Fuzzy-Based Simulation Modelling of Process Parameters Toward a Hybrid Optimisation Framework for Sustainable Glass Manufacturing

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***Abstract*—Glass manufacturing is an energy-intensive process where small changes in operational parameters can significantly impact efficiency, emissions, and quality. This paper presents a fuzzy-based simulation model developed as a first phase of a broader hybrid optimisation framework aimed at improving sustainability and performance. The model uses fuzzy logic to estimate key performance indicators (KPIs) based on configurable input parameters and integrates a reliability function to capture forming machine degradation. An interactive tool was implemented in Julia programming language to support simulation, visualise KPI trends, and extract performance insights. Initial results show consistent system behaviour and provide a foundation for optimisation in future phases of the framework.**

Keywords—Glass manufacturing; Fuzzy logic; Simulation model; Process optimisation; Sustainability

I. Introduction

The glass manufacturing industry plays a significant role in modern society, producing materials essential for architectural, automotive, electronic, and consumer applications. However, it is also among energy-intensive sectors, with substantial environmental impact. Glass production relies heavily on fossil fuel combustion to melt raw materials and maintain high temperatures throughout the production line, making it a major contributor to industrial greenhouse gas emissions [1-2]. These demands highlight a pressing need to improve sustainability and operational efficiency across the sector.

Beyond emissions, poor control over process parameters can lead to high defect rates, raw material waste, and unbalanced throughput, each of which reduce product quality and profitability. Today, there is a clear need for integrated strategies that enhance energy efficiency, lower emissions, and ensure consistent, high-quality output [3-4].

Among promising directions in advancing sustainability is the transition to low-carbon or renewable energy sources, especially hydrogen. H2GLASS project [5] is one of the industrial decarbonisation initiatives that explores the use of hydrogen as a clean alternative to fossil fuels in high-temperature processes, including glass melting [2]. In this context, advanced modelling and simulation tools can play a vital role. They offer a way to assess the feasibility and implications of fuel transitions by simulating and evaluating key performance indicators (KPIs) under various combustion scenarios. These tools enable glass manufacturers to better understand the trade-offs between energy use, emissions, and product quality when considering fuels like hydrogen.

The process of glass manufacturing is complex and highly nonlinear, involving interactions of parameters such as furnace temperature, air-to-fuel ratio, batch composition, and forming speed. Numerical simulations have been applied to model specific forming processes like glass pressing [6], though such approaches often lack interpretability and real-time adaptability. Other works have explored simulation-based optimisation in glass manufacturing, particularly for scheduling in make-to-order production environments [7], but these do not focus on multi-KPI estimation or system degradation. Small deviations in these parameters can lead to significant variations in quality metrics like surface defects and dimensional consistency [8–10].

Recent studies have increasingly turned to soft computing techniques such as fuzzy logic, evolutionary algorithms, and hybrid modelling approaches to build predictive systems that are both flexible and data-driven [8, 11].

Fuzzy inference systems (FIS) have demonstrated strong potential in modelling complex manufacturing environments where data may be incomplete, uncertain, or based on expert knowledge rather than purely empirical measurements [8]. By translating linguistic rules into computational logic, fuzzy models can accurately reflect the relationships between process parameters and KPIs. When combining these systems with optimisation techniques like Genetic Algorithms (GAs), they enable the identification of parameter combinations that maximize energy efficiency, minimize defects, and ensure high throughput, within a multi-objective optimisation framework [8, 11-12].

To contribute to this growing area of research, this paper introduces a generalized and adaptable Hybrid Fuzzy-GA Framework for optimising glass manufacturing process parameters, as illustrated in Fig. 1. The framework consists of three core phases:

- **Phase 1**: Build a fuzzy-based simulation model that maps process parameters to key KPIs (e.g., energy efficiency, emissions, defect rates). This model also serves as a fitness function for the next phase.

- **Phase 2**: Use Genetic Algorithms to identify optimal parameter combinations based on fuzzy simulations.
- **Phase 3**: Deployment and continuous learning, where the optimised parameters are applied in real production, performance is monitored, and the fuzzy-GA model is refined over time for adaptability and robustness.

This framework aims to support decarbonisation initiatives in the glass industry through simulating KPI behaviour under alternative fuel options, including hydrogen. The model can serve as a decision-support tool in assessing new combustion strategies and their effects on process and product performance. This paper focuses specifically on Phase 1: the construction and implementation of the fuzzy-based simulation model.

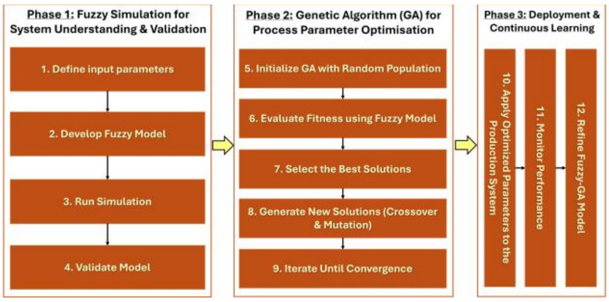

Fig. 1. Overview of the Hybrid Fuzzy-GA optimisation framework for glass manufacturing process paramaters.

The uniqueness of the proposed framework lies in its integration of fuzzy logic and reliability modelling within a simulation environment developed for KPI estimation in glass manufacturing. This combined approach enables a holistic assessment of both operational performance and machine degradation, offering a novel and practical pathway for early-stage optimisation. While simulation platforms such as Aspen Plus [13], FlexSim [14], and custom digital twins exist for industrial processes, they typically lack built-in interpretability and reliability analysis adapted to the glass manufacturing domain. By combining a fuzzy knowledge-based system with KPI-focused outputs and degradation-aware modelling, our tool enables experimentation and decision support under uncertainty, with capabilities not commonly found together in existing tools. This highlights the value of a specialised simulation tool in sustainability-oriented process optimisation contexts.

II. Fuzzy-Based Simulation Model

This section introduces the fuzzy-based simulation model developed as the first phase of the Hybrid Fuzzy-GA Framework. The objective of this model is to simulate the behaviour of key performance indicators (KPIs) in response to variations in critical process parameters within the glass manufacturing process. The model serves as a foundational tool for system understanding, early-stage evaluation, and eventual integration into optimisation workflows.

Given the absence of real-time plant data at this stage of model development, and the complexity of interdependent process dynamics, the model is built using a knowledge-driven approach. Expert understanding, literature-based insights, and typical industry process behaviour were used to define the relationships between in-puts and KPIs. This enables the simulation of system performance under a range of operating conditions, while maintaining interpretability and flexibility for future refinement.

A. Model Architecture

The architecture of the fuzzy simulation model mirrors the typical stages of the glass manufacturing line, including the melting of raw materials in the furnace and the glass forming process used to shape the final product. The model architecture is summarised in Fig. 2, which illustrates input parameters grouped into two categories based on their point of influence in the production line:

- **Furnace inputs**, including parameters such as Flame Temperature (T_{flame}), Molten Glass Temerature ($T_{molten-glass}$), Air-to-Fuel Ratio ($R_{air-to-fuel}$), and Molten Glass Flow Rate (G_{flow}).
- **Forming inputs**, such as Gob Temperature (T_{gob}), Mould Temperature (T_{mould}), Gob Weight (W_{gob}), Blow Pressure (P_{blow}), Cooling Air Flow Rate ($A_{cooling-flow}$), and Forming Time ($TM_{forming}$).

The KPIs, Energy Efficiency (EE), Combustion Emissions (CE), and Defect Rate (DR), are derived as outputs of fuzzy system and are intended to reflect operational performance.

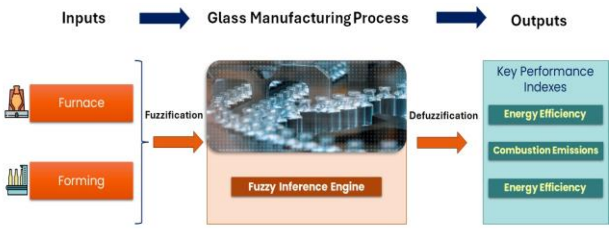

Fig. 2. Simulation model architecture showing inputs, processes, and resulting KPIs.

The relationships between input parameters and KPIs are mapped based on expert interpretation supported by literature. Fig. 2 illustrates these relationships, showing how furnace and forming parameters jointly influence the three selected KPIs.

For example, increasing furnace temperature may improve melting completeness (thus reduce defects) but can also increase emissions and reduce energy efficiency if not properly balanced with air-to-fuel ratio. Forming parameters such as gob weight and cooling control are linked to product quality but can have secondary effects on energy.

By structuring these interactions within a fuzzy inference system, the model enables a rule-based simulation of process behaviour. It also accommodates ambiguity in the input-output relationships, which is important when dealing with multi-objective trade-offs such as balancing energy use with product quality and/or emissions.

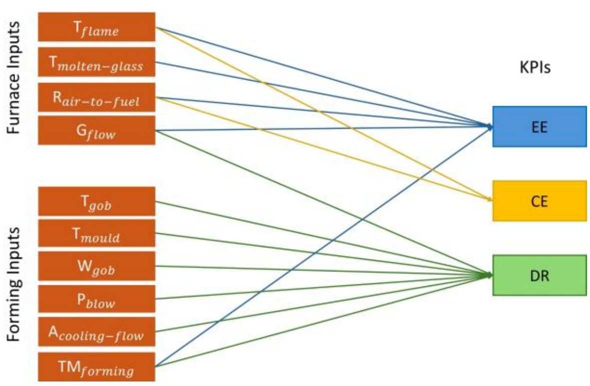

Fig. 3. Input parameters and KPIs relationship.

B. Development of Fuzzy Rules and Membership Functions

Fuzzy logic provides a powerful method for modelling complex industrial systems where relationships between inputs and outputs are not precisely known, but can be described using expert knowledge, heuristics, or linguistic approximations. In this context, it allows for the simulation of glass manufacturing performance, especially under uncertain or nonlinear conditions with unavailability of data, by mapping input parameters to key performance indicators (KPIs) through interpretable rules. For more details on fundamentals of fuzzy logic and the inference process, readers are referred to [15].

To demonstrate the development process, we use the example of Combustion Emissions (CE), which depends on two input parameters: T_{flame} (flame temperature) and $R_{air\_to\_fuel}$ (air-to-fuel ratio). Each input is divided into three linguistic categories, resulting in 3×3=9 rules.

a) Linguistic Variables and Membership Functions Definition: Input and output variables were categorised into three linguistic terms each, reflecting typical industrial operating ranges and expert judgment. Triangular fuzzy number is used to express the membership functions (MFs) for inputs and outputs. It is fast in computation and ensures smooth transitions between linguistic categories due to the simple shape of its MF. Fig. 4 shows the MFs for the T_{flame}, $R_{air\_to\_fuel}$ and CE.

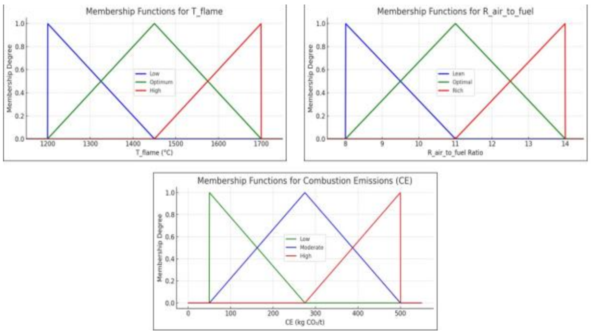

Fig. 4. Triangular MFs T_{flame}, $R_{air\_to\_fuel}$ and CE.

b) Rule Construction: The fuzzy rules were generated systematically by synthesising expert-assigned im-pact scores for each linguistic input, weighted by their relative importance to the output. Each input's contribution to a given output (e.g., CE) is quantified by assigning a numerical impact to each linguistic term, as shown in Table I.

TABLE I. WEIGHT OF INPUT PARAMETERS, THEIR LINGUISTIC VALUES AND IMPACT ON CE

Variable	Linguistic Value	Impact on CE	Impact Value (I)	Weight (W)
T_{flame}	Low	Low (Less combustion, incomplete burning)	50	0.5
	Optimum	Moderate (Best balance of fuel burn)	275	
	High	High (More emissions from excess temp.)	500	
$R_{air\_to\_fuel}$	Lean	High (More emissions)	500	0.5
	Optimal	Low (Best combustion efficiency)	50	
	Rich	Moderate (More fuel burned)	275	

The combined impact score, S, for a rule is calculated as the weighted sum of im-pacts across variables using Eq. 1:

$$S = \sum_{i=1}^{n} W_i \times I_i \qquad (1)$$

Where W_i is the weight for input variable i, I_i is the assigned impact score for linguistic value of variable i, and n is the number of variables.

This score is then mapped to a linguistic output using predefined scale based on KPI's MF, as shown in Fig. 5.

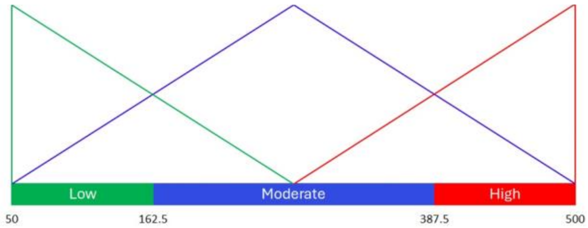

Fig. 5. Mapping scale for CE's rule linguistic output.

This approach allows rules to be automatically generated while still grounded in expert-derived influence scores, which enables interpretability and scalability across other KPIs such as Energy Efficiency (EE) and Defect Rate (DR). Table II presents the full rule set for CE that has been generated automatically.

TABLE II. RULE SET GENERATED FOR CE

Rule #	T_{flame}	$R_{air\_to\_fuel}$	Impact Score	CE Linguistic Value
R1	Low	Lean	275	Moderate
R2	Low	Optimal	50	Low
R3	Low	Rich	162.5	Moderate
R4	Optimum	Lean	387.5	High
R5	Optimum	Optimal	162.5	Moderate
R6	Optimum	Rich	275	Moderate
R7	High	Lean	500	High
R8	High	Optimal	275	Moderate
R9	High	Rich	387.5	High

C. Fuzzy Inference Process

A fuzzy inference process is a collection of fuzzy membership functions, fuzzy If-Then rules and fuzzy logical (or linguistic) operators to perform the necessary reasoning. It maps input variables data onto the output space based on a procedure that consists of: fuzzification of input variables, evaluation of fuzzy rules (fuzzy inference), aggregation of fuzzy rules into a single fuzzy output and defuzzification of the fuzzy output [16].

The process of mapping input data onto the output space for a multi-inputs single-output fuzzy inference system can be expressed mathematically in a generic form as in Eq. 2.

$$F(y) = \bigcup_{k=1}^{r} ((\bigcap_{i=1}^{n} \mu_{ik}) \bigcap \gamma_k) \qquad (2)$$

Where $F(y)$ is the aggregate output fuzzy value of the rules, μ_{ik} is the membership grade of the linguistic value of the i^{th} input variable in k^{th} rule, γ_k is the membership grade of the linguistic value of the output variable in k^{th} rule, n is the number of input variables and r is the number of rules.

Given next is an illustrative example of a MISO fuzzy rule-based system showing how the fuzzy inference mechanism work for estimating the CE.

a) Fuzzification of the Input Variables: The crisp inputs (e.g., T_{flame} = 1550°C, $R_{air\text{-}to\text{-}fuel}$ = 1.5) are mapped to degrees of membership in their respective MFs, shown in Fig 4. The results are presented below.

$$\mu(T_{flame}) = \left\{\frac{0}{Low}, \frac{0.6}{Optimum}, \frac{0.4}{High}\right\}$$

$$\mu(R_{air-to-fuel}) = \left\{\frac{0}{Lean}, \frac{0.667}{Optimal}, \frac{0.333}{Rich}\right\}$$

b) Rules Evaluation: Now, we match the propositions (linguistic values) obtained in the fuzzification to the rule set in order to determine firing rules, which are R5, R6, R8 and R9, in this case. Then, we evaluate the fired rules to get single output value for each rule using "min" operator. This single output value called the firing strength of the rule will be used to truncate the output membership function of the rule, as presented below.

$$F(CE)^{R5} = \min(0.6, 0.667) = \frac{0.6}{Moderate}$$

$$F(CE)^{R6} = \min(0.6, 0.333) = \frac{0.333}{High}$$

$$F(CE)^{R8} = \min(0.4, 0.667) = \frac{0.4}{High}$$

$$F(CE)^{R9} = \min(0.4, 0.333) = \frac{0.333}{Moderate}$$

c) Aggregation of Fuzzy Rules: Now, we combine rules' outputs using the aggregate operator "max", then we obtain the following combined output fuzzy set of linguistic values for estimating the combustion emissions (CE).

$$F(CE) = \left\{\max\left(\frac{0.333}{Moderate}, \frac{0.6}{Moderate}\right), \max\left(\frac{0.333}{High}, \frac{0.4}{High}\right)\right\}$$
$$= \left\{\frac{0.6}{Moderate}, \frac{0.4}{High}\right\}$$

d) Defuzzification of the Fuzzy Output: This is the last step in which the output fuzzy set obtained in the previous step is defuzzified to obtain a crisp output value indicating the combustion emissions. Weighted average defuzzification method, as shown in Eq. 3, is used in this example.

$$CE_{crisp} = \frac{\sum(\mu_i \times v_i)}{\sum \mu_i} \quad (3)$$

Where μ_i is the membership degree, and v_i is the singleton value for each fuzzy linguistic value, which are 275 for Moderate, and 500 for High based on Fig. 4.

$$CE_{crisp} = \frac{(0.6 \times 275) + (0.4 \times 500)}{0.6 + 0.4} = \frac{165 + 200}{1.0}$$
$$= 365.0\ (kg\ CO_2/ton)$$

This result reflects a moderate-to-high emission level under the input conditions.

D. Reliability-Based Availability Modelling

The fuzzy simulation model incorporates a reliability function to estimate the availability of forming machine over time through predicting maintenance needs. We use Weibull function, which is commonly applied in industrial contexts to model time-to-failure behavior and degradation of mechanical systems. The function used is given in Eq. 4.

$$R(t) = e^{-(\frac{t}{\eta})^{\beta}} \quad (4)$$

Where *R(t)* is the probability that the forming section is operational at time *t*, η is the scale parameter (characteristic lifetime), and β is shape parameter (indicating failure rate).

Integrating this reliability function into our simulation enables estimating how degradation of the forming section impacts machine availability, which allow for more realistic and robust simulation of manufacturing uptime.

Given that glass operations cannot be paused mid-process, prediction accuracy is critical. While the current tool operates in a simulation context, it uses expert-derived rules and reliability functions to provide robust output trends. In real deployments, integrating feedback loops and historical plant data will allow the system to adapt over time and reduce prediction error risks before control-level implementation

This paper focuses on Phase 1 of the hybrid framework, and thus GA-related setup will be discussed in detail in subsequent work under Phase 2.

III. Development and Implementation of a Simulation Tool

To implement the proposed fuzzy simulation model, a custom simulation tool was developed to execute the logic described in the framework introduced in section (II). This section introduces the simulation tool, focusing on the overall environment, structure, and execution flow. It provides a high-level view of how the tool was built and how it operates to generate and interpret simulation results.

A. Simulation Environment and Tool Architecture

The simulation tool was developed using Julia programming language and is structured around frontend and backend, enabling interactive use and robust model execution.

The frontend is a web-based application built using advanced Julia packages that support dynamic dashboards. The users can configure simulation parameters, including the number of furnaces and forming machines, simulation duration, reliability threshold, and furnace-to-machine assignments. This provides a user-friendly setup for running simulation experiments, showing the simulation log and progress in real time.

The backend handles the core logic of the simulation, including fuzzy knowledge base construction, rule evaluation, KPI calculations, reliability analysis, and data output.

Fig. 6 shows the system components and the flow from user input through simulation execution to results display.

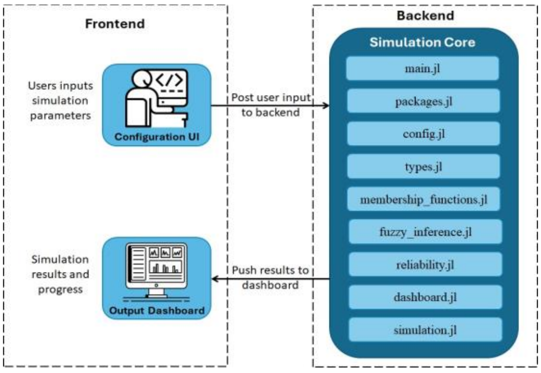

Fig. 6. Glass manufacturing simulation tool architecture.

B. Simulation Execution Scenario

A simulation scenario was configured using the built-in interface, such that the user defines the simulation inputs through a dedicated configuration screen, shown in Fig. 7. These inputs include the number of furnaces (set to 2), the number of forming machines (set to 4), the total simulation duration in hours (set to 100), and a reliability threshold (set to 0.5) to inform when forming machines should be taken offline for maintenance.

Each forming machine is assumed to consist of a single section, and furnace-to-machine assignments are defined through a dropdown interface. This setup allows tracking the performance and reliability of machines as they operate under assigned furnace conditions.

The simulation then runs across the defined time horizon, evaluating process behaviour, computing KPI values, and capturing system responses such as degradation events and scheduled maintenance. Results and discussion of this simulation scenario are presented in the following subsection.

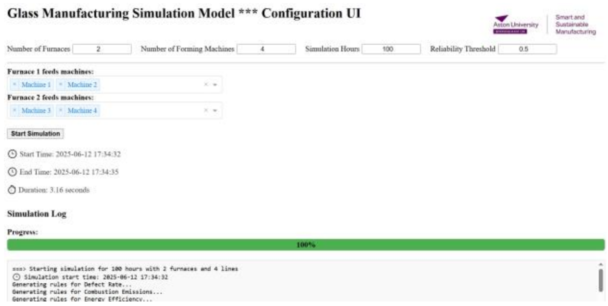

Fig. 7. Configuration user interface for simulation scenario.

C. Simulation Results and Discussion

As shown in Fig. 8, the interactive dashboard displays KPIs such as Energy Efficiency (EE), Defect Rate (DR), Combustion Emissions (CE), and Reliability as time-series plots, allowing users to monitor fluctuations and trends across the full simulation period.

The dashboard also presents summary metrics for each forming machine and furnace. For forming machines, this includes uptime, maintenance time, and number of production stops, in addition to the minimum, average, and maximum values for both EE and DR. Similar metrics are available for each furnace, focused on combustion emissions. These outputs help assessing stability, spot anomalies, and compare performance under varying configurations. The dashboard allows users to select specific machines or furnaces to compare performance side by side. This functionality helps manufacturers exploring operational adjustments.

Moreover, all simulation results are automatically saved in CSV format and can be downloaded directly through the interface. This supports further offline analysis, reporting, or integration into other decision-support tools.

The dashboard visualisation, though based on simulated data, illustrates the model's ability to capture dynamic trends in performance and reliability. The parameters used in this simulation are derived from typical industrial ranges found in literature and expert knowledge. While this paper presents an early prototype, future phases will incorporate data-driven calibration and validation. At this stage, our goal was not to benchmark against state-of-the-art tools but to demonstrate the stability and internal consistency of the model. Comparative evaluations and sensitivity analyses will be explored in Phase 2 of the framework.

Machine	Simulation Time (hr)	Uptime (hr)	Maintenance Time (hr)	No. of Stops	EE (%)			DR (%)		
					Min	Avg	Max	Min	Avg	Max
Machine 1	100	90.0	10.0	1	64.0	73.12	81.0	5.3	9.67	13.5
Machine 2	100	94.0	6.0	1	63.5	73.33	80.1	5.9	9.67	12.4
Average	**100**	**92.0**	**8.0**	**1**	**63.75**	**73.23**	**80.55**	**5.6**	**9.67**	**12.95**

Furnace	Simulation Time (hr)	CE (kg CO_2/t)		
		Min	Avg	Max
Furnace 1	100	155.0	309.28	420.0
Furnace 2	100	143.0	289.11	419.8
Average	**100**	**149.0**	**299.2**	**419.9**

Fig. 8. KPIs and metrics dashboard.

IV. Conclusion and Future Work

This paper presented phase 1 of a hybrid fuzzy-GA framework developed to optimise process parameters in glass manufacturing. A fuzzy-based simulation model is designed to estimate KPIs such as energy efficiency, defect rate, and combustion emissions based on process parameters configurations. A tool was developed in Julia and supported by an interactive dashboard that enables users to configure scenarios and extract results.

Initial results demonstrate stable model behaviour and provide useful feedback on process interactions. However, further validation with data-driven approach and domain experts is planned to ensure industrial relevance. In future work, the fuzzy model will be integrated with GAs to begin Phase 2 of the framework, focusing on multi-objective optimisation of process parameters. It will be followed by deployment and adaptive learning in Phase 3 to support continuous improvement and de-carbonisation efforts within glass industry.

The current simulation tool operates offline; however, it has been developed with a modular architecture to support future integration with real-time industrial systems. This integration can be achieved through standard communication protocols such as OPC UA or IoT middleware, enabling live data input and adaptive feedback for enhanced decision-making.

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