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Multi-objective optimization of a sterilization process in a fruits and vegetables processing industry

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Abstract

This study aims at optimizing food sterilization processes in sauce production within a fruits and vegetables processing industry to minimize energy, water consumption, and cost. A detailed process model characterizes heat and mass transfer dynamics based on temperature and time parameters. Pareto-optimal trade-offs for resource consumption objectives are generated, and optimal operating conditions incorporating sustainability and economic criteria are identified. Results show that optimal settings can achieve significant reductions in resource use. The proposed methodology provides a robust and generalizable decision support tool for industrial process engineers seeking to improve the environmental and economic sustainability of food processing operations.

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Keywords: Sustainable development; Optimization; Agri-food

1. Introduction

In recent times, the food manufacturing industry has been subject to mounting pressures to enhance its environmental performance, whilst simultaneously preserving economic competitiveness and maintaining product quality. In the context of resource-intensive sectors such as food manufacturing, enhancing the sustainability of production processes has become a critical priority [1], [2]. This necessity arises from a combination of factors, chief among them the escalating global demand, a phenomenon that has been further catalyzed by population growth. This growth has led to a concomitant increase in energy consumption and environmental pressures, most notably in sectors that are energy-intensive, such as the processing of fruit and vegetables [3]. At the same time, the sector functions within stringent economic constraints, rendering operational efficiency a key factor in determining profitability. Ensuring food safety and product integrity while minimizing energy use, waste, and emissions has therefore become a pressing challenge across the agri-food value chain.

Accounting for nearly 29% of global greenhouse gas emissions [3], the agri-food sector is a central focus in the transition toward more sustainable industrial systems. Recent research highlights the growing importance of food processing in meeting sustainability goals, shifting focus from the traditionally emphasized upstream stages like agriculture and sourcing. This phase is frequently directly under the control of manufacturing firms and represents a tangible area for intervention. For instance, Taselli et al. [4] have identified environmental hotspots along food production lines, and Kumar

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et al. [5] proposed sustainability assessment frameworks tailored to industrial operations.

Within this domain, the fruits and vegetable processing industry present unique challenges. High levels of thermal energy demand, water consumption, and process inefficiencies - particularly in operations such as cooking and sterilization - carry both economic and environmental implications [6]. These challenges underscore the need for integrated approaches that manage interdependent objectives, including energy and water efficiency, waste minimisation, and food quality. In line with this, Grinberga-Zalite and Zvirbule [7] and Ringler et al. [8] emphasise the adoption of both conventional and advanced technologies -including renewable energy integration- as key to process redesign. Case studies in tomato processing, for instance, highlight the inefficiencies of traditional methods like steam and lye peeling, reinforcing the need for parameter optimisation [9]. Similarly, Lu and Yu [10] demonstrate the potential of multi-objective optimization (MOO) to extend beyond environmental assessments by incorporating factors such as shelf-life and food waste, while Tassielli et al. [4] show how optimisation models can align industry practices with evolving regulatory and environmental expectations. Together, these studies frame MOO not simply as a computational tool, but as a practical decision-support framework. It enables manufacturers to systematically navigate trade-offs between competing objectives - environmental, economic, and quality-related - by identifying non-dominated solutions along the Pareto front [11]. Despite its growing application, few studies have examined the application of MOO to the production of semi-liquid food products such as sauces, where sterilization processes are both resource-intensive and safety-critical.

The objective of this study is to address this gap by developing an integrated optimisation framework tailored to the sterilisation phase in sauce production. Among the various approaches available, the Non-dominated Sorting Genetic Algorithm II (Nsga-II) has emerged as a widely adopted solution method for tackling complex optimization problems in manufacturing systems [12]. Its efficacy has been demonstrated in a range of domains, including heat exchanger design and food processing [9]. This approach empowers decision-makers to explore trade-offs between competing objectives on the Pareto front. Leveraging the Nsga-II in combination with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [13], this study aims to identify optimal trade-offs between energy and water consumption. In doing so, it seeks to demonstrate the applicability of advanced optimisation methods for improving the environmental and economic performance of agri-food manufacturing systems.

2. Production process description

The production process under analysis concerns the manufacturing of jarred sauce in glass containers, carried out by the Italian company F.lli Saclà S.p.A. As a representative example, an average production volume for such processes is considered. This is estimated at 30000 jars per day. As shown in Fig. 1, the production line is structured into two primary flows: the handling of raw materials and the preparation of jars. These flows converge in a series of thermal and mechanical operations, including cooking, filling, capping, sterilization, and packaging. While each stage contributes to the quality and safety of the final product, sterilization is the most critical in terms of energy and water consumption and food safety. Conducted in autoclaves with a processing capacity of up to 4,000 jars per cycle, sterilization involves the maintenance of specific thermal and pressure conditions to ensure the eradication of pathogenic microorganisms. This step is subject to close monitoring using probes placed in the geometric center of selected jars, which record temperature data to calculate the sterilization factor (F). The process operates within a temperature range of 30°C to 120°C and pressure levels from 300 mbar to 1600 mbar. Given the significant resource intensity of the process and its role in ensuring product safety, the sterilization process is the primary focus of the optimization model developed in this study.

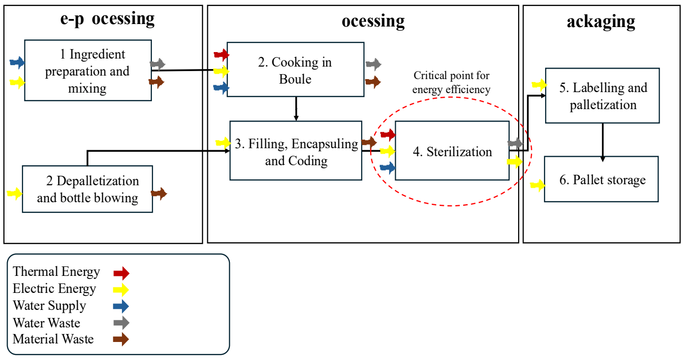

Fig. 1. Schematic of the production process of the considered sauce, including the associated flows of energy (thermal and electric), water, and raw materials.

3. Sterilization Process

Sterilization is a critical heat treatment in agri-food production, particularly in the production of sauces, where it is requested to ensure microbial safety and product stability, while maintaining organoleptic characteristics. Nevertheless, this phase is also one of the most resource-intensive, characterized by considerable energy and water consumption. Consequently, the development of accurate models to predict and optimize the sterilization process parameters is crucial to enhance sustainability while maintaining process efficiency and product quality.

3.1. Parameters

The sterilization process involves maintaining specific thermal and pressure conditions for a defined period to achieve the required microbial inactivation. These parameters - sterilization temperature, time, and associated thermodynamic properties - affect not only food safety and shelf life but also environmental and economic performance indicators. Higher temperatures have been shown to reduce processing time, but to significantly increase energy requirements and alter organoleptic and nutritional characteristics. Conversely, lower temperatures have been shown to increase water consumption due to longer cycle times. Consequently, achieving an optimal balance between these variables is crucial to minimize environmental burdens and operating costs without compromising product quality or regulatory compliance.

3.2. Sterilization process modelling

The energy and water modelling for the sterilization process is grounded in the thermodynamic framework developed by Barreiro et al. [14]. This framework has been adapted in recent literature for analogous food processing contexts [15]. The analysis is centered on the steady-state phase, during which the system can maintain the target sterilization temperature and pressure. Under these assumptions, the total energy introduced into the system via steam is assumed to be equal to the sum of all energy outputs from the system. The total energy requirement, denoted as Q_s, can be expressed as:

$$Q_s = Q_j + Q_w + Q_b + Q_{rt} + Q_e + Q_c + Q_r \quad (1)$$

where Q_j is the energy required to heat the jars, Q_w is the energy carried away by the condensate, Q_b is energy loss through steam bleeds, Q_{rt} is the energy required for heating the retort shell, Q_e is the energy required to heat the containers and Q_c and Q_r are respectively energy losses due to convective and radiative mechanisms.

As with energy, the total amount of water per time ($\dot{m}_s$) in the form of steam can be expressed as the sum of two components: the mass flow rate that leaves the system ($\dot{m}_b$) and the mass flow rate of water that condenses within the system ($\dot{m}_w$):

$$\dot{m}_s = \dot{m}_w + \dot{m}_b \quad (2)$$

Each term in Eqs. (1) and (2) corresponds to a specific contribution, as detailed below.

Thermal energy loss through steam bleeds (Q_b)

A portion of the steam exits the system to maintain stable temperature and pressure conditions. In [14], venting is assumed to be continuous, with the valve fully open throughout the process. In this case, based on company data, it is assumed that the autoclave's valve remains open for one-fifteenth of the cycle time. Therefore, a factor of 1/15 was applied for the calculation of Q_b:

$$Q_b = \dot{m}_b \cdot H_s \cdot \frac{P_t}{15} \quad (3)$$

where H_s represents the enthalpy of steam, as a function of the sterilization temperature T_s, and P_t is the sterilization time. The time-temperature relationship is governed by the integral lethality concept (F), which is fundamental for food safety:

$$F = \int_0^{P_t} 10^{\frac{T_s(t)-T_{ref}}{z}} dt \quad (4)$$

where T_{ref} and z are the reference temperature and the temperature increment required to reduce the sterilization time by a factor of 10, respectively. In the case study, a target lethality value F = 9 was used to derive the empirical relationship between P_t and T_s shown in Fig. 2.

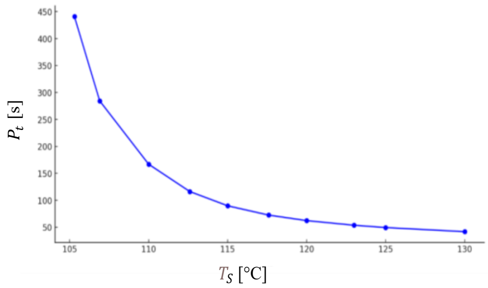

Fig. 2 Empirical relationship between sterilization temperature (T_s) and sterilization time (P_t).

The mass flow rate, $\dot{m}_b$, is calculated following the formulation proposed by Barreiro et al. [14] using the following parameters: a vent valve area A_0 = 4.91·10^{-6} m^2, the ideal gas constant R = 8.314 J/(mol·K), atmospheric pressure P_a = 101.325 Pa, and process-specific pressure P_s = 1683,827 Pa, derived from steam tables in agreement with company data. The adiabatic index γ = 1.3 is also incorporated to account for the compressibility of the steam flow.

Thermal energy required to heat the jars (Q_j)

To calculate the energy required to heat the jars (Q_j), three contributions are considered: the energy required to heat the sauce (Q_p), the glass (Q_g), and the lids (Q_l).

$$Q_j = Q_l + Q_g + Q_p \quad (5)$$

The energy required to heat the sauce (Q_p) is calculated as:

$$Q_p = m_p c_p (T_s - T_0) \quad (6)$$

where m_p represents the mass of the sauce to be heated, c_p is the specific heat capacity of the sauce, T_s is the sterilization temperature and T_0 is the initial temperature of the sauce. For 3000 jars (loading of a cycle), with 411 g of sauce each, m_p =1233 kg, and T_0 = 60 °C.

The energy required to heat the glass (Q_g) is calculated as:

$$Q_g = m_g c_g (T_s - T_0) \quad (7)$$

where m_g = 615 kg (205 g per jar) and c_g is the specific heat capacity of the glass, which in this case is 0.84 kJ/(kg·K).

The energy required to heat the lids (Q_l) is calculated as:

$$Q_l = m_l c_l (T_s - T_0) \quad (8)$$

with $m_l = 27$ kg (9 g per lid) and $c_l = 0.9$ kJ/(kg·K)

Thermal energy required to heat retort (Q_{rt}), and lost by convection (Q_c) and radiation (Q_r)

Due to the high insulation efficiency of the autoclave in the case study, the energy required to heat the walls of the autoclave (Q_{rt}) and the energy lost through convection (Q_c) and radiation (Q_r) are estimated according to the company at 10% of the jar heating energy Q_j (see Eq. (5)):

$$Q_{rt} + Q_c + Q_r = 0.1 \cdot (Q_l + Q_g + Q_p) \quad (9)$$

Thermal energy leaving with the condensate (Q_w)

A portion of the energy is released due to steam condensation upon contact with the elements inside the autoclave. This contribution is calculated using the following expression:

$$Q_w = \dot{m}_w \cdot H_w \cdot P_t \quad (10)$$

where H_w is the is the enthalpy of saturated water and the mass flow rate of condensed water ($\dot{m}_w$) is derived from:

$$\dot{m}_w = \frac{Q_j + Q_{rt} + Q_c + Q_r}{(H_s - H_w) \cdot P_t} \quad (11)$$

In addition, the calculation of $\dot{m}_w$ enables the calculation of the mass of steam entering per time ($\dot{m}_s$), according to Eq. (2).

4. Multi-objective optimization

The mathematical formulation of the sterilization process forms the basis of the subsequent development of a MOO framework. MOO problems are especially relevant in real-world engineering contexts [16], as they frequently depend on parameters that influence objective functions in conflicting ways. De Weck [17] offers a reconstruction of the historical evolution of this type of problem, which reveals the reality that no single solution can simultaneously satisfy all objectives. Instead, the optimal set is represented by the Pareto front, which contains non-dominated solutions – those where no objective can be improved without worsening another.

In this study, the objective is to optimize the balance between energy consumption and water usage. These two factors are modelled as functions of a single process parameter, the sterilization temperature T_s. It is noteworthy that the two objective functions attain their respective minimum at different temperatures, resulting in a continuous spectrum of Pareto-optimal solutions within the explored range (104 °C – 130 °C). This interdependence forms the foundation for applying an evolutionary multi-objective algorithm.

4.1. Optimization model using Nsga-II

The Pareto front is identified by means of the Nsga-II. The Nsga-II, as initially introduced by Srinivas and Deb [12], has a proven track record in addressing problems characterized by conflicting objectives. Rather than seeking a single optimal solution, Nsga-II aims to identify a set of trade-off solutions that are distributed along the Pareto frontier.

The key components of Nsga-II (which is diagrammed in Fig. 3) include:

- Population Initialization: This involves the generation of a random initial population of candidate solutions.
- Objective Evaluation: Each individual is then assessed using the defined objective functions.
- Non-Dominated Sorting: Solutions are then ranked based on Pareto dominance.
  - Level 1: No solutions on this level are dominated by any other.
  - Level 2: Dominated exclusively by solutions in Level 1, and so forth.
- Crowding Distance: A measure of solution density is computed in order to maintain diversity on the Pareto front.
- Selection, Crossover, and Mutation: Genetic operations are used to generate new solutions from existing individuals.
- Survivor Selection: Current and offspring populations are then merged, sorted, and truncated to retain the most promising candidates.
- Termination: The algorithmic process is repeated iteratively until a specified number of generations have been reached.

In this study, the problem is initiated with four parameters: the independent variable T_s, two objective functions (Q_s and $\dot{m}_s$), and bounds defined by the operating temperature range. The execution of the algorithm is undertaken with a population size of 100, and the termination of the algorithm occurs after 100 generations, yielding 100 Pareto-optimal solutions.

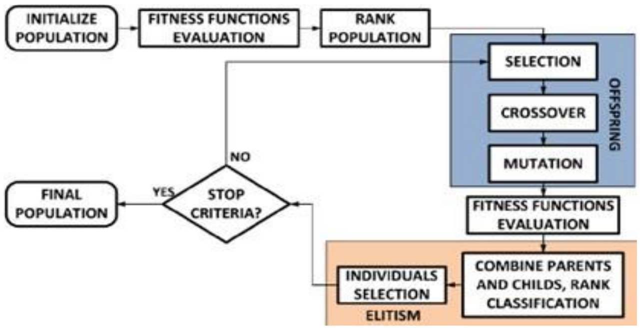

Fig. 3 Nsga-II Framework. Source: Dendaluce et al [21]

4.2. Decision-Making using TOPSIS

Although all Pareto solutions are non-dominated, the selection of a single configuration for implementation requires a decision-making approach. The TOPSIS is adopted for this purpose. This approach was first introduced by Hwang and Yoon [18] and has since become a widely adopted Multi-Criteria Decision-Making (MCDM) method in industrial applications. TOPSIS facilitates the ranking of alternatives based on their relative proximity to a reference point, defined as the ideal solution. The ideal solution is defined as a hypothetical point that achieves the best value across all criteria simultaneously, while the negative ideal represents the worst-case configuration. The geometric distance of each alternative from these two reference points is then used to determine its relative ranking. In this study, each of the 100 Pareto-optimal configurations is regarded as an alternative, and the evaluation criteria consist of four environmental impact categories typically used for Life Cycle Assessment (LCA) study [19] - Global Warming Potential (GWP), Eutrophication, Acidification, and Water Consumption - [19] along with one economic indicator: the Life Cycle Cost of Operation (LCOP) [20].

To ensure the objective weighting of these criteria, the entropy method is adopted. This approach assigns greater importance to criteria that exhibit higher variability across the solution set, reflecting their greater influence on the differentiation among alternatives. Following the process of normalization and weighting of the decision matrix, TOPSIS calculates the relative proximity of each alternative to the ideal solution. The most balanced configuration is the one with the highest proximity index, as it best manages trade-offs between energy and water use, environmental impact, and economic performance. This integrated method strengthens the optimization framework by merging evolutionary algorithms with decision-analysis tools, leading to more informed, sustainability-focused decisions in industrial food processing.

5. Results and Discussion

5.1. Pareto Front Analysis and Optimal Solution Selection.

The model was constructed with two objective functions in mind: energy consumption (Q_s) and the combined mass of steam and water per time ($\dot{m}_s$). The respective minimum was identified at 116.14 °C for energy (770.21 MJ) and 114.03 °C for water (447.73 kg), as illustrated in Fig. 4. The mass value was obtained by considering a sterilization time P_t = 3371 s. The boundaries delineate the feasible solution space for Pareto optimization.

Using the Nsga-II algorithm, the 100 Pareto-optimal solutions were computed, capturing the trade-off surface between the two conflicting objectives. Fig. 5 shows the inverse relationship between energy and water consumption across the Pareto front: increasing the sterilization temperature favors reduced water usage at the expense of higher energy input. This trend underscores the inherent conflict between thermal and hydraulic efficiency in steam-based sterilization processes.

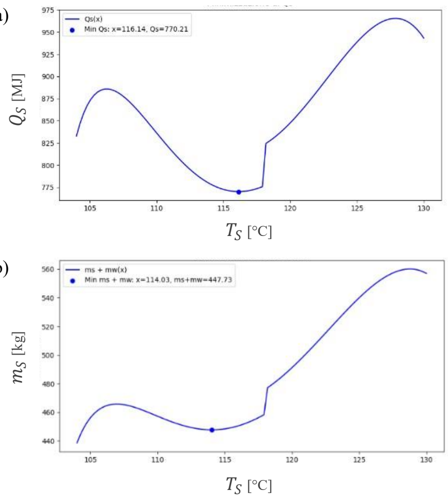

Fig.4. (a) Energy minimization and (b) Water consumption minimization in the sterilization process

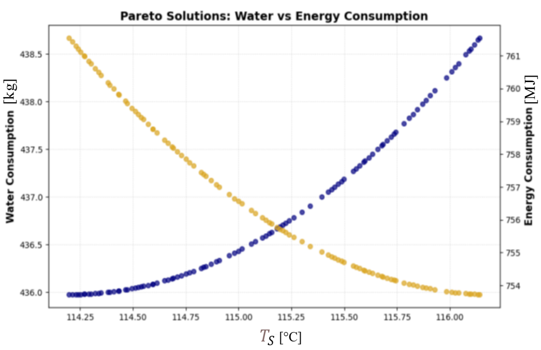

Fig. 5. Trade-off between energy (blue) and water (yellow) consumption across 100 Pareto-optimal solutions as a function of sterilization temperature T_s

5.2. Sustainability-Based Decision using TOPSIS

To identify the most balanced solution, the Pareto set was evaluated using the TOPSIS method. A decision matrix was constructed with impact indicators across the four sustainability dimensions and the economic one, mentioned in Section 4.2, i.e. GWP, Acidification, Eutrophication, Water Consumption, and LCOP. Table 1 shows an example for the first five records of this matrix. Weighting was determined using the entropy method to preserve objectivity across criteria. The optimal configuration corresponds to a sterilization temperature T_s = 115.33 °C, with associated consumption values of 755.23 MJ (energy) and 436.89 kg (water). This setting offers a balanced compromise between environmental externalities and operational efficiency.

Table 1. Example of TOPSIS matrix Pareto solutions

	T_S	GWP [10^{-2}]	Water Cons. [10^{-4}]	Eutrophication [10^{-8}]	Acidification [10^{-5}]	LCOP [10^{-2}]
Meas. unit	[°C]	[kg CO_2 eq.]	[m^3]	[kg P eq.]	[kg SO_2 eq.]	[€/jar]
1	115.3	5.051	1.438	2.391	4.963	1.637
2	114.9	4.998	1.436	2.377	4.960	1.632
3	116.1	5.010	1.437	2.384	4.962	1.635
4	115.7	5.011	1.436	2.385	4.960	1.635
5	114.1	5.000	1.436	2.379	4.960	1.633

5.3. Quantified Economic and Environmental Gains

The implementation of the optimal T_s has been demonstrated to provide considerable sustainability and economic benefits. All differences are calculated with respect to the company's current reference process, which operates at a sterilization temperature T_s = 121 °C. In comparison with this baseline, energy consumption is reduced by 826.17 MJ (- 9.86%) and water consumption by 455.65 kg (- 9.44%). These reductions in consumption translate into corresponding environmental impact decreases: the GWP, Eutrophication, Acidification, and Water consumption all show a decrease, with the percentage changes being - 4.38%, - 5.38%, - 1.34%, and - 0.54%, respectively. From an economic perspective the optimized process yields a 2.98% cost reduction, which translates to annual savings of 4.6 k€. This demonstrates the potential for integrating environmental performance into cost-based decision-making, a priority for the food manufacturing sector under increasing regulatory and market pressure. Furthermore, while all the principles described remain valid, it is possible to adapt the calculations to context-specific production values. In the case of the company studied, these production values can reach up to 60000 jars per day.

6. Conclusions

This study addresses the growing demand for sustainable and cost-efficient practices in agri-food manufacturing by developing an optimization framework based on Nsga-II and TOPSIS. Applied to a real case in sauce production, the authors identified sterilization as the most resource-intensive phase, enabling targeted improvements that would reduce both energy and water consumption. The findings highlight the practical value of multi-objective optimization as a transferable decision-support tool for enhancing sustainability in food processing.

While the model demonstrates strong potential, its scope is limited to a single production phase and assumes steady-state conditions based on data from a single company, which may constrain its broader applicability. Furthermore, the absence of detailed process data in numerous food SMEs continues to act as a substantial impediment to the adoption of such methodologies. Subsequent developments are focused on broadening the scope of the model by addressing these two aspects: extending the optimization framework to multiple production stages and enhancing its generalizability through the integration of data from a broader range of industrial contexts.

Overall, the study underscores the benefit of integrating optimization into process management and encourages policymakers to promote data transparency and support digitalization efforts that facilitate resource-efficient manufacturing.

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