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Applications of process and digital twin models for production simulation and scheduling in the manufacturing of food ingredients and products

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ABSTRACT

Food Processing Industries are bound to increasingly adopt digital technologies in order to ensure product safety and quality, minimize costs in the face of low profit margins, shorten lead times and guarantee timely delivery of an increasing number of products despite production dead times and uncertainties. The concept of a digital twin put forward in the context of Industry 4.0 encompasses a digital model of the production model that mimics the physical system, interacts with it and can be used to design, monitor and optimize its performance. In this paper, the application of integrated process and digital twin models in food processing is discussed in the context of process simulation and production scheduling. The modeling challenges, opportunities and special characteristics that distinguish food from other process industries are also discussed. The potential benefits from implementing a digital modeling approach on a food process are presented with the help of a large-scale brewery case study.

1. Introduction

Food Processing Industries (FPIs) are struggling with low profit margins while being forced to shorten lead times for an ever-increasing number of products. New processes and new products are added continuously to meet customer demands for products that satisfy specialized nutritional requirements, packaging sizes and labels. Food plants are flexible, multi-product, multi-purpose plants with variable degree of automation; a great deal of time is spent in equipment cleanings and sterilizations, set-ups and changeovers which, in most cases, are product sequence-dependent. The perishable nature of most food products makes the timely production and delivery of products a necessity. In order to increase product safety and quality, minimize costs and assure timely delivery of orders, it is necessary to optimize the food process both at the design as well as at the operation level.

Digital technologies serve major business objectives in the process industries such as promoting innovation, improving productivity and increasing profitability (Legner et al., 2017). The idea of Industry 4.0 that has been put forward by the industrial community encompasses the development and use of new digital advancements such as in artificial intelligence, internet of things devices, big data analytics, digital twins etc. The implementation of these technologies will make feasible the transition to smart manufacturing characterized by a high level of automation due to the extended use of remote sensing, real-time data acquisition and monitoring and advanced visualization tools (Chen et al., 2020).

The concept of a Digital Twin (DT) was developed by Michael Grieves at the University of Michigan in 2002 to define a digital informational construct of a physical system used to simulate the behavior and linked to the physical system (Grieves, 2014; Chen et al., 2020). Kritzinger et al. (2018) presented the following classification categories of Digital Twins in manufacturing based on the level of integration between the physical and digital system: a Digital Model is a digital representation of a physical system with no automated data exchange with it, a Digital Shadow has automated one-way data flow from the physical system to its digital counterpart while a Digital Twin has fully integrated automated communication between the two. In a recent industrial global survey conducted by Siemens AG (Bruckner et al., 2020), the majority

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of the participants converged on the definition of a digital twin as "a virtual replica of a planned or already existing physical entity" or as "a simulation model of the plant/product"; these definitions imply that the aspect of automated communication between the physical and the virtual systems is not considered in practice necessary to exist. Nevertheless, the digital twin concept aims to integrate the mathematical models into the actual operation (Verboven et al., 2020) and, in that respect, some form of data exchange (manual or automated) between the physical and the digital system must exist to justify the "repackaging" of a process model into a digital twin.

Verboven et al. (2020) discuss how the DT idea can be used in food process operations by extending the scope of food process modeling and present the first applications in the agrifood sector. At the heart of any DT implementation in manufacturing lays a mathematical model of a process or a product. Such a simulation model can be embodied by a complex multi-physics mathematical model to capture the behavior of a product or of an individual process or by a simpler in details, but broader in scope, model of the integrated process that represents the entire production system. Models of the latter type can be used to serve all activities that require an integrated process perspective such as green field and retrofit design, off-line and on-line optimization, operator training, supply-chain management, production planning, real-time process scheduling etc. According to the Siemens survey (Bruckner et al., 2020), simulation is valued as an important technological trend and innovation driver with increasing importance in the future for both discrete and process industries.

FPIs are not characterized by a fast adoption of the state-of-the-art digital technology achievements. For example, even though the use of process simulation as a design and modeling tool dates back many decades in the bulk chemical and petrochemical industry, the food sector joined by high added value product industries (such as pharmaceutical and biotech industries) were much slower in adopting such technologies. Industry-specific characteristics such as complex chemistry, quality considerations and specialized equipment are responsible for this delay; food industries that process bulk raw materials with operations similar to traditional chemical processing were faster in adopting process simulators. It is true that the incentive of using any technology that would achieve even a small operational improvement is much higher in industries that produce huge quantities of bulk materials, however, nowadays with the domination of a global competitive market, the potential of increasing operational efficiency cannot be overlooked by any industrial sector.

FPIs can, indeed, benefit considerably from the advancements in digitization to achieve efficient, flexible and profitable manufacturing. In this paper, this potential is investigated in the context of utilizing process simulation and production scheduling tools at the manufacturing floor. More specifically, this paper presents the unique challenges that FPIs face, the different methodological approaches and tools that exist and highlights the opportunities from adopting these technologies. Special emphasis is given in the representation aspect of modeling with the objective being to create accurate, realistic and suitable for their role as digital counterparts of the production processes. Such models can be used to serve the needs of both process simulation and scheduling, bridging essentially the two technologies.

Throughout the paper, an industrial-scale beer production and filling facility operating in batch mode is used as a case study in order to demonstrate the process of developing and using a model in the context of simulation and scheduling. Process analysis and improvement via modeling in areas such as debottlenecking, capacity analysis, planning in the face of uncertainty and reactive scheduling will be demonstrated with the use of the case study. The brewery model was developed on SuperPro Designer v11, while SchedulePro v9.1 was used to cope with the planning and scheduling challenges in the context of a multi-product facility. It should be emphasized that the paper makes no claims of optimality either in the proposed methods or the generated solutions. Guided by their extensive collaboration with the food and other related industries, the authors' objective is to present their assessment of the challenges faced by FPIs and present solutions that, albeit not necessarily optimal, are straightforward to implement, generate realistic representations of the production processes and could have a significant impact in improving the design and operation of food manufacturing facilities.

2. Integrated process simulation

2.1. *Challenges and opportunities in FPIs*

According to Maroulis and Saravacos (2008), the food processing plants can be divided into three major groups, i.e., Food Preservation Plants, Food Ingredient Manufacturing Plants, and Food Product Manufacturing Plants. Food preservation plants utilize agricultural raw materials (usually seasonal) and implement preservation processes such as thermal treatment, refrigeration, freezing, concentration, dehydration etc. Food ingredients plants use commodity bulk agricultural products or by-products of food processing to produce various ingredients (such as sugars, starches, oils, proteins, pectins, gums etc.) used in food processing. These plants often employ operations and equipment units which are closer to traditional chemical processing. Food product manufacturing plants utilize material transformation and preservation processes along with packaging to deliver a multitude of final products to the consumers.

The challenges that different food industry types face and, consequently, the objectives and expected benefits from the use of process modeling and simulation also vary. Among Food Ingredient Plants, cereal wet milling processes are well understood and largely optimized in terms of yields and product qualities of the wide range of products produced in the fractionation. Cereal wet milling plants typically are integrated with processes that hydrolyze part of the produced starch to produce sugar syrups such as glucose and fructose syrups as well as crystalline dextrose. Moreover, a range of biotechnological processes that produce food ingredients use glucose syrups as the basic raw material, since it is the carbon source for most fermentations. Another agricultural raw material, which produces a large category of food ingredients, is the oilseeds processing in the crush plants. Crush plant processes typically include oil extraction with solvent, such as hexane. The production costs and ultimately the selling price of the different products of the above industries have low margins and are mainly driven by the cost of the commodity bulk purchase price. However, there is still hidden value to be identified and exploited around other factors contributing to the operating costs, such as the consumption of secondary raw materials and energy. These are variable from plant to plant. An improvement can be achieved by, for example, extensive water recycling and heat recovery within the process (Galitsky et al., 2003; Martinho et al., 2008; Cheng and Rosentrater, 2017). This value can only be fully realized by developing and experimenting with a very detailed model of the plant which will capture the interactions within the already highly integrated process, and then improve/optimize key performance indicators, while respecting typical quality specifications for the different products. The above key food ingredient processes produce also low value by-products which are used as animal feed, therefore they indirectly influence farming and related food industries such as milk and milk-products and meat and meat-products.

Food product manufacturing plants (such as dairy industries) have processes, which are different from the agricultural and bulk raw materials industries because they consist of batch and (semi-)continuous processes. The processes are simple and the equipment is specialized, however, the batch mode of operation creates scheduling challenges, as described later on. Further optimization regarding heat recovery opportunities are particularly challenging in batch mode of operation, yet recognizable via appropriate process modeling.

What hinders the more extensive deployment of modeling and simulation tools in the food industry is the lack of reliable physicochemical data. Traditional chemical industry, which typically processes molecules with well-characterized properties, benefits from the availability of extensive libraries of components and their physicochemical properties, predictive models to estimate missing properties (from molecular thermodynamics and group contribution techniques) and extensive thermodynamic models to predict the distribution of these components in various phases (usually vapor and liquid). In contrast, food processing deals with very complex and diverse food systems with poorly characterized properties (even basic ones, such as the molecular weight), complex phase distributions (e.g. emulsions) and poorly understood thermodynamics. Not only food compositions are of high complexity but also their properties can change irreversibly during the process (Bon et al., 2010). In addition, properties (such as the pH or water activity) that cannot be easily calculated and predicted by the typically-used conservation principles are very important in food processing. Because of the above difficulties, it is hard to have predictive models of unit operations in food processing at the macroscopic level as utilized in process simulation.

Nevertheless, even with the use of non-predictive or lumped models of individual operations, it is possible to reap the benefits of process simulation to design and analyze a food process from a technological, economic or environmental point of view. Process models can be used in all FPIs to calculate material and energy requirements and the expected process yield, estimate plant capacity, cycle times and production cost, pinpoint the economic “hot-spots”, i.e. the steps of high capital and operating cost or of low yield throughput, or to identify the environmental hot-spots such as materials that are costly to dispose. The findings from such analyses can be used in process design, process and product development, technology transfer and process fitting, process optimization, production scheduling and resource utilization and, in general, streamlining of manufacturing operations. At the end, the facilitation of all these activities through modeling can have a profound impact on the business bottom-line.

2.2. *Process simulation tools in FPI*

Spreadsheet applications, such as Microsoft Excel, are commonly used for process calculations and analyses because they are readily available and familiar to the vast majority of scientists, engineers, and other professionals. The user can enter data in different “cells” of the spreadsheet, perform calculations, and generate results. Results from spreadsheets can be easily plotted in a variety of graphs.

Process simulators are software applications that enable the user to readily represent and analyze integrated processes. Established simulators for petrochemical and other bulk chemical industries include: Aspen Plus and Aspen HYSYS from Aspen Technology, Inc. (Burlington, MA, USA), ChemCAD from Chemstations, Inc. (Houston, TX, USA), UniSim Design from Honeywell (Charlotte, NC, USA), ProSimPlus from ProSim SA (Labege, France) and PRO/II from AVEVA Group plc (Cambridge, UK). These simulators have been designed to model primarily continuous processes and their transient behavior. Most food products, however, are produced in batch and semi-continuous mode (Korovessi and Linninger, 2006). Such processes are best modeled with batch process simulators that account for time-dependency and sequencing of events. The first simulator designed specifically for batch processes was called Batches (from Batch Process Technologies in West Lafayette, IN, USA). It was commercialized in the mid 1980′s. All of its operation models are dynamic and simulation always involves integration of differential equations over a period of time. In the mid 1990’s, Aspen Technology (Burlington, MA, USA) introduced Batch Plus (now called Aspen Batch Process Developer), a recipe-driven simulator that targeted batch pharmaceutical processes. Around the same time, Intelligen, Inc. (Scotch Plains, NJ, USA) introduced SuperPro Designer, a simulator with a focus in biotech, pharmaceutical, food and other industries that implement a batch, continuous or semi-continuous production mode.

There is a growing scientific literature on using process simulation tools, which involve structural process improvements and development of process alternatives on existing processes, conceptual process development within the broader food waste valorization concept, debottlenecking, techno-economic analyses (TEA) and economic feasibility studies. With no intention to make a comprehensive review of the relevant literature, some of these papers covering a wide range of food applications are cited next. Aspen Plus was used by Ribeiro and Andrade (2007) to perform analysis of a milk concentrating system from a Brazilian milk powder plant, by Silva and Andrade (2013) to simulate a novel oil extraction process from the fruit of macauba palm tree, by Han et al. (2016) to perform a TEA for a novel bioprocess for hydrogen production from food waste, by Gómez-Ríos et al. (2017) to evaluate chitosan production from shrimp shell waste, by Sowgath and Mujtaba (2019) to study the performance of an ammonia fertilizer plant under conditions different from the original design and by Janošovský et al. (2020) to design and economically evaluate a project of a new milk drying processing unit using biogas produced by an adjacent facility. PRO/II was used by Martinho et al. (2008) to simulate vegetable oil processes with emphasis on predicting food properties using group contribution methods. ProSimPlus was used by Bon et al. (2010) to create models and perform optimization of milk pasteurization processes and by Lambert et al. (2018) to perform Pinch and exergy analysis in an existing French sugar beet factory. gPROMS was used by Oreggioni et al. (2017) to perform a TEA of biogas upgrading to bio-methane by food industry waste. SuperPro Designer was used by Kotoupas et al. (2007) to conduct an environmental impact assessment study for cheese whey wastewater treatment processes, by Misailidis et al. (2009) to produce arabinoxylans in the context of wheat biorefinery aiming mainly at producing bioethanol, Alshekhli et al. (2011) to simulate and debottleneck an existing industrial cocoa manufacturing process, by Tusé et al. (2014) to perform techno-economic analysis of a plant that produces biologics such as therapeutic and industrial enzymes, by Kwan et al. (2015) to perform TEA of a food waste valorization process, by Huang et al. (2016) to perform TEA analysis of biodiesel and ethanol co-production from lipid-producing sugarcane, by Mupondwa et al. (2016) to perform a TEA for biodiesel production using Camelina oil, by Cheng and Rosentrater (2017) to perform an economic feasibility analysis of soybean oil production by hexane extraction, by Vardanega et al. (2017) for obtaining Brazilian ginseng extracts, by Somavat et al. (2018) to perform TEA of anthocyanin extraction and ethanol production from blue and purple corn, by Arora et al. (2018) to perform TEA of an integrated mango processing waste biorefinery, by Kwan et al. (2018) to perform a TEA of a food waste valorization process, and by Dursun et al. (2020) for astaxanthin production from agro-industrial wastes.

2.3. Developing an integrated food process model

The development of a model for an integrated food process starts with the definition of the modeling objectives (Foo et al., 2017). A model is always an approximation of reality and different objectives may lead to different modeling abstractions that embody variable amount of details with respect to the real process; this is why it is important to specify from the start what purpose the model will serve once developed.

Next, the process boundaries and interactions with the environment through mass and energy streams should be defined. Then, the internal structure of the system should be defined, i.e. develop the process flowsheet by identifying the individual procedures/operations within the system and their material and energy stream connections. Depending on the modeling objectives, this description can be coarse or detailed; sometimes, adopting a multi-level hierarchical approach (levels of variable detail) may be advantageous as for example in designing a new process (Douglas, 1988). In order to optimally design traditional chemical processes, a superstructure approach may be used. This involves the definition of a process structure that encompasses all options for possible flowsheets and, through mathematical optimization, select the best alternative. Even though the production of many food products is characterized by rigid recipes, such an approach could be useful in designing food ingredient manufacturing plants or for investigating heat or material integration opportunities.

The identification of components present in the system and their properties is an important step in developing a model and quite challenging for food processes. The level of detail in describing the actual components in a process is closely related to the modeling objectives and their expected process 'behavior'. Components that move through the flowsheet together (i.e. they are not individually separated in any process step), they can be lumped in a single virtual component (e.g. 'proteins'). This, obviously, creates some extra challenge in assigning physico-chemical properties to these lumped components; borrowing the properties of the dominant ingredient in a lumped component system may be one solution to this problem without loss of generality since all other ingredients are assumed to behave in a similar way (otherwise, they would not have been lumped together). The type of operations to which some components are subjected to within a food process may also offer some relief with respect to the demand for property values. For example, carbohydrates, proteins, fats etc. are complex systems but are rarely expected to be found in a vapor phase; therefore the knowledge of their vapor properties or of thermodynamic models for transitioning to the vapor phase is not necessary. In general, the types of processes included in the flowsheet would dictate both how many and what components to identify and which property values are needed in a given modeling scenario.

For every procedure/operation block within the system, the operating conditions must then be specified. For a running process, this step may require the collection and validation of data from the actual plant. When designing a new process, some assumptions have to be made based on experiments at the bench or pilot-plant scale or data available in literature or previous experience in similar processes. This may also be challenging task especially if reactions are to be used to model the consumption and generation of components. Reaction mechanisms are typically complex (e.g. in biochemical processes); again, depending on the modeling objective, a lumped approach using a simple reaction scheme representing just the reaction stoichiometry and the reaction extent may be sufficient. In other cases, a more detailed modeling approach involving kinetic expressions may be required, in which case, kinetic parameters can be estimated in lab or pilot plant scale by appropriately designed experiments. These parameters can then be used to design the production scale reactor. When modeling existing facilities, batches or periods of plant operation with slightly deviated conditions might be helpful for fine-tuning and/or for validating the predictions of a process model. Scale-up and scale-down related activities can be challenging for some operations exhibiting non-linear behavior. For example, differences between the lab and the plant scale may be observed on the achieved homogeneity of solutions in mixing vessels because of different vessel geometries and/or different agitators. Differences in the implemented control systems may also create scalability issues.

Finally, the specification of the flow, composition and condition of the process feed streams (or product streams in some cases where optimization is sought) is necessary before the process simulator takes over to set-up and solve the material and energy balances using the user-provided data and the models of the individual processes as they exist in the simulator's process library.

2.4. Process simulation case-study

The process of developing a model in a simulator and the types of analyses that can be run on the model are demonstrated here with the help of a case study on an industrial-scale beer production and filling facility. The plant is fed with barley malt and corn grits which are processed in batches and converted to beer through the fermentation of starch-derived sugars by brewer's yeast (Sachcaromycaes cerevisiae).

The model is intended to be used to calculate the process cycle time, estimate and improve the plant capacity by identifying and eliminating bottlenecks. It is also desirable to perform an economic analysis by estimating the capital investment required and the operating costs. It follows that, in order to satisfy these modeling objectives, the model needs to accurately capture the operation timing and the utilization of resources contributing to cost. The model was developed on SuperPro Designer v11. The data used were obtained from open literature on the subject (Bamforth, 2003; Goldammer, 2008) and also from actual breweries.

The basic building blocks of flowsheets in SuperPro Designer are the *unit procedures*; each unit procedure is executed in a specific equipment unit and is composed of *operations*. The operation level is where the information about the operating conditions, timing (relative start time and duration) and resource consumption (materials, auxiliary equipment, labor, utilities etc.) can be declared. In a continuous process, a unit procedure typically coincides with the single operation that it contains (e.g. a continuous reactor allows the execution of a reaction among the continuously fed materials.) In batch processing, however, the operations within a unit procedure constitute a local 'recipe' of all the tasks that are to be executed within some equipment unit with a specified timing hierarchy (e.g. in a batch reactor, solvents and reactants may

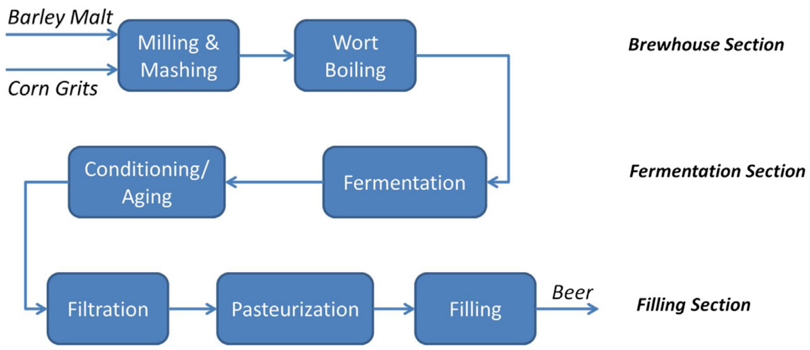

Fig. 1 – The process block diagram of the brewery process.

Table 1 – Feed composition for the beer process.

Component	Barley Malt (%w/w)	Corn Grits (%w/w)
Starch	70	73
Proteins	11	8
Fibers	8	10
Fat	2	3
Minerals	1	1
Water	8	5

be fed separately, the mixture is agitated and heated, left to react and eventually transferred out.) Unit procedures bound by some common processing purpose or common economic parameters can optionally be lumped together into a higher level in the representation hierarchy called a process section.

The brewery process under study (shown in the process block diagram of Fig. 1) is separated into three sections, namely: brewhouse, fermentation, and filling. Fig. 2 shows the SuperPro Designer flow sheet of the entire process with the exception of the filling/packaging section which, for simplicity of the presentation, has been excluded. For the selected brewery flow sheet, two different carbohydrate sources are employed, specifically malted barley and corn grits. In the model, they are represented as mixtures whose assumed composition (Goode and Arendt, 2006) is shown in Table 1. The input data used in this model pertain to one of the brewery products; however, the model could be used for other beer products if the necessary adjustments in fermentation/aging times, ingredients used etc. are done.

The scale of the modeled process is 12 metric tons (MT) of malted barley and 6 MT of corn grits per batch. Using the procedure/equipment names shown in Fig. 2, the process is as follows. Malted barley is grinded in Mill-1 and collected in the SB-101 solids bin. Likewise, corn grits are grinded also in Mill-1 and collected in solids bin SB-102. Batch processing makes possible the sharing of the same equipment (Mill-1) to perform different tasks at different time points.

The next step is the mashing stage. Mashing is the process of mixing the milled barley malt and cereal adjuncts (corn grits) with hot water and letting the mixture stand at an appropriate temperature, while the enzymes degrade the proteins and starch to yield the malt extract (i.e., the wort) that is used as the substrate for fermentation. The corn grits are mashed-in first because of the higher temperature that is required for the gelatinization of corn starch. The contents of SB-102 are transferred into the mash vessel (MK-1) where they are mixed with hot water. A small quantity of barley malt (around 20% by weight of corn grits) is also added at this stage. After the completion of the adjunct mashing stage, sparge water of ambient temperature is added to the vessel to cool down the contents. The malted barley is then transferred into the mashing vessel and is mashed according to the following schedule:

- Heat to 45 °C and hold for 15 min. This stage represents the proteolysis reaction where the protein content is extracted from the malt and transferred into the wort.
- Heat to 65 °C and hold for 180 min. This stage represents the saccharification reaction where the starch is broken down to sugars which are dissolved in the wort. The conversion of starch into sugars is represented by the following reaction:

$$(C_6H_{10}O_5)_n + nH_2O \rightarrow nC_6H_{12}O_6$$

Using the corresponding molecular weights, the above reaction can be written in mass basis as:

$$9(C_6H_{10}O_5)_n + 1H_2O \rightarrow 10C_6H_{12}O_6$$

The component "Glucose" in the reaction products represents a variety of fermentable and non fermentable sugars that are extracted from the malt into the wort (e.g., maltose, dextrins, maltotriose, glucose, fructose and sucrose). The extent of the reaction is set to 90% with respect to starch to indicate that, on average, 90% of the starch contained in the barley malt and corn grits is extractable.

- Heat to 75 °C and hold for 10 min in order to terminate enzyme activity, reduce the viscosity and promote the coagulation of particles, thereby improving the fluidity of the mash.

Next, the mash is transferred to the lauter tun (LT-1) where the separation of the wort from the solids is performed. The solid–liquid separation is represented by a filtration operation (P-6) accompanied by a recycling of the wort through a tank (P-7) until a desired clarity is achieved. In the end, the solids bed that remains in the lauter tun is washed with sparge water in order to increase the yield of the process.

The clarified wort is then transferred back to the mash vessel (MK-1) where hops are added and the resulting mixture is boiled. The boiling of the wort serves a number of purposes including sterilization, extraction of the bittering and aromatic compounds (iso-α-acids) from the hops, as well as coagulation of excess proteins and other undesirable flavoring substances. The Mashing (P-5) and Wort Boiling (P-8) procedures utilize the same vessel (MK-1). Before the fermentation stage, the hops and hot trub that are formed during wort boiling are removed by sedimentation in a Whirlpool (WhP-1).

The clarified wort from the whirlpool is cooled down by heating the water utilized in the brewhouse section (P-10/HX-

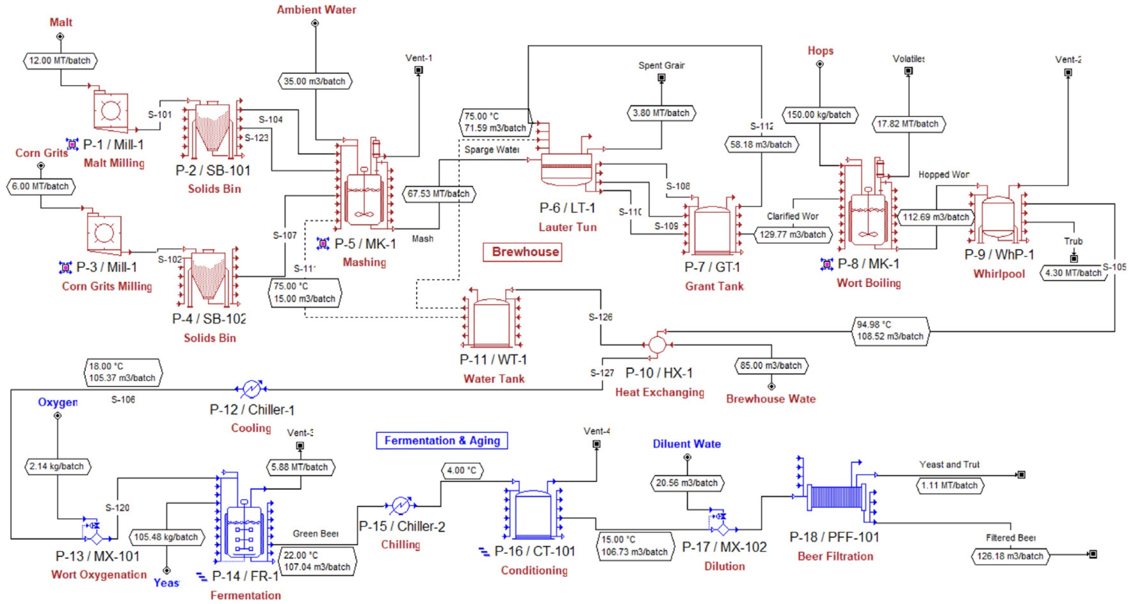

Fig. 2 – The process flowsheet of the brewery model.

1). Heat integration improves the economics of the process and its environmental footprint. The cooling of the wort is completed using Chiller-1 where it is cooled down to 18 °C and then oxygenated in MX-101 to a dissolved oxygen concentration of 0.02 g/L. The oxygenated wort is transferred to a fermentor (FR-101) where brewing yeast is pitched to a concentration of 1 g/L (corresponding to approximately 6E-09 cells/L). The fermentation of sugars to ethanol is represented by the following mass stoichiometry (Bamforth, 2003):

$$105.5C_6H_{12}O_6 \rightarrow 5.2H_2O + 49C_2H_5OH + 46.3CO_2 + 5Yeast$$

The extent of the fermentation reaction is set to 88% to indicate that only a portion of the sugars contained in the wort are actually fermentable. Fermentation lasts for 5 days and the temperature is maintained at 22 °C by flowing chilled water in the jacket of the fermentor. After the completion of fermentation, the immature (green) beer is cooled to 4 °C in Chiller-2 during its transfer to the conditioning tank CT-101. The fermentor is cleaned using both caustic (NaOH) and acid (H_3PO_4) solutions. The conditioning and aging of the beer in CT-101 takes about a week. Next, the beer is diluted in mixer MX-102 with water to 5% alcohol by volume (4% w/w) prior to filtration in PFF-101. The plate and frame filter (PFF-101) removes all suspended solids.

It is assumed that 20% of the produced beer is packaged in 50 L kegs while the remaining 80% is bottled in 0.5 L glass bottles. The beer of the keg-line is pasteurized in bulk form while the pasteurization of the bottled beer is performed inside the bottles. The filled and pasteurized bottles are labeled and then packed in dozen-bottle cartons.

2.4.1. *Throughput analysis*

The modeled process as described above produces approximately 126,000 L of beer per batch. The process cycle time (i.e. the time lag between the start of two consecutive batches) is 8.57 days, which allows for a maximum of 37 batches per year (assuming a 330-day annual operation) and an annual throughput of 4,670,000 L of filtered beer. Fig. 3a shows the equipment occupancy Gantt chart for this base case and for one month of production. Each line in the chart corresponds to a different plant resource utilized in the production (e.g., main and auxiliary equipment). Different colors represent different batches. A uniformly colored bar in the chart represents the execution of a unit procedure for a batch; black vertical lines shown in each bar are used to identify the operations executed within the corresponding procedure.

As seen in Fig. 3a, with the assumed plant resources only 3 batches can be initiated within a month. From a comparison of the process times of all equipment, it can be easily verified that the conditioning step is the process bottleneck while the brewhouse equipment and the filling lines are underutilized. It is possible to reduce the cycle time of the process and increase its throughput by installing additional conditioning tanks operating in staggered mode (alternating among batches in an out of phase mode). When new conditioning tanks are introduced the cycle time is recalculated, it becomes obvious that the fermentor becomes the bottleneck; therefore, to further decrease the cycle time and improve throughput more fermentors must also be introduced. Fig. 3b shows the equipment occupancy Gantt chart of the main equipment for one month of production for a plant with 6 fermentors (FR-1 to FR-6), 10 conditioning tanks (CT-101 to CT-110) and 2 filtered beer tanks (FBT-1 and FBT-2) operating in stagger mode. In this case, 16 batches (instead of 3) can be started within a month because the minimum cycle time of the process has been reduced to 20.93 h. Rounding the cycle time to 24 h (i.e. start a new batch every day), results in 315 batches per year and an annual throughput of 39,758,000 L of filtered beer. This represents a throughput increase of 750% compared to the base case.

2.4.2. *Cost analysis*

Table 2 displays the material requirements in kg/batch for the improved case. Based on the material demands per batch and the number of batches that can be executed per year, the annual material cost can be estimated to be around $5 million. The assumed purchasing price for barley malt was 0.2$/kg, for corn grits 0.15$/kg and for hops 1.5$/kg. The estimated annual operating cost (including materials, utilities, labor and facility-dependent costs such as depreciation and maintenance), is $24.2 million, which translates to a unit cost of $0.61 per kg of filtered beer. With an assumed selling price of $6 per twelve

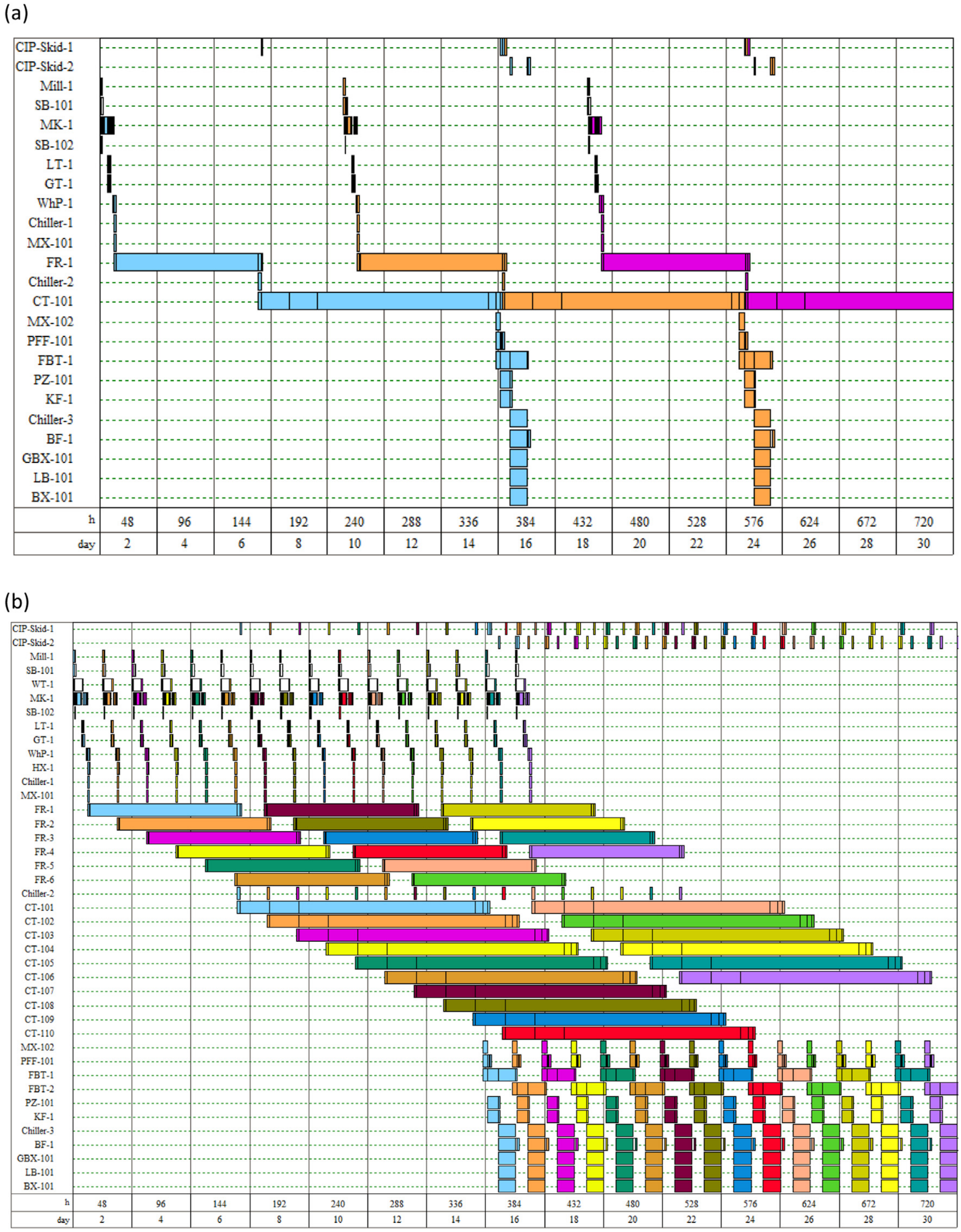

Fig. 3 – The equipment occupancy Gantt chart of the beer making process (a) base case, (b) improved case.

Table 2 – Material requirements per batch for the beer process.

Material	kg/batch
Water	211,828
Barley Malt	12,000
Hops	150
Corn Grits	6000
Brewing Yeast	106
NaOH (2.5% w/w)	20,084
H_3PO_4(0.2 M)	19,971

half-liter-beer-bottle cartons and of $20 per 50 L beer kegs, the total annual revenues are estimated to be around $34.8 million resulting in a gross margin of 30.8%.

Using vendor quotations and empirical cost models, the total equipment cost for a plant of this capacity (39,758,000 L of filtered beer per year) was estimated at around $8.8 million resulting in a total capital investment of around $60.9 million. Based on all above economic results, the process seems to be economically viable with a Return on Investment (ROI) index at 20%, payback time of 5 years and Net Present Value of $21.9 million at 7% interest rate.

This case study demonstrates some of the analyses that can be performed with the help of an integrated process model. At design phase, it can be used to size equipment and help identify the proper number of units and the mode of their use to achieve the desired throughput. In this case, an impressive result is realized by performing throughput and debottlenecking analysis; the plant capacity was increased by a factor of 7.5 with the targeted installation of additional equipment based on the identified bottlenecks. However, this is only part of the story. In reality, brewery facilities typically produce a number of different brands with similar (but not identical) recipes sharing the same resources. Actual manufacturing in the production floor is characterized by unpredictable events (operational delays, breakdowns etc.) which present scheduling challenges and have an impact on plant performance. The following section introduces production planning and scheduling, and then analyzes the same case study using the process model as a necessary component in a digital twin setting.

3. Production planning and scheduling

3.1. *Challenges and opportunities in FPIs*

Production planning and scheduling are activities understood mainly in the context of multi-product/multi-purpose facilities. They can be integrated into the process of designing a new or retrofitting an existing facility and are conceptually linked with activities such as capacity analysis and debottlenecking. The production plan is a ‘wish-list’ of final products and their amounts to be produced in a given period of time (e.g., one or a few months), usually divided in smaller time buckets (e.g., of one week duration each). A production plan is composed based on actual or predicted demand taking into account estimates (however lumped they may be) of plant capacity. On the other hand, scheduling is the task of assigning and reserving specific time slots for specific resources to be engaged in executing the planned production; compared to planning, the time horizon of interest in scheduling is shorter (e.g., a day or a week).

By its nature, scheduling demands a very detailed accounting of both the tasks to be performed as part of the production activities and of the resources that are available with any limitations in their use. Timely “coupling” of tasks with resources is the objective and the outcome of a scheduling activity. To accomplish this task, a model of the production process (the ‘digital twin’ of the actual production floor) must be available and it is imperative that this model to encompass a realistic and accurate representation of the processing tasks to be executed and the available plant resources. This consideration should be enforced even before deciding which method will be used to generate the production schedules.

What makes production planning and scheduling a difficult task especially in the food industry is that it is very case-specific. It is hard to formulate generalized problem representations and apply them to different production scenarios; the constraints under which different FPIs operate are very different and not easy to generalize. As pointed out in Harjunkoski (2016), implementations of scheduling solutions are strongly tailored to the problem at hand and not reusable. Compared to other industrial fields, production in the FPIs is additionally characterized by a series of unique features which translate into big challenges in planning and scheduling. Some of these features are presented in Table 3. The variability in the composition, size and quality of food raw material, the rigidity in executing the production recipes and the limited shelf-life of food raw material and products are responsible for many of these challenges.

Within FPIs, there exist many examples (e.g. dairy industries) where batch and (semi-) continuous processes are mixed and that creates scheduling challenges. The need for regular (usually sequence-dependent) equipment cleanings, setups and changeovers between different batches or campaigns increases down time and reduces capacity. In many cases, the demand is seasonal and the plants need to implement just-in-time manufacturing. The mode of production also introduces difficulties in the scheduling activity. It is quite common for FPIs to adopt a combination of Make-to-Stock (MTS) and Make-to-Order (MTO) mode of operation. On the one hand, the increase in product variability, the unpredictability of demand and the limited shelf-life of food push for an MTO production strategy. On the other hand, resource limitations and the long, costly cleanings and changeovers that a pure MTO strategy would require, make the partial adoption of a MTS strategy also necessary (Soman et al., 2007). The necessary adoption of a hybrid MTS-MTO operation mode makes the management of production even more complicated.

The dynamic and unpredictable nature of production renders the need for flexible and fast adaptation of production plans and schedules equally, if not more, important than the ‘optimality’ of the initially produced schedule. Based on their work on several case studies, Van Wezel et al. (2006) concluded that “the main problem in planning in SME FPI is in adapting plans rather than creating them.” The variability on the duration of many food-related operations (partially related to the complex and variable nature of food materials themselves), rush orders, the limited capacity on auxiliary resources such as CIP/SIP skids, the variability on labor resources availability, equipment break-downs etc. almost guarantee that the schedule will not be executed as planned. It is, therefore, imperative that there is a mechanism in place that will gracefully react to changes, update the production schedule based on the actual execution in the plant floor while respecting the work already in progress. An effective scheduling tool must be flexible enough to allow easy handling of such disruptions in the production. User control through suitable graphical interfaces (such as interactive Gantt charts) enables a more efficient use of any scheduling tool (Harjunkoski, 2016).

3.2. *Proposed solutions for scheduling in FPIs*

In the scientific literature and in industrial practice there exists a multitude of different approaches in treating the scheduling problem in the FPIs. There exist solutions that treat scheduling as part or extension of the functionality of Enterprise Resource Planning (ERP) systems. In this context, the scheduling activities can be supported by a Manufacturing Execution System (MES) (Wauters et al., 2012) or by an APS (Advanced Planning Systems) or APO (Advanced Planner and Optimizer) system in conjunction with an ERP. Irrespectively of whether scheduling is part of an ERP or MES system, it is important that it communicates with them to get information about orders, material inventories, the status of the production execution etc. A scheduling tool is only a part of the overall production support system and effective system integration is a must (Harjunkoski, 2016).

The most popular approach to scheduling in the research literature is to model it and solve it as a mathematical optimization problem. The objective is to find the optimal sizing of batches (“batching decisions”) along with their opti-

Table 3 – Scheduling-related special characteristics of food processing.

Raw material related	- Raw-material-size dependent processing (e.g. fish or fruit size) - Processing times and material balances dependent on variable raw material composition (e.g. water content) - Wastage dependent on raw material quality
Product related	- Inverted Bill of Materials or 'dis-assembly' (single raw material, multiple final products) - Recycling/reuse of expired products (e.g. return of milk) - Product maturation (degrading or increasing in value while stored) - Very large number of final products (e.g. different filling sizes), possibly combining different intermediates (e.g. mixed salads)
Resource related	- Multi-purpose equipment that can be used by different tasks/stages (e.g. same tank for yoghurt fermentation and for holding before filling) - Multi-tasking equipment used for same task but serving different batches (e.g. ovens) - Equipment connectivity (topology) and product specificity constraints - Auxiliary resources (e.g. CIP/SIP skids, transfer panels/manifolds, trolleys) can become bottlenecks - Finite intermediate storage with limited holding time - Storage is frequently done in the same units used for processing - Common tank holding constraints: o No simultaneous depositing and drawing (i.e. first fill, then empty) o No simultaneous multiple deposits or multiple drawings o Holding (for QC) before making material available - Most food facilities do not work on a 24/7 basis so outages are common - Labor availability not even throughout the day
Processing related	- Blend of continuous and batch processes - Automation varies from highly automated to manual operation (e.g. sorting of vegetables or fruits) - Process durations are product, equipment and, sometimes, labor dependent (i.e. tasks whose duration depends on how many people are involved in carrying them out) - Material transfers are not (or cannot be modeled as) instantaneous. Two equipment units (the source unit and the receiving unit) are engaged in every transfer - Limited flexibility in the execution of a recipe, (e.g. no-wait policy) - Limited capability to interrupt a process and resume later on - Sequence-dependent cleanings and changeovers
Production Management	- Capacity utilization may vary based on availability of raw material resources (milk, tomato etc.) - Frequent arrival of rush orders - Inventory-driven processing (i.e. process whatever amount of intermediate becomes available) - Scheduling driven by labor availability

mal sequencing, timing of their tasks and the allocation of resources ("scheduling decisions"). If batching decisions are treated first and separately from scheduling decisions which are tackled at a second stage, then the approach is called sequential (Novara et al., 2016). Floudas and Lin (2004) and Méndez et al. (2006) (among others) present extensive reviews of the state of the art in short-term scheduling of chemical processes. Harjunkoski et al. (2014) provide a very extensive review of all possible formulations and solution of production scheduling as an optimization problem in the process industries. Harjunkoski (2016) presents a thorough, multi-faceted analysis of all challenges in deploying production scheduling solutions in industrial settings.

Research papers addressing optimal planning and scheduling issues within the realm of food industry applications have appeared mainly over the last two decades with dairy and yoghurt production, in particular, being, by far, the most commonly referenced industry. Lütke Entrup et al. (2005) developed different optimization formulations for weekly production planning of a yoghurt facility while also integrating shelf-life limitations. Doganis and Sarimveis (2007) implemented an optimal scheduling formulation in a yoghurt production line while addressing the special features of yoghurt production such as limitations in sequencing due to different fat contents and flavors. Marinelli et al. (2007) devised a two stage optimization heuristic to decouple the batching from the scheduling problem for a yoghurt producing packaging company. Amorim et al. (2011) formulated lot-sizing and scheduling as multi-objective optimization problems to address the complexities of production systems of perishable foods and the required trade-offs that a decision maker must resolve. Gellert et al. (2011) proposed a formulation addressing the problem of integrated sequencing and scheduling of filling lines in diary industry. Kopanos et al. (2011) addressed the resource-constrained planning problem for yoghurt production with emphasis on resource sharing among the packing lines. Kopanos et al. (2012) presented mathematical formulations for detailed production scheduling tailored for the food industries and implement them in an ice-cream producing facility that was introduced as a benchmark scheduling problem by Bongers and Bakker (2006). The same benchmark problem was addressed by Wari and Zhu (2016) within the context of a multi-week scheduling horizon. Sel et al. (2015) considered the integrated planning and scheduling problem in a set yoghurt production facility by using a multi-bucket time decomposition heuristic to improve computational efficiency. Claassen et al. (2016) introduced a formulation that takes into account sequence-dependent set-ups and product decay in food processing facilities. Niaki et al. (2017) addressed the integrated lot sizing and scheduling problem in a batch production plant and implement their formulation in a dairy plant. Escobet et al. (2019) used a combined optimization and constraint programming approach for optimal scheduling of a batch powder milk/yoghurt process. Angizeh et al. (2020) implemented an optimization technique for optimizing the operation of multiple production lines in a multi-product food production facility. Georgiadis et al. (2020) addressed the optimal weekly production scheduling of a fish canning facility. Lee and Maravelias (2020) managed to combine modeling flexibility with computational efficiency using a discrete and continuous-time model formulation and implemented it in a real-world brewing process.

In the literature, it is also possible to find mathematical optimization approaches that propose plant design modifications motivated by the needs of scheduling. These modifications can be either in the form of reconfigurations in equipment assignments for equipment-sharing process tasks (as in Basán et al., 2020), in the form of small cost investments to increase productivity (as in Kopanos et al., 2010) or as formulations that completely integrate process design and scheduling (as, for example, demonstrated in Vieira et al., 2020 as a way to handle demand uncertainty). There exist also approaches that integrate the scheduling and control problems (as in Dias and Ierapetritou, 2020).

A common criticism of optimization-based methods is that they require mathematically sophisticated users for the formulation of the problem. In addition, the ability of current solvers to handle real-world problems may still be limited. This means that even more sophisticated skills are required by the user of such tools to be able to apply custom tailoring of the solution process to make the problem computationally tractable. The strong tailoring of the proposed solution to the problem at hand and the non-reusability of the derived solutions mentioned earlier are even stronger in optimization-based methods. Sometimes, in order to make the scheduling problem mathematically tractable, the model representation may be deduced to an approximated rather than an actual depiction of the production reality. For example, applying mathematically tractable linear representations (as in mixed-integer linear programming) may result in loss in representation accuracy (Harjunkoski, 2016). Akkerman and van Donk (2009) refer to scheduling research as of m̈yopic naturec̈laiming that it deals only with simplified or partial situations in comparison to the actual problems. An automated scheduling tool must also be able to handle uncertainty effectively, flexible enough to handle production disruptions and allow manual modifications and robust enough to always produce a feasible solution even if the optimization algorithm fails to find the optimum (Harjunkoski, 2016). All these hurdles should be overcome before optimization-based approaches can gain extensive acceptance in real-world scheduling in the process industries.

In order to efficiently play the role of a digital twin of the physical system (production plant), a scheduling model must adopt a high-level representation of the processing tasks and resources as understood in the production floor. This is important in order to ensure effective two-way communication between the twins (deployment of schedule to the production floor and uploading of the true production status to the scheduling model for updating) irrespectively of whether this communication is done manually or automatically (through standards like the ANSI/ISA-95 as proposed in Harjunkoski, 2016). A recipe-based representation, as presented earlier in the context of process simulation, is a suitable basis for creating and deploying scheduling solutions and could bridge the gap between batch process simulators and mathematical optimization scheduling tools.

In a recipe-based representation, the production process is captured by a recipe which describes a series of steps, the resources they require, and their relative timing and precedence. The recipe, by construction, encompasses all constraints present in actual production. This feature can be exploited in the schedule generation process. In mathematical optimization formulations processing tasks are treated as independently floating (in time) activities and then constraints are utilized to enforce the process "reality" (e.g. declare through a constraint that the end of one task must coincide with the start of a subsequent task). However, unlike discrete manufacturing industries, the execution of recipes in the process industry, and FPIs in particular, is by its nature very constrained; processing tasks must be executed in a particular order with no or limited delay between the processing steps. So, instead of representing the process with the outmost flexibility and then use constraints to tighten up its execution, it may be more efficient to start with a rigid recipe representation and then add flexibilities (where applicable) which could be used in the scheduling generation phase to overcome potential conflicts. A recipe-based representation may enforce rigidity in the execution of individual batches and thus, leave not much room for optimization when scheduling a single batch, but other scheduling decisions could benefit from an optimization-based approach. Optimization methods could still be used to optimally resolve conflicts among batches or solve the batching problem (number and size of batches) or the product sequencing problem in multi-product facilities.

3.3. Scheduling tools in FPI

In theory, there is a great variety of tools to be used for scheduling in the food process industries; in reality, only a few of those are actually implemented in practice. Spreadsheet tools are by far the most commonly used tools in practice; coloring spreadsheet cells is the preferred routine in creating a schedule in the form of a Gantt chart. This, however, is a very tedious and time-consuming task and, in addition, it is almost impossible to readily update the schedule without replicating the entire effort. Yet, it is currently the most commonly used approach due to the general availability of spreadsheet tools and the limited availability of suitable scheduling tools.

Discrete Event Simulation (DES) is a popular technique for modeling of multiproduct batch plants. With DES, a series of dispatch rules govern which tasks may begin or end depending on the state and time. An advantage of DES is the ability to perform stochastic modeling by accounting for the uncertainty and variability of certain input parameters. However, dispatch rules and state calculations must often be custom-coded. In addition, DES tools are not convenient to use for scheduling on a day-to-day basis because the user cannot easily update the model to account for actual plant events and delays. Established DES tools include ProModel from ProModel Corporation (Orem, UT), Arena and Witness from Rockwell Automation (Milwaukee, WI), and Simio from Simio LLC (Sewickley, PA).

Mathematical optimization tools use optimization methods to generate the best feasible solution within the constraints set by the user. Such tools have been successfully used in industry for supply chain optimization and strategic planning for processes that can be modeled by simplified recipes. However, as mentioned earlier, generating optimal solutions for problems that utilize detailed recipes with many constraints could be quite challenging. Established mathematical optimization tools with production planning and scheduling capabilities include SAP APO from SAP AG (Walldorf, Germany), IBM ILOG Plant PowerOps from IBM Corporation (Armonk, NY, USA), Aspen Plant Scheduler from Aspen Technology (Burlington, MA, USA), etc.

With respect to recipe-based scheduling tools, a number of them are available on the market, such as Opcenter APS (formerly known as "Preactor APS") from Siemens AG (Munich, Germany) and Access Orchestrate from The Access Group (Colchester, UK). However, these scheduling tools mainly target applications in the discrete manufacturing industries (assembly-type of production). SchedulePro from Intelligen (Scotch Plains, NJ, USA) is a recipe-based finite-capacity scheduling tool for batch chemical and biochemical manufacturing and, therefore, closer to food processing.

3.4. Developing a production system model

A recipe-based model of the production process can play the role of a digital twin of the actual plant encompassing all entities needed in planning, executing, and monitoring production. The production model should include accurate representations of all available resources (equipment, utilities, labor etc.) with any constraints on their capacity and limitations in their use, of the recipes involved in various products with all the processing steps, timing information and candidate resources to be used, and, finally of the production campaigns to be executed with target amounts for each product.

The recipe representation can have the same hierarchical structure as discussed in the process simulation context. The difference here is that a recipe in a scheduling context need not include operational details not related to timing and resource utilization. Even though the recipe is the 'mold' through which all production batches will be generated, its representation should also allow the declaration of any processing flexibilities available during actual execution. Example of such flexibilities are the declaration of pools of candidate equipment units for the execution of a task, the use of flexible time shifts in the start of certain operations (i.e. an operation can have a delayed start up to a maximum time delay), the ability to interrupt an operation and resume it at a later point etc. At scheduling time, these flexibilities can be used, when needed, to overcome conflicts caused by the non-availability of resources (e.g. occupancy by competing tasks, downtimes) necessary to execute a task.

The role of the human scheduler is, therefore, to use the digital model to generate a feasible and, to the extent possible, optimal schedule that can be deployed to the plant floor (physical twin). The generated schedule should satisfy all processing constraints declared in the model and, at the same time, exploit all declared flexibilities to resolve conflicts. The schedule should then be commissioned to the plant. Rarely, however, will the actual execution match the planned production; in this case, an important aspect of the digital twin formulation is for actual execution data from the plant to be forwarded back to the digital model so that the latter can update the proposed plan of future activities based on the knowledge of how things are progressing in the plant. This interplay between the physical and the digital model is shown in Fig. 4. This communication could be automated (through an MES or process automation system) in which case, according to the categorization proposed in Kritzinger et al. (2018) the integrated system can be called a Digital Twin (or a Digital Shadow if only the plant data are fed automatically). Alternatively, both communication channels could be accomplished with manual entries, in which case, the term Digital Model is more appropriate. In either case, what is essential is that the production schedule gets updated in a fast and efficient way based on the actual data (this many times may involve manual modifications by the expert) and this adaptation is even more important than the optimality of the initially generated schedule. An optimal schedule based on wrong data

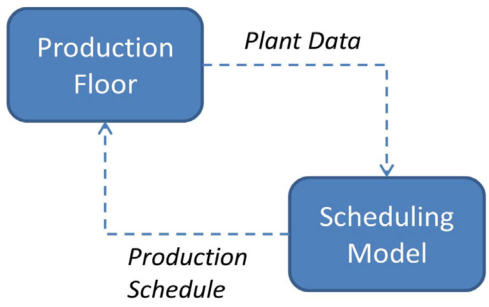

Fig. 4 – Data exchange between the scheduling tool and the production floor.

Table 4 – Scheduling differences among the beer recipes.

Beer Type	Fermentation Time (days)	Aging time (days)
AA	6	15
BB	8	10
CC	7	10
DD	5	20
EE	5	20

may not even be feasible when applied to the production floor.

3.5. *Production scheduling case-study*

To demonstrate the process of generating a production model, developing production schedules and adapting them based on plant data, the beer process presented earlier and the same recipe-based model will be used. In this case, however, a plant-centric modeling approach will be employed; rather than focusing the analysis on a single recipe (as was the case for the simulation model), the focus is shifted to modeling a multi-product plant using common resources to execute multiple (similar) recipes corresponding to different beer products. The production recipes utilized are, therefore, simplified versions of the simulation model stripped by any information not relevant (e.g. operating conditions) in the context of planning and scheduling. The demonstrated production model was developed in SchedulePro v9.1.

The plant is assumed to produce five different types of beer (named AA to EE) following the same process steps. In other words, it is a multi-purpose plant or a flow-shop as defined in the operations management literature operating in a MTS mode. The plant has 8 fermentors and 18 beer aging tanks. Even though the production stages are the same, the various product recipes differ in the raw materials used and the fermentation and aging (conditioning) times. Table 4 shows the recipe differences from a scheduling point of view for the different beer products. There are also connectivity constraints on how auxiliary equipment (e.g. transfer lines) can be matched to main equipment. Production is planned on a monthly basis with all five types of beer being produced within every month based on their expected demand.

A production run is represented as a prioritized set of campaigns each containing a defined set of batches of the same product. Batches are scheduled in sequence and assigned to resources in priority order. The scheduling algorithm generates feasible solutions that do not violate constraints related to the limited availability of resources. Partial optimization could be used to solve localized problems. Obviously, with this approach global optimality of the derived solution cannot be guaranteed. However, the representation of the actual problem can be much richer and much closer to reality without the concern that adding more complexity into the representation may render the problem intractable.

Fig. 5 shows a typical production schedule (for one month of new brews) developed in SchedulePro. To generate this schedule, SchedulePro was provided with an ordered set of campaigns (16 in total, recognized in the chart by different colors) each consisting of a user-specified number of batches for one of the 5 beer products. In other words, the batching decisions have been made a priori by the human scheduler based on the expected product demand. The same release date was set for all campaigns. While respecting campaign execution priorities, the scheduling algorithm of SchedulePro identified proper start times (after the release date) for each batch and allocated the earliest available resources in an attempt to reduce the makespan without generating resource utilization conflicts. Each batch was instantiated as an exact replica of its master recipe and then the conflict resolution mechanism was applied to resolve any conflicts. As indicated earlier, the scheduler applies a ̈local ̈(one conflict at a time) 3-tier conflict resolution mechanism: first, resource reallocation is attempted, then, operational flexibilities (if any) defined at the recipe level are used to shift or break individual operations and, finally, if none of the above works, the entire batch is moved forward in time. Conflicts that could be resolved in this way include: overlaps in equipment use, operating over outages/downtimes, exceeding the availability rate of utilities, depletion of inventories etc. In other words, it is a scheduling strategy that may not guarantee optimality but can be applied to a variety of constraints emanating from the process or the facility and is able to produce feasible and acceptable schedules that could, then, be further improved interactively by the user.

In this case study, conflicts mainly arise from the antagonism of the product campaigns on the utilization of common resources. This antagonism is more apparent in the use of fermentors (FR-1 to FR-8) which, as seen in Fig. 5, are the bottlenecks; they determine the pace at which campaigns and batches are laid out in time. Any delay in the completion of the fermentation process in any batch could render infeasible the execution of all future activities as planned and would signal the need for a schedule update.

A process schedule should be considered as a dynamically evolving entity. The concept of the ̈current time ̈is important in separating the production tasks that have already been executed and completed in the past (and, therefore, can no longer be changed), from the tasks currently executed (whose start is fixed in time but duration is still uncertain) and from future tasks which can still be re-planned. Past and current tasks can only be updated with actual data from their execution in the plant floor. If different from the planned, this information can be used to reschedule future activities. In the case of SchedulePro, an auxiliary utility called WebTracker (www.intelligen.com) can be used to enter through a web browser actual execution data and transfer them through an SQL Server database to the scheduling tool.

To demonstrate this dynamic process, let us assume that at some time point there exist unexpected deviations from the schedule as originally laid out. More specifically, Fig. 6 shows the status of the original schedule if towards the end of fermentation of batch CC-1-1 it is realized that fermentation will need another 2 days to complete and also that Aging-Tank-7 will soon be decommissioned for 3 days due to

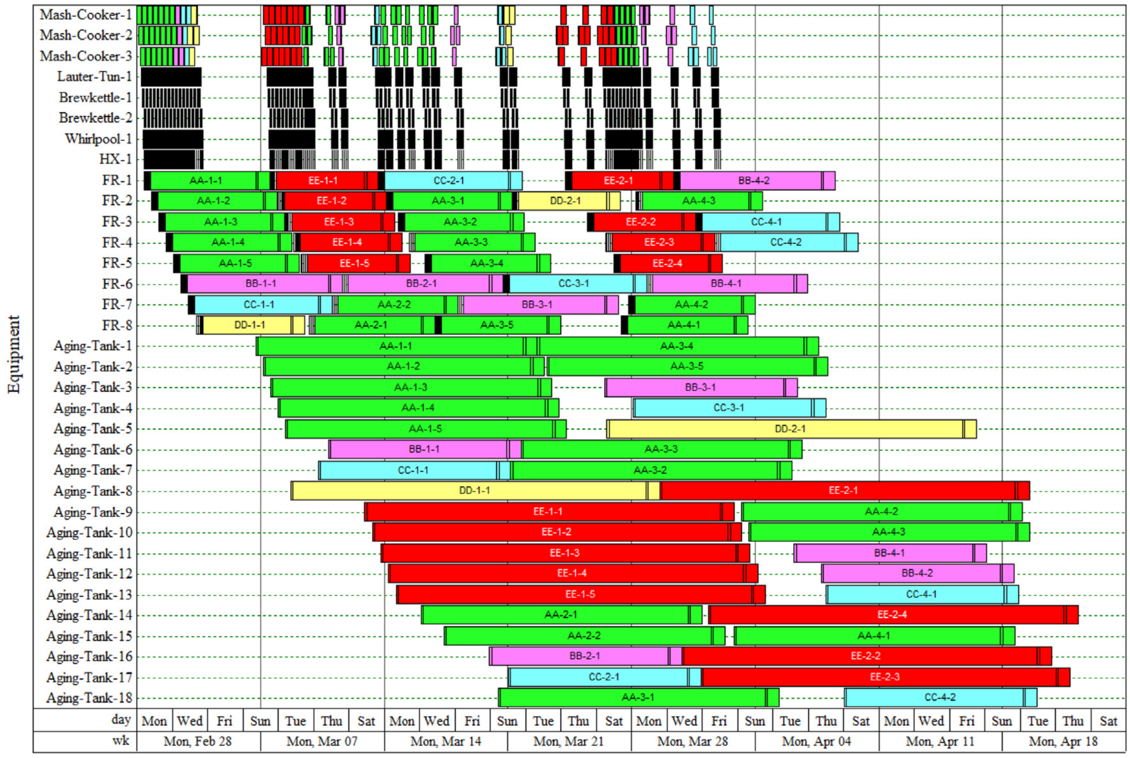

Fig. 5 – Monthly production schedule of the beer plant.

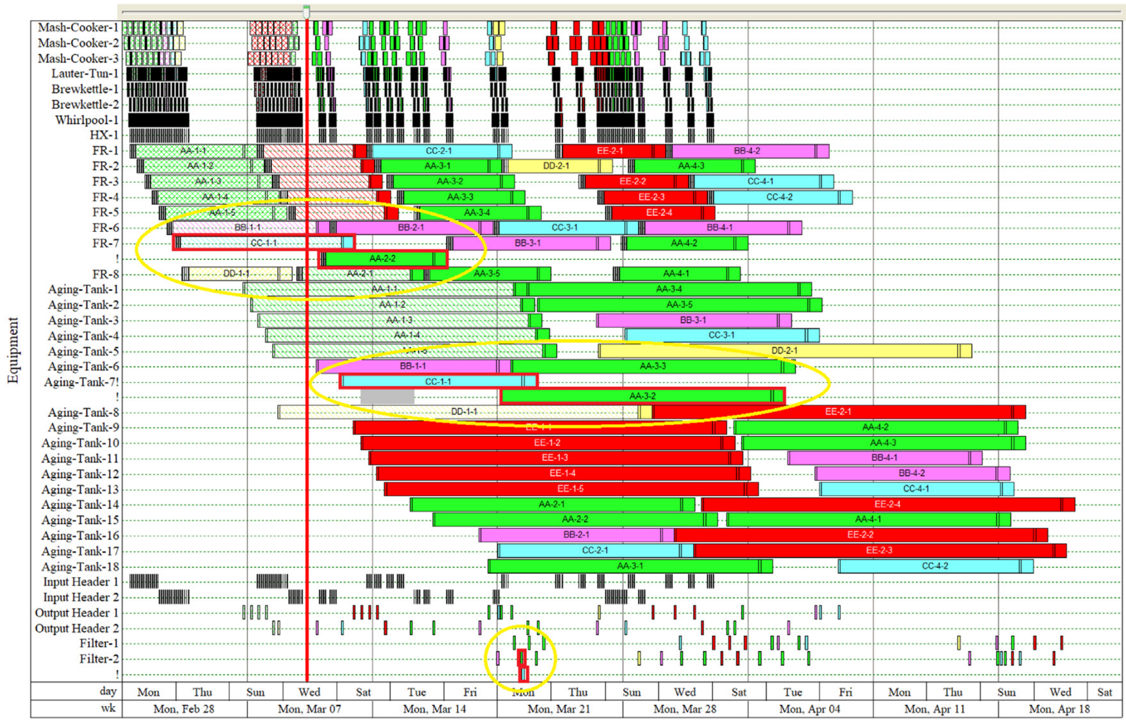

Fig. 6 – Original production schedule after introducing a delay in fermentation for batch CC-1-1 and a downtime for Aging Tank 7.

emergency maintenance. The current time when this information is communicated from the plant floor (physical twin) to the production model is indicated in Fig. 6 by the red vertical line. The introduction of the fermentation delay and the tank downtime is causing a conflict in the execution of batch AA-2-2 which was planned to use the same fermentor (FR-7) and also a conflict in batches CC-1-1 and AA-3-2 which were originally planned to use the Aging-Tank-7. Graphically, these conflicts are shown with a red border around the conflicting activities and the introduction of an extra line in the Gantt chart for the corresponding conflicting resources so that the conflict becomes apparent.

At that point, the planner must react by updating the schedule restoring its feasibility. For better version controlling of the plan, this process should be initiated by the planner; the actual plan updating, however, could be done either by the planner manually or automatically by the scheduling software (as is the case here). Fig. 7 shows an updated schedule after the

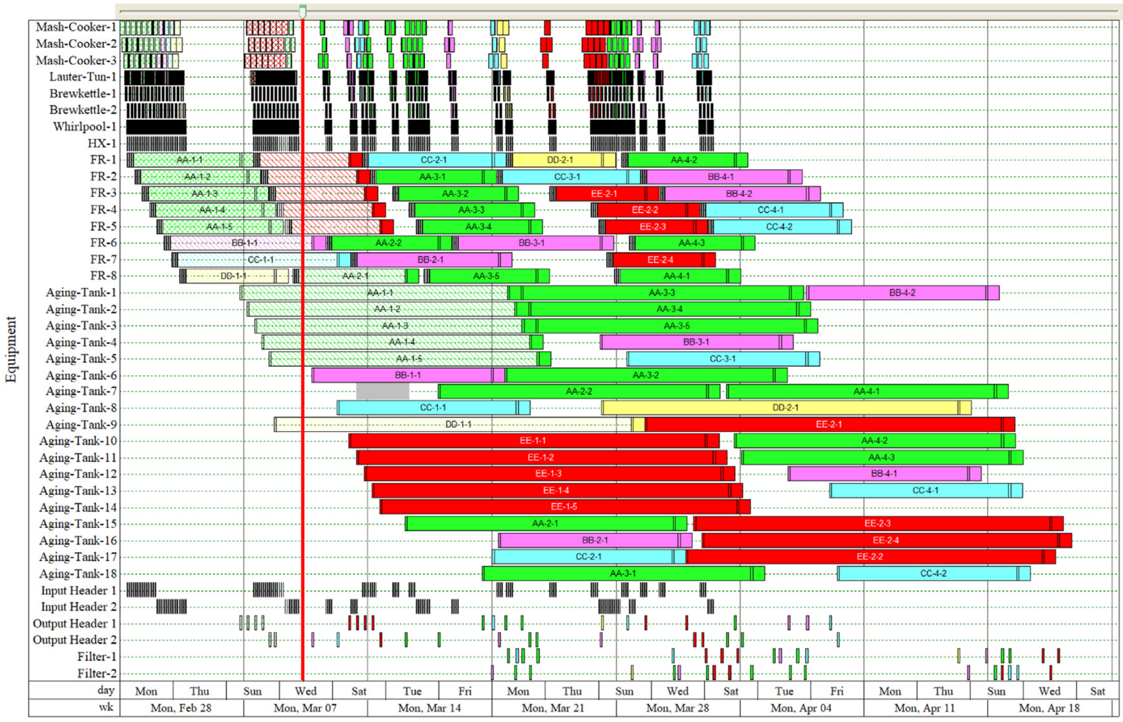

Fig. 7 – Updated monthly production schedule after resolving conflicts introduced by the delay in fermentation for batch CC-1-1 and a downtime for Aging-Tank-7.

above conflicts are resolved. In order to avoid any delay in its execution batch AA-2-2 is now moved to FR-6 which becomes available earlier than the originally assigned FR-7. To avoid the downtime of Aging-Tank-7, the aging step for batch CC-1-1 is moved to Aging-Tank-8 creating a limited cascade of reassignments of aging tanks allocated for future batches. However, the updating is done in a way that absorbs some of the delays introduced by the 2-day prolongation of the fermentation time and the 3-day downtime of the aging tank. Indeed, the overall delay in the make span is around 10 h since the make span of the original schedule was 53.3 days and the make span of the updated schedule is 53.7 days.

During the planning or updating phase, it is also important to be able to follow the assignment of all resources other than equipment. Fig. 8 shows the labor utilization chart for six weeks of production based on the updated schedule. In the chart, the red line indicates the instantaneous labor demand (how many people needed at every instant to run production), the blue line shows the average demand over a day and the green line shows the cumulative demand over a period of a week. Changes in the production schedule should immediately be reflected on the utilization of any resource and any constraints on the availability of that resource should be taken into account when checking the feasibility of the plan. In all cases, following the planned utilization of all resources through charts or reports is important in order to efficiently plan for their availability during production execution or for costing purposes.

3.5.1. *Handling of uncertainty*

Real-time scheduling can afford to implement a deterministic approach provided that there is a reactive scheme in place to respond in real time to any deviations from the nominal execution. In short-term scheduling, the most successful approach in handling uncertainty is via rescheduling or control actions (Harjunkoski, 2016). Uncertainty, as a probabilistic entity, manifests itself best in long time horizons. Therefore, in the context of long-term planning or capacity analysis, the effects of variability should be taken into account in order to reliably assess whether the production goals can be achieved. This information can, in turn, be used to make realistic production plans and/or make appropriate decisions on plant capacity changes.

In general, the probability distribution of the duration of different operations in any plant can be easily estimated by examining historical data of the process. In this case study, the duration of the fermentation is surely an uncertain variable. To illustrate the process of executing an uncertainty analysis, it will be assumed (purely for demonstration purposes) that the fermentation duration has a triangular probability distribution with its minimum and maximum value being ±2 days around the nominal. This applies to all five products that have different fermentation durations.

A Monte-Carlo-type simulation was run on the five uncertain variables and the production make span for the 16 campaigns was recorded in every run. Fig. 9 shows the result of this analysis; it shows the probability by which a certain value of the total make span is expected to be achieved. The nominal value of the make span is 53.3 days; however, as Fig. 9 shows, due to uncertainty in the fermentation times, the make span can go up to 57.1 days with a median value of 54.6 days. The minimum value (52.7 days) is close to the nominal, so, it is obvious that uncertainty skews the results to higher make span values which correspond to decreased plant throughput.

If a desired make span is set, then the probability of achieving it can be estimated. Inversely, if one sets a desired certainty, the make span value that can satisfy this certainty value can be calculated. In this case study, the make span will be less than 56 days with a certainty of 97%. If the desired make span is 55 days or less, then the probability of achieving it is considerably shorter, i.e. 70%. In general, these analyses build confidence on the ability of a production system to achieve specific production goals in the face of uncertainty.

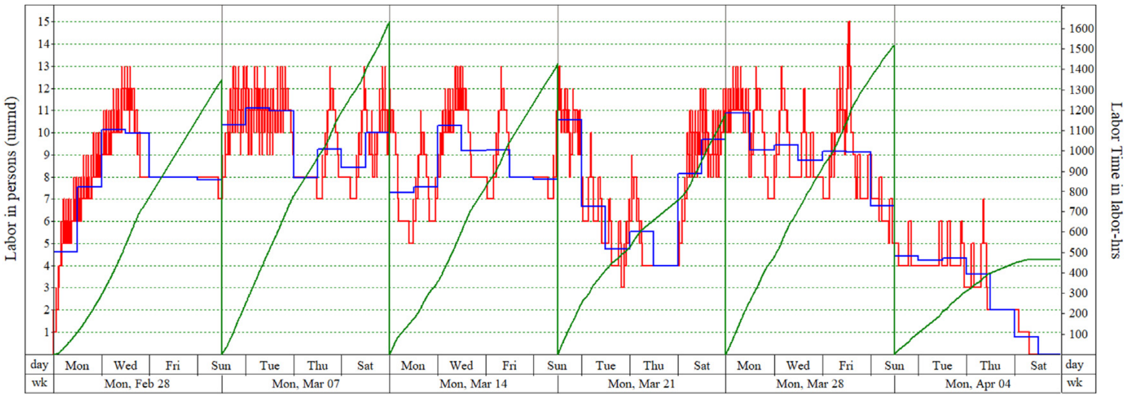

Fig. 8 – Labor utilization chart during the execution of the monthly schedule.

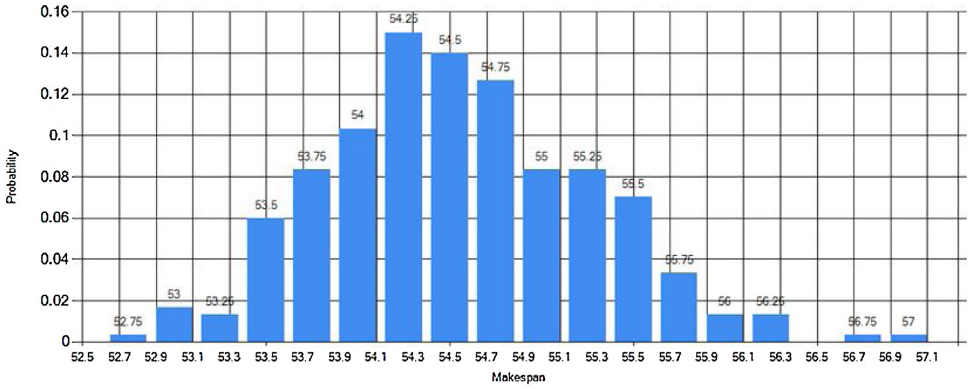

Fig. 9 – The results of the Monte-Carlo simulation for the production make span.

4. Conclusions

In this paper, the challenges, methodologies and opportunities of implementing a digital twin approach in food processing were presented in the context of process simulation and production scheduling. It is argued that in order to reap the benefits of digital modeling, it is important to create realistic and accurate, to the extent required by their role, representations of the production processes; this is especially true in scheduling where the generated solutions must respect all constraints as they exist in the real plants with no sacrifices on representational accuracy.

Food processes are rigid structures with only a few flexibilities in their execution. Food plants are multi-product facilities using similar recipes to produce a variety of products in multiple repeating campaigns. Therefore, a recipe-based approach was proposed as the most suitable method for developing models and representing the production process. In a recipe-based approach, the production process is composed of interconnected steps (procedures) which contain the actual operations that consume the resources required for production. Such a representation can be used to readily transfer lab-scale recipes to industrial production in the context of process design, perform capacity, economic and environmental impact analyses, retrofit and debottleneck existing processes.

In the context of scheduling, a recipe-based representation of the production tasks coupled with an accurate accounting of the available resources and limitations in their use can be used to generate (at minimum) feasible production schedules. Opportunities for optimization, whether global or local in the decision process, should be exploited to deliver, to the extent possible, optimal solutions. What is more important, however, is that the scheduling tool is robust (always produces feasible solutions), is interactive (to allow modifications by the human scheduler) and is readily amenable to update its solution by incorporating real-time information coming from the plant. In this case, communication between the physical and the digital twin is deemed necessary in order to achieve efficient production. In the context of long-term planning, a digital model can also be used to perform capacity analysis while, at the same time, taking into account the effects of process variabilities in order to estimate the certainty by which production goals can be achieved, rationalize the production plans or initiate capacity changes.

FPIs are in many respects unique in the world of process industries because of their special characteristics stemming from the complexity and variability of the raw materials used, the rigidity in processing and the limited shelf-life of both food raw material and products. However, they can still benefit considerably from the advancements in digitization to achieve efficient, flexible and profitable manufacturing.

Conflict of interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

The co-authors Nikiforos Misailidis and Demetri Petrides are affiliated with Intelligen Inc. whose software products (SuperPro Designer and SchedulePro) were used to conduct the case study presented in the paper.

Declaration of Competing Interest

The authors report no declarations of interest.

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