoyo.com/production-planning-software/ (accessed on 10 July 2023)
Odoo	Can manage production orders, repair orders, work orders, barcodes, unbilled orders, among others, and also plan manufacturing.	It provides support for South America and Central America in Spanish and English and allows developments to be added via the API.	It is an ERP; therefore, it requires global implementation, which is not always convenient for SMEs.	https://www.odoo.com/es_ES/app/manufacturing-features (accessed on 10 July 2023)
Siemens m-plant	Offers to digitize production and create 3D models of facilities and work lines using an object-oriented architecture.	Improves the productivity of existing production facilities and reduces investment and the inventory and production time via optimizing system dimensions, including buffer sizes, reducing risks from the beginning.	It is not strictly a production planning software; rather, it is plant and facility design software.	https://www.plm.automation.siemens.com/global/en/ (accessed on 10 July 2023)

Table 2. *Cont.*

Software	Description	Strengths	Weaknesses	Web Page
Infor	Specifically designed to handle formula or recipe processing and automate calculations with integrated product development tools.	It has an ERP LN suite for discrete operations and has advanced analysis tools. It has an ERP module for manufacturing processes, which is an ERP solution designed specifically to manage the processing of formulas or recipes and automate calculations with integrated product development tools.	The main weakness Is the same as that of other highly complex ERPs: it must be implemented and integrated into operations, which is difficult to achieve in an SME.	https://www.infor.com/es-la/manufacturing-industries (accessed on 17 October 2023)
PlanetTogether APS	APS is offered as a program that performs fast and flexible capacity planning and also offers MRP solutions.	It has built-in artificial intelligence that calculates complex production plans in seconds, seamlessly connecting production data from the user's ERP or MES system with priorities set by production planners. Built-in AI reacts to continuous changes in production and keeps it optimized, in the same way a GPS navigator calculates a route.	It does not have a specific operations programming module; it is an integrated system that plans the entire factory as a complete system.	https://www.planettogether.com/ (accessed on 12 October 2023)
iGromi	Has three different solutions: industrial product and raw material manufacturing, consumer goods and packaging manufacturing, and assembly and contract manufacturing.	It is an advanced manufacturing platform that helps to transform the plant into a smart factory, integrating hardware and software with artificial intelligence solutions and IoT connectivity, to analyze large amounts of production data.	It is not particularly oriented towards process production or resource control. It is not customizable to adapt to the particular needs of the company.	https://igromi.com/ (accessed on 17 October 2023)
Chronos	Software that offers production scheduling optimization and planning, as well as production order execution time reduction.	All users work on the same data repository, with the advantage that all information is available and synchronized. Data exchange between the server and the client is achieved using network software. Within the software, extensive use is made of workflows (workflow model) that can be integrated with its different modules.	Like other comprehensive ERPs, it is an application that requires global implementation in the company and specialized IT personnel, something that usually does not exist in SMEs.	https://www.chronosps.com/ (accessed on 18 October 2023)
QAD	Comprehensive software that, among other functions, offers optimal production planning to reduce manufacturing costs, minimize shop floor interruptions, limit product waste, and improve customer satisfaction.	Flexible, cloud-based enterprise resource software for global manufacturing companies. In the area of production planning, it uses constraint-based optimization to comprehensively synchronize material flow and resource utilization in multi-stage, multi-site production environments while respecting all required constraints.	QAD is an extremely specialized ERP suite that is designed primarily for manufacturers. It mainly focuses on six industries: cars, consumer products, food and drink, high technology, industrial, and life sciences. This means that QAD can be a great option if the user's company fits into one of these industries. If not, other options may be more suitable.	https://www.qad.com/ (accessed on 18 October 2023)

1.3. Problems and Contributions

The Latin American region faces the challenge of increasing the productivity of its industries to generate economic and social development, and this challenge is particularly difficult for micro, small, and medium-sized enterprises (MSMEs). In the region, 99% of formal companies are MSMEs, and 61% of jobs are generated by them. Despite the above, the contribution to GDP observed in 2020 is only 25%, a far cry from the 56% contribution observed in the European Union [46]. Between 2000 and 2019, the world's large and dynamic economies such as China and the United States experienced economic growth in which productivity contributed 96% and 64%, respectively. In Latin America, only 24% of economic growth was contributed by productivity in the same years [47]. In particular, the manufacturing industry provides employment to 12.8% of the population of Latin America and the Caribbean. The sector's contribution to GDP is 12.6% on average, considering differences between countries [48].

In part, the region has not been able to take advantage of the information and telecommunications technology (ICT) revolution and is behind in the implementation of Industry 4.0 methodologies. On the other hand, business legislative regulation is different in Latin America than in the countries and regions compared above [49]. In production companies in Latin America, the lack of efficient planning is a recurrent problem and it affects the productivity of machines and workers, the use of raw materials, and the achievement of economic goals, among other negative effects. It also leads to stockouts, which affects the relationship with the distribution channels and affects costs and therefore the entire business. In addition, most small and medium-sized companies in Latin America do not have technically and professionally trained personnel capable of operating operations scheduling methods and software.

Evidence of the weaknesses above is the information provided in a study by the Chilean Association of Engineers, whose president, Mr. Fernando Agüero, indicates that less than 3% of companies have an engineer and that the only sector where 4% of companies have engineers is the food industry [50]. The situation is similar in Mexico, where about 24,000 engineers graduate each year, while in developed countries there are about 60,000 graduates [51]. For this reason, the aim of this work was to provide a conceptualization that facilitates the construction of the APP mathematical computational model without necessarily being operated by an experienced engineer. This conceptualization is intended to allow a technician without a specialty in operations research and/or computer science to generate the production program. The idea is that from the knowledge of the production process, using the definition of process icons, sub-processes, resources, parameters, and layout, the user can generate the mathematical model implicitly. That is, without realizing that they are writing a mathematical model, just following the logic of the visual planning methodology, the user can be able to generate the appropriate model for the specific situation.

Associated with this methodology and conceptualization, a simple prototype has been developed to illustrate the application and demonstrate its function with this new approach. The prototype is a DSS that follows the methodology, and it is implemented on an Excel spreadsheet, which has three sheets. In the first one, the general layout of the plant is defined, and the process parameters are entered, such as costs, demand, inventories, and resources. In the second sheet, the information is summarized, and in the third one, the solver is executed delivering the aggregated production plan.

The main contributions of this research are as follows:

- Proposing a methodology based on icons to obtain optimal aggregate production plans without the need to perform mathematical modeling;
- Suggesting a prototype that applies the icon-based methodology to achieve optimal production planning based on the flowchart representation of a target production system and its information;
- Providing companies without sufficient resources to invest in ICT, a tool to improve their productivity;
- Noting that visual modeling using icons can be used to implement different engineering methodologies, simplifying their application.

2. Definitions and Structure of the Methodology

2.1. Icon-Based Methodology

In industrial production, it is necessary to plan how much and when to produce in order to meet the demand, considering limitations in available resources such as labor force, machine capacity, and inventory space.

When the production plan is generated by using an operations research tool, then it is optimal and allows the objective to be achieved at a minimum total cost.

This study proposes an optimal aggregate production planning tool for production systems with multiple products and multiple processes, based on icons. The editable figure containing the data matrix to be entered is represented by a virtual icon. A prototype implemented on an Excel spreadsheet is presented. With this methodology, the complexity of the mathematical modeling process involving the formulation of the objective function and constraints is reduced.

The tool is a DSS called Icons-Based Methodology for Aggregate Production Planning (hereinafter IBPlanner) and has been designed to be applied in steps as described below:

Step 1 (S1): Introduce in an Initial Diagram the distribution and physical arrangement of the machines, stages, and/or workstations, which we will henceforth understand as the sub-processes of the different working lines of the production process. This corresponds to the first stage of the methodology as shown in Figure 1. The spatial configuration of the factory is obtained from a flowchart of the production process or directly from the layout of the plant; the important issue is that the user knows their production process well and ideally is able to make a flow diagram, thus facilitating the visual modeling. By activating and deactivating specific cells of the Initial Diagram spreadsheet, it is possible to enable or disable work lines to reproduce the plant layout, which allows IBPlanner to be adaptable for multiple companies. We understand the work lines as parallel processes that can deliver the various products independently.

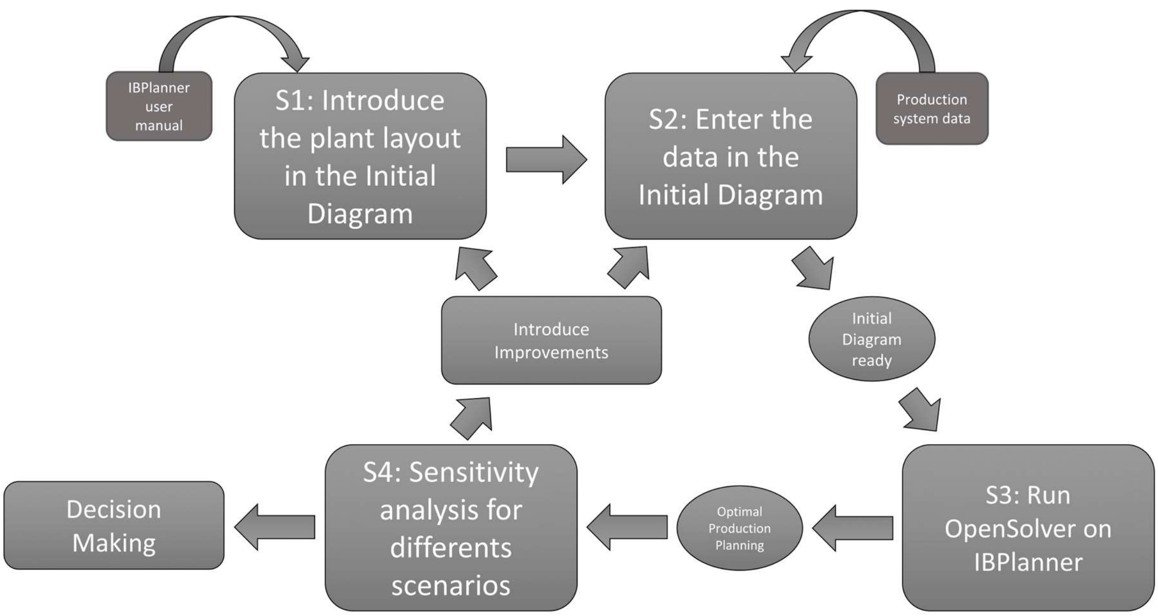


Figure 1. Proposed methodology for using IBPlanner.

Step 2 (S2): Enter the data of the production process in the Initial Diagram. The following data are required:

a. For each product in each desired planning period, the following are required:
   i. Demand in units;
   ii. Unit cost to inventory and available inventory capacity.

b. For each sub-process of each work line, in each planning period and for each product, the following are required:
   i. Unit cost of production;
   ii. Machine hours required per unit;
   iii. Worker hours required per unit.
c. Machine hours and worker hours available for all planning periods and for each work line, as applicable. This is understood as the number of hours operated by a machine or worker in a sub-process for the manufacture of a unit of the product.

Step 3 (S3): Solve the model by obtaining the optimal production and inventory planning by product and by period using the Excel OpenSolver add-in.

Step 4 (S4): Analyze the detailed information for each work line regarding the use of its resources and capacities for decision making by performing sensitivity analysis for different scenarios to facilitate decision making.

Once the stages of the methodology have been completed, it is possible to introduce improvements in the Initial Diagram that respond to changes in the conditions of the productive environment, for example, an investment in capacity, or changes suggested by the analysis of Step 4. This allows the use of IBPlanner to be iterative in the search for optimal planning.

2.2. Mathematical Model and Icons of the Initial Diagram

Before presenting the icons of the diagram and the model, we will define the following indexes, variables, and parameters with which the icons work:

Indexes

- $t = 1, 2, \ldots, T$ index of planning periods;
- $i = 1, 2, \ldots, N$ index of products;
- $j = 1, 2, \ldots, J$ index of work lines;
- $k = 1, 2$ index of Resources, $k = 1$ (machine hours), $k = 2$ (worker hours);
- $l = 1, 2, \ldots, L$ index of serial sub-processes;
- $p = 1, 2, \ldots, P$ index of parallel sub-processes.

Variables

➢ X_{ijt}—Number of product units i manufactured by work line j in period t;
➢ I_{it}—Number of product units i in inventory at the end of period t.

Parameters

➢ D_{it}—Forecast of units demanded of the product i in a period t;
➢ H_{it}—Inventory cost for a product unit i in period t;
➢ C_{ijt}—Cost of producing a unit of product i in process j and period t;
➢ cc_{ijlt}—Cost of producing a unit of product i in process j, stage l, and period t;
➢ ccc_{ijplt} Cost of producing a unit of product i, process j, stage l, parallel machine p, and period t;
➢ R_{kjt}—Amount available of resource k for work line j in period t;
➢ r_{kij}—Required amount of resource k per unit of product i if processed in j;
➢ rr_{kilj}—Required amount of resource k for a product unit i processed in stage l of process j;
➢ rrr_{kiplj}—Required amount of resource k for a unit of product i processed in stage l of process j on the parallel machine p.

The model used in the planning tool is multi-process and multi-product. Figure 2 shows the methodology icons and a summary of the equations used, graphically representing the idea that each virtual icon contributes with variables and parameters to the model configuration. The model has an objective function that minimizes the total cost of production and inventory in the desired planning horizon and capacity constraints of the resources machine hours and worker hours; it also has inventory and demand constraints that apply to each product in each time period. The cost constraints collect unit information for each serial or parallel sub-process. The model allows the different products to be manufactured in all work lines or only in a subset of them. It does not consider the possibility of a product changing work line in the middle of manufacturing execution. Each work line can have multiple stages, where there can be serial and parallel configurations for the machines. As initial research, it does not consider setup costs, but this is not ruled out in future implementations. Some logical decisions are not shown in Figure 2, but in the prototype tool, there are switches that activate and deactivate the work lines.

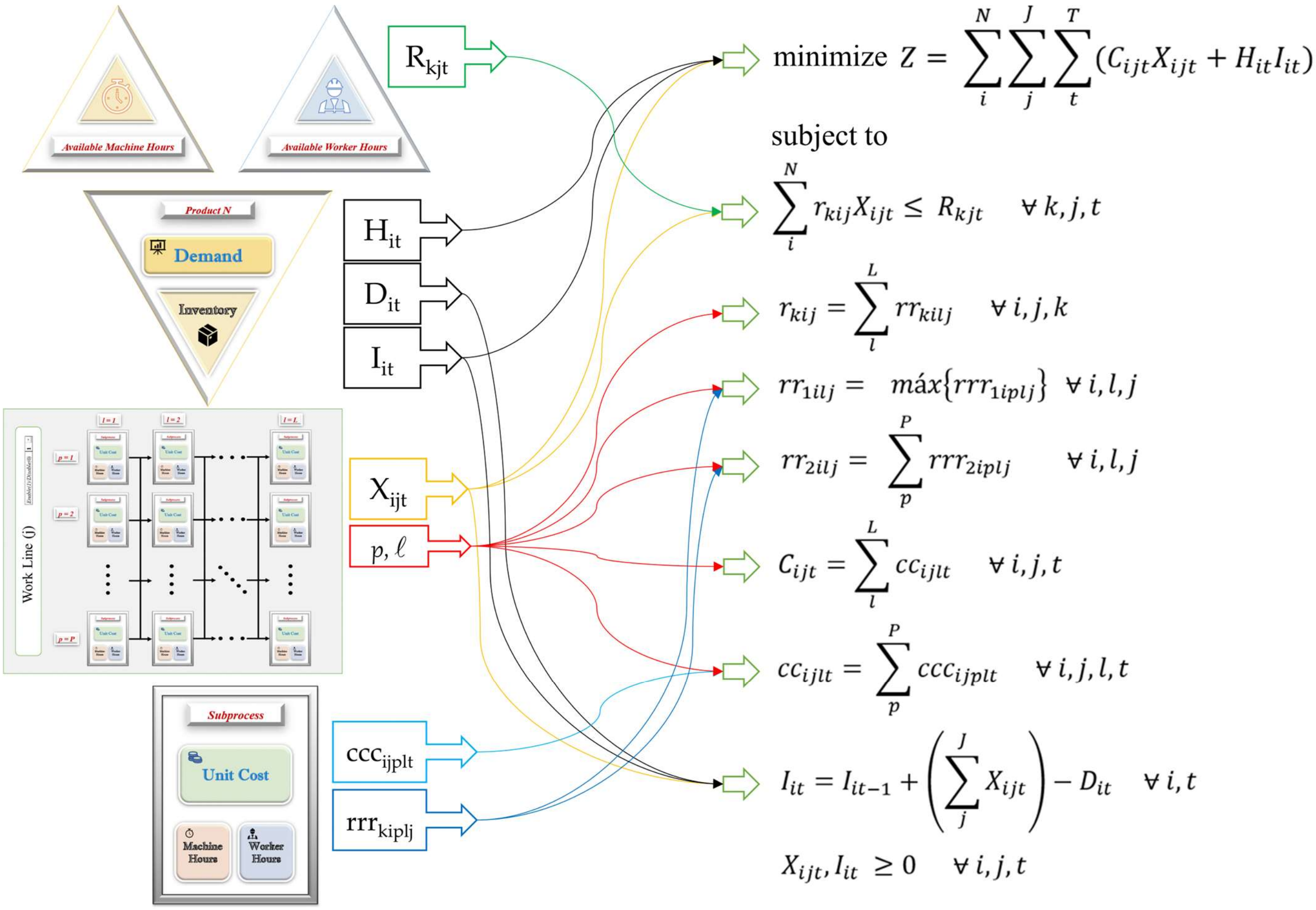


Figure 2. Virtual icons of the IBPlanner tool and its contribution of variables and parameters to the main constraints and objective function of the mathematical model that solves the APP problem.

The unit cost parameter (C_{ijt}) is modeled with an if–then cycle; in the spreadsheet, the formula "=IF(logical_test; value_if_true; value_if_false)" is employed, where the logical test is whether the work line is active or not. The true value (work line active) is the C_{ijt} equation represented in Figure 2, and the false value (work line inactive) gives an extremely high penalty cost so that those cells are not considered and therefore are not assigned a production quantity. In the case of the required resource parameter for machine hours r_{1ij}, the same logical test holds for the unit cost, where the true value is the equation of r_{kij} shown in Figure 2 and the false value is 1.

Figure 3 depicts the virtual icons of the methodology in the Initial Diagram. On the left are the available resources, in the center are the work lines, and on the right are the finished product inventories. Depending on the spatial configuration of the target production plant, the work lines are activated or deactivated and sub-processes used or not in series or parallel. Next, we will review in detail each of these virtual icons and how they work to build the model.

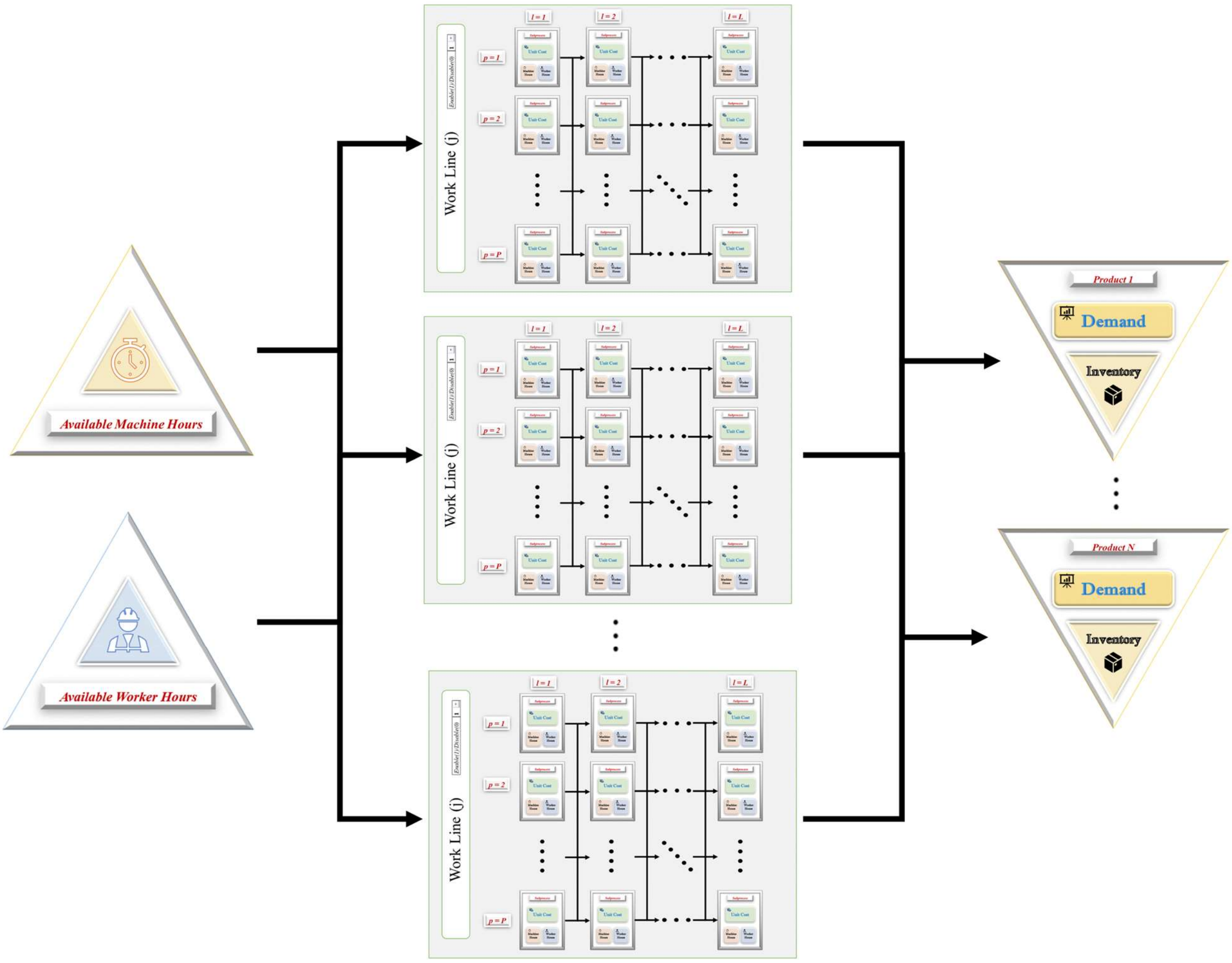


Figure 3. Overview of the Initial Diagram.

2.2.1. Sub-Processes Icon

The sub-process icon represents single machines, stages, or workstations that are part of a work line, as shown in Figure 4. The user must enter the parameters of the sub-process previously defined, in the matrices contained.

Figure 4. Sub-process icon.

In the Initial Diagram, we can observe for each work line the sub-process icons placed in series and parallel configurations, as shown on the right side of Figure 5. If one or more sub-processes are not part of the target production system, it is acceptable to leave the editable data matrices of those icons blank. That is, the user will enter the required data only in the icons that represent machines, stages, or workstations effectively arranged in the plant layout.

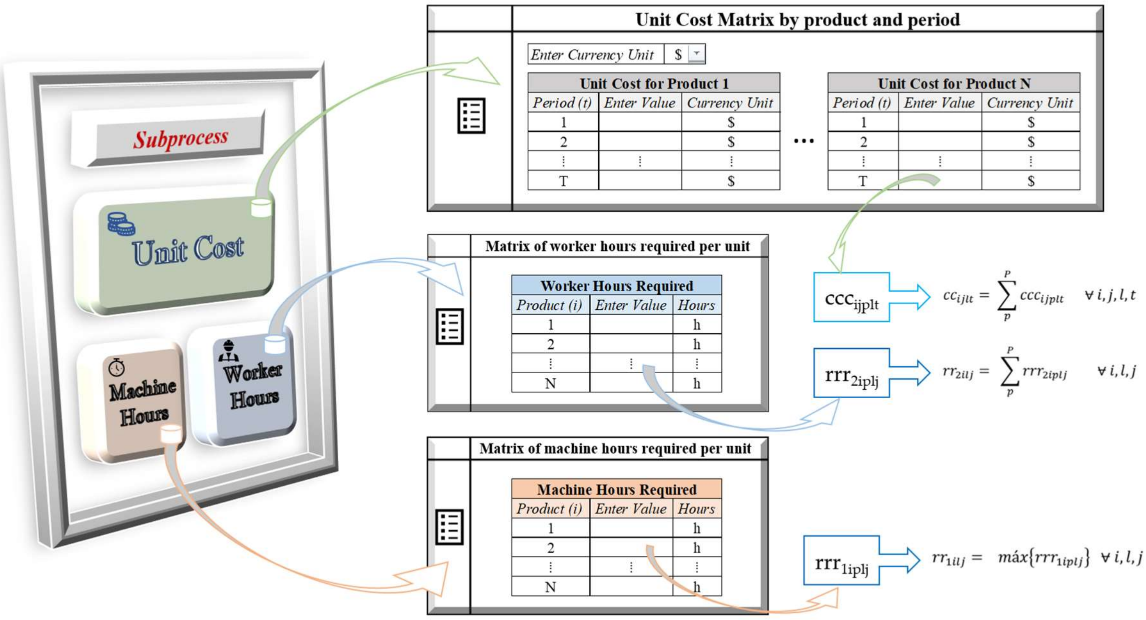


Figure 5. Editable sub-process icon arrays.

Three editable data matrices are embedded in each sub-process:

1. Unit cost: matrix designed to enter the unit cost of production of the sub-process for the different products in the different planning periods;
2. Machine hours: matrix designed to enter the machine hours required for one unit of the different products;
3. Worker hours: matrix designed to enter the worker hours required for one unit of the different products.

Figure 5 shows the editable data matrices and the parameter of the mathematical model to which they correspond. As long as the number of products and the number of periods is lower than this limit capacity, the unused boxes remain blank, which applies to the three matrices.

Once the data per product and per period have been entered in the "EnterValue" column, the parameters will be automatically recognized in the model depending on the matrix:

1. Unit cost will generate the parameter ccc_{ijplt};
2. Machine hours will generate the parameter rrr_{kiplj} with $k = 1$;
3. Worker hours will generate the parameter rrr_{kiplj} with $k = 2$.

The assignment of the parameter in the p and l index domain is automatically generated according to the position of the sub-process icon in the diagram.

2.2.2. Work Line Icon

In the Initial Diagram, the user will observe work lines that contain the sub-process icons; if one or more sub-processes do not correspond to the target production system, it is sufficient to leave their data matrices blank. However, if one or more work lines do not correspond to the target production system, they must be deactivated with a button, as shown in Figure 6. Within each work line icon, each column of sub-process icons corresponds in the model to the index of sub-processes in series L, while each row corresponds in the model to the index of sub-processes in parallel P. On the other hand, activating a work line implies adding one more value to the index of the j-th work line. As shown in Figure 6, the sub-process icons are previously configured in all serial and parallel combinations, and it is enough to fill in the data matrices of those corresponding to the target production system to configure the work line.

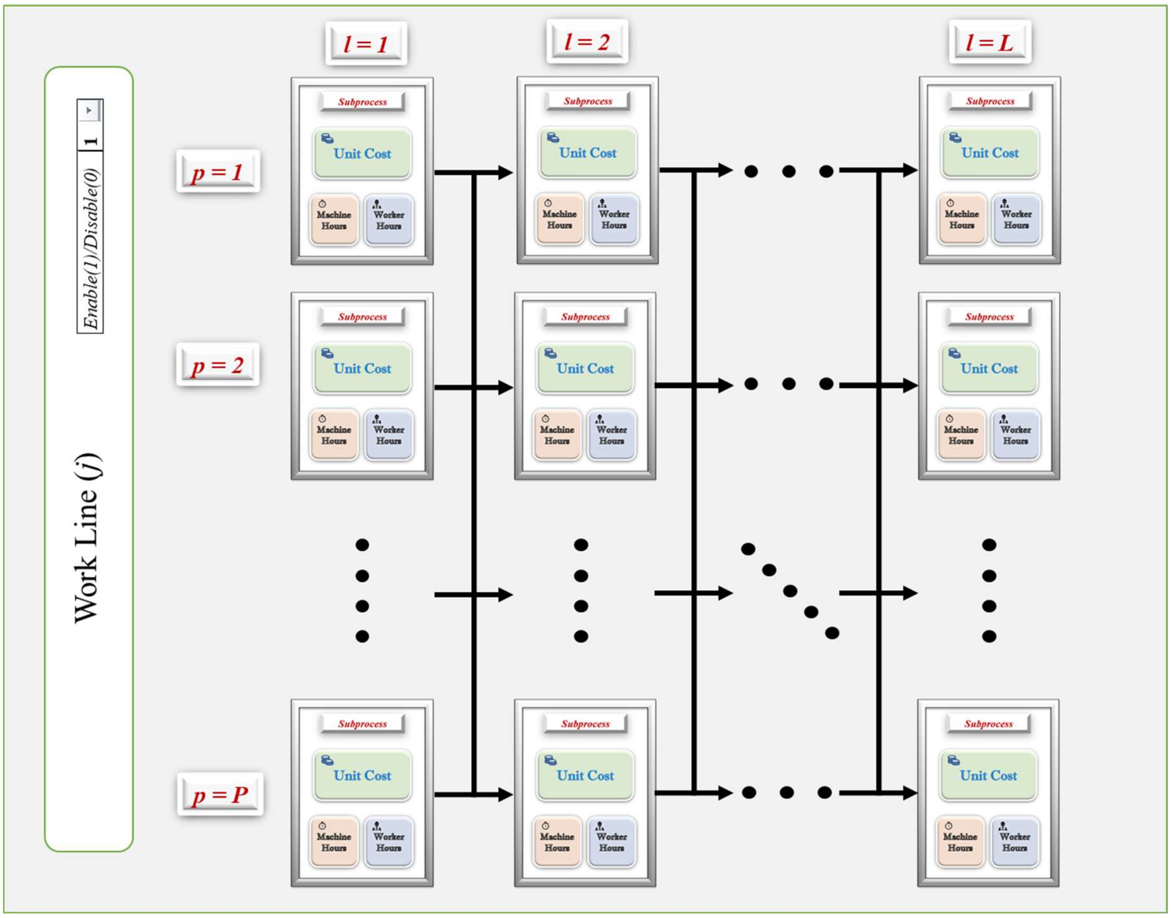


Figure 6. Work line icon.

2.2.3. Available Resources Icons

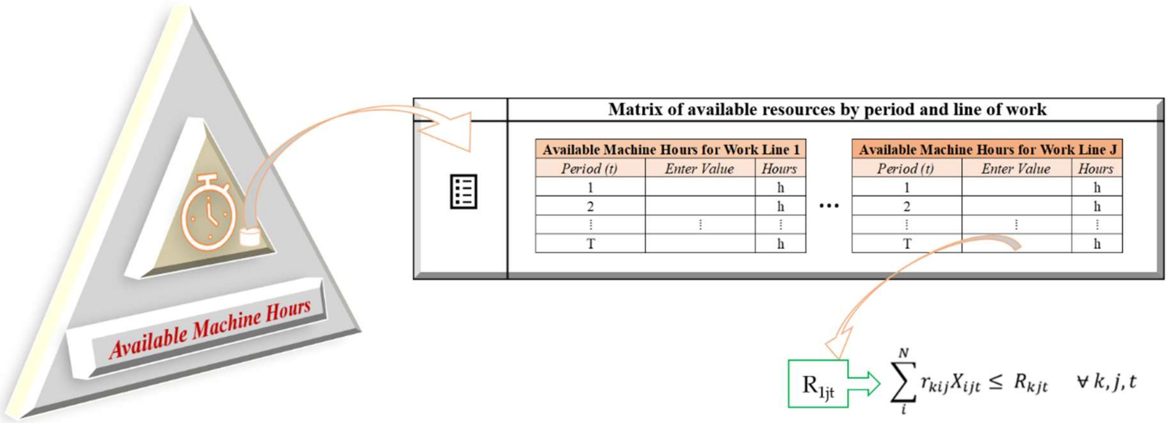
In the Initial Diagram, we can observe, to the left of the work lines, the icons representing the available machine hours and worker hours resources as shown in Figure 7.

In both cases, the user can edit a data matrix as shown in Figure 8. The resources available depend on the planning period and the work line.

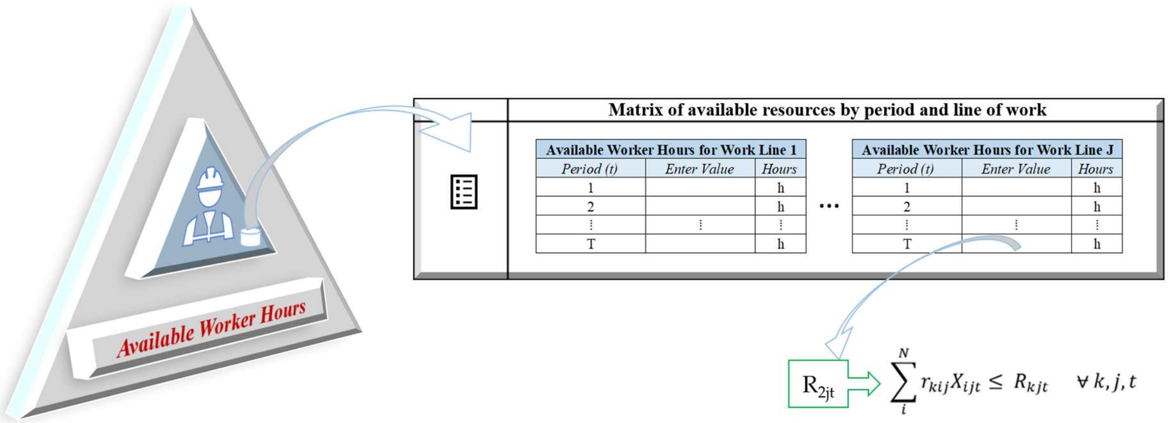
The matrix of available machine hours will generate the parameter R_{kjt} for k = 1, while the available worker hours matrix will generate the parameter R_{kjt} for k = 2 in the mathematical model.

The user must consider the calculation of available machine hours according to the time that the machines can effectively operate in each work line. When a stage has multiple sub-processes operating in parallel, the user must consider the time of the sub-process that takes the longest and not the algebraic sum of all of them, unlike the available worker hours that depend exclusively on the duration of the shift and the number of operators for each planning period.

Figure 7. Available resources icons.



(**a**)



(**b**)

Figure 8. Editable matrices of available resources, (**a**) corresponds to the availability of machine hours and (**b**) to the availability of worker hours.

2.2.4. Demand and Available Inventory Icons

In the Initial Diagram, the user can observe, to the right of the work lines, the icons for demand and available inventory per product. If the diagram has more icons than necessary, it will be sufficient to leave the surplus demands at zero. Figure 9 shows the icons for N different products.

The demand matrix by product will generate the parameter D_{it} in the mathematical model, while the available inventory matrix must be activated with a button. If activated, the user can enter data such as the unit cost of inventory per period and the units available at the beginning, generating the parameters CI_{it} and I_{i0}, respectively, in the mathematical model.

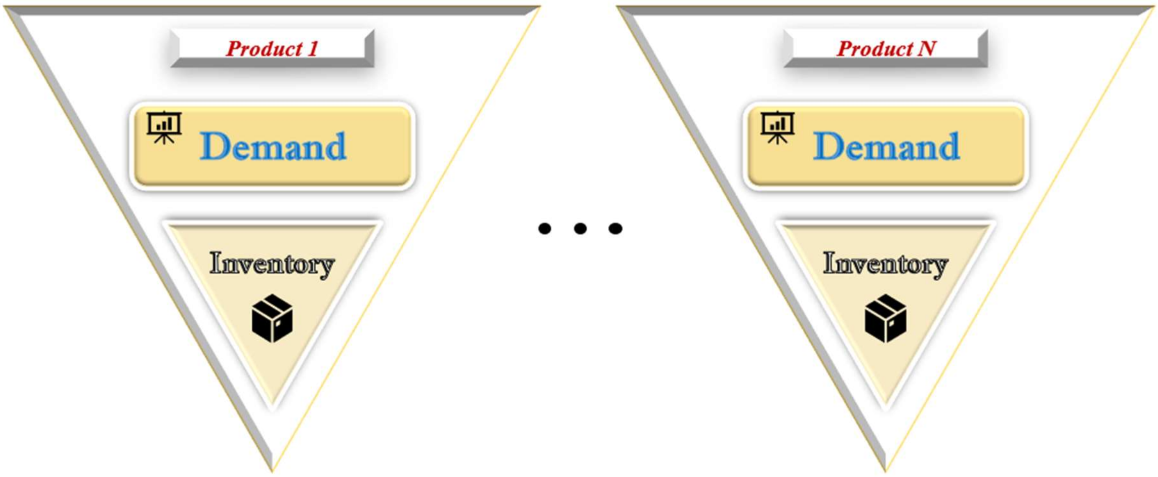


Figure 9. Demand and inventory icons by product.

Figure 10 shows the editable matrices of the demand and inventory by product icon.

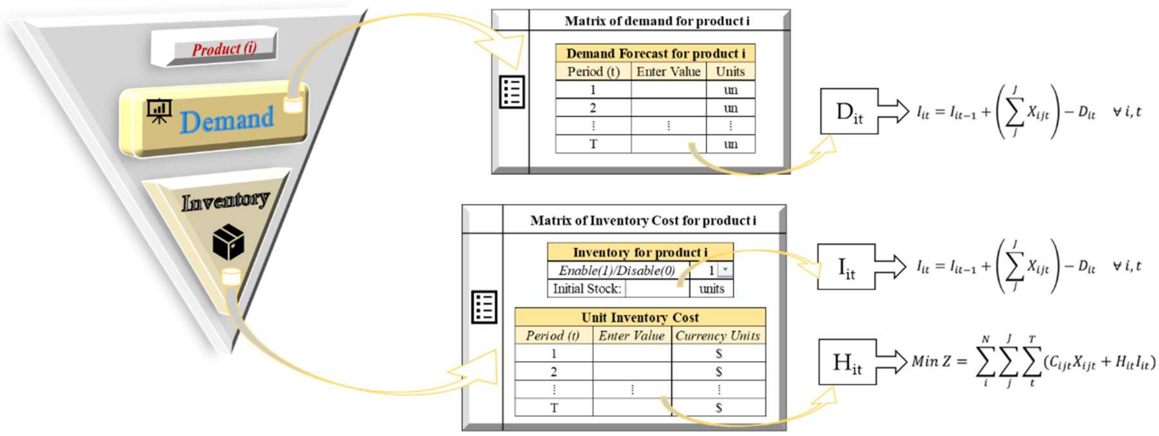


Figure 10. Editable demand and inventory by product matrices.

Once all the target system data have been entered into the matrices, and once it has been defined which work lines need to be active, the optimal solution to the APP problem can be requested, resulting in the planning of the quantity and timing of production and inventory management over the desired planning horizon. The following section presents a case study to test the prototype based on the proposed methodology.

3. Prototype and Case Study: Sausage Products Factory

A theoretical case has been selected to test the tool. It should be noted that the prototype is in its initial stage; however, it is functional.

The prototype has been designed in Excel spreadsheets, and it currently has a capacity of four products, four planning periods, and four work lines, each with four serial sub-processes, where each serial sub-process has room for four parallel machines. The solution was obtained using the Excel OpenSolver add-in, and it has been tested on Windows 10 with an Intel(R) Core(TM) i5-10300H CPU @ 2.50 GHz, 2496 Mhz; four main processors; and eight logical processors.

A flow shop case of a fictitious plant that produces three types of sausages in two working lines is proposed. The process starts with the sausage dough mixers, which supply parallel fillers to be precooked in industrial ovens and finally packaged in parallel packers.

Work line 1 has one mixer, four stuffers, one oven and three packers as shown in Figure 11, while work line 2 has two mixers, four stuffers, two ovens and four packers as shown in Figure 11.

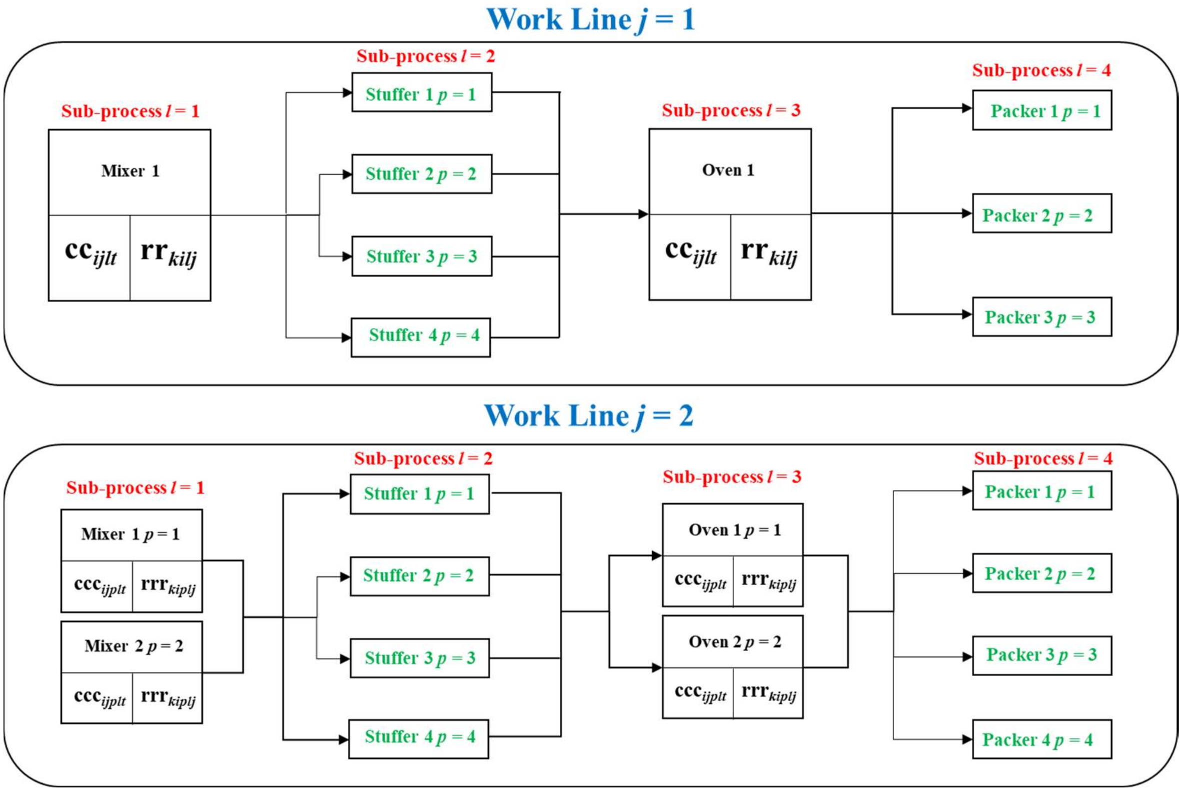


Figure 11. Flowchart for the proposed case study.

In addition, it should be considered that work line 1 can only process sausages 1 and 3, while work line 2 can only process sausages 1 and 2.

We assume that 100 finished units of sausage 1, 50 units of sausage 2, and 40 units of sausage 3 are currently available.

The forecasted demand for the next 4 weeks is 1000, 1050, 1100, and 950 units of sausage 1; 500, 600, 550, and 500 units of sausage 2; and 750, 800, 650, and 500 units of sausage 3, respectively.

Inventory unit costs and available capacities in hours per week and per line are shown in Table 3, for a 4-week planning horizon.

Table 3. Availability in hours per line and inventory cost per product.

	Availability Line 1		Availability Line 2		Inventory Cost		
Week	**Machine h.**	**Worker h.**	**Machine h.**	**Worker h.**	**Sausage 1**	**Sausage 2**	**Sausage 3**
1	5000 *	7500	5000	13,000	5 **	6	3
2	5000	7500	5000	13,000	6	7	4
3	5000	7500	5000	13,000	5	7	5
4	5000	7500	5000	13,000	6	8	6

* Availability in hours; ** Costs in monetary units.

The unit production costs and the requirements for machine hours and worker hours per work line and per product are shown in Table 4.

Table 4. Unit production costs per sausage, per line, per week.

Line 1	Unit production cost for Sausage 1								
Week	**Mixer 1**	**Stuffer 1**	**Stuffer 2**	**Stuffer 3**	**Stuffer 4**	**Oven**	**Packing 1**	**Packing 2**	**Packing 3**
1	98 *	46	77	85	96	77	72	95	60
2	84	87	47	61	55	58	68	53	60
3	57	96	93	78	54	46	95	61	48
4	72	90	45	90	85	98	96	93	48
M. H. required	1 **	0.5	0.5	0.5	0.5	1.5	0.2	0.2	0.2
W. H. required	2 ***	0.5	0.5	0.5	0.5	1.5	0.2	0.2	0.2

Line 1	Unit production cost for Sausage 3								
Week	**Mixer 1**	**Stuffer 1**	**Stuffer 2**	**Stuffer 3**	**Stuffer 4**	**Oven**	**Packing 1**	**Packing 2**	**Packing 3**
1	60	98	42	60	86	62	52	63	97
2	89	71	72	87	49	62	60	40	61
3	54	71	51	86	68	70	57	89	46
4	71	68	96	88	48	65	68	55	96
M. H. required	1	0.5	0.5	0.5	0.5	1.5	0.2	0.2	0.2
W. H. required	2	0.5	0.5	0.5	0.5	1.5	0.2	0.2	0.2

Line 2	Unit production cost for Sausage 1											
Week	**Mixer 1**	**Mixer 2**	**Stuffer 1**	**Stuffer 2**	**Stuffer 3**	**Stuffer 4**	**Oven 1**	**Oven 2**	**Packing 1**	**Packing 2**	**Packing 3**	**Packing 4**
1	54	90	87	81	65	47	79	78	94	85	65	43
2	71	85	86	54	66	61	79	56	45	91	68	56
3	92	73	46	48	53	50	96	91	42	62	76	47
4	77	61	68	45	64	58	90	43	69	85	56	46
M. H. req.	1	1	0.5	0.5	0.5	0.5	2	2	0.2	0.2	0.2	0.2
W. H. req.	2	2	0.5	0.5	0.5	0.5	2.5	2.5	0.2	0.2	0.2	0.2

Line 2	Unit production cost for Sausage 2											
Week	**Mixer 1**	**Mixer 2**	**Stuffer 1**	**Stuffer 2**	**Stuffer 3**	**Stuffer 4**	**Oven 1**	**Oven 2**	**Packing 1**	**Packing 2**	**Packing 3**	**Packing 4**
1	91	58	52	96	84	67	85	81	105	87	107	78
2	74	82	61	88	87	82	71	72	92	85	78	59
3	101	73	66	57	81	99	60	95	79	91	70	56
4	106	108	74	68	100	79	104	93	67	56	71	91
M. H. req.	1	1	0.5	0.5	0.5	0.5	2	2	0.2	0.2	0.2	0.2
W. H. req.	2	2	0.5	0.5	0.5	0.5	2.5	2.5	0.2	0.2	0.2	0.2

* Costs in monetary units; ** Machine hours required; *** Working hours required

In Appendix A are attached images of the case proposed in the prototype. To show the solution of this problem, APP should be considered in that, to activate a work line, the user must activate a manual switch in a cell of the icon of each line. In addition, obtaining a product to be produced on one line and not on another is achieved by penalizing with high costs.

Figure 12 shows the optimal solution for the case of study in the prototype interface. The solution of the production variable can be observed on X_{ijt} table, being the quantity of sausages to be produced for each line in each of the four weeks.

X(ijt)	Period 1	Period 2	Period 3	Period 4
Item 1 Line 1	249	699	579	729
Item 1 Line 2	651	351	521	221
Item 1 Line 3	0	0	0	0
Item 1 Line 4	0	0	0	0
Item 2 Line 1	0	0	0	0
Item 2 Line 2	450	750	580	320
Item 2 Line 3	0	0	0	0
Item 2 Line 4	0	0	0	0
Item 3 Line 1	980	530	650	500
Item 3 Line 2	0	0	0	0
Item 3 Line 3	0	0	0	0
Item 3 Line 4	0	0	0	0
Item 4 Line 1	0	0	0	0
Item 4 Line 2	0	0	0	0
Item 4 Line 3	0	0	0	0
Item 4 Line 4	0	0	0	0

I(it)	Period 1	Period 2	Period 3	Period 4
Item 1	0	0	0	0
Item 2	0	150	180	0
Item 3	270	0	0	0
Item 4	0	0	0	0

Objetive Function	min 6,531,640

Figure 12. Sausage case solution with the IBPlanner prototype.

The number of units of sausages to be stored in inventory each week is also shown, and the value of the total cost of the APP operation in this case is 6,531,640 currency units.

It is important to note that, although it is an initial prototype, in the solution spreadsheet, it is also possible to observe the slack in machine hours and worker hours. With this information, it is possible to make decisions, for example, to level the workforce or invest in machine capacity. The slack of the constraints in this case can be seen in Appendix B.

4. Discussion of Results

IBPlanner provides the solution to a classical APP problem, with the objective of minimizing the total cost associated with planning. It is noteworthy that there are currently numerous variations of this problem, and many authors have ventured into presenting multi-objective models with different approaches. Examples include Rasmi et al. (2019) [34] and Aydin et al. (2022) [8], who propose models incorporating sustainability aspects. Darvishi et al. (2020) [32] investigated APP in the textile industry under uncertainty conditions, while Jamalnia et al. (2019) [36] worked on comparing APP strategies under uncertainty conditions. Genetic algorithms have also been a focus of analysis in APP problems for researchers such as Goli et al. (2019) [1] and Yuliastuti et al. (2019) [37]. The fuzzy logic approach has been a recurrent focus for authors like Zaidan et al. (2019) [35] and Djordjevic et al. (2019), [40]. As authors, we align with their approaches in recognizing the need to diversify the possibilities of APP problems to have a broad range of methods that can adapt to the productive system we aim to enhance. The authors declare that this trend is necessary for the development of knowledge, and the complexity of associated mathematical modeling will continue to increase.

Therefore, the authors believe it is important to advance approaches that simplify the application of these advancements in productive industries; otherwise, it will be increasingly difficult for companies with little investment capacity to use these methodologies.

The authors agree with Jonsson and Ivert (2015) [44] that a company that plans its production with a tool, such as IBPlanner, obtains better and more feasible plans; we also disagree with Vlckova and Patak (2011) [45], who indicate that effective production planning can only be carried out through an integrated information system and not with spreadsheet-based methods, although this discrepancy lies in the fact that the prototype proposed by this research is not a conventional spreadsheet that applies a trial-and-error method but one that applies linear programming.

Although there are other examples of commercial production planning software, what makes IBPlanner unique is the reduction in resources that must be invested in to model the APP problem to meet an optimal solution. Starting from a process flow diagram or a plant layout, a user who is not necessarily a professional qualified to model mathematically a manufacturing situation can use the proposed conceptualization of icons to represent the elements of the production plant such as machines, work lines, or the resources involved.

Our approach is much more specific than software such as QAD, which offers a wide range of services and solutions for at least six different types of industries, or Solvoyo, that offers supply chain planning using artificial intelligence and machine learning. However, our methodology and tool are adapted to other types of needs and companies with a low level of investment and digital development, with few qualified personnel in operations management, such as SMEs. However, the potential of the proposed methodology can scale to be useful to any productive company, as, in agreement with Peter C. Bell (1988), interactive visual modeling benefits the development of operations research [52].

5. Conclusions

In this paper, a methodology based on icons was introduced for performing aggregate production planning without the need for the mathematical modeling inherent in linear programming problems. To apply this methodology, a software prototype named IBPlanner was presented. IBPlanner, based on Excel spreadsheets, is capable of solving multi-process and multi-product aggregate production planning problems with the objective of minimizing the total cost of production and inventory over a desired planning horizon. Based on the results from a case study, the authors conclude that this approach is particularly valuable for small and medium-sized enterprises or companies lacking qualified personnel for modeling or financial resources for research and development, although they must know the parameters and data of their production system.

The authors agree that the optimal solution of the case study is a good signal to implement the prototype in a real case and measure productive performance to test the hypothesis that IBPlanner improves productivity.

The authors anticipate that the use of the proposed tool will enhance company productivity. This tool offers a systematic approach to optimizing aggregate production planning, enabling companies to strategically plan production quantities for each product across various processes throughout predefined time periods. Additionally, the tool facilitates inventory planning by allowing companies to determine the optimal storage quantity per period, provided that storage space is available. Importantly, these benefits are achieved at a significantly lower total cost compared to current commercial programs in the market. This cost reduction is attributed to the tool's user-friendly operation by company personnel and the straightforward nature of the prototype.

This conclusion holds both academic and managerial implications.

The icon-based methodology has the theoretical potential to be extended to more complex APP models, incorporating multiple objectives such as maximizing quality while minimizing costs (Galankashi et al. 2022, [18]). It could also be applied to models using genetic algorithms to address seasonal demands under uncertainty conditions (Goli et al. 2019, [1]), the optimization of renewable energy under uncertainty conditions (Islam et al. 2022, [15]), fuzzy programming (Sutthibutr et al. 2020), [31], or workforce leveling considerations (Jang et al. 2020, [33]). Exploring this potential would involve developing new icons to represent the desired implementations.

IBPlanner holds the potential to evolve into an integrated management tool for decision making. The authors conclude that its utility lies in the widespread accessibility of Excel within companies. However, being an initial prototype, the authors do not rule out the future possibility of programming it in another language to enhance its usability, interface, or modeling capabilities. Furthermore, the authors assert that IBPlanner can be adapted to solve other supply chain optimization problems, such as procurement, transportation, and distribution, as known linear programming models exist to address these issues. This conclusion motivates further research to make the icon-based methodology and IBPlanner a practical solution for integrated supply chain management while preserving the essence of simplifying modeling through icon usage.

The researchers conclude that the tool simplifies the intricacies of mathematical modeling in aggregate production plans. Designing a model that accurately represents the production plant typically demands a comprehensive understanding of linear programming. In this context, the tool offers the advantage of dispensing with the need for such specialized knowledge. Instead, users can operate the tool using editable virtual icons, simulating the target production system and deriving optimal aggregate production plans for a specified time horizon. This feature is particularly valuable for companies lacking the resources for extensive research and development in their production processes, with small and medium-sized enterprises (SMEs) being the archetypal entities falling within this category. However, it is crucial to note that while the methodology streamlines the modeling process, it does not alleviate the complexities associated with data collection, classification, and simulation for decision making.

In conclusion, the authors hope that the use of this tool and methodology will contribute to the development of the global industrial manufacturing sector, with a particular emphasis on the Latin American region. Their aspiration is that it may foster economic and social growth in a region aspiring to compete with major world economies.

Author Contributions: Conceptualization, I.D.; methodology, E.M.-M.; software, E.M.-M.; validation, E.M.-M. and J.M.S.; formal analysis, I.D.; investigation, I.D.; data curation, E.M.-M.; writing—original draft preparation, E.M.-M.; writing—review and editing, J.M.S.; visualization, J.M.S.; supervision, I.D. and J.M.S.; project administration, I.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Dicyt-USACH and Industrial Engineering Department of Universidad de Santiago de Chile.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

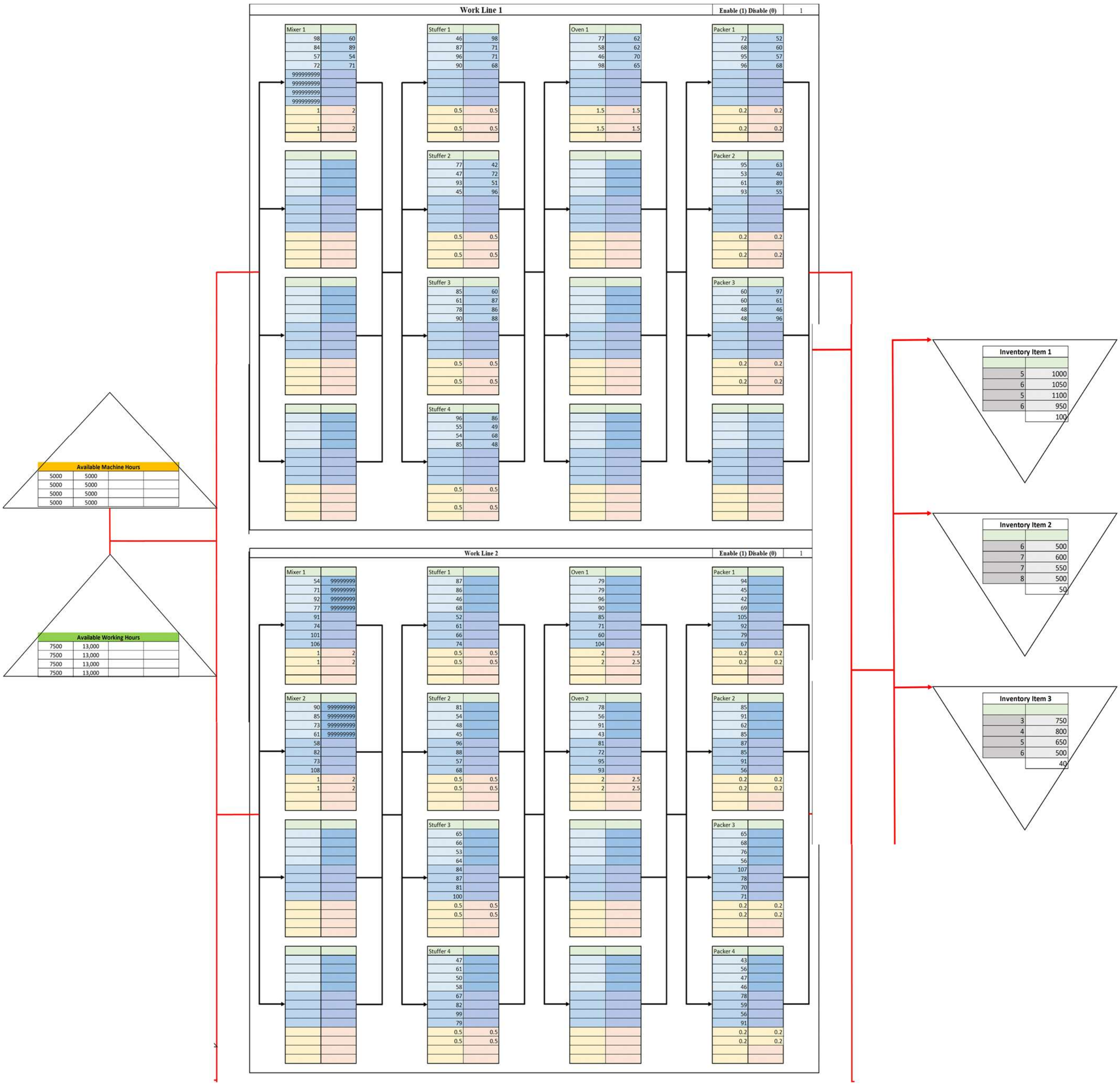


Figure A1. Initial Diagram. Initial diagram viewed from the IBPlanner prototype in the case study.

Appendix B

Constraint

Machine Hours	Line 1		Line 2		Line 3		Line 4	
Period 1	3932.8	5000	4073.7	5000	0	0	0	0
Period 2	3932.8	5000	4073.7	5000	0	0	0	0
Period 3	3932.8	5000	4073.7	5000	0	0	0	0
Period 4	3932.8	5000	2001.7	5000	0	0	0	0

Inventory		
Item 1 Period 1	0	0
Item 1 Period 2	0	0
Item 1 Period 3	0	0
Item 1 Period 4	0	0
Item 2 Period 1	0	0
Item 2 Period 2	150	150
Item 2 Period 3	180	180
Item 2 Period 4	0	0
Item 3 Period 1	270	270
Item 3 Period 2	0	0
Item 3 Period 3	0	0
Item 3 Period 4	0	0
Item 4 Period 1	0	0
Item 4 Period 2	0	0
Item 4 Period 3	0	0
Item 4 Period 4	0	0

Working Hours	Line 1		Line 2		Line 3		Line 4	
Period 1	7496.9	7500	12,992	13,000	0	0	0	0
Period 2	7496.9	7500	12,992	13,000	0	0	0	0
Period 3	7496.9	7500	12,992	13,000	0	0	0	0
Period 4	7496.9	7500	6383.8	13,000	0	0	0	0

Figure A2. Constraints. Cells containing the constraints of the APP problem in the case study, where the slack of the resources machine hours and worker hours can be observed.

References

1. Goli, A.; Tirkolaee, E.B.; Malmir, B.; Bian, G.-B.; Sangaiah, A.K. A multi-objetive invasive weed optimization algorithm for robust aggregate production planning under uncertain seasonal demand. *Computing* **2019**, *101*, 499–529. [CrossRef]
2. Mirzapour Al-e-hashem, S.M.J.; Baboli, A.; Sazvar, Z. A stochastic aggregate production planning model in a green supply chain: Considering flexible lead times, nonlinear purchase and shortage cost functions. *Eur. J. Oper. Res.* **2013**, *230*, 26–41. [CrossRef]
3. Nam, S.; Logendran, R. Aggregate production planning—A survey of models and methodologies. *Eur. J. Oper. Res.* **1992**, *61*, 255–272. [CrossRef]
4. Miltenburg, J. Setting manufacturing strategy for a factory-within-a-factory. *Int. J. Prod. Econ.* **2008**, *113*, 307–323. [CrossRef]
5. Eilon, S. Five approaches to aggregate production planning. *AIIE Trans.* **1975**, *7*, 118–131. [CrossRef]
6. Cheraghalikhani, A.; Khoshalhan, F.; Mokhtari, H. Aggregate production planning: A literature review and future research directions. *Int. J. Ind. Eng. Comput.* **2019**, *10*, 309–330. [CrossRef]
7. Jamalnia, A.; Yang, J.-B.; Feili, A.; Xu, D.-L.; Jamali, G. Aggregate production planning under uncertainty: A comprehensive literature survey and future research directions. *Int. J. Adv. Manuf. Technol.* **2019**, *102*, 159–181. [CrossRef]
8. Aydin, N.S.; Tirkolaee, E.B. A systematic review of aggregate production planning literature with an outlook for sustainability and circularity. *Environ. Dev. Sustain.* **2022**, 1–42. [CrossRef]
9. Werner, F. Special Issue "Scheduling: Algorithms and Applications". *Algorithms* **2023**, *16*, 268. [CrossRef]
10. Elidrissi, A.; Benmansour, R.; Hasani, K.; Werner, F. Scheduling on parallel machines with a common server in charge of loading and unloading operations. *arXiv* **2023**, arXiv:2306.16669.
11. Yazd, S.; Salamirad, A.; Kheybari, S.; Ishizaka, A. An efficiency-based aggregate production planning model for multi-line manufacturing systems. *Oper. Manag. Res.* **2023**, *16*, 2008–2024. [CrossRef]
12. Özelkan, E.; Torabzadeh, S.; Demirel, E.; Lim, C. Bi-objective aggregate production planning for managing plan stability. *Comput. Ind. Eng.* **2023**, *178*, 109105. [CrossRef]
13. Tirkolaee, E.B.; Aydin, N.S.; Mahdavi, I. A Hybrid Biobjective Markov Chain Based Optimization Model for Sustainable Aggregate Production Planning. *IEEE Trans. Eng. Manag.* **2022**, 1–11. [CrossRef]
14. Gomez-Rocha, J.E.; Hernandez-Gress, E.S. A Stochastic Programming Model for Multi-Product Aggregate Production Planning Using Valid Inequalities. *Appl. Sci.* **2022**, *12*, 9903. [CrossRef]
15. Islam, S.R.; Novoa, C.; Jin, T.D. Multi-facility aggregate production planning with prosumer microgrid: A two-stage stochastic program. *J. Clean. Prod.* **2022**, *367*, 132911. [CrossRef]
16. Singh, N.K.; Kuthambalayan, T.S. Integrating operations and marketing decisions to manage perishability risks with target minimum remaining shelf-life available to consumers. *Comput. Ind. Eng.* **2022**, *163*, 107812. [CrossRef]
17. Matos, C.; Sola, A.V.H.; Matias, G.D.; Lermen, F.H.; Ribeiro, J.L.D.; Siqueira, H.V. Model for Integrating the Electricity Cost Consumption and Power Demand into Aggregate Production Planning. *Appl. Sci.* **2022**, *12*, 7577. [CrossRef]
18. Galankashi, M.R.; Madadi, N.; Helmi, S.A.; Rahim, A.A.; Rafiei, F.M. A Multiobjective Aggregate Production Planning Model for Lean Manufacturing: Insights from Three Case Studies. *IEEE Trans. Eng. Manag.* **2022**, *69*, 1958–1972. [CrossRef]

19. Yu, V.F.; Kao, H.C.; Chiang, F.Y.; Lin, S.W. Solving Aggregate Production Planning Problems: An Extended TOPSIS Approach. *Appl. Sci.* **2022**, *12*, 6945. [CrossRef]
20. Liu, L.F.; Yang, X.F. A Multi-Objective Model and Algorithms of Aggregate Production Planning of Multi-Product with Early and Late Delivery. *Algorithms* **2022**, *15*, 180. [CrossRef]
21. Dohale, V.; Ambilkar, P.; Gunasekaran, A.; Bilolikar, V. A multi-product and multi-period aggregate production plan: A case of automobile component manufacturing firm. *Benchmarking Int. J.* **2022**, *29*, 3396–3425. [CrossRef]
22. Yaghin, R.G.; Darvishi, F. Integrated textile material and production management in a fuzzy environment: A logistics perspective. *J. Text. Inst.* **2022**, *113*, 1380–1400. [CrossRef]
23. Liu, L.F.; Yang, X.F. Multi-Objective Aggregate Production Planning for Multiple Products: A Local Search-Based Genetic Algorithm Optimization Approach. *Int. J. Comput. Intell. Syst.* **2021**, *14*, 156. [CrossRef]
24. Khalili, J.; Alinezhad, A. Performance evaluation in aggregate production planning using integrated RED-SWARA method under uncertain condition. *Sci. Iran.* **2021**, *28*, 912–926. [CrossRef]
25. Tuang, D.H.; Chiadamrong, N. A Fuzzy Credibility-Based Chance-Constrained Optimization Model for Multiple-Objective Aggregate Production Planning in a Supply Chain under an Uncertain Environment. *Eng. J.* **2021**, *25*, 31–58. [CrossRef]
26. Rehman, H.U.; Ahmad, A.; Ali, Z.; Baig, S.A.; Manzoor, U. Optimization of Aggregate Production Planning Problems with and without Productivity Loss using Python Pulp Package. *Manag. Prod. Eng. Rev.* **2021**, *12*, 38–44.
27. Krajcovic, M.; Furmannova, B.; Grznar, P.; Furmann, R.; Plinta, D.; Svitek, R.; Antoniuk, I. System of Parametric Modelling and Assessing the Production Staff Utilization as a Basis for Aggregate Production Planning. *Appl. Sci.* **2021**, *11*, 9347. [CrossRef]
28. Ning, Y.F.; Pang, N.; Wang, S.; Chen, X.M. An Uncertain APP Model with Allowed Stockout and Service Level Constraint for Vegetables. *Symmetry* **2021**, *13*, 2332. [CrossRef]
29. Rahmani, D.; Zandi, A.; Behdad, S.; Entezaminia, A. A light robust model for aggregate production planning with consideration of environmental impacts of machines. *Oper. Res.* **2021**, *21*, 273–297. [CrossRef]
30. Torabzadeh, S.; Ozelkan, E.C. Fuzzy aggregate production planning with flexible requirement profile for plan stability in uncertain environments. *Eur. J. Ind. Eng.* **2021**, *15*, 514–549. [CrossRef]
31. Sutthibutr, N.; Chiadamrong, N. Integrated Possibilistic Linear Programming with Beta-Skewness Degree for a Fuzzy Multi-Objective Aggregate Production Planning Problem under Uncertain Environments. *Fuzzy Inf. Eng.* **2020**, *12*, 355–380. [CrossRef]
32. Darvishi, F.; Yaghin, R.G.; Sadeghi, A. Integrated fabric procurement and multi-site apparel production planning with cross-docking: A hybrid fuzzy-robust stochastic programming approach. *Appl. Soft Comput.* **2020**, *92*, 106267. [CrossRef]
33. Jang, J.; Chung, B.D. Aggregate production planning considering implementation error: A robust optimization approach using bi-level particle swarm optimization. *Comput. Ind. Eng.* **2020**, *142*, 106367. [CrossRef]
34. Rasmi, S.A.B.; Kazan, C.; Turkay, M. A multi-criteria decision analysis to include environmental, social, and cultural issues in the sustainable aggregate production plans. *Comput. Ind. Eng.* **2019**, *132*, 348–360. [CrossRef]
35. Zaidan, A.A.; Atiya, B.; Abu Bakar, M.R.; Zaidan, B.B. A new hybrid algorithm of simulated annealing and simplex downhill for solving multiple-objective aggregate production planning on fuzzy environment. *Neural Comput. Appl.* **2019**, *31*, 1823–1834. [CrossRef]
36. Jamalnia, A.; Yang, J.B.; Xu, D.L.; Feili, A.; Jamali, G. Evaluating the performance of aggregate production planning strategies under uncertainty in soft drink industry. *J. Manuf. Syst.* **2019**, *50*, 146–162. [CrossRef]
37. Yuliastuti, G.E.; Rizki, A.M.; Mahmudy, W.F.; Tama, I.P. Optimization of Multi-Product Aggregate Production Planning Using Hybrid Simulated Annealing and Adaptive Genetic Algorithm. *Int. J. Adv. Comput. Sci. Appl.* **2019**, *10*, 484–489. [CrossRef]
38. Aazami, A.A.; Saidi-Mehrabad, M. Bender's decomposition algorithm for robust aggregate production planning considering pricing decisions in competitive environment: A case study. *Sci. Iran.* **2019**, *26*, 3007–3031.
39. Ning, Y.F.; Pang, N.; Wang, X. An Uncertain Aggregate Production Planning Model Considering Investment in Vegetable Preservation Technology. *Math. Probl. Eng.* **2019**, *2019*, 8505868. [CrossRef]
40. Djordjevic, I.; Petrovic, D.; Stojic, G. A fuzzy linear programming model for aggregated production planning (APP) in the automotive industry. *Comput. Ind.* **2019**, *110*, 48–63. [CrossRef]
41. Penlesky, R.; Srivastava, R. Aggregate production planning using spreadsheet software. *Prod. Plan. Control* **2007**, *5*, 524–532. [CrossRef]
42. Brown, G.; Keegan, J.; Vigus, B.; Wood, K. The Kellogg company optimizes production, inventory, and distribution. *Interfaces* **2001**, *31*, 1–15. [CrossRef]
43. Zago, C.F.; Mesquita, M.A. Advanced planning systems (APS) for supply chain planning: A case study in dairy industry. *Braz. J. Oper. Prod. Manag.* **2015**, *12*, 280–297. [CrossRef]
44. Jonsson, P.; Ivert, L.K. Improving performance with sophisticated master production scheduling. *Int. J. Prod. Econ.* **2015**, *168*, 118–130. [CrossRef]
45. Vlckova, V.; Patak, M. Barriers of demand planning implementation. *Econ. Manag.* **2011**, *1*, 1000–1005.
46. Dini, M.; Stumpo, G. *Mipymes en América Latina: Un Frágil Desempeño y Nuevos Desafíos Para las Políticas de Fomento*; Documentos de Proyectos (LC/TS.2018/75/Rev.1); Comisión Económica Para América Latina y el Caribe (CEPAL): Santiago, Chile, 2020.
47. The Conference Board. Total Economy Database. 2020. Available online: https://conference-board.org/data/economydatabase (accessed on 15 April 2023).

48. OIT (Organización Internacional del Trabajo). ILOSTAT. 2020. Available online: https://ilostat.ilo.org/es/ (accessed on 17 April 2023).
49. Grosman, N.; Braude, H.; Rovira, S.; Patiño, A. *Hecho en América Latina: Fabricación Inteligente y Una Nueva Esperanza de Industrialización en la Región*; Documentos de Proyectos (LC/TS.2021/111); Comisión Económica Para América Latina y el Caribe (CEPAL): Santiago, Chile, 2021.
50. Available online: https://www.ingenieros.cl/wp-content/uploads/2014/03/Especialidad-INDUSTRIAL1.pdf (accessed on 22 April 2023).
51. Available online: https://blogs.unitec.mx/vida-universitaria/la-unitec/mexico-necesita-ingenieros/ (accessed on 25 April 2023).
52. Bell, P.C. Visual interactive modelling: The past, the present, and the prospects. *Eur. J. Oper. Res.* **1988**, *54*, 274–286. [CrossRef]