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Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process: A dairy case study

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ABSTRACT

The activity of scheduling the production plan with the aim of achieving an optimal criterion has been explored in literature for several manufacturing sectors, in particular when it comes to solving scheduling NP-complete problems. In Dairy Manufacturing, determining an optimum criterion for the scheduling process has numerous internal and external challenges due to the complexity of this environment.

The initial stages in the Dairy process are characterised by a continuous manufacturing environment and specific operational issues are observable: interruptions for the accomplishment of Cleaning-In-Place (CIP); a short raw material lifespan which demands a fast processing rate; and the stochastic raw material supply variation. By highlighting these three aspects, a critical trade-off emerges: CIP cycle-times heavily reduce the processing capacity, whereas the raw material processed requires an increase in available capacity due to the impact of seasonality, perishability and stochastic deliveries. Therefore, the scheduling plan must be dynamically readapted based on the current inventory, volume and frequency supplied, CIP cycle-times, maximum equipment running hours and downstream capacities.

The aim of this research is to develop an integrated approach for generating equipment schedules under supply uncertainty typically observed in the dairy sector where criteria of sustainability are effortlessly incorporated for an improved decision-making process. An efficient Multi-objective Algorithm (MOA) combining conflicting key performance metrics such as minimising Work-In-Process (WIP), maximising Service Level Agreement (SLA), Utilisation and Energy consumption is proposed.

The novelty consists of the ability to dynamically select trade-off criteria and visualise the optimum production plan according to the conditions defined by the decision-maker. The appropriate schedules are presented in a Pareto Frontier graph highlighting the entire non-dominance region according to the volume and frequency supplied. Even though sustainability metrics are usually ignored during production plan definitions, namely when a weak correlation between both environmental and profitable criteria is identified, the results demonstrate improved performance when both sustainable approaches are well explored.

1. Introduction

Balancing supply and demand are the main objectives sought in several sectors managed at three levels of decisions: Strategic, Tactical and Operational. At the operational level, the production plans are developed to achieve improved utilisation of resources and also comply with tactical/strategic decisions previously defined [1].

Just-in-Time (JIT) philosophy emphasises a stable manufacturing process involving all the three decision levels where the supply and demand are successfully balanced and the raw material is systematically supplied according to the planned demand [2]. According to [3] pull systems follow the main three mechanisms: (i) controlling raw material triggered by current demand, (ii) authorising releases based on Work-In-Process (WIP), and (iii) responding to known demand.

Despite the effort in balancing supply and demand in the dairy sector, several challenges were identified when compared to other industrial manufacturing processes regarding scheduling.

One of the first challenges, from the perspective of planning, is the presence of stochastic events on the supply-side as a consequence of the

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closeness to natural resources and the inability to store the raw material for an extended period. Even though the supply is planned between manufacturers and farmers, a level of variability is observed throughout the day. The schedule plan changes according to the level of supply, and this condition is aggravated by the short raw material lifespan where the decision-makers have a limited window to reschedule the previous production plan due to unforeseen events.

The second challenge concerns the capacity of the separation stage, which is heavily impacted by the fouling effect. The fouling effect is a critical issue for dairy equipment requiring constant Cleaning-In-Place (CIP) cycles and must be considered in the overall production plan and performance assessment. The time to complete the cycle varies according to the equipment [4–6]. Due to the constant interruptions for cleaning, this process requires parallel pieces of equipment to maintain an efficient processing flow. In addition, the reliability of the downstream processes also increases the variability in the system.

The scheduling plan activity must comply with governmental regulations, tactical directions and a variety of restrictions at the operational level; therefore, by incorporating additional criteria such as environmental metrics, the complexity in determining an optimum schedule is amplified.

Despite the outnumbered initiatives observed, metrics of sustainability are usually ignored during production plan definitions, particularly when a weak correlation between both environmental and profitable criteria is identified. In addition, the daily production process not only requires engagement from manufacturers in incorporating sustainable measures in the decision-making process but also appropriate data-driven tools to support decision-makers.

In order to address the main challenges identified in defining efficient scheduling plans for dairy manufacturing, a novel Multi-Objective Algorithm (MOA) to support decision-makers is proposed. The main objective of the Recommended Cleaning Scheduling (RCS) algorithm is to optimise the separation process according to the trade-offs defined by an optimal set of suggested schedules. Conflicting performance metrics such as minimising the level of WIP, maximising Service Level Agreement (SLA) and combining Energy Consumption are explored.

The main benefit of the proposed RCS is to fill the knowledge gap by optimising the key performance metrics in the production plan given the number of external and internal factors identified in the dairy sector. Stochastic events such as supply volume and frequency are aligned with internal factors such as maximum running hours, minimum CIP hours, equipment set, CIP star-time cycle, and the restrictions caused by downstream variabilities. In addition, by reducing the effect of external factors caused by the supply variability on the process flow, improved performance regarding sustainability is achieved according to the recommended scheduling plan.

The algorithm was developed in RStudio and the main advantage of choosing RStudio as a platform for development is the ability to support large vector operations rather than accessing individual elements in a loop structure. This process is called *vectorisation* where a Single Instruction is applied to Multiple Data (SIMD) [7]. The population is created according to the search space based on the parameters defined by the user rather than probabilistic approaches in order to guarantee a complete set of possible conditions. The performance results demonstrated an efficient method to recommend distinct scheduling plans according to the defined optimal criteria with reduced processing time.

The resulting optimum schedules are presented in a Pareto Frontier graph highlighting the entire non-dominance region where it is possible to observe the best suggested RCS to be selected by the decision-maker according to the external and internal factors.

The remainder of this paper is organised as follows. Previous research in scheduling problems applied to the dairy environment and extended to other sectors is explored in Section 2, providing valuable insight into understanding the current solutions and their applicability to real case studies. Section 3 provides the main issues to be addressed in developing a schedule recommendation tool for dairy manufacturing at the separation stage. The model formulation proposed is described in Section 4, where the decision variables, restrictions, and objective functions are defined.

In Section 5, the search space and algorithm performance efficiency are evaluated by simulating several schedules. Section 6 presents the results comparing thirty days of supply and the best schedule recommended according to the criteria selected. Section 7 concludes the paper and provides directions for future research.

2. Background

Production Planning is essential to efficiently transform resources and raw material into finished products in order to meet customer demand. Much research has been focused on planning and scheduling where a broad application of distinct algorithms for production sequencing problems such as those examined in the literature.

Scheduling problems were originally classified in a three-field notation $\alpha|\beta|\gamma$ by [8]. The first parameter α defines the Machine Environment which refers to single or parallel processing, for example. The second parameter β refers to the Job Characteristics where preemption and precedence are defined. The last parameter γ defines the Optimality criteria which usually involves minimising or maximising objectives.

In optimisation problems, a quantitative objective criterion is defined and the best solution is calculated satisfying all problem constraints [9]. Specific problems are referred to as NP “hard” when the computational effort and complexity is unknown. In job shop and multiprocessor, scheduling activities are referred to as NP-Complete problems [10], for example.

Current research regarding current algorithms was studied and the effort to effectively find a unique optimal solution is being replaced by heuristic and meta-heuristic algorithms to deal with an optimised set of solutions. Algorithms such as Simulated Annealing, Threshold Acceptance, Tabu Search and Branch-and-Bound are widely applied to different NP scheduling problems, as found in [11]. Evolutionary Algorithms (EA) or Differential Evolution have increased in popularity and have also been proven by [12] to be more efficient than Simulated Annealing.

EA, for example, consists of setting initial values known as a population and according to the crossover and mutation rate, new chromosomes are generated and compared to an optimal criterion. The dominant set of chromosomes is promoted as a new population, and this process is repeated throughout a specific criterion. In a multi-objective optimisation problem, a set of non-dominated trade-off solutions is presented instead of a single optimal solution as found in [13]. A heuristic two-phase approach based on the Adaptive Genetic Algorithm (AGA) was developed to address an NP-hard problem in [14]. The main differences between EA and AGA are: (i) the optimisation of an initial population, which can enhance the efficiency and accuracy of the algorithm and (ii) the adjustment of crossover and mutation rates.

Even though EA is commonly considered in optimising multi-response problems, the following drawback was identified during the modelling phase of the dairy scheduling plan: (i) The initial schedule or initial population considers all equipment available and the number of pieces of equipment in each interaction is then reduced. According to the initial population combined with the variability in the supply deliveries, the time required to find the optimal set increases dramatically. Furthermore, (ii) the evaluation is performed according to a predefined criterion; thus, an initial objective function must be defined in anticipation to suggest the best schedule. (iii) Probabilistic or learning rate are then applied in the Mutation phase and influences the optimum result. (iv) After providing the non-dominant scheduling plans, it was identified that the objective function (minimising WIP and maximising SLA) was achieved; however, vital requirements for dairy manufacturing such as maximum running hours and minimum time needed to perform CIP were violated.

Mixed-Integer Programming (MIP) models are also widely applied for single and multi-stage planning problems to solve constraints and to achieve an optimum criterion in several manufacturing sectors. Examples of MIP applications focused on optimising dairy scheduling processes were found in [15] where an MIP was modelled to find a feasible schedule for a dairy product considering the intermediate and final stages in the production flow. Even though the model addressed issues such as short shelf-life and changeover due to the cleaning process given initial insights to this research, the solution proposed concentrates on evaluating the cost of producing a specific product and the seasonality identified in the raw material supply was not explored. A similar approach considering costs and the best production sequence was also proposed by [16] in a discrete-time scheduling lot-sizing for a dairy company where the third party packaging for finished goods storage activities were also incorporated.

The impact of the seasonality was explored by [17], however, the research is concentrated on seasonal costs of raw milk supply rather than planning the raw material received and the influence on the manufacturing environment. Multi-objective criteria were explored in [18] though techniques have traditionally concentrated on dairy fresh end-products production and distribution planning.

Optimisation and scheduling problems are also a subject for computer processing in simulation models [19], large data analysis [20], flexible manufacturing systems for Small and Medium-Sized Enterprises (SMEs) [21], and the Nurse Scheduling Problem (NSP) [22]. NSP involves the construction of schedules for nursing staff and assigns the nurses to shifts per day taking both hard and soft constraints into account, for example. In computing, the technique of abstracting a physical system in order to facilitate the access is called virtualisation and contributes to improved utilisation of resources [23]. Such examples provided significant insights into the application of scheduling in several distinct real-world problems.

Recent research methods applying metaheuristic algorithms were proposed to solve scheduling problems with more than one optimal criterion, emphasising the increase in scheduling problems complexity. Problems in minimising the makespan are fully explored in general cases of shop scheduling such as job, flow, and open shops as found in [24–27], minimisation of overall material handling costs [28]. A relevant piece of research comparing different scheduling solutions was identified by [29] exploring the performance of a lot-sizing in determining the best schedule where four adapted mathematical models were developed to consider several decisions and constraints.

The majority of the research seeks to optimise one objective function. Thus, an exploration of relevant models and algorithms focused on scheduling problems beyond current models is conducted due to the necessity of providing a flexible tool for support production planning decision-making based on more than one objective criterion easily accessed by end-users, allowing the combination of sustainable metrics, such as energy consumption with critical production metrics.

Due to the limitation of natural resources, potential impacts on global climate change, chemicals and waste, resource efficiency, sustainable consumption, and production; sustainability is claimed to be an emerging environmental concern of global importance by the United Nations Environmental Program (UNEP 2019) [30]. Supply Chain activities such as producing, packaging, moving, storing, repacking, delivering and returning can also increase the impact on the environment regarding scrapped toxic products, carbon emissions, waste produced, and several forms of industrial pollution [31] should be also incorporated into optimum production scheduling plans.

Existing current Corporate Sustainability Assessment (CSA) methods, for example, are based on the integration of development and environmental goals where sustainability is typically represented as a triple bottom line or composite indicators [32]. Energy efficiency consumption is increasing among modelling and optimisation tools, as observed in [33] where the research investigated Discrete Event Simulation (DES) models for manufacturing energy consumption. An optimisation model for machining processes focuses on the prediction of energy consumption is explored and validated by means of simulation [34] based on kinematic and dynamic models of machine tools.

Energy-oriented maintenance decision-making for sustainable manufacturing was proposed by [35]. The framework is based on real-time information to dynamically identify energy-saving opportunities and enhance energy efficiency. Areas of energy flexibility is studied by [36]. Manufacturing facilities include storing energy off-peak in devices such as thermal energy storage (TES) tanks or adjusting equipment operating schedules.

Given the complexity in scheduling and current advances in data acquisition, real-data combined with artificial intelligence (AI) is also increasing in optimising algorithms integrating physical and system levels as explored by [37,38] for a predictive maintenance model and by [39] in dynamic scheduling based on Radio Frequency Identification (RFID). The growth of blockchain in structuring a decentralised source of information to support social manufacturing is also proposed by [40]. Individualised product demands require a high level of flexibility in the manufacturing process where the current centralised structure is insufficient to achieve mass personalisation.

Even though all the research explored presents significant results and provides recent trends and algorithms, the complexity observed in the dairy industry requires a specific and efficient method focused on the nature of the environment where the main issues identified for an optimum production plan were identified: raw material seasonality, stochastic supply delivery, short WIP lifespan, limited WIP capacity, minimum CIP hours to comply with external regulations, maximum running hours to reduce operational costs, time to start the CIP cycle, number of pieces of equipment required and downstream efficiency. All these factors are heavily dependent on one another which increases the complexity of identifying an optimum solution.

In addition, given the initiative to incorporate sustainable metrics, the algorithm must incorporate criteria of sustainability into the recommended production schedule and support the decision-maker at the operational level in defining the most appropriate production plan.

3. Dairy scheduling problem – case study

In this section, a simplified production flow is demonstrated highlighting three main stages in dairy manufacturing in order to clarify the critical issues addressed in the scheduling processes.

3.1. The process flow

The raw material is supplied and stored into silos to be further processed by two subsequent stages. Both stages store the WIP produced in intermediate silos. This process is described as follows:

- Stage B0 – Raw material storage: Due to the variability in the supply frequency, the planning process is heavily impacted at the operational level. Therefore, an efficient production plan needs to cope with the inevitable variability in delivery and volumes that are supplied hourly. The flow is limited by B0 Stage capacity and truck queues are likely to form during high season.
- Stage Manufacturing Process 1 (MP1) – The raw material is separated according to the separator capacity at this stage and the WIP processed is divided into two branches in the manufacturing process. This stage is also restricted by the silo storage capacity.
- Stage Manufacturing Process 2 (MP2) – The WIP processed is evaporated and the final product is stored in powder form to be further processed by the packaging area.

3.2. Raw material supply

The raw material is supplied daily and despite the delivery schedule provided by farmers, a high concentration during specific hours of the

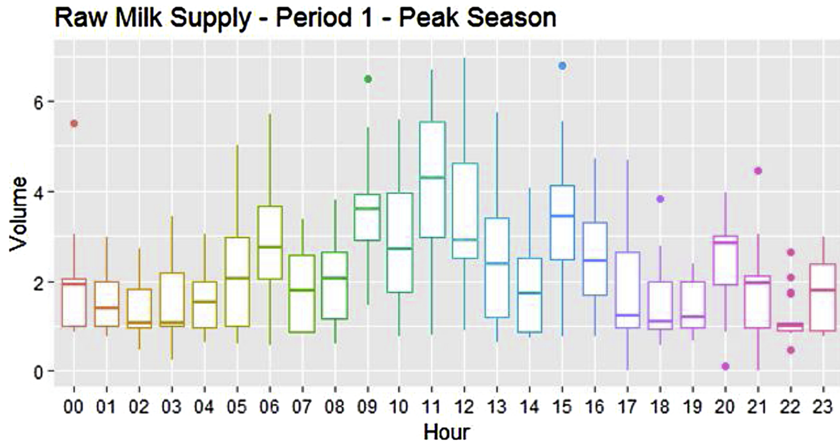

Fig. 1. Raw Material Supplied – Volume per hour.

day is observed as presented in Fig. 1. The boxplot graph shows the behaviour of the supply throughout the day. The dataset aggregates the volume supplied for one specific month during the peak season. According to [31] peak season is related to the lactation period, which increases the availability of raw material to manufacturers. The X-axis shows the hours, starting from 0 to 23 and the Y-axis shows the supply volumes transformed into lot-sizes to guarantee data confidentiality.

The variability observed in the graph increases the instability in the processing flow despite the intermediate buffer silos. In addition, the raw material has a short lifespan and requires a fast processing rate due to the risk of perishability. A similar behaviour is found in [36] where each operating day is unique in terms of variable operating energy schedules and production processes with non-Gaussian data s observed in [41].

Table 1 demonstrates the analysis for each day during the peak season, where the distribution and rank were calculated by the *StatFit* package as shown in the table. The supply volume was converted into lot-sizes in order to maintain data anonymity and confidentiality.

According to [42] transient and steady-stated density functions for a particular stochastic process are conditions for stabilising a process since the distributions from a specific point will be approximately similar to one another. By analysing 30 days of supply, diverse distributions were identified showing clear evidence that the stochastic behaviour in volume and frequency varies each day and the probability that various states will be repeated is not constant.

3.3. The separation scheduling problem

At this specific Industrial Partner, the stage MP1 is responsible for removing the fat from the whole milk through a process called separation. After dividing the milk into fat and proteins through a centrifugal separator, the standardisation process is required to guarantee the correct level of fat in the milk. The separation efficiency is one of the most critical steps for skimmed milk powder manufacturers due to

Table 1
Supply variability for 30 days.

Days	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)	Rank
1	2.101	1.140	0.649	4.965	0.543	0.959	Logistic,3.98e-002,3.38e-002	98.2
2	2.744	1.788	0.583	7.194	0.651	0.863	Pearson Type 5,-4.32e-002,6.64,0.482	99.4
3	2.500	1.068	0.667	4.866	0.427	0.625	Cauchy, 4.41e-002,1.21e-002,	96.8
4	2.274	1.337	0.558	4.841	0.588	0.437	Power Function,-1.75e-003,0.102,0.761,	99.2
5	2.570	1.501	0.840	6.492	0.584	0.929	Johnson SU,-3.31e-002,1.78e-002,-5.75,2.76	99.8
6	1.994	1.232	0.601	5.339	0.618	0.789	Weibull,-3.07e-003,1.51,4.94e-002	61.2
7	2.172	1.321	0.234	5.712	0.608	1.478	Laplace,4.08e-002,1.96e-002,	89.5
8	2.380	1.120	0.585	4.802	0.471	0.361	Normal,4.17e-002,2.8e-002	97.0
9	2.418	1.146	0.860	5.620	0.474	0.839	Logistic,4.12e-002,2.44e-002	100.0
10	2.302	1.221	0.710	4.721	0.530	0.151	Power Function,-3.16e-003,0.103,0.826,	68.6
11	2.361	1.608	0.930	7.830	0.681	1.990	Extreme Value IA,4.11e-002,3.26e-002	98.9
12	1.937	1.006	0.468	4.173	0.519	0.602	Weibull,-6.12e-003,2.16,5.39e-002	99.9
13	2.046	1.216	0.787	4.829	0.595	1.054	Pearson Type 5,-6.26e-002,13.1,1.26	99.4
14	2.053	1.154	0.634	4.442	0.562	0.619	Triangular,-7.27e-003,0.112,1.84e-002	96.7
15	2.165	1.186	0.772	4.741	0.548	0.609	Inverse Gaussian,-4.51e-002,8.68e-002,0.622	98.2
16	2.240	1.814	0.755	6.947	0.810	1.549	Johnson SU,1.62e-002,3.41e-003,-1.1,0.616	100.0
17	2.775	1.327	0.853	5.731	0.478	0.301	Normal,4.17e-002,2.83e-002	97.9
18	2.622	1.359	0.677	5.063	0.518	0.034	Power Function,-2.48e-003,0.104,0.705,	100.0
19	2.257	1.165	0.785	5.219	0.516	0.650	Weibull,-8.45e-003,2.07,5.65e-002	98.3
20	2.178	1.506	0.769	6.313	0.691	1.074	Erlang,-3.84e-003,4.55e-002,2.	67.0
21	2.499	1.352	0.747	5.247	0.541	0.351	Weibull,-7.63e-003,1.95,5.55e-002	95.2
22	2.215	1.052	0.838	4.072	0.475	0.153	Gamma,-1.1,8.75e-004,1.3e+003	99.8
23	2.544	1.529	0.835	7.422	0.601	1.614	Laplace,3.91e-002,1.84e-002,	98.3
24	2.487	1.481	0.844	5.815	0.596	0.656	LogNormal,-2.96e-002,7.16e-002,3.6e-002	96.5
25	2.375	1.180	0.483	4.764	0.497	0.377	Gamma,-0.215,2.48e-003,104	100.0
26	2.207	1.741	0.733	5.699	0.789	1.051	Inverse Weibull,-3.36e-002,2.36,19.4,	100.0
27	2.042	1.470	0	5.212	0.720	0.694	LogNormal,-1.51e-002,5.79e-002,4.42e-002	94.5
28	2.014	1.527	0.002	6.270	0.758	1.086	Inverse Weibull,-0.172,8.14,5.09,	98.5
29	2.625	1.869	0.776	6.707	0.712	1.121	LogLogistic,-0.18,9.63,0.213	100.0
30	2.340	1.509	0.88	5.830	0.645	1.126	Johnson SU,2.49e-002,1.18e-002,-0.353,0.467	100.0

the impact of fat content on the drying process [4,6].

The separation capacity is heavily impacted by the fouling effect which is a common consequence of the gradual accumulation of residuals over the surface, reducing the output volume processed. The fouling effect is a critical issue for dairy equipment requiring constant cleaning cycles. CIP cycle-time is an essential process for dairy equipment and must be considered in the overall production plan and performance assessment.

The main objective of the dairy production plan is to guarantee that the raw material is rapidly converted into added-value products [43]. For this specific manufacturing stage, the scheduling plan is heavily impacted by external and internal factors. In addition, the strategy varies according to the seasonality.

During the peak season, the equipment set runs at the maximum capacity and CIP is performed at a minimum time. During the off-season defining an optimum schedule for separators is a complex task due to the number of variables (internal and external) involved. Maximum running hours and minimum hours for CIP cycle-time, for example, must comply with authorities and equipment supplier recommendations. However, minimum running hours or shutdowns to reduce processing capacity are related to internal decisions such as costs involved in running a specific equipment set. The starting time for CIP cycle-times has a strong dependence on the internal and external variables previously mentioned.

During off and medium seasons, decisions regarding shutdowns and equipment running hours are related to the frequency of supply during the day. In addition, the WIP produced by this stage is stored in silos with limited capacity; therefore, the output silo capacity is also a restrictive condition.

A simplified example is demonstrated in Tables Table22 and Table33 where three scenarios for medium season volumes were simulated. The volume is supplied hourly where $h = \{1, \ldots H\}$. In this context, the equipment set and running hours are restricted due to the excess of processing capacity. For example, let equipment set be $e = \{1,2,3\}$. The possible sets of equipment are: $se = \{\{1\},\{2\},\{3\},\{1,2\},\{1,3\},\{2,3\},\{1,2,3\}\}$.

Considering the individual capacities in lot-sizes, let capacity per piece of equipment be $cap_e = \{2.5, 3.0, 2.5\}$; thus, the maximum capacity per hour is defined by $Totcap_{Se} = \{\{2.5\},\{3.0\},\{2.5\},\{5.5\},\{5.0\},\{5.5\},\{7.5\}\}$.

The decision variable controlling the equipment flow is represented by 0 (turned-off or in CIP) and 1 for running. Based on these definitions, three scenarios with distinct scheduling plans for 24 h are detailed in Table 2 as follows:

The results of each scenario on WIP levels is presented in Table 3. The supply volumes are completely authorised and processed due to the excess of processing capacity.

CIP cycle-time starts at hour 1 for all three experiments. The problem intensifies when the supply volumes increase. WIP level increases when the processing capacity is below the amount supplied and decreases when the capacity is higher. In the table, it is evident that despite scenario 1 having a lower processing capacity when compared to scenarios 2 and 3 additional investigation is required to identify the best scenario performance.

Table 2
Equipment Set Scheduling Plan.

Scenario	Equipment set	Maximum Running hours	Minimum CIP hours	Total Capacity (Lots)
1	$e = \{1,3\}$	7	3	5.0
2	$e = \{1,2\}$	8	4	5.5
3	$e = \{1,2\}$	8	4 and 2	5.5

3.3.1. Comparing schedules through different metrics

The performance metrics calculated for each scenario are shown in Table 4. Scenario 2 presents an undesired performance for three metrics: Energy Consumed, WIP and Equipment Utilisation levels, whereas Scenario 1 presents an improved trade-off when compared to all four metrics demonstrated. Scenarios 2 and 3 consumed higher energy hours.

The results provided by the simulation demonstrate the importance of multi-objective criteria to improve decision-making in defining an appropriate scheduling plan for the separation process in the dairy environment. Decisions regarding increasing processing capacity in hours at this stage are not entirely correlated with desired performance metrics as proven by the results presented in the table. The following section explores the space required to optimise the scheduling plan based on a recommendation MOA to support decision-makers.

4. Model formulation

The notation referring to variables and indices formulated is presented in Table 5 where the volume supplied is provided in hours. A discrete time period is represented by $(h = 1, \ldots H)$ for simplification and the volume is processed in parallel according to e equipment. Storage and equipment capacities limit the processing flow.

4.1. Equipment Set

The equipment set is created according to the number of pieces of equipment e, which can be combined according to r. An extra set is added $(+1)$ as shown in Eq. 4.1.

$$E(e, r) = \left(\frac{e!}{r!(e-r)!}\right) + 1 \tag{4.1}$$

4.2. Decision variables

The notation referred to the binary decision variable $R_{s_e}^h$ considering the following condition: when the total running hours $(\sum_{h=1}^{H} R_{s_e}^h)$ reach the maximum running hour, the equipment e, at stage s is interrupted for hour h, otherwise it keeps running, as demonstrated in Eq. 4.2. The same criteria are defined regarding CIP hours in Eq. 4.3, where the minimum hours for cleaning must be performed and also in Eq. 4.4 regarding starting the cleaning process.

$$R_{s_e}^h = \begin{cases} 0, & \sum_{h=1}^{H} R_{s_e}^h \geq Run_{s_e} \\ 1, & \sum_{h=1}^{H} R_{s_e}^h < Run_{s_e} \end{cases} \tag{4.2}$$

$$R_{s_e}^h = \begin{cases} 1, & \sum_{h=1}^{H} R_{s_e}^h \geq Cip_{s_e} \\ 0, & \sum_{h=1}^{H} R_{s_e}^h < Cip_{s_e} \end{cases} \tag{4.3}$$

$$R_{s_e}^h = \begin{cases} 1, & \sum_{h=1}^{H} R_{s_e}^h \geq StCip_{s_e} \\ 0, & \sum_{h=1}^{H} R_{s_e}^h < StCip_{s_e} \end{cases} \tag{4.4}$$

4.3. Objective functions

In order to provide a flexible recommendation tool for scheduling plans, the overall objective functions are calculated and stored in a

Table 3
Scheduling the Raw Material Supply (Lots).

H = Hour	Volume Supplied	Scenario 1			Scenario 2			Scenario 3		
		Capacity	WIP	Volume Processed	Capacity	WIP	Volume Processed	Capacity	WIP	Volume Processed
1	0	0	0	0	0			0		
2	0	0	0	0	0			0		
3	2.5	0	2.5	0	0	2.5		0	2.5	
4	2.5	5.5	0	5.0	0	5.0	0	0	5.0	0
5	5.0	5.5	0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
6	5.0	5.5	0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
7	5.0	5.5	0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
8	5.0	5.5	0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
9	10.0	5.5	4.5	5.5	5.0	10.0	5.0	5.0	10.0	5.0
10	7.5	5.5	6.5	5.5	5.0	12.5	5.0	5.0	12.5	5.0
11	7.5	0	14.0	0	5.0	15.0	5.0	5.0	15.0	5.0
12	2.5	0	16.5	0	5.0	12.5	5.0	5.0	12.5	5.0
13	5.0	0	21.5	0	0	17.5	0	0	17.5	0
14	5.0	5.5	21.0	5.5	0	22.5	0	0	22.5	0
15	2.5	5.5	18.0	5.5	0	25.0	0	5.0	20.0	5.0
16	2.5	5.5	15.0	5.5	0	27.5	0	5.0	17.5	5.0
17	2.5	5.5	12.0	5.5	5.0	25.0	5.0	5.0	15.0	5.0
18	2.5	5.5	9.0	5.5	5.0	22.5	5.0	5.0	12.5	5.0
19	2.5	5.5	6.0	5.5	5.0	20.0	5.0	5.0	10.0	5.0
20	0	5.5	0.5	5.5	5.0	15.0	5.0	5.0	5.0	5.0
21	0	0	0.5	0	5.0	10.0	5.0	5.0	0	5.0
22	0	0	0.5	0	5.0	5.0	5.0	5.0	0	0
23	0	0	0.5	0	5.0	0	5.0	0	0	0
24	0	0	0.5	0	5.0	0	0	0	0	0
TOTAL	75.0	77.0		74.5	80.0		75.0	80.0		75.0

Table 4
Performance Metrics.

Scenarios	Energy (H)	Average WIP (Lots)	Utilisation %	VP (Lots)
1	46	6,208	0.97	74,50
2	56	12,159	0.94	75,00
3	56	8,977	0.94	75,00

Table 5
Related Notations in the defined metrics for the RCS model.

	Description
h,H	Production period in hours where $1 \le h \le H$
e, E	Piece of equipment where $1 \le e \le E$
s, S	Production stage where $1 \le s \le S$
$\boldsymbol{s_e, S_E}$	Piece of equipment at s stage
$\boldsymbol{DC}$	Demand defined by contracts
$\boldsymbol{I_s^h}$	Inventory held in the output buffer of production at stage s in period h
$\boldsymbol{I_s max}$	The maximum inventory capacity to store the production of stage s
$\boldsymbol{LA_{s_e}^h}$	Lot-size Authorised for e equipment at stage s in period h
$\boldsymbol{P_{s_e}^h}$	Production capacity for e equipment at stage s in period h
$\boldsymbol{Cmin_{s_e}}$	Minimum cycle-time for CIP e equipment at s stage
$\boldsymbol{Cmax_{s_e}}$	Maximum cycle-time for CIP e equipment at s stage
$\boldsymbol{Cip_{s_e}}$	CIP running for e equipment at s stage, where $Cmin_{s_e} \le Cip_{s_e} \le Cmax_{s_e}$
$\boldsymbol{Rmin_{s_e}}$	Minimum running time e equipment at s stage
$\boldsymbol{Rmax_{s_e}}$	Maximum running time e equipment at s stage
$\boldsymbol{Run_{s_e}}$	Running time e equipment at s stage, where $Rmin_{s_e} \le Run_{s_e} \le Rmax_{s_e}$
$\boldsymbol{E_{s_e}^h}$	Energy consumption for e equipment at stage s in period h
$\boldsymbol{StCipx_{s_e}}$	Start CIP cycle-time for e equipment at s stage
$\boldsymbol{R_{s_e}^h}$	Decision variable to determine the CIP cycle-time

separated summary dataset for each production plan to be further selected.

The equipment utilisation (EU) average is individually calculated for each stage s, which in this specific case study is stage 1. The volume authorised at this stage $LA_{s_e}^h$ is subjected to the running hour authorised by the decision variable $R_{s_e}^h$ which controls the cleaning scheduling. The total volume capacity $P_{s_e}^h$ for equipment set E is then calculated by hour as shown in Eq. 4.5.

$$EU_{s_E} = \frac{1}{H}\left(\sum_{h=1}^{H}\left(\frac{\sum_{e=1}^{E} (LA_{s_e}^{h} * R_{s_e}^{h})}{\sum_{e=1}^{E} (P_{s_e}^{h})}\right)\right) \tag{4.5}$$

To obtain the total energy consumption (EC) computed for each production plan, the energy consumed for equipment $E_{s_e}^h$ is doubled according to a specific range of hours ($1 \le h \le 8$) in Eq. 4.6; subjected to the running hours defined by $R_{s_e}^h$ and the Energy coefficient $CE_{s_e}^h$ as shown in Eq. 4.7.

$$CE_{s_e}^h = \begin{cases} E_{s_e}^h, & 1 \le h \le 8 \\ E_{s_e}^h * 2, & otherwise \end{cases} \tag{4.6}$$

$$EC = \sum_{h=1}^{H}\left(\sum_{s=1}^{S}\left(\sum_{e=1}^{E} (R_{s_e}^{h} * CE_{s_e}^{h})\right)\right) \tag{4.7}$$

Since the demand is determined by contracts (DC), no probability at this stage is required for the SLA. The total lot authorised $LA_{S_e}^h$, for equipment set E, for the last stage S is considered as shown in equation 4.8.

$$SLA = \frac{\sum_{h=1}^{H} (\sum_{e=1}^{E} (LA_{S_e}^{h}))}{DC} \tag{4.8}$$

The separation rate (SR) measures the effectiveness performance between the raw material authorised into the system and the volume processed at the first stage. It is calculated according to the total lot authorised $LA_{s_e}^h$ at stage 1 where ($s = 1$), the volume authorised in the system represented by stage 0 where ($s = 0$) for equipment set E, as shown in Eq. 4.9.

$$SR = \frac{1}{H}\left(\sum_{h=1}^{H}\left(\frac{\sum_{e=1}^{E} (LA_{1_e}^{h})}{\sum_{e=1}^{E} (LA_{0_e}^{h})}\right)\right) \tag{4.9}$$

The WIP average (AWIP) is calculated according to the inventory levels at stage *s*. The inventory (I_s^h) is computed according to the inventory level from the previous period ($I_s^{(h-1)}$) to which is added the total volume authorised for production at stage *s* $\sum_{e=1}^{E}(LA_{s_e}^h)$; then the volume sent to the next stage $\sum_{e=1}^{E}(LA_{(s+1)_e}^h)$ is subtracted according to Eq. 4.10.

The inventory (I_s^h) is subjected to the maximum silo storage capacity defined by each stage *s* in Eq. 4.11, and then calculated for the total scheduling period defined in equation 4.12.

$$I_s^h = I_s^{(h-1)} + \sum_{e=1}^{E}(LA_{s_e}^h) - \sum_{e=1}^{E}(LA_{(s+1)_e}^h) \quad (4.10)$$

$$I_s^h \le I_{s}max \quad (4.11)$$

$$AWIP = \sum_{h=1}^{H}\left(\frac{I_s^h}{H}\right) \quad 4.12$$

Ultimately, the WIP remaining is calculated according to the to the storage capacity at stage *s,* as shown in equation 4.13.

$$\text{RWIP}= \frac{I_s^H}{I_{s}max} = \sum_{h=1}^{H}\left(\frac{I_s^h}{H}\right) \quad 4.13$$

5. Search space and performance analysis

Multi-objective decision making is a sequence of steps such as defining the problem, setting the system boundaries, and then choosing the decision rules, as stated by [13]. In order to overcome the drawbacks identified in the probabilistic methods previously explored, the RCS algorithm proposed was developed based on the following steps:

1 The population or search space (1) is dynamically defined by combining all equipment sets and the range of decision variables: $Rmax_{s_e}$, $Rmin_{s_e}$, $Cmin_{s_e}$, $Cmax_{s_e}$, $StCip_{s_e}$.
2 All performance metrics defined in section 0 are calculated for all schedules.
3 The criteria are available to be selected by the decision-maker.
4 The Optimum set is presented in a Pareto Frontier Graph.

5.1. Search space and planning schedules

An example of equipment set was created according to a binary variable (0,1) and an extra combination for all pieces of equipment to be running is added according to the Eq. 4.1. According to the equation, four pieces of equipment combined 2 by 2 is shown in Table 6 is presented where the last set refers to the total number of pieces of equipment running at full capacity.

A function created in R ***ScheduleStage*** receives three parameters: the manufacturing stage, the number of pieces of equipment and the number of combinations allowed for each schedule. This function creates the vector ***CIPvector*** for the decision variable $R_{s_e}^h$ according to the range defined. An example is presented for Maximum Running hours 8 and Minimum CIP hours 3 in Fig. 2.

The scheduling plan as presented in Fig. 2 is created according to the supply volumes imported from csv files. The rules defined from Eq. 4.2 to 4.4 are verified hourly in order to determine whether the equipment should start the CIP cycle. The inventory is computed for each stage at hour *h* according to Eq. 4.10.

Table 6
Example - Equipment Set - 2 by 2.

Equipment Set	Eq1	Eq2	Eq3	Eq4
1	0	0	1	1
2	0	1	0	1
3	0	1	1	0
4	1	0	0	1
5	1	1	0	0
6	1	0	1	0
7	1	1	1	1

After performing each schedule, a summary with all key metrics is calculated according to equations 4.5, 4.7, 4.10, 4.12 and 4.13. The criteria are then available for selection (maximising or minimising) to the user as shown in Fig. 3.

The non-dominant set is calculated according to the variance between the two objective criteria and the Gaussian Eq. 5.1 to determine the first minimum point and the Least Square Distance (LSD) according to the Euclidean Distance in Eq. 5.2 [13] for the entire dataset. The optimum set is then further visualised in a Pareto Frontier Graph.

$$g(x, x') = exp - \left(\frac{(x - x')^2}{2\sigma^2}\right) \quad (5.1)$$

$$(x, x') = \sqrt{\sum_{i=1}^{n}(x_i - x_i')^2} \quad (5.2)$$

5.2. Evaluating the algorithm performance

Due to the large amount of data generated, the performance evaluation is a vital step in identifying the effectiveness of the proposed algorithm by running the worst-case scenario or the most significant range possible combinations, as shown in Table 7.

The decision variables: Maximum and minimum hours allowed for CIP/OFF time (*columns a* and *b*), Maximum and Minimum Running Hours *(columns c and d), and* Equipment Set *(column e)* are shown in the table. The Total Scheduling Plans generated (*column f*) decreases by reducing the range of the input parameters (*a,b,c and d*). The equipment set remains the same, 4 pieces of equipment according to the number of separators in this experiment.

The Total Scheduling Plans (*column f*) is calculated from Eq.s (2) and (3) as shown in the Appendix. As the range becomes more restrictive, the dataset observations and the process time are both reduced. The time in seconds (*column g*) was extracted from the *Profile option* available in the RStudio package.

The experiments were reproduced by restarting the environment for each sequence (*Seq*); therefore, no previous updated variable influenced the next execution.

In order to evaluate the results performed by the simulation, the worst scenario case regarding processing time (*S*eq 1 is explored. In this scenario, 1820 simulations were generated based on real data. These observations refer to the number of scheduling plans giving the range defined.

6. Data Analysis and results

The first sequence simulated (Seq1) shown in Table 7, presents 1820 scheduling plans which are demonstrated in Fig. 4. This graph shows the correlations among all performance metrics calculated for the scheduling plans created.

The objective of this initial analysis is to evaluate significant correlations between all the objective functions defined. Observing the correlations presented in this graph it is possible to conclude:

1 Despite the weak and negative correlation between Utilisation Level and Energy Hours (-0.46), several scheduling plans reach a high level of Utilisation at a lower level of Energy Hours given the schedules plotted in the graph (row 2 col 1).
2 Regarding SLA and Energy Hours, a strong correlation was found (0.82) as a result of equipment running hours. Nevertheless, a maximum level of SLA at a reduced Energy Hours consumption is achievable.
3 A similar pattern between Separation Rate and Energy Hours is observed; a strong correlation between both criteria (0.84) is shown. Scheduling production plans aim to optimise resource utilisation, minimise costs and maximise profitability. Despite environmental

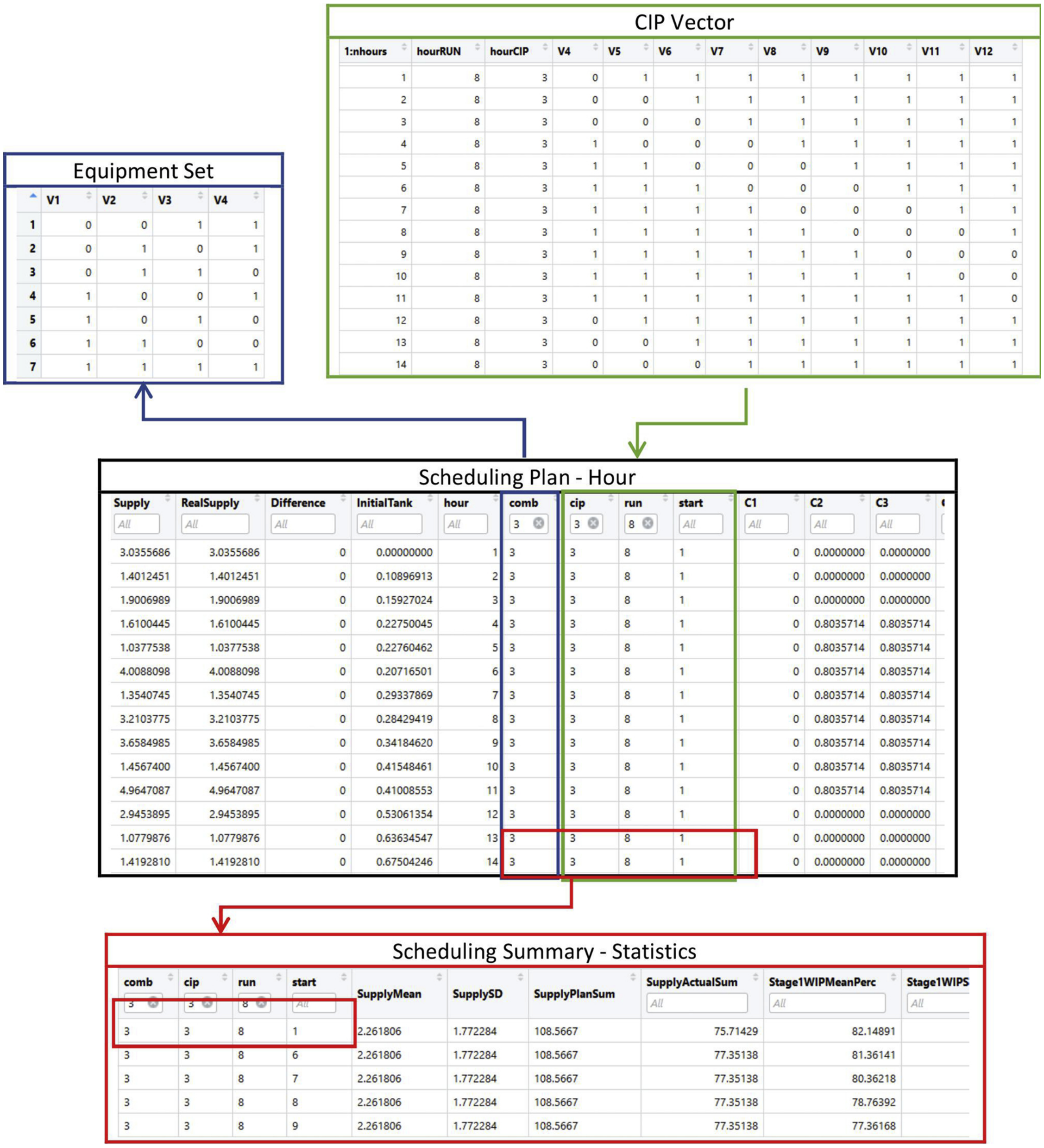

Fig. 2. Scheduling Plans and Scheduling Summary for Optimal Criteria Selection.

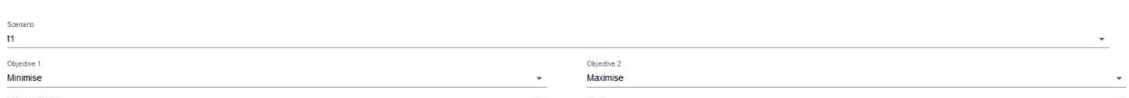

Fig. 3. RCS Interface.

metrics usually being ignored during production plan definitions in particular when a weak correlation between both criteria environmental and profitable is identified, the correlations between the Objective Functions show improved performance when both sustainable approaches are well explored. In this environment it is clear that a multi-objective optimisation is more suitable to support the decision-maker in selecting the best schedule.

In order to highlight the impact of the supply distribution on the key metrics results and the benefits for decision-makers in performing a proper production plan according to their objectives, the supply distribution for 30 days presented in Table 1 was imported into the RCS algorithm. Therefore, a set of optimum scheduling plans is suggested for each day.

Presenting the best schedules in a frontier graph, the main advantage is graphically identifying the existence of trade-offs when comparing more than one optimal solution. By maximising the Separation Rate and minimising the Energy in hours, the trade-off between both objective criteria is shown in Fig. 5for Day 1 and Fig. 6 for Day 30. The increase in separating raw material directly influences energy consumption. However, limited schedules provide the optimum volume processed with a minimal energy consumption as illustrated in both graphs.

The impact of supply variability on the objective functions caused by distinct days is also highlighted. Day 1 presents the maximum separation rate achievable for less than 75 h of energy consumption, whereas Day 30 requires higher energy hours for a lower separation rate, which remains below 1.

Table 7
Performance Evaluation.

	Decision Variables					Performance	
Seq	*Maximum Hours Cip/OFF (a)*	*Minimum Hours Cip/OFF (b)*	*Maximum Running Hours (c)*	*Minimum Running Hours (d)*	*Equipment Set (e)*	*Total Scheduling Plans (f)*	*Time in seconds (g)*
1	14	2	8	4	7	1820	11.23
2	14	2	8	5	7	1,274	6.24
3	14	2	8	6	7	819	3.69
4	14	2	8	7	7	455	1.97
5	13	2	8	4	7	1,680	10.35
6	13	2	8	5	7	1,176	5.75
7	13	2	8	6	7	756	3.29
8	13	2	8	7	7	420	1.63
9	12	2	8	4	7	1,540	11.00
10	12	2	8	5	7	1,078	5.39
11	12	2	8	6	7	693	2.98
12	12	2	8	7	7	385	1.53
…	….	….	…	…	…	….	….

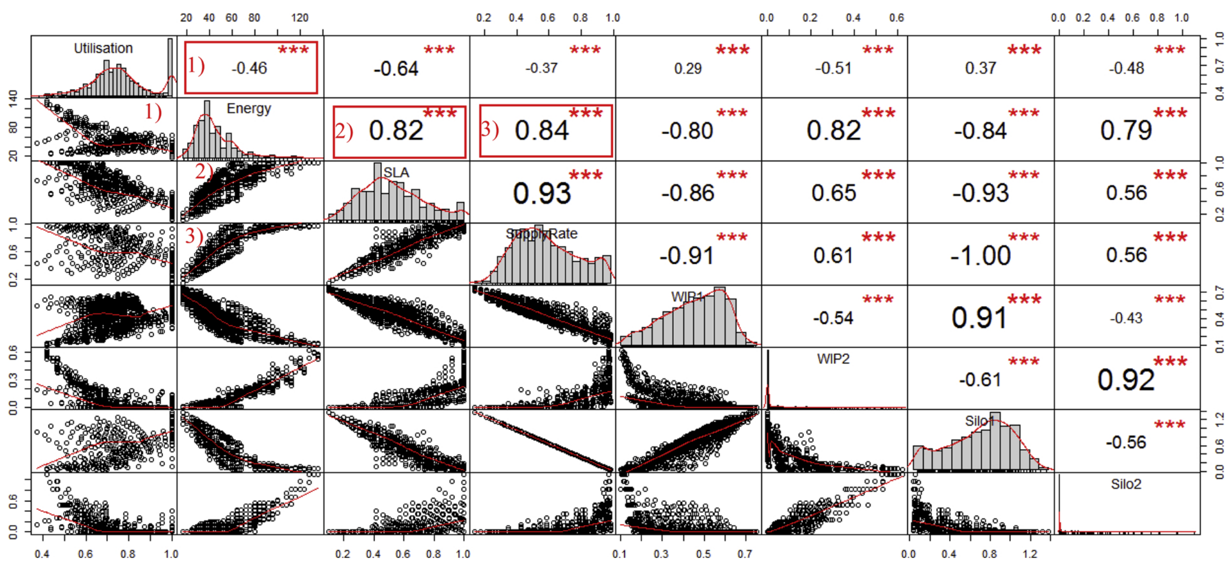

Fig. 4. Correlation Objective Functions.

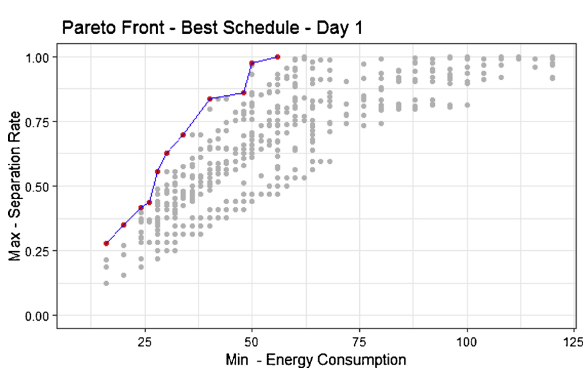

Fig. 5. Schedules for Day 1 - Separation & Energy.

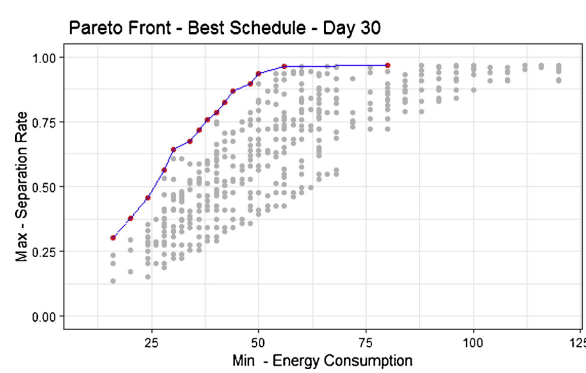

Fig. 6. Schedules for Day 30 - Separation & Energy.

Fig. 7 presents the complete set of optimum schedules recommended for each day presented in Table 1. Despite the variability in the supply frequency, the optimum trade-off suggested guarantees an improved performance since a similar pattern is observed for each day according to both criteria selected.

For this specific trade-off, even though a strong and positive correlation between both criteria (0.84) was previoulsy shown in Fig. 4 suggesting a dependency of both objective functions, a region for optimising these conflicting criteria was explored. Thus, by minimising energy consumption and maximising the volume separated, decision-makers are well supported in incorporating sustainable metrics into their daily scheduling process.

Table 8 demonstrates the optimum scheduling sets for a five-day sample. *Pareto-Optimal Set* column shows the total number of non-dominant schedules recommended to achieve an improved trade-off. The supply variability is also evident in this table since distinct optimum schedules and equipment sets are shown in the *Equipment Set* column.

In addition, *CIP/OFF, Running Hours and Start CIP* columns also present diverse schedule hours. The number of total observations was

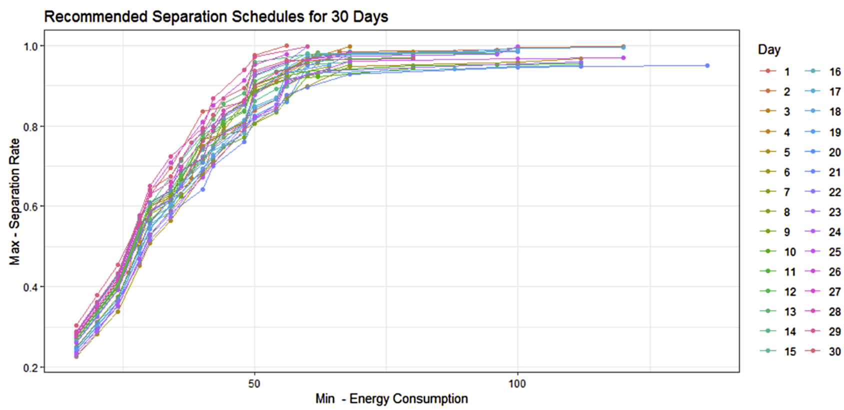

Fig. 7. Recommended Schedules for 30 Days - Separation Rate and Energy.

Table 8
Scheduling Plan for 5 Days - Maximising Separation Rate & Minimising Energy Hours.

Day	Pareto Optimum Set	Equipment Set	CIP OFF	Running Hours	Start CIP	% Util	Energy Hours	Stage 2 SLA	Sep. Rate	Avg WIP1	Avg WIP2	Inv Silo1	Inv Silo2
1	32	4	3	5	1	0.867	50	0.764	0.972	0.219	0.051	0.048	0.125
		4	6	8	1	0.954	44	0.611	0.856	0.263	0.055	0.247	0.100
2	50	2	3	8	5	0.826	62	0.767	0.952	0.182	0.007	0.075	0.015
		1	2	6	1	0.810	60	0.767	0.933	0.217	0.007	0.103	0.015
3	32	4	3	5	1	0.823	50	0.764	0.958	0.224	0.051	0.070	0.125
		4	4	4	1	0.871	40	0.611	0.810	0.311	0.033	0.314	0.100
4	43	2	2	6	1	0.842	60	0.767	0.937	0.203	0.007	0.101	0.015
		4	4	4	1	0.871	40	0.611	0.833	0.309	0.033	0.268	0.100
30	39	4	3	6	7	0.823	56	0.733	0.937	0.186	0.008	0.177	0.210
		4	5	8	1	0.823	48	0.736	0.963	0.228	0.006	0.108	0.225

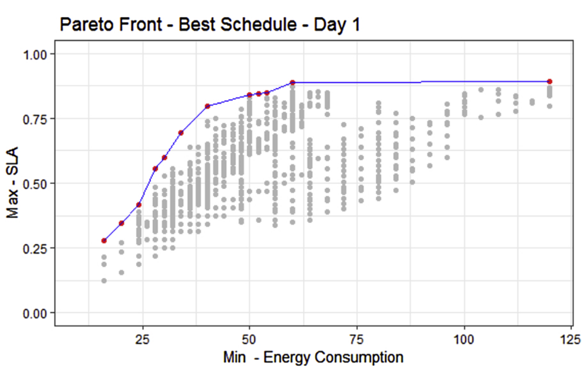

Fig. 8. Schedules for Day 1 - SLA & Energy.

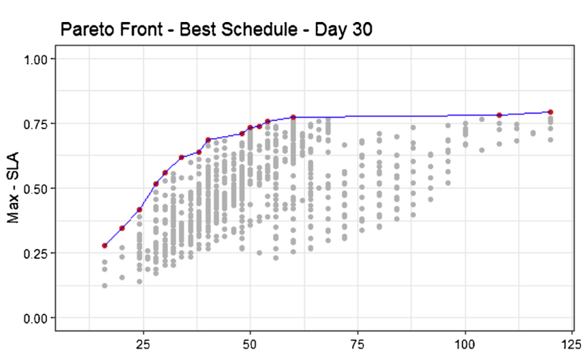

Fig. 9. Schedules for Day 30 - SLA & Energy.

reduced to also guarantee an improved equipment set for each day greater than 80 %.

By maximising the SLA and minimising the energy consumption as a distinct trade-off, it is evident that the supply variability in volumes and frequency heavily impacts the results metrics as shown in Fig. 8 for Day 1 and in Fig. 9 for Day 30. However, despite the variability observed, an optimum SLA and minimum energy consumption are achievable as illustrated in both graphs.

Fig. 10 presents the total optimum schedules recommended for each day presented in Table 1. Despite the variability in the supply frequency, a similar pattern is also observed for each day according to the new criteria selected.

The same pattern regarding SLA and Energy Hours correlation is applied. Despite the strong and positive correlation between both objective functions, a range for optimising these conflicting criteria is observed.

Table 9 demonstrates the optimum scheduling sets for the same five days. By changing the criteria, the number of recommended non-dominant schedules was reduced. In addition, it is also possible to observe distinct schedules for all five days when compared to the results previously presented in Table 8.

The recommended schedule for Day 3, for example, provides clear evidence that reducing energy consumption (50 h) is the most sustainable option and provides a similar SLA when compared to the first recommended schedule, highlighting the fact that the criteria: maximising SLA and a minimum energy consumption are both achievable by changing the equipment set.

As shown in Tables 8 and 9, only one schedule suggested full capacity as observed in Day 30. However, the implications of running all the pieces of equipment are evident when the increase of energy consumption is observed. For the remaining days, the daily supply is lower when compared to the available capacity and no extra capacity is required.

7. Conclusion and future work

In this research, the results provided by the RCS algorithm to suggest the optimum set of schedules in a Pareto-Frontier graph set is

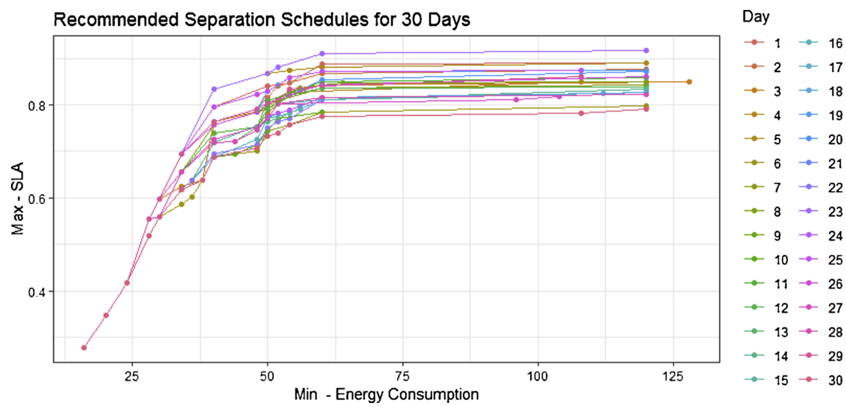

Fig. 10. Recommended Schedules for 30 Days - SLA and Energy.

Table 9
Scheduling Plan for 4 Days - Maximising SLA & Minimising Energy Hours.

Day	Pareto Optimum	Equipment Set	CIP/OFF	Running Hours	Start CIP	% Util	Energy Hours	Stage 2 SLA	Sep. Rate	Avg WIP1	Avg WIP2	Inv Silo1	Inv Silo2
1	23	4	2	5	1	0.806	54	0.875	0.964	0.180	0.054	0.061	0.025
		4	3	6	1	0.800	50	0.792	0.897	0.256	0.056	0.176	0.075
2	24	2	2	7	1	0.810	60	0.769	0.933	0.192	0.007	0.103	0.010
		4	5	8	1	0.804	50	0.694	0.929	0.244	0.067	0.110	0.150
3	24	2	2	6	1	0.842	60	0.767	0.911	0.214	0.007	0.147	0.015
		4	3	5	1	0.823	50	0.764	0.958	0.224	0.051	0.070	0.125
4	26	2	2	6	1	0.842	60	0.767	0.937	0.203	0.007	0.101	0.015
		1	2	5	1	0.823	54	0.688	0.813	0.248	0.005	0.300	0.003
30	28	7	2	4	5	0.817	108	0.783	0.910	0.134	0.087	0.151	0.072
		4	3	6	1	0.823	54	0.757	0.9366	0.213	0.092	0.107	0.1450

proposed. As previously described, the scheduling plan must comply with the tactical directions and a variety of restrictions at the operational level. By evaluating the graphs and the optimal set area, it is possible to conclude that more than one schedule could be selected. Furthermore, the ability to dynamically select the optimum criteria provides more insights into choosing a suitable scheduling plan.

The algorithm consisted of creating a population and defining the search space based on the parameters specified by the user rather than probabilistic methods in order to guarantee the evaluation of all possible conditions. The performance results demonstrated an efficient method to recommend different scheduling plans according to different trade-offs such as optimal criteria consuming minimum time processing.

Ultimately, a production planning tool capable of processing different views enhances decision-making processes. The algorithm presents the most appropriate schedule plan for separation processes by evaluating the impact on the subsequent operation flow.

This research provides an efficient and reliable method to support decision-makers in considering the current planning process adopted by the dairy sector in a more sustainable manufacturing environment. Despite the correlations between objective criteria presenting an initial misinterpretation in comparing metrics of sustainability, improved overall performance metrics are achievable as the RCS algorithm suggested.

As future work, the integration between the algorithm developed and the simulation model in [2] is proposed where the raw material supplied is connected to distinct stages in the dairy manufacturing process. This will increase the visualisation impact from the initial stages to the final production process. Moreover, by adding waste produced and water consumption as optimal criteria, a high level of sustainable measure for the scheduling plan process is available.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Dataset Equations

$$TSch = \begin{pmatrix} Cequip(e, r)^* \\ StCipx_{s_e}{}^* \\ ((Rmax_{s_e} - Rmin_{s_e}) + 1)^* \\ ((Cmax_{s_e} - Cmin_{s_e}) + 1) \end{pmatrix} \quad (1)$$

The combination according to the equipment sets $Cequip(e, r)$, the start CIP cycle − times $StCipx_{s_e}$, the range of running hours $((Rmax_{s_e} - Rmin_{s_e}) + 1)$ and the range of CIP hours $(Cmax_{s_e} - Cmin_{s_e}) + 1)$ are then used as a limit to calculate the total Schedules.

$DataPoints = (TSch * H)$ The hours per schedule (H) is used to calculate the total data points according to the total schedules created. (2)

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jmsy.2020.02.008.

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