



7th International Conference on Industry of the Future and Smart Manufacturing  
(former International Conference on Industry 4.0 and Smart Manufacturing)

# Energy-Aware Production Planning and Control in Container Glass Manufacturing with Hydrogen-Fueled Furnace

Hossein Arshad<sup>a\*</sup>, Giulia Fede<sup>a</sup>, Chiara Caccamo<sup>b</sup>, Fabio Sgarbossa<sup>a</sup>

<sup>a</sup> *Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology (NTNU),  
Richard Birkelands vei 2B, 7034, Trondheim, Norway*

<sup>b</sup> *SINTEF Energy Research, Kolbjørn Hejes vei 1A, 7034, Trondheim, Norway*

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## Abstract

This paper presents a mixed-integer linear programming (MILP) model for energy-aware production planning and control (PPC) in container glass manufacturing, focusing on furnaces that supply molten glass to parallel molding machines. The model represents a real-world setting in which furnaces operate continuously, utilizing hybrid energy configurations that combine hydrogen (H<sub>2</sub>) or natural gas (NG) with electrical boosting (EB). The model also accounts for energy-related characteristics, such as melting efficiency and moisture rate, that influence furnace performance and molten glass quality.

The proposed model incorporates key operational features, such as color campaign scheduling, product changeovers, machine efficiency, and inventory dynamics, while ensuring demand satisfaction across multiple periods. The objective is to minimize total costs, including energy consumption, CO<sub>2</sub> emissions penalties, inventory holding, and setup costs. The MILP formulation is implemented in Python and solved using the Gurobi Optimizer.

A case study involving container glass production (e.g., bottles and jars) demonstrates the model's capability to generate sustainable, cost-efficient production plans that account for energy configurations and furnace-machine interdependencies. The findings suggest that technological advancements and/or pricing adjustments are crucial to facilitate a cost-effective transition toward more sustainable manufacturing practices.

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Peer-review under responsibility of the scientific committee of the 7th International Conference on Industry of the Future and Smart Manufacturing (former International Conference on Industry 4.0 and Smart Manufacturing)

*Keywords:* Production planning and control; Glass manufacturing; Hydrogen fuel; Furnace performance; Optimization modeling.

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\* Corresponding author. Tel.: +47 41260719

E-mail address: [hossein.arshad@ntnu.no](mailto:hossein.arshad@ntnu.no)

## 1. Introduction

Energy-intensive industries, such as the glass, steel, and aluminum sectors, accounts for approximately 30% of global greenhouse gas emissions [1], primarily due to their high-temperature heat requirements. Achieving the EU's carbon neutrality targets necessitates overcoming the specific challenges these sectors face in reducing emissions, one of which is their dependence on natural gas (NG) as a combustion fuel. As a matter of fact, the use of NG to meet the elevated thermal demands results in significant CO<sub>2</sub> emissions released during combustion. One promising solution for the decarbonization of energy-intensive industries is the use of green hydrogen (H<sub>2</sub>), produced through electrolysis powered by renewable energy sources [2]. H<sub>2</sub> combustion generates no direct CO<sub>2</sub> emissions, making it a clean alternative. However, it also presents some disadvantages compared to NG, most notably its significantly lower volumetric heating value. Approximately three times the volume of H<sub>2</sub> is needed to deliver the same energy [3], affecting the overall economic feasibility of the transition. Nonetheless, several EU initiatives are actively exploring the feasibility of H<sub>2</sub> integration in energy-intensive industrial processes. Among them, the H2GLASS project focuses on the adoption of H<sub>2</sub> in glass manufacturing [4]. In this context, H<sub>2</sub> can replace NG, which is the primary energy source currently used for glass melting, in combination with electrical boosting (EB). Initial trials involving partial substitution have demonstrated the practical viability of this transition, with promising results in maintaining process stability and product quality [5, 6].

However, the combustion characteristics of H<sub>2</sub> still require careful consideration, especially at high H<sub>2</sub> shares in the fuel mix. In particular, H<sub>2</sub> has different combustion conditions compared to NG, such as increased laminar flame speed and adiabatic flame temperature, as well as changes in flame length, all of which affect the heat transfer to the molten glass [2, 7].

Furthermore, H<sub>2</sub> combustion generates a greater amount of water vapor, which increases the moisture content in the combustion environment, referred to as the moisture rate in this study [7]. Elevated moisture rates can lead to increasing foam formation on the molten glass surface [8], which may compromise the quality of the final glass product. These effects highlight the criticality of maintaining optimal operating conditions to ensure a controlled combustion environment.

Within glass manufacturing, the furnace is the most critical component of the process, as it accounts for the largest share of energy consumption, used to melt raw materials, and is the primary source of CO<sub>2</sub> emissions. The selection of combustion fuel and the share of EB play a critical role in determining energy efficiency and emissions levels [9, 10].

In addition, furnace operating conditions influence the thermal properties of the molten glass, which are critical for achieving the desired product specifications. In particular, fluctuations in the temperature of the gob, which is the molten glass drop delivered to the molding machine, can affect shaping performance. If the temperature is too low, the glass may not form properly, leading to defects; if it is too high, it can cause deformation or damage to the forming equipment. Since molding machines require gobs within a specific temperature range, their performance is tied to stable and consistent furnace operation [11]. This interdependence highlights the importance of synchronized control between the furnace and forming stages, collectively referred to as the hot area.

Existing Production Planning and Control (PPC) models in the literature with application in glass manufacturing aim to define furnace color campaigns, as well as lot size and product sequencing for each molding machine. A key constraint is the absence of intermediate buffers between the furnace and the molding machines, requiring continuous operation of these machines in synchronization with the furnace. Additional constraints stem from the need for limited color changeovers due to high sequence-dependent setup times, and machine eligibility restrictions based on product characteristics. This planning problem has been addressed at the single-facility level by Almada-Lobo et al. [12] using a variable neighborhood search approach focused on minimizing glass waste, inventory, and stockout costs. Fabiano Motta Toledo et al. [13] extended the problem to a multi-facility context, adding the complexity of managing product transfer flows among facilities to meet demand. Similar objectives were considered, with the addition of minimizing transfer costs, and a multi-population genetic algorithm was used for optimization.

While cost-effectiveness remains a key factor for competitiveness in process industries, energy consumption is often overlooked in PPC models, despite its critical importance in glass manufacturing. As global glass demand continues to grow, driven in part by the expansion of renewable energy technologies such as solar panels and wind turbines, where glass is a key component, the need for planning approaches that are not only economically efficient

but also energy-aware is evident. For instance, Cui & Yuan [14] propose a hybrid genetic algorithm enhanced with reinforcement learning to optimize glass production while minimizing total machine energy consumption.

Drawing on the above considerations and in response to the identified needs, the present paper develops an energy-aware PPC model for container glass manufacturing. The objective is to optimize production operations while minimizing energy consumption, emissions, and operational costs. The model accounts for the use of alternative fuels, H<sub>2</sub> or NG, combined with EB, and incorporates energy-related characteristics, including melting efficiency and moisture rate, which directly influence furnace performance and molten glass quality. The contributions of the paper are summarized as follows:

- It proposes a mixed-integer linear programming (MILP) model for energy-aware PPC in container glass manufacturing;
- It accounts for hybrid energy configurations (H<sub>2</sub> or NG and EB) and their impact on energy consumption, emissions, and furnace behavior;
- It integrates operational features, including furnace color campaigns, machine efficiency, product changeovers, and inventory dynamics.

Section 2 outlines the problem statement for the energy-aware glass PPC model. Section 3 presents the mathematical formulation of the optimization model, followed by a discussion of the case study results in Section 4. Finally, Section 5 concludes the paper by addressing the study's limitations and proposing directions for future research.

## 2. Problem Statement

Glass manufacturing is a continuous, high-temperature process characterized by substantial energy requirements. Figure 1 schematically illustrates the overall glass manufacturing process.

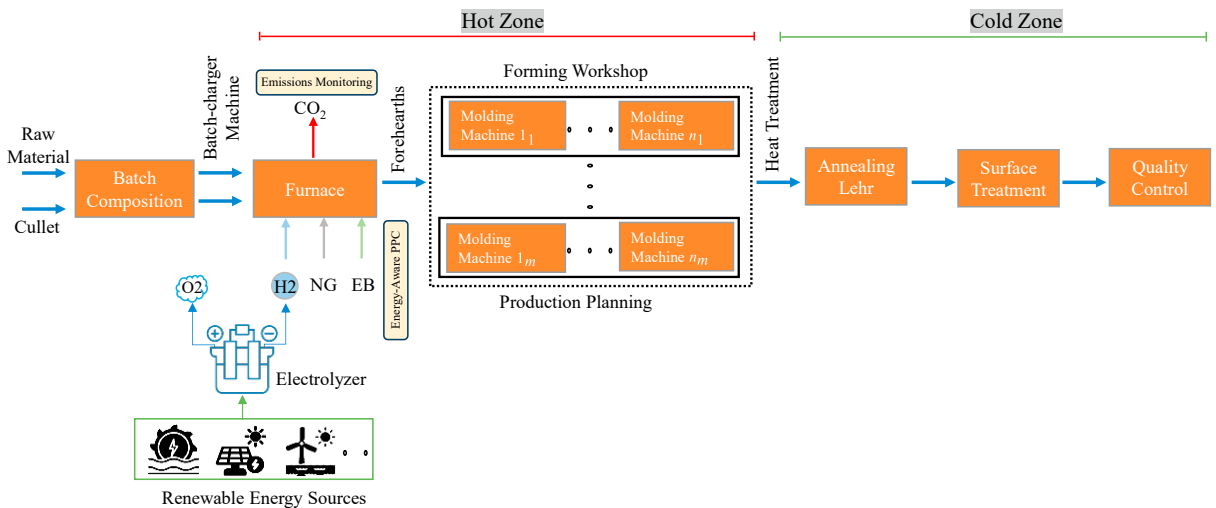


Figure 1. Energy-aware production planning and control framework in glass manufacturing.

Raw materials and recycled cullets are melted in furnaces and the resulting molten glass is directly transferred to molding machines, which shape the final products. Post-processing steps, including cooling and surface treatment, are then carried out to ensure product quality before storage or delivery to customers.

PPC in container glass manufacturing is particularly challenging due to the complexity of scheduling color campaigns and changeovers. These changeovers are highly time-consuming, often resulting in significant production downtime and costs. The absence of intermediate buffers between furnaces and molding machines further increases this complexity, requiring strictly synchronized operation to maintain process stability, minimize energy waste and

prevent quality issues. Additionally, the system must meet customer demand over time while respecting production capacity constraints, with penalties applied for any unmet demand.

In this context, energy considerations are of central importance, as the continuous operation of furnaces necessitates a stable and uninterrupted energy supply. This requirement introduces additional constraints on PPC and contributes to the overall high energy demand of the process. NG combustion has traditionally served as the primary energy source for furnaces, supported by EB to enhance thermal efficiency. However, due to the high CO<sub>2</sub> emissions associated with NG combustion and in alignment with decarbonization goals, the adoption of alternative energy sources, including H<sub>2</sub>, is being explored. H<sub>2</sub> does not produce CO<sub>2</sub> emissions during combustion, and when generated via water electrolysis powered by renewable energy sources (green H<sub>2</sub>), it serves as a carbon-free energy carrier, offering a significant improvement in emissions compared to continued reliance on NG.

However, these fuels differ in both combustion characteristics and thermal properties, ultimately affecting their melting efficiency. When considering only volumetric heating values, approximately three times the volume of H<sub>2</sub> is required to deliver the same amount of energy as NG combustion, significantly reducing the unit melting efficiency of H<sub>2</sub>. Combined with the current higher unit cost of H<sub>2</sub> relative to NG, this makes H<sub>2</sub> significantly less economically competitive as an energy source. Additionally, the higher moisture rate associated with H<sub>2</sub> combustion may impose limits on its consumption to avoid final product quality issues, constraints that do not apply when relying on NG.

These trade-offs across energy sources not only motivate the model development but also underscore the relevance of an energy-aware PPC model that explicitly integrates energy-related constraints alongside conventional operational requirements within the production planning framework. Specifically, the proposed optimization model incorporates cost, CO<sub>2</sub> emissions, melting efficiency, and utilization constraints for each energy source (e.g., moisture rate for H<sub>2</sub>). These factors influence the objective function through their impact on overall production costs, ultimately guiding the selection of the optimal fuel for each time period to be used in combination with EB, the corresponding flow rate, and the total energy consumption of each furnace, while ensuring compliance with energy-related constraints.

### 3. Mathematical Optimization Model

This subsection introduces the mathematical formulation used to represent the energy-aware glass PPC optimization model, including the associated notation and corresponding units of measure.

Sets:

$y$	Furnace ( $y = 1, \dots, Y$ )
$k$	Molding machine ( $k = 1, \dots, K$ )
$l, u$	Product color ( $l, u = 1, \dots, L$ )
$t$	Period ( $t = 1, \dots, T$ )
$j$	Customer ( $j = 1, \dots, J$ )
$i$	Product ( $i = 1, \dots, N$ )
$f$	Energy source ( $f = H_2, NG, EB$ )
$f'$	Combustion fuel ( $f' = H_2, NG$ )
$f''$	( $f'' = H_2$ )
$f'''$	( $f''' = EB$ )

Parameters:

$K_y$	Set of molding machines fed by furnace $y$
$ K_y $	Number of molding machines fed by furnace $y$
$N_l$	Set of products with color $l$
$d_{ijt}$	Demand for product $i$ from customer $j$ at the end of period $t$ (tons)
$\varepsilon_{ij}$	Penalty cost for unsatisfied demand for product $i$ from customer $j$ (€/tons)
$Q_t$	Number of days in period $t$ (days)
$\alpha_{ly0}$	$\begin{cases} 1 & \text{if furnace } y \text{ is initially setup for color } l \\ 0 & \text{otherwise} \end{cases}$
$I_{i0}$	Initial inventory of product $i$ (tons)
$\gamma_{uly}$	Changeover cost from color $u$ to color $l$ in furnace $y$ (€)

$h_i$	Inventory holding cost for product $i$ (€/tons)
$C_y$	Melting capacity of furnace $y$ (tons/days)
$\eta_k$	Efficiency of molding machine $k$
$\theta_{ik}$	Production capacity of molding machine $k$ for product $i$ (tons/days)
$s_{uly}$	Changeover time from color $u$ to color $l$ in furnace $y$ (days)
$\lambda_{uly}$	Remaining production time after a non-integer changeover from color $u$ to color $l$ in furnace $y$ (days)
$M_{ikt}$	Maximum processing time of product $i$ on molding machine $k$ in period $t$ (days)
$\beta_f$	Consumption cost for energy source $f$ (€/MWh)
$\mu_f$	Emission factor for energy source $f$ (kg/MWh)
$\omega_f$	Melting efficiency of energy source $f$
$\delta$	Emissions cost factor (€/kg)
$\varphi$	Required energy (MWh/day)
$\psi$	Maximum H <sub>2</sub> share to limit moisture-related defects
$\epsilon$	EB energy contribution factor
$A$	Big number

*Decision variables:*

$X_{ikt}$	Number of days in which product $i$ is produced on molding machine $k$ in period $t$ (days)
$Y_{ikult}$	$\begin{cases} 1 & \text{if product } i \in N_l \text{ is partially produced on machine } k \text{ after a non – integer changeover from } u \text{ to } l \\ 0 & \text{otherwise} \end{cases}$
$I_{it}$	Inventory for product $i$ in period $t$ (tons)
$q_{ij}$	Unsatisfied demand of product $i$ for customer $j$ (tons)
$Z_{yt}$	$\begin{cases} 1 & \text{if furnace } y \text{ is active in period } t \\ 0 & \text{otherwise} \end{cases}$
$\alpha_{lyt}$	$\begin{cases} 1 & \text{if furnace } y \text{ is setup for color } l \text{ at the beginning of period } t \\ 0 & \text{otherwise} \end{cases}$
$T_{ulyt}$	$\begin{cases} 1 & \text{if a changeover occurs on furnace } y \text{ from color } u \text{ to color } l \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$
$B_{lyt}$	Campaign duration for color $l$ on furnace $y$ in period $t$ (days)
$V_{lyt}$	Order value of color $l$ in furnace $y$ in period $t$
$E_{ytf}$	Consumption of energy source $f$ from furnace $y$ in period $t$ (MWh)
$H_{ytf}$	$\begin{cases} 1 & \text{if combustion fuel } f \text{ is used on furnace } y \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$

Using the above notation, the MILP model can be formulated as follows.

Minimize

$$\sum_{ytf} E_{ytf} * \beta_f + \sum_{ytf} E_{ytf} * \mu_f * \delta + \sum_{ulyt} T_{ulyt} * \gamma_{uly} + \sum_{it} I_{it} * h_i + \sum_{ij} q_{ij} * \epsilon_{ij} \quad (1)$$

Subject to

$$I_{it} + d_{ijt} = I_{i0} + q_{ij} + \sum_y \sum_{k \in K_y} \left( X_{ikt} + \sum_u \lambda_{uly} * Y_{ikult} \right) * \theta_{ik} * \eta_k \quad \forall l, j, i \in N_l, t = 1 \quad (2)$$

$$I_{it} + d_{ijt} = I_{i(t-1)} + q_{ij} + \sum_y \sum_{k \in K_y} \left( X_{ikt} + \sum_u \lambda_{uly} * Y_{ikult} \right) * \theta_{ik} * \eta_k \quad \forall l, j, i \in N_l, t > 1 \quad (3)$$

$$\sum_{i \in N_l} Y_{ikult} = \begin{cases} T_{ulyt}, & \lambda_{uly} > 0 \\ 0, & \lambda_{uly} = 0 \end{cases} \quad \forall u, l, y, t, k \in K_y \tag{4}$$

$$B_{lyt} = \sum_{i \in N_l} X_{ikt} + \sum_u (s_{uly} + \lambda_{uly}) * T_{ulyt} \quad \forall k \in K_y, l, y, t \tag{5}$$

$$Z_{yt} \leq Z_{y(t-1)} \quad \forall y, t > 1 \tag{6}$$

$$\sum_l B_{lyt} \leq Q_t \quad \forall y, t = 1 \tag{7}$$

$$\sum_l B_{lyt} \leq Q_t * Z_{y(t-1)} \quad \forall y, t > 1 \tag{8}$$

$$\sum_l B_{lyt} \geq Q_t * Z_{yt} \quad \forall y, t \tag{9}$$

$$\sum_{k \in K_y} \sum_{i \in N_l} \left( X_{ikt} + \sum_u \lambda_{uly} * Y_{ikult} \right) * \theta_{ik} + C_y * \sum_u s_{uly} * T_{ulyt} \leq C_y * B_{lyt} \quad \forall (l, y, t) | \exists (k \in K_y, i \in N_l) \tag{10}$$

$$\Rightarrow \theta_{ik} > \frac{C_y}{|K_y|}$$

$$X_{ikt} + \sum_u \lambda_{uly} * Y_{ikult} \leq M_{ikt} * \left( \alpha_{lyt} + \sum_{u \neq l} T_{ulyt} \right) \quad \forall l, y, t, k \in K_y, i \in N_l \tag{11}$$

$$\sum_l \alpha_{lyt} = 1 \quad \forall y, t \tag{12}$$

$$\alpha_{lyt} + \sum_u T_{ulyt} = \alpha_{ly(t+1)} + \sum_u T_{ulyt} \quad \forall l, y, t \tag{13}$$

$$V_{lyt} \geq V_{ulyt} + L * T_{ulyt} - (L - 1) - L * \alpha_{ulyt} \quad \forall l \neq u, y, t \tag{14}$$

$$Z_{yt} = 1 \quad \forall y, t \tag{15}$$

$$E_{ytf} \leq A * H_{ytf} \quad \forall f \in f', y, t \tag{16}$$

$$\sum_{f \in f'} H_{ytf} = 1 \quad \forall y, t \tag{17}$$

$$E_{ytf} * \omega_f \geq \epsilon * \varphi * Q_t * Z_{yt} \quad \forall y, t, f \in f''' \tag{18}$$

$$\sum_{f \in f'} E_{ytf} * \omega_f \geq (1 - \epsilon) * \varphi * Q_t * Z_{yt} \quad \forall y, t \tag{19}$$

$$E_{ytf''} \leq \psi * \sum_f E_{ytf} \quad \forall y, t \quad (20)$$

$$I_{ipt}, q_{ij}, B_{lyt}, V_{lyt}, E_{ytf} \geq 0 \quad (21)$$

$$Z_{yt}, \alpha_{lyt}, T_{ulyt}, H_{ytf} \in \{0,1\} \quad (22)$$

$$X_{ikt} \in \mathbb{Z}^+ \quad (23)$$

This model builds on the multi-facility glass container production planning model proposed in [13], which includes multiple products, colors, machines, furnaces, and periods. The model developed in this study focuses on a single facility and extends the original by incorporating multiple customers, diverse energy sources (H<sub>2</sub>, NG, and EB), CO<sub>2</sub> emission considerations, melting efficiency based on fuel type, and the impact of moisture released during H<sub>2</sub> combustion.

To reflect the energy-aware nature of the PPC problem, the objective function (1) minimizes the overall operating cost, including energy consumption costs, CO<sub>2</sub> emissions costs associated with energy use, setup costs from color changeovers, inventory holding costs, and penalties for unmet demand. Constraints (2) - (15) relate to glass PPC and are adapted from [13], with modifications to reflect the single-facility setting and the inclusion of multiple customers, as previously discussed. These constraints are briefly described below.

Constraints (2) and (3) ensure inventory balance by requiring that all products produced, including partial production following non-integer color changeovers (i.e., changeovers whose duration covers a non-integer number of days), are either used to meet demand, stored as inventory, or accounted for as unsatisfied demand. Constraint (4) enforces partial production in a period when residual time for production is available after a non-integer color changeover ( $\lambda_{uly} > 0$ ). For example, if a color changeover lasts 1.4 days, the remaining 0.6 days within the same time period can be allocated to production. Constraint (5) defines the total campaign duration for each color as the sum of production time for all products of that color and the time required for changeovers from the preceding color. Constraint (6) prevents the reactivation of furnaces after they have been deactivated.

Constraint (7) guarantees that the total duration of color campaigns does not exceed the available number of days in the respective period. Constraints (8) and (9) prevent furnaces from producing once deactivated, while enforcing continuous production during active periods. Constraint (10) ensure capacity balance. Specifically, it guarantees that the total workload assigned to a furnace, including the time required to produce all products of a given color and the time lost due to changeovers, does not exceed the available furnace capacity during the corresponding color campaign.

Constraint (11) permits the production of a product on a machine only if the corresponding furnace is set up for the product's color, either at the beginning of the period ( $\alpha_{lyt} = 1$ ) or through a changeover from a previous color ( $T_{ulyt} = 1$ ). The total production time, including any partial production following a changeover, is then limited by the maximum allowable time for that product on that machine. Constraint (12) ensures that each furnace is set up to produce only one color at the beginning of each period, while Constraint (13) ensures that furnaces remain set up for the same color across consecutive periods, unless a changeover to a different color occurs. Constraint (14) prohibits color subtours within a period, which is typically undesirable in practice.

Lastly, Constraint (15) is introduced to ensure the continuous operation of all furnaces in the facility, prohibiting their deactivation in line with process requirements. Notably, this constraint reflects the specific context of the problem but can be omitted in more general settings where furnace deactivation is permitted.

To extend the model toward energy-aware PPC, additional Constraints (16) - (20) are incorporated into the formulation. Constraint (16) enforces fuel consumption in a given time period if the corresponding fuel is selected to supply energy to the furnace during that period. Constraint (17) ensures that only one combustion fuel, either NG or H<sub>2</sub>, is used in each furnace at any given time period. Constraints (18) and (19) guarantee that each furnace receives the required energy input in each time period, while accounting for the melting efficiencies of the different energy sources. Specifically, Constraint (18) defines the electricity consumption based on the EB energy contribution factor, while Constraint (19) ensures that the remaining energy demand is met by fuel combustion.

Constraint (20) limits H<sub>2</sub> consumption based on a maximum allowable share defined to prevent moisture-induced defects in the glass production process. Finally, variable domains are specified in Constraints (21) - (23).

#### 4. Results and discussion

The MILP formulation presented above is implemented in Python and solved using the Gurobi Optimizer. This section presents the results obtained by applying the proposed formulation to a case study in the container glass manufacturing industry. The analysis considers a facility equipped with two furnaces: one furnace supplies a single molding machine, while the other is connected to two molding machines. Together, they produce eight products in three different colors to meet the demands of three main customers over a three-period planning horizon.

In alignment with the reference local context, NG is assumed to be the least expensive energy source (51 €/MWh), followed by electrical boosting EB (134 €/MWh). H<sub>2</sub> results in the most expensive energy source (198 €/MWh), assuming a green production method is employed. This assumption is consistent with the objective of decarbonization, as alternative production routes (e.g., steam methane reforming) could lead to a worsening of the overall environmental performance. Regarding CO<sub>2</sub> emissions, the trend is the opposite. Green H<sub>2</sub> is considered emission-free, followed by EB, reflecting the relatively low carbon intensity of the electrical grid in the reference context (61 kgCO<sub>2</sub>/MWh). In contrast, NG combustion leads to the highest emissions (194 kgCO<sub>2</sub>/MWh), estimated through stoichiometric calculations and assuming a composition of 100% methane. Differences in melting efficiency among combustion fuels are considered solely based on their volumetric heating values without considering additional effects related to combustion conditions. Therefore, H<sub>2</sub> is assumed to have one-third the melting efficiency of NG.

Finally, an energy contribution factor of 10% for EB is assumed, while the share of H<sub>2</sub> to the overall energy consumption is restricted to 60% to avoid potential adverse effects on equipment integrity and glass product quality.

Under the reference context and assumptions, the relative results of the optimization model are summarized in Table 1. Inventory holding costs and setup costs associated with color changeovers have no impact on the overall objective value. In contrast, energy consumption accounts for 80% of the total cost, underscoring the industrial relevance of an energy-aware approach. CO<sub>2</sub> emissions costs follow at 19%, with unmet demand penalty costs contributing the remaining 1%. NG is the selected combustion fuel due to its low cost and relatively high melting efficiency. Although overall CO<sub>2</sub> emissions costs are moderate, reflecting the relatively low carbon pricing in the current market (i.e., 0.077 €/kgCO<sub>2</sub>), NG combustion accounts for 97% of total emissions, highlighting the importance of fuel switching as a decarbonization strategy.

Table 1. Optimization model relative results under the reference context.

Objective function component	Share on total cost
Energy consumption cost	80%
CO <sub>2</sub> emissions cost	19%
Unmet demand penalty cost	1%
Total cost	100%

As illustrated in Table 2 (Test instances 1 to 4), a sensitivity analysis reveals that varying H<sub>2</sub> melting efficiency, H<sub>2</sub> cost, or CO<sub>2</sub> emissions cost, either independently or simultaneously, while keeping other parameters fixed, does not affect the optimization outcome when changes are moderate. This is primarily due to the imposed restriction on H<sub>2</sub> share, limited EB contribution factor and the assumption that only one combustion fuel can be used at a time, which leads to continued reliance on NG to meet energy demand.

However, under optimistic conditions, specifically when H<sub>2</sub> melting efficiency and cost are assumed comparable to NG (i.e., reducing H<sub>2</sub> cost from 198 €/MWh to 51 €/MWh), and CO<sub>2</sub> emissions cost increases substantially (from 0.077 €/kgCO<sub>2</sub> to 0.465 €/kgCO<sub>2</sub>), the model favors H<sub>2</sub> (Test instance 5 in Table 2). This transition occurs despite the constraints on H<sub>2</sub> share and EB contribution, but leads to energy oversupply, as the model increases total energy input to satisfy both constraints simultaneously. Importantly, the specific threshold values are highly dependent on the electricity characteristics of the reference context, particularly in terms of cost and carbon intensity.

Table 2. Sensitivity analysis results.

Parameters	Test instance									
	Reference	1	2	3	4	5	6	7	8	9
H <sub>2</sub> melting efficiency	0.33	<b>1</b>	0.33	0.33	<b>0.8</b>	<b>1</b>	0.33	0.33	0.33	<b>1</b>
H <sub>2</sub> cost (€/MWh)	198	198	<b>100</b>	198	<b>140</b>	<b>51</b>	198	198	198	<b>105</b>
CO <sub>2</sub> emissions cost (€/kgCO <sub>2</sub> )	0.077	0.077	0.077	<b>0.4</b>	<b>0.2</b>	<b>0.465</b>	0.077	0.077	0.077	<b>0.28</b>
Max. share H <sub>2</sub>	0.6	0.6	0.6	0.6	0.6	0.6	<b>1</b>	0.6	<b>0.8</b>	<b>0.9</b>
Max. share EB	0.1	0.1	0.1	0.1	0.1	0.1	0.1	<b>0.4</b>	<b>0.2</b>	0.1
Optimal energy mix	NG+EB	NG+EB	NG+EB	NG+EB	NG+EB	H <sub>2</sub> +EB	NG+EB	NG+EB	NG+EB	H <sub>2</sub> +EB

On the other hand, increasing the allowable H<sub>2</sub> share or the EB contribution factor, independently or simultaneously, while keeping all other parameters fixed, would theoretically enable exclusive use of H<sub>2</sub> without causing energy oversupply. However, as shown in Table 2 (Test instances 6 to 8), this still does not alter the outcome, due to the current non-competitive conditions of the H<sub>2</sub> market compared to NG.

Based on the above discussion, H<sub>2</sub> become competitive only when both technical and economic barriers are addressed simultaneously. Key technical factors include the ability to manage moisture-related effects from H<sub>2</sub> combustion, increase EB contribution, and improve H<sub>2</sub> melting efficiency. Economic factors include reductions in H<sub>2</sub> production costs and increases in carbon pricing.

If technological advancements, such as improved methods for monitoring and measuring exhaust gases to help mitigate the adverse effects of moisture from H<sub>2</sub> combustion, or improved furnace design to compensate for H<sub>2</sub> lower melting efficiency, can mitigate current technical barriers, the model favors H<sub>2</sub> under less extreme pricing scenarios. For instance, assuming a maximum allowable H<sub>2</sub> share of 90% and a melting efficiency comparable to NG, the model selects H<sub>2</sub> as the combustion fuel when the H<sub>2</sub> cost is reduced from 198 €/MWh to 105 €/MWh and the CO<sub>2</sub> emissions cost increases from 0,077 €/kgCO<sub>2</sub> to 0.280 €/kgCO<sub>2</sub> (Test instance 9 in Table 2).

## 5. Conclusions

This study developed a MILP optimization model to represent energy-aware PPC in container glass manufacturing. In addition to traditional cost components commonly considered in production planning models, such as inventory holding costs, setup costs, and penalties for unmet demand, the model explicitly incorporates energy consumption costs and CO<sub>2</sub> emissions costs associated with energy use. This approach provides a more suitable and comprehensive framework for addressing today's manufacturing challenges, particularly in energy-intensive processes such as glass manufacturing.

While the model can be applied to current operating contexts based on NG to enhance existing performance, this study focuses on its application in supporting the transition to H<sub>2</sub>. The model enables the selection among different energy sources, accounting for their respective combustion performance, costs, and CO<sub>2</sub> emissions, thereby further extending its capabilities and relevance for supporting decarbonization strategies in the sector. In this regard, the results indicate that adjustments in current technologies and/or pricing mechanisms are necessary to facilitate an economically viable transition toward cleaner manufacturing practices.

As research on H<sub>2</sub> combustion and its effects continues to advance, new insights can inform the refinement of the energy-aware model to better capture the operational limitations and opportunities associated with its adoption. For instance, although differences in volumetric heating values have been considered, the model should be further developed to account for specific H<sub>2</sub> combustion characteristics (e.g., flame speed), which influence both the melting efficiency of glass and the overall performance of the furnace.

Building on this, future research could address some of the current model's limitations by investigating how the inclusion of uncertainty in key parameters, such as H<sub>2</sub> cost, melting efficiency, and moisture content, might influence the optimal solution. Additionally, the current single-objective formulation could be extended to a multi-objective optimization approach, enabling a more balanced trade-off between energy consumption, CO<sub>2</sub> emissions, and

traditional economic objectives in production planning. Another promising direction for model extension is to include hybrid fuel configurations (e.g., simultaneous use of H<sub>2</sub> and NG) to explore solutions that allow for a gradual rather than complete fuel substitution, which may be more viable in practice. Lastly, future research could expand the model to account for the impact of different energy sources on molding machine efficiency, as variations in combustion environments may influence the quality of the molten glass and subsequently affect downstream process performance.

## Acknowledgements

This work received funding from the European Union's Horizon Europe research and innovation program under the Grant Agreement No. 101092153. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or European Health and Digital Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

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