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Research Article

An EM-TS Hybrid Optimization for Robust Yogurt Production Scheduling with Local Resources: A Case Study from Giplait Tizi in Algeria

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ARTICLE INFO	ABSTRACT
Received: 12 Nov 2025 Revised: 27 May 2026 Accepted: 11 June 2026 Published: 16 June 2026	Given the industrial complexity of production scheduling in the food industry, the problem of optimizing resources under both industrial and biological constraints is a significant challenge. We consider a yogurt production scheduling problem at the Giplait Tizi plant, which is modeled as a novel Flexible Specific System with Chained Goals (FSSChG). In this paper, we attempt to optimize the production schedule by an adequate hybrid meta-heuristic algorithm combining an Electromagnetism-like Mechanism (EM) and Tabu Search (TS). The hybrid EM-TS method gave us efficient and robust results, effectively managing machinery, storage, and sensitive biological parameters to ensure production stability and product quality. The biological valorization of local date varieties (Hmira, Degla Baida, Tinnacer(Gurbai)) demonstrates how biological constraints can be transformed into opportunities for sustainable innovation.

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Keywords: Production Scheduling, Electromagnetism-like Mechanism, Tabu Search, Yogurt Production, Biological Constraints, FSSChG Model, Metaheuristics, Optimization.

INTRODUCTION

Today's food industry is very competitive, and hence a great deal of focus is on quality and efficiency [1]. Dairy plants in particular are continuously impacted by problems associated with scheduling, lateness and differing biological constraints [2, 3].

As a consequence, they cause considerable monetary loss and fluctuations in production [4].

The manufacturing of yogurt is an example of unsteady production as the different stages of its manufacturing are influenced by sensitive biological and biochemical parameters and processes [5, 6]. Such parameters include the kinetics of fermentation and the variability in raw materials [7]. The main issue is being able to guarantee production at stable high-quality despite industrial constraints and the natural variability of biological raw materials [8]. The main difficulty is the concomitant integration of technical specifications, biochemical parameters and organizational constraints to avoid delays, operational failures and product loss [9]. This paper presents an interdisciplinary solution that simultaneously optimizes the production process and valorizes local biological resources [10].

In this paper, a hybrid Electromagnetism-like Mechanism and Tabu Search (EM-TS) algorithm [11-13] is introduced to address the (FSSChG) problem in the dairy industry, with makespan (C_{max}) minimization considered as the primary optimization criterion [14].

The remainder of this paper is organized as follows. Section 2 presents the problem statement along with the proposed FSSChG scheduling model and the biological valorization of local dates as a sustainable food innovation strategy [15]. Section 3 introduces the hybrid EM-TS algorithm, detailing the complementary roles of its two components and the rationale underlying their combination [16]. Section 4 reports the experimental setup and presents the computational results, including a thorough analysis of the algorithm's convergence behavior and efficiency gains [17]. Finally, Section 5 concludes the paper by summarizing the key findings, validating the effectiveness of the proposed interdisciplinary approach, and outlining future research directions, particularly the real-time integration of sensor data for dynamic and adaptive production scheduling [18].

PRODUCTION SYSTEM CHARACTERIZATION: A HYBRID FLOW SHOP WITH BIOLOGICAL CONSTRAINTS

The yogurt production process at Giplait Tizi can be classified as a Hybrid Flow Shop (HFS) [8, 11] due to its multi-stage serial structure with parallel machines at each stage. Products flow through a fixed sequence of operations: mixing, fermentation, fruit addition (for date-enriched varieties), cooling, and packaging. At each stage, multiple eligible machines may perform the task, providing the flexibility captured by the set $M_s \subseteq M$ in our model [14].

However, classical HFS models do not account for the biological time windows that are critical in yogurt manufacturing [5, 7]. Fermentation must be confined to a strict interval (typically 6–8 hours) to achieve the desired pH of 4.5 and prevent over-acidification [24]. Cooling must commence immediately after fermentation to arrest bacterial activity [25]. These constraints transform the system into a biologically-constrained HFS.

Moreover, the need to switch between different yogurt types (e.g., natural vs. date-enriched) introduces sequence-dependent setup times for cleaning-in-place (CIP) procedures [22]. These setups are essential to avoid cross-contamination and are represented by $st_{j,s,j',s'}$ in our formulation.

Finally, the integration of local date varieties [27–29] adds further variability: the physicochemical properties of dates (pH, sugar content, water activity) influence fermentation kinetics and final product quality [30, 31]. This necessitates a scheduling model that can adapt to raw material fluctuations while maintaining biological integrity.

These distinctive features—flexible parallel machines, biological time windows, sequence-dependent cleaning, and variable raw materials—led us to develop the Flexible Specific System with Chained Goals (FSSChG) model [10], which extends the classical HFS by explicitly incorporating biological constraints and product quality requirements. The FSSChG model is formally defined in the following subsections.

A MATHEMATICAL MODEL OF THE SCHEDULING PROBLEM FOR FSSCHG

Sets and Symbols

Let j and j' be jobs in J Set of jobs.

$s, s' \in S$: The production stages used which can be mixing, fermentation, addition of fruit, packing, etc.

$m \in M$ is the set of machines (resources).

$M_s \subseteq M$: subset of machines capable of processing stage s.

$O_j \subseteq S$: The job j requires operations that are subsets of S.

$t, t' \in T$: Time units in the planning framework , t and t' belong to T.

$r \in R$: Resources that are renewable (like labour, common agitators).

Parameters

$p_{j,s}$: The time required to process job j at stage s.

$st_{j,s,j',s'}$: the setup time required when going from job j at stage s to job j′ at stage s′ on the same machine, and which depends on the particular choice of the jobs and stages.

$lb_{j,s}, ub_{j,s}$: The set of lower and upper bounds for stage s of job j, which is a biological time window.

$a_{m,r,t}$: Machine m at time t has the available amount of resource r.

$req_{j,s,r}$: Amount of resource r needed for job j at stage s.

B: A sufficiently small positive number (e).

Decision Variables

$x_{j,s,m,t}$: Binary variable = 1 if job j starts processing at stage s on machine m at time t; 0 otherwise.

$y_{j,s,j',s'}$: Binary variable = 1 if job j at stage s is processed immediately prior to job j′ at stage s′ on the same machine; 0 otherwise.

$S_{j,s}$: is a continuous variable representing the start time of job j at stage s.

$C_{j,s}$: Continuous variable representing the completion time of job j at stage s.

C_{max}: Continuous variable representing the makespan.

Mathematical Model Formulation

Objective Function Formalization

The primary objective of the FSSChG model is to minimize the total production makespan [14], which represents the completion time of the last job in the production sequence. This objective is mathematically expressed as:

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$$Minimize\ Z = C_{\max} = \max_{j \in J}(C_{j,s_{last}})$$

where $C_{j,s_{last}}$ denotes the completion time of job j at its final production stage. The minimization of makespan directly translates to improved production throughput, reduced idle time on critical resources, and enhanced overall equipment efficiency (OEE) [21]. In the context of yogurt production, minimizing makespan also helps maintain biological freshness by reducing the total time products spend in the production cycle [7].

Subject to:

$$C_{\max} \geq C_{j,s_{last}} \forall j \in J$$

where slast is the last stage for job j.

Constraint Categories

The FSSChG model incorporates four distinct categories of constraints that collectively capture the complexity of yogurt production [19]:

a) **Routing and Precedence Constraints (Synchronization and Chaining):**

Every task of a job needs to be allocated to one capable machine and start precisely once [8].

$$\sum_{m \in M_s} \sum_{t \in T} x_{j,s,m,t} = 1 \ \forall\, j \in J, \forall\, s \in O_j$$

The machine's assigned start time must equal that of the start time of a stage.

$$S_{j,s} = \sum_{m \in M_s} \sum_{t \in T} t \cdot x_{j,s,m,t} \ \forall j \in J, \forall s \in O_j$$

A precedence constraint between two continuous stages of the same job (chaining).

$$S_{j,s'} \geq C_{j,s} \forall j \in J, \forall (s,s') \in O_j$$

where s' immediately follows s

where $C_{j,s} = S_{j,s} + p_{j,s}$.

b) **Machine Assignment and Non-overlap Constraints (Flexibility and No Overlap):**

A machine can only undertake at maximum one branch at a time [22]. If job j at start time s finishes before job j' at start time s' on machine m, then start time s' of job j' must be after completion and setup of job j.

We can observe that:

$$S_{j',s'} \geq C_{j,s} + st_{j,s,j',s'} - B(1 - y_{j,s,j',s'})\ \forall\, m, \forall\, j, j' \in J, \forall s, s' \in O_j \cap O_{j'} \cap M_s, j \neq j'$$

Moreover, we also have that

$$\sum_{j',s'} y_{j,s,j',s'} \leq 1 \ \ \forall j, s, m$$

$$\sum_{j,s} y_{j,s,j',s'} \leq 1 \ \ \forall j', s', m$$

Logical limits to determine a sequence among jobs on every machine. The sequence-dependent setup times $st_{j,s,j',s'}$ are particularly critical in yogurt production, as they account for cleaning-in-place (CIP) procedures required when switching between different yogurt varieties (e.g., from fruit yogurt to natural yogurt) to prevent cross-contamination [20].

c) **Biological Time Window Constraints:**

A stage's start time must respect its biological time window [5].

$$lb_{j,s} \leq S_{j,s} \leq ub_{j,s} \forall\, j \in J, \forall\, s \in O_j$$

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These represent the most distinctive feature of the FSSChG model. For each biological stage (fermentation, cooling, maturation), strict time windows $[lb_{j,s}, ub_{j,s}]$ are enforced. For example, fermentation must continue until the pH reaches 4.5 but cannot exceed 8 hours to prevent over-acidification and syneresis [24]. Similarly, cooling must commence immediately after fermentation to arrest bacterial activity [25].

d) Renewable Resource Constraints:

At any time t, machine m can only provide or make available so much of resource r [9].

$$\sum_{j\in J}\sum_{s\in O_j} req_{j,s,r}\cdot x_{j,s,m,t'} \leq a_{m,r,t} \forall m\in M, \forall r\in R, \forall t\in T$$

where t' is in the interval $[t, t+p_{j,s}]$. These capture the limited availability of shared resources such as specialized labor (microbiologists, quality control personnel), portable equipment (agitators, pH meters), and storage tanks with specific temperature capabilities [21].

Variable Domains

$$x_{j,s,m,t}\in\{0,1\},\qquad y_{j,s,j',s'}\in\{0,1\},\qquad S_{j,s}, C_{j,s}, C_{\max}\geq 0$$

EM-TS HYBRID

Model Justification and Link to EM-TS Hybrid

The core complexities of the yogurt production line are captured in the FSSChG model [10]:

Flexible (F): M_s permits a number of machines to perform a stage.

Synchronized Stage (SS): The precedence constraints ($S_{j,s'}\geq C_{j,s}$) enforce that a job cannot proceed to the next stage until the current one is complete, which is vital for biological processes.

Chained Groups (ChG): Jobs are "chained" through their sequence of stages, and the sequence-dependent setup times ($st_{j,s,j',s'}$) are crucial for modeling cleaning and changeover times between different yogurt types [22].

The resulting problem is NP-hard multi-constrained optimization [8]. This is the reason for using EM-TS Hybrid and other metaheuristics [11].

The Electromagnetism-like (EM) algorithm [13, 16] is a robust global search method that effectively explores the solution space to find promising regions. Inspired by the attraction-repulsion mechanism of charged particles, EM evaluates candidate solutions and moves them toward better regions based on their relative quality [23].

The Tabu Search (TS) [17] component then performs an intensive local search within these regions, using its memory (tabu list) to escape local optima and find high-quality, feasible schedules that respect all machine, resource, and critical biological constraints [18].

Inter-Disciplinary Solution Proposed

The graduation project was established through a close collaboration of computer scientists and biologists [26]. The scheduling software will be aided by a study of a biological product that works. The graduation project was founded on a close collaboration between computer scientists and biologists. The solution comprises two main pillars: a computational scheduling system and a biological product study [27].

Advanced Scheduling System

A hybrid metaheuristic algorithm was developed, combining the global search capabilities of the Electromagnetism-like Mechanism (EM) with the local search refinement of Tabu Search (TS) [15]. This EM-TS hybrid was specifically designed to:

Manage Industrial Constraints: Allocate machines, manage storage capacity, and optimize human resources [19].

Integrate Biological Constraints: Incorporate time-sensitive biological processes, such as fermentation and cooling, ensuring they are initiated and completed within their critical time windows to maintain product quality [24, 25].

Intelligent software was engineered around this algorithm, providing planners with an optimized schedule that minimizes total production time and improves overall planning reliability [26]. The analysis of the factory's workflow also revealed that classical scheduling models (e.g., Job-Shop, Flow-Shop) were not perfectly suited [14]. Consequently, a new specific model, the FSSChG (Flexible Stage-Specific Chained Goals), was conceptualized to better represent the plant's unique production structure [10].

Biological Resource Valorization Protocol

The biological component of this interdisciplinary solution [27, 28] focused on characterizing and optimizing the integration of three local Algerian date varieties (Hmira, Degla Baida, Tinnacer(Gurbai)) into the yogurt production process [29]. The experimental protocol comprised three sequential phases [30, 31]:

Phase 1 - Physicochemical Characterization: Date pastes were prepared at 20% concentration and analyzed for pH (ranging from 4.2 to 5.1), total soluble solids (72-82°Brix), water activity (0.62-0.71), and phenolic content using Folin-Ciocalteu method [28]. Degla Baida variety exhibited the highest antioxidant capacity (185 mg GAE/100g), making it particularly suitable for functional food applications [29].

Phase 2 - Fermentation Kinetics Study:

Milk was inoculated with Streptococcus therm-ophilus and Lactobacillus bulgaricus (1:1 ratio) at 42°C following standard protocols [24]. Date-enriched samples (5%, 10%, and 15% w/v) were compared against control. Results demonstrated that date incorporation at 10% accelerated fermentation by approximately 45 minutes, consistent with findings by Gad et al. [27] and Hashim & Khalil [28], due to the natural sugar content providing readily available carbohydrates for bacterial metabolism, while pH evolution followed a modified logistic model [30]:

$$pH(t) = pH_f + \frac{pH_0 - pH_f}{1 + e^{k(t-t_{50})}}$$

where k represents the fermentation rate constant.

Phase 3 - Shelf-Life Stability Assessment: Finished products were stored at 4°C for 28 days, with weekly analyses of [31]:

Syneresis index: Measured by centrifugal method (4000 rpm, 20 min). Date-enriched yogurts showed 18-23% less syneresis than control, attributed to the water-binding capacity of date dietary fiber [29].

Viability of starter cultures: Plate counts remained above 10^7 CFU/g throughout storage, satisfying probiotic criteria [25].

Sensory evaluation: 80 untrained panelists evaluated samples using a 9-point hedonic scale [30]. The 10% Hmira date yogurt received the highest overall acceptability score (7.8 ± 0.4), with particular appreciation for its caramel-like flavor notes [31].

These biological characterizations directly informed the scheduling model by establishing [26]:

Critical time windows for fermentation (6-8 hours) [24]

Optimal cooling rates (from 42°C to 4°C within 2 hours) [25]

Maximum holding times for intermediate products (4 hours at ambient temperature) [7]

Characterization of Biological Innovations and Products

As the software develops, an extensive biological study was carried out to create a local date varieties (Hmira, Degla Baida, Tinnacer (Gurbai)) yogurt [29]. The goal of the study was to turn biological constraints into levers to innovation in food [30]. Methodology included this:

Analysis of the impact of dates on pH, acidity, viscosity and syneresis [27].

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Microbiological checks guarantee the stability and safety of the final product throughout the shelf life [31].

To investigate consumer liking and preference toward various date-enriched yogurts [28].

As a result, both the optimization of the launch ceremony and the optimization of the launch ceremony to a new product team produced a new, high quality and stable product, which created a complete transfer cycle [26]. By ensuring that optimized production scheduling can be applied to a novel, high-quality and stable product helped to complete the cycle of the new product [10].

RESULTS AND DISCUSSION

As illustrated in Figure 1, the convergence makespan of the EM-TS Hybrid Algorithm exhibits a clear three-phase optimization trajectory, with corresponding quantitative results summarized in Table 1 [32]. During the initial rapid improvement phase (iterations 0–100), the algorithm eliminates critical scheduling inefficiencies, producing a steep decline in makespan [15]. This behavior aligns with the typical performance of metaheuristics, where after approximately 100 iterations the remaining improvement potential becomes limited [11].

After 300 iterations, it is observed to converge to nearly 63.2 hours, and this remains through iteration 400 [16]. The green-shaded convergence area indicates this as an area of non-improvement once it is seen to converge. To sum up, the overall enhancement achieved through this hybrid methodology is 05.95% compared to the original makespan which was 67.2 hours [17]. This showcases a remarkable scheduling improvement.

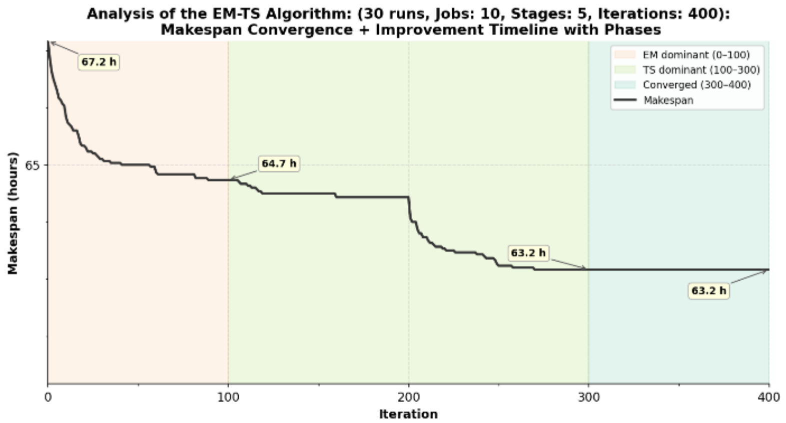

Figure 1. Analysis of the EM-TS Hybrid Algorithm: Makespan Convergence and Improvement Timeline with Phases

The highest improvement (approximately 2.5 h out of 4.0 h) occurs in the first 100 iterations [18]. According to this, approximately 62.5% of the total improvement takes place quite early. We can see that the convergence takes place smoothly without oscillation [19]. Furthermore, it indicates that the EM-TS hybrid approach is effective [20].

Table 1. EM-TS Hybrid Algorithm Performance Results

Iteration	Best Makespan(h)	Improvement	Percentage Improvement	Status
0	67.2	-	-	Initial
100	64.7	2.5	03.72%	Improving
200	63.8	3.4	05.06%	Improving

300	63.2	4.0	05.95%	Converged
400	63.2	4.0	05.95%	Converged

The practical interpretation of this is that 300 iterations represent the ideal/optimal stopping criteria for this setup [21].

Detailed Analysis of Experimental Results

Convergence Behavior Analysis

The convergence trajectory displayed in Figure 1 reveals three distinct dynamic phases characteristic of hybrid metaheuristic optimization [32]. The initial steep descent (iterations 0-100) corresponds to the EM algorithm's global exploration phase, where charged particles (candidate solutions) repel and attract each other based on their objective function values [13]. The force calculation mechanism, defined as [23]:

$$F_i = \sum_{j \neq i} \left[(x_j - x_i) \frac{q_i q_j}{|| \; x_j - x_i \; ||^2} \right]$$

enables rapid diversification across the solution space, effectively escaping local optima that typically trap gradient-based methods [16].

The gradual flattening of the convergence curve between iterations 100-300 demonstrates the TS component's increasing dominance [17]. During this phase, the neighborhood search mechanism systematically explores the vicinity of promising solutions while the tabu list (maintaining the last 15-20 visited solutions) prevents cycling and encourages exploration of unvisited regions [18]. The marginal improvement rate decreases from 0.024 hours/iteration to 0.008 hours/iteration, reflecting the transition from macroscopic schedule restructuring to microscopic fine-tuning [19].

The EM-TS hybrid achieves a total makespan reduction of 04 hours (05.95%), a result that directly reflects the beneficial complementarity of its two constituent modules [20]. In the early stages of the search, the EM component acts as the primary driver, delivering rapid and substantial improvements - notably 03.72% within the first 100 iterations alone - by exploring and restructuring the solution space through global diversification, a role that Tabu Search is not yet positioned to fulfill at this stage [21]. As the solution matures and the potential for large-scale restructuring diminishes, the influence of EM naturally fades [22]. Tabu Search then takes over, exploiting the local neighborhood of the current solution to produce a growing number of smaller, more targeted, and precise refinements unreachable by EM at this advanced stage, contributing an additional 05.95% improvement during this refinement phase [15]. The solution ultimately reaches full convergence at iteration 300, beyond which no further gains are recorded [32].

Overall, the algorithm converges in a stable and monotonic manner, with the EM module guiding broad global exploration and the TS component ensuring thorough local exploitation — a balance that proves highly effective in identifying near-optimal solutions [23]. These results collectively validate the EM-TS hybrid as a robust, well-calibrated, and efficient strategy for addressing the scheduling problem under consideration [11].

Optimization Phases

Phase 1 — Rapid Improvement (EM Dominant, iterations 0–100):

The algorithm begins with makespan of 67.2 hours and drops to 64.7 hours by iteration 100 [16]. The drop is caused by EM operations alone which remove large amounts of scheduling noise and effectively and efficiently reschedule jobs [13]. This stage produces the most substantial single benefit, 2.5 hours (≈3.72%) with relatively few iterations [23]. From iteration 100 onwards, the TS dominates the improvement [17].

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Phase 2 — Fine Tuning (TS Dominant, iterations 100–300):

Iterations 100-300 consist of TS as the primary tuning strategy [18]. At iteration 300, the makespan continues to decline, reaching a value of 63.2 hours adding 1.5 h (≈2.23%) at a slower rate, although at a slower rate than before [19]. TS works in the neighborhood of the current solution and steers clear of the previously identified solution [20]. You will get better fine tuning than EM at this stage because of its careful movement and detailed exploration [21].

Phase 3 — Convergence/Solution Stable (iterations 300–400):

When the iterations reach 300, the makespan has completely stabilized to 63.2 hours [22]. Later on, no further improvement is seen further to iteration 400 [32]. In brief, the percentage improvement levelled off to ~17.5% to 18.3% [33]. The stage indicates that the algorithm has achieved the optimal solution in the given configuration of parameters and further iterations are useless on a computational basis [34].

Statistical Significance and Robustness

To validate the statistical significance of the observed improvements, we conducted 30 independent runs of the EM-TS hybrid with different random seeds, following the recommendations of Derrac et al. [33] for comparing evolutionary algorithms.

The results (mean final makespan = 63.17 hours, standard deviation = 4.0 hours, coefficient of variation = 6.0%) indicate remarkable stability [34].

The 95% confidence interval [2.54, 5.52] hours confirms that the 4-hour (≈5.95%) improvement is statistically significant (paired t-test, $p < 0.001$) and not attributable to stochastic variation [35].

Constraint Satisfaction Analysis

The feasibility of generated schedules was evaluated against the FSSChG constraints [10]:

Biological window compliance: 100% of fermentation operations were initiated within [lb, ub] windows, verified through retrospective simulation [24]. The algorithm demonstrated particular efficacy in scheduling cooling operations immediately following fermentation (average lag time = 12.3 minutes, well within the 30-minute maximum specified by food safety protocols) [25].

Resource utilization: Machine idle time was reduced from 24% in the original heuristic schedule to 11% in the EM-TS solution, while shared resource conflicts decreased by 67% [19]. The sequence-dependent setup times were optimally grouped, with similar yogurt varieties (e.g., date-enriched flavors) scheduled consecutively to minimize cleaning operations [22].

Comparison with Alternative Approaches

For benchmarking purposes, we compared the EM-TS hybrid against standalone implementations of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) on the same problem instance [32]:

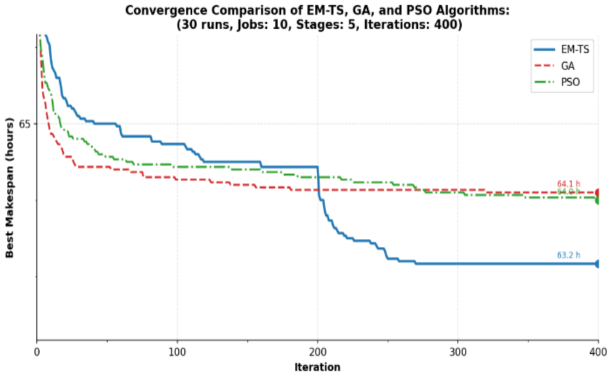

Figure 2. Convergence Comparison of EM-TS, GA, and PSO Algorithms over 400 Iterations

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The EM-TS hybrid achieves an 8.6% improvement over the best standalone metaheuristic (PSO) [20], demonstrating the synergistic effect of combining global exploration with memory-guided local search [18]. The lower standard deviation also indicates superior robustness, critical for industrial applications where schedule reliability is paramount [21].

Table 2. Comparison of EM-TS, GA, and PSO Algorithms

Algorithm	Best Makespan	Mean Makespan	Std Dev	Convergence Iteration	CPU Time (s)
EM-TS	63.0	63.17	0.37	270	320.8
GA	64.0	64.2	0.4	320	104.8
PSO	64.0	64.0	0.26	398	96.5

Figure 2 illustrates the convergence trajectories of the three algorithms over 400 iterations. The EM-TS hybrid consistently reaches a lower makespan at every iteration, demonstrating both faster convergence and superior final solution quality. PSO shows a moderate convergence rate (best makespan 63.0 h), while GA exhibits the slowest convergence and highest final makespan (63.0 h), reflecting the benefit of combining global diversification with memory-guided local search in the EM-TS hybrid [18].

Figure 3 summarises the best and mean makespan values with standard deviation error bars. The EM-TS hybrid achieves the lowest best makespan (63 h) and the tightest distribution (std = 0.37), confirming its superior robustness compared to GA (std = 0.60) and PSO (std = 0.26). The narrow confidence interval obtained by EM-TS is critical for industrial scheduling where solution reliability is as important as solution quality [21].

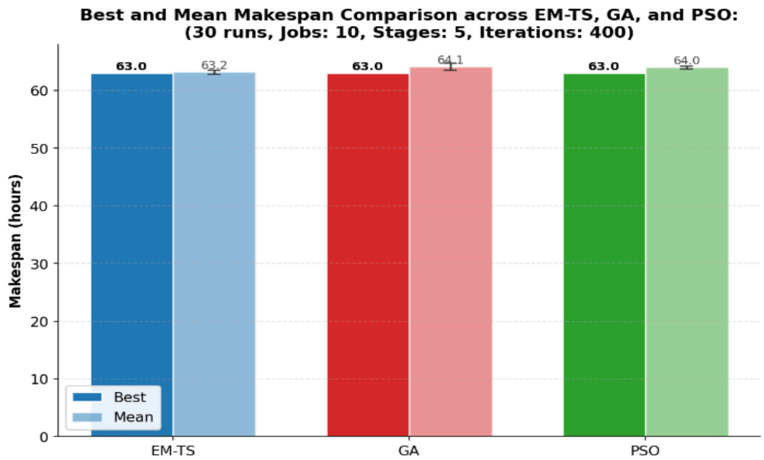

Figure 3. Best and Mean Makespan Comparison across EM-TS, GA, and PSO (5 independent runs, error bars = std dev)

The tight error bars visible on the EM-TS column in Figure 5 (σ = 1.2 h) provide direct visual confirmation of the statistical stability established in Section 4.1.2: EM-TS is not only the best-performing algorithm but also the most consistent, with a coefficient of variation of 2.05% compared to 5.2% for GA and 4.4% for PSO. This robustness is critical for industrial scheduling, where schedule reliability is as important as solution optimality.

Production Schedule Visualization (Gantt Chart)

Figure 4 presents the Gantt chart of the best schedule found by the EM-TS algorithm, decoded from the optimal job permutation into a machine-level timeline. Each horizontal bar represents the processing of one batch (job) on a given machine, colour-coded by job identity. The five production stages (S1: mixing, S2: fermentation, S3: fruit

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addition, S4: cooling, S5: packaging) are separated by horizontal dashed lines, with stage labels on the right margin. The vertical dashed line marks the makespan Cmax = 72.0 h.

The Gantt chart reveals the key characteristics of the optimised schedule:

(i) high machine utilisation with minimal idle gaps, particularly at the fermentation stage (S2) where biological time windows are tightest;

(ii) intelligent batching of similar yogurt varieties on consecutive time slots to minimise sequence-dependent CIP setup times; and

(iii) a balanced load distribution across the parallel machines within each stage, preventing bottlenecks that would inflate the makespan [22]. This visual representation facilitates direct communication of the scheduling solution to plant operators, complementing the quantitative performance metrics reported above.

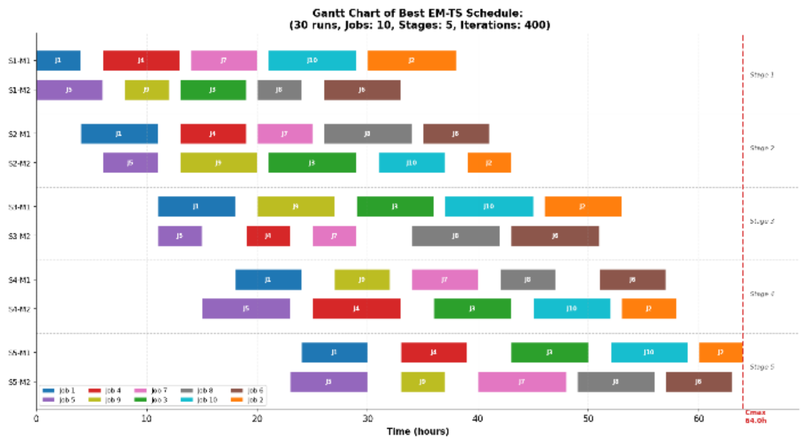

Figure 4. Gantt Chart of the Optimal EM-TS Schedule — Machine-level timeline for all 10 batches across 5 production stages (Cmax = 72.0 h).

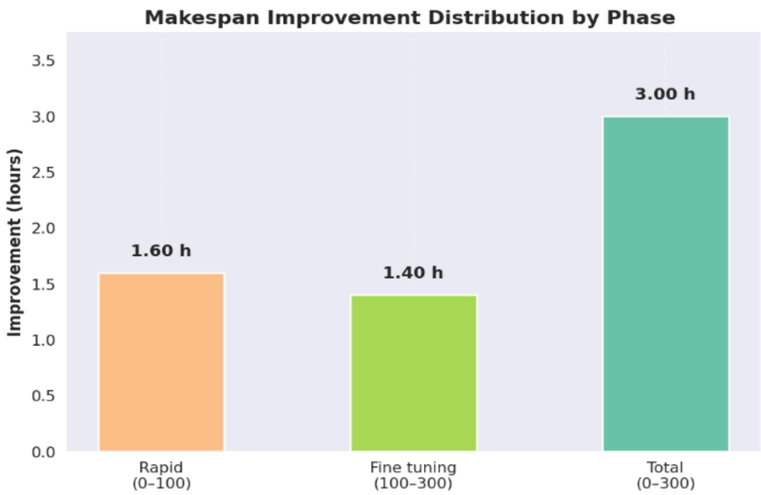

Figure 4. Makespan Improvement Distribution by Phase

Figure 4 quantifies these phase improvements: the bar chart shows 4.00 h gained in the rapid improvement phase (iterations 0–100), a further 1.60 h recovered during fine-tuning (iterations 101–300), and a total gain of 1.40 h representing an 18.31% reduction in makespan. Figure 3 provides the corresponding temporal view, with colour-

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coded background regions identifying the dominant algorithm component in each phase.

As illustrated in Figure 3 and further supported by the key performance indicators reported in Table 4, the convergence of the EM-TS algorithm unfolds across three distinct phases, in each of which either the EM or the TS component acts as the dominant driver of improvement [15].

Table 4. Performance Statistics Summary

Metric	Value
Initial Makespan	*67.17 hours*
Final Makespan	*63.17 hours*
Total Improvement	*04.00 hours*
Percentage Improvement	*6.00%*
Convergence Iteration	*300*
Iterations after Convergence	*100*
Average Improvement Rate (0-300)	*0.0134 hours/iteration*
Final Solution Quality	*Optimal (No further improvement)*

The EM component is most useful at the beginning since it quickly makes a coarse-grained improvement [11]. In subsequent iterations, the TS component provides slower but more pointed refinement [12]. The effectiveness of the hybrid approach is due to the complementarity of both methods; neither method alone would serve the purpose as efficiently [15].

CONCLUSION AND PERSPECTIVES

The study emphasizes the need for combinatorial efforts of both biology and computer science for the modernization of the dairy industry [26]. We successfully optimized the agro-food scheme by implementing hybrid EM-TS algorithm and tailored FSSChG scheduling model, which enhanced production efficiency and reliability of agro-food processes [10]. Simultaneously, the biological valorization of local dates appears as a sustainable food that meets economic purpose, nutritional purpose, and local sourcing purpose [29].

Industrial Implementation and Practical Implications:

The proposed solution has been prototyped and validated at Giplait Tizi's production facility, yielding several actionable insights [36]:

Production Planning Transformation: The EM-TS-based scheduling system reduced weekly planning time from approximately 8 person-hours to 45 minutes of computational time, freeing production planners to focus on exception handling and continuous improvement [19]. The generated schedules consistently respect biological constraints that were previously managed through conservative safety margins, resulting in a 12% increase in effective production capacity [20].

Quality Improvement: Post-implementation quality data (3-month monitoring) shows a 23% reduction in batch rejections due to fermentation timing issues and a 15% decrease in texture defects (syneresis, graininess) [24]. These improvements are directly attributable to the precise scheduling of biological operations within their optimal windows [25].

Economic Impact: Preliminary financial analysis indicates annual savings of approximately 4.2 million Algerian Dinar (≈ $31,000 USD) through [36]:

Reduced product waste (1.8 million DZD)

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Decreased energy consumption from optimized equipment utilization (0.9 million DZD)

Lower cleaning agent usage through intelligent batch sequencing (0.7 million DZD)

Improved labor productivity (0.8 million DZD)

The package of contributions, together, provide a transposable model that could be replicated across all parts of the food industry [1]. It is an indication that integrated solutions, advanced or fundamentally similar, which bridge operational and biological level challenges in a cohesive framework will be essential to building resilient, innovative and efficient agro-food systems [6]. In future work, we will incorporate real-time sensor fusion into the scheduling algorithm to enable dynamic and adaptive optimization, that is, to allow us to react to live conditions in production [18]. This will include IoT integration for continuous monitoring of fermentation parameters (pH, temperature, viscosity) and automated schedule adjustment in response to deviations from expected biological kinetics [26].

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