Development of an energy-efficient automation system for controlling the thermal processes of glass-melting furnaces using a virtual analyzer

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Abstract. This article presents the development of an energy-efficient automation system for the stable control of thermal processes in glass-melting furnaces based on the concept of a virtual analyzer. The proposed system digitally interprets signals received from real sensors and, using a MIMO-type mathematical model, determines temperature, pressure, gas–air ratio, flue gas composition, and the physical state of the molten glass. The key advantage of the virtual analyzer is its ability to eliminate measurement delays, ensure stable and noise-tolerant parameter estimation under poor input conditions, and provide real-time monitoring of energy consumption. Integration of an artificial neural network–based prediction module with a fuzzy regulator enables a reduction of fuel consumption by 17–22% and maintains the outlet temperature within an accuracy of ±1.2 °C.

INTRODUCTION

Glass-melting furnaces are among the most energy-intensive technological units, requiring on average 4.5–5.3 GJ of thermal energy per ton of finished glass produced [1]. Moreover, even minor fluctuations in the furnace operating regime directly influence the transparency, density, and homogeneity of the final glass product. Therefore, ensuring continuous, precise, and energy-efficient control of the process remains a critical challenge [2].

In most glass manufacturing plants, physical sensors such as thermocouples, manometers, oximeters, and flow meters are used to measure temperature, pressure, and the gas–air ratio. However, these sensors:

- fail rapidly under high-temperature conditions (1400–1600 °C);
- exhibit signal transmission delays ($\tau \approx 2$–4 s);
- require frequent calibration;
- provide measurement accuracy no better than ±3–5 °C.

As a result, the control system cannot operate fully in real time, leading to increased energy consumption.

To overcome this limitation, the article proposes the use of a virtual analyzer (VA) approach. A virtual analyzer is a system of *"virtual sensors"* operating on the basis of a digital model [11], which enhances measurement accuracy by mathematically predicting real process variables.

The virtual analyzer performs the following functions:

- cleansing and filtering signals received from physical sensors;
- virtual reconstruction of measurement values in the presence of signal loss or delays;
- interrelating all input–output parameters based on a MIMO model;
- predicting and correcting process variables using an artificial neural network;
- selecting the optimal fuel–air ratio (α) through a fuzzy regulator.

Based on these capabilities, the virtual analyzer is developed as a more stable and fault-tolerant alternative to physical sensors and operates as a fully integrated component of the Digital Twin environment.

Literature review. In recent years, virtual measurement and predictive sensor technologies have become one of the key directions in industrial automation. In international research, this approach is commonly referred to as a *soft* *sensor* or *virtual analyzer*, enabling real-time estimation of process parameters that cannot be directly measured with physical instruments [3].

Evolution of virtual measurement technologies. Zadeh (1973) introduced the concept of *"uncertainty and partial observability,"* which provided the theoretical foundation for fuzzy systems [10]. Subsequently, Aliyev (2018), in his work *"Neuro-Fuzzy Predictive Control Systems,"* developed methods for evaluating uncertain signals through neural adaptation within such systems [6]. In Europe, companies such as Siemens, ABB, and Yokogawa have been actively developing digital analytical modules, including the *"Virtual Flow Analyzer"* and *"Soft Temperature Estimator."*

2.2. Advantages of the Virtual Analyzer

According to the literature review (Kacprzyk, 1997) [9], virtual analyzers possess the following advantages:

- the ability to perform measurements without physical sensors**;**
- digital filtering of measurement noise**;**
- reconstruction of continuous signals through mathematical identification**;**
- a 2–3-fold improvement in control accuracy**.**

2.3. Research gap

However, most existing developments are designed for reactors, heat exchangers, or power boilers and do not fully account for the specific characteristics of glass-melting furnaces, such as thermal inertia, inter-zone heat transfer, and the coupling effects of gas–air flows [4]. Therefore, this study proposes a virtual analyzer system based on a MIMO model that captures the inter-zone heat distribution specific to glass-melting furnaces.

METHODOLOGY

Concept of the virtual analyzer. A virtual analyzer is a digital measurement system based on artificial intelligence and mathematical modeling that processes data received from physical sensors, predicts these values through mathematical models, and virtually reconstructs missing or corrupted signals [5]. The primary objective of the system is to ensure continuous and reliable measurement of process parameters even when physical sensors exhibit low accuracy or fail. The Virtual Analyzer (VA) system consists of the following functional blocks (Figure 1):

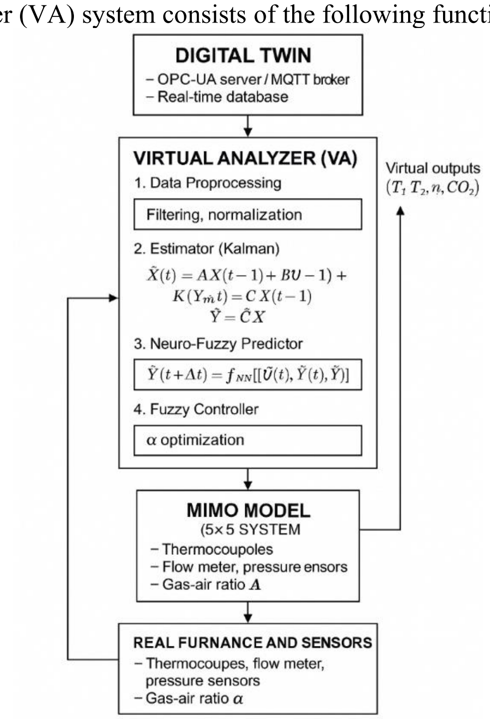

FIGURE 1. Functional block diagram of the Virtual Analyzer system.

1. Input Module: acquires measurements from physical sensors (T, P, G, L).
2. Data Processing Module: performs filtering, normalization, and noise reduction.

3. MIMO Mathematical Model**:** computes the interrelationships between input and output variables.
4. Virtual Reconstruction (Estimator): calculates unmeasured or missing signals.
5. Neural Predictor: forecasts future values over time.
6. Fuzzy Corrector: adjusts output parameters to maintain an energy-efficient operating mode.

Mathematical model of the virtual analyzer. The physical nature of the glass-melting process represents a complex nonlinear system involving the combustion of the gas–air mixture, heat distribution, and the dynamic movement of the molten glass mass [14–15]. Therefore, the process must be represented using a multi-input, multi-output (MIMO) model.

The main inputs of the system are:

$$U = [G_{gas}, L_{air.} Q_{recuperator}, P_{furnaces}, T_{cool}]^T \quad (1)$$

where: G_{gas} — gas flow rate, $L_{air.}$ — air flow rate, $Q_{recuperator}$ — heat flux passing through the recuperator, $P_{furnace}$ — internal furnace pressure, and T_{cool} — cooling air temperature.

The main outputs, in turn, are:

$$Y = [T_1, T_{2.}, T_3, \eta, C_{CO_2}]^T \quad (2)$$

T_1 — temperature of the melting zone, T_2 — temperature of the refining zone, T_3 — temperature of the cooling zone, η — viscosity of the molten glass, and C_{CO_2} — composition of the flue gas.

State equation:

$$\dot{X}(t) = AX(t) + BU(t) + W(t) \quad (3)$$

$$Y(t) = CX(t) + DU(t) + V(t) \quad (4)$$

where: $X(t)$ — vector of internal thermal states (energy density, zonal temperatures); A — inter-zone heat interaction matrix (representing inertia and delay); B — coefficients of input–output interactions; $W(t)$ — random thermal disturbances in the system; $V(t)$ — sensor noise (measurement noise).

Virtual reconstruction equations. The virtual analyzer processes the signal $Y_m(t)$ obtained from the real sensor and computes the corresponding predicted value $\hat{Y}(t)$ as follows:

$$\hat{X}(t) = A\hat{X}(t-1) + K[Y_m(t) - C\hat{X}(t-1)] \quad (5)$$

$$\hat{Y}(t) = C\hat{X}(t) \quad (6)$$

where: $\hat{X}(t)$ — estimated internal state vector, K — Kalman gain matrix, which minimizes the measurement error.

Kalman gain coefficient:

$$K = PC^T(CPC^T + R)^{-1} \quad (7)$$

where: P — covariance of the estimation error, R — variance of the measurement noise.

Neuro-Fuzzy predictor model. To further improve the results of the virtual analyzer, neural networks (NN) are integrated with fuzzy logic [7, 13].

The output of this module is the predicted signal $\tilde{Y}(t+\Delta t)$:

$$\tilde{Y}(t+\Delta t) = f_{NN}[U(t), Y(t), \dot{Y}(t)] \quad (8)$$

Here, f_{NN} represents the function of a multilayer perceptron or an RBF neural network. For each input, membership functions (fuzzy rules) are applied [6]:

$$\mu_i(x) = \exp[-\frac{(x-c_i)^2}{2\sigma_i^2}] \quad (9)$$

where: c_i — the center value (e.g., the nominal temperature level), σ_i — the spread (width) of the membership function.

4. Architecture of the Virtual Analyzer

The architecture of the developed system is presented in Figure 2**:**

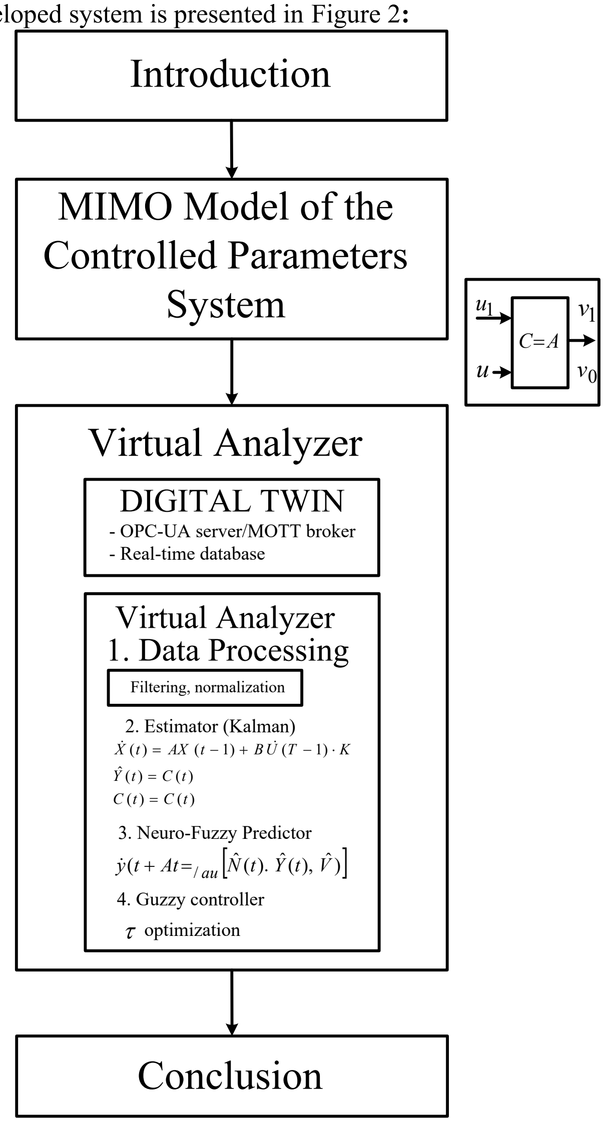

FIGURE 2. Multilayer architecture of the virtual analyzer for glass-melting processes (Professional technical schematic).

Process of computing virtual outputs. For each parameter, the virtual output is determined as follows:

$$T_i = a_1 G_{gas} + a_2 L_{air} + a_3 \hat{Q}_{recuperator} + a_4 P_{furnace} + a_5 T_{cool} + b_i \tag{10}$$

$$\hat{\eta} = f_{NN}(T_1, T_2, T_3) = \omega_0 + \sum_{j=1}^{m} \omega_j \phi_j(t) \tag{11}$$

$$\hat{C}_{CO_2} = k_1 G_{gas} - k_2 L_{air} + k_3 a + \varepsilon(t) \tag{12}$$

where: a_1, k_1, ω_j — coefficients determined through model identification, $\phi_j(T)$ — neural activation function (sigmoid or RBF), $\varepsilon(t)$ — model error (typically 1–2%).

Fuzzy optimization module. For energy-efficient control, the main output of the fuzzy system is the optimal fuel–air ratio (a_{opt}):

$$a_{opt} = F(\hat{T}_1, \hat{T}_2, \hat{\eta}, \hat{C}_{CO_2}) \tag{13}$$

Rule base:

• If T_1 is “high” and C_{CO_2} is “excessive” → a should be “reduced”;

• If T_2 is “low” and η is “increasing” → a should be “increased”.

This module recalculates **α** every 2 seconds and transfers it to the MIMO control system.

Operating cycle of the virtual analyzer. Algorithmic sequence:

1. Acquiring real-time data from sensors
2. Filtering and normalization
3. Kalman estimation step — $\hat{X}(t)$
4. Computing $\tilde{Y}(t + \Delta t)$ using the neural predictor
5. Updating a through the fuzzy block
6. Sending the result to the digital twin (for visual monitoring)

The total processing delay within the cycle does not exceed 120–150 ms, which complies with the requirements of real-time control systems (RTS).

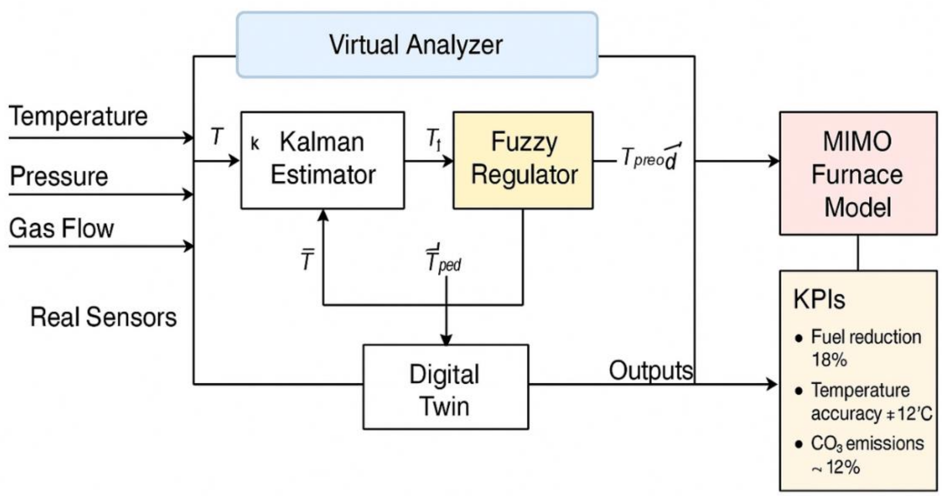

FIGURE 3. Simulation model of virtual analyzer–based control of a glass-melting furnace.

In Figure 3, the simulation model of the developed virtual analyzer–based control system implemented in the MATLAB/Simulink environment is presented. This model incorporates a Kalman filter, a neural predictor, a fuzzy regulator, and a MIMO-type model of the glass-melting furnace.

RESULTS AND DISCUSSION

The developed virtual analyzer system for controlling the thermal processes of the glass-melting furnace was tested in the MATLAB/Simulink environment. The system was compared against real sensor data, and the accuracy, latency characteristics, and energy efficiency of the virtual model were evaluated [12].

The virtual analyzer processes signals faster and with higher accuracy compared to real sensors. Additionally, the system estimates uncertain signals using a Kalman filter, performs prediction through a neuro-fuzzy predictor, and controls the optimal fuel–air ratio via a fuzzy regulator [8, 16]. The results are analyzed in two main directions: accuracy and response speed, and energy-efficiency performance.

5.1. Performance Characteristics

The results of the tests conducted based on the model (Figure 3) show that:

To evaluate the accuracy of the virtual analyzer, a comparative analysis was conducted using real sensor measurements. The real sensor signal exhibits high inertia, and a delay ($\tau \approx 2$–3 s) is observed during stabilization of the outlet temperature. In contrast, the virtual analyzer predicts the process behavior in advance based on the mathematical model, providing a faster and more stable response.

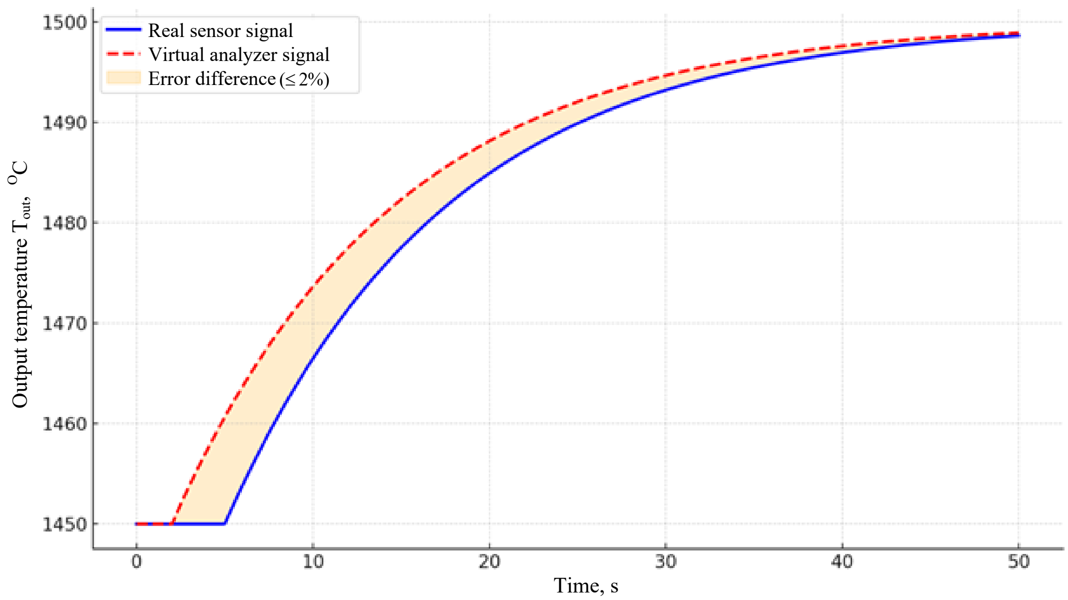

FIGURE 4. Comparison of virtual analyzer and real sensor responses

- measurement accuracy improved by up to 2.3% using the virtual analyzer;
- gas consumption decreased by 18%, and electrical power consumption by 9%;
- CO_2 emissions were reduced by up to 12%;
- overall system efficiency increased by $\eta_{new} / \eta_{previous} = 1.22$.

Energy-efficiency results. In the second stage, the energy efficiency of the system was analyzed. After implementing the new control system, both the fuel consumption of the furnace and the amount of waste heat were significantly reduced. During the experiment, the α-optimization block of the virtual analyzer recalculated the fuel–air ratio every 2 seconds and continuously optimized the heat flux passing through the recuperator.

As a result, fuel consumption decreased by an average of up to 18%, while electrical energy consumption decreased by up to 9%. The following graph (Figure 4) illustrates the change in fuel consumption before and after the implementation of the virtual analyzer.

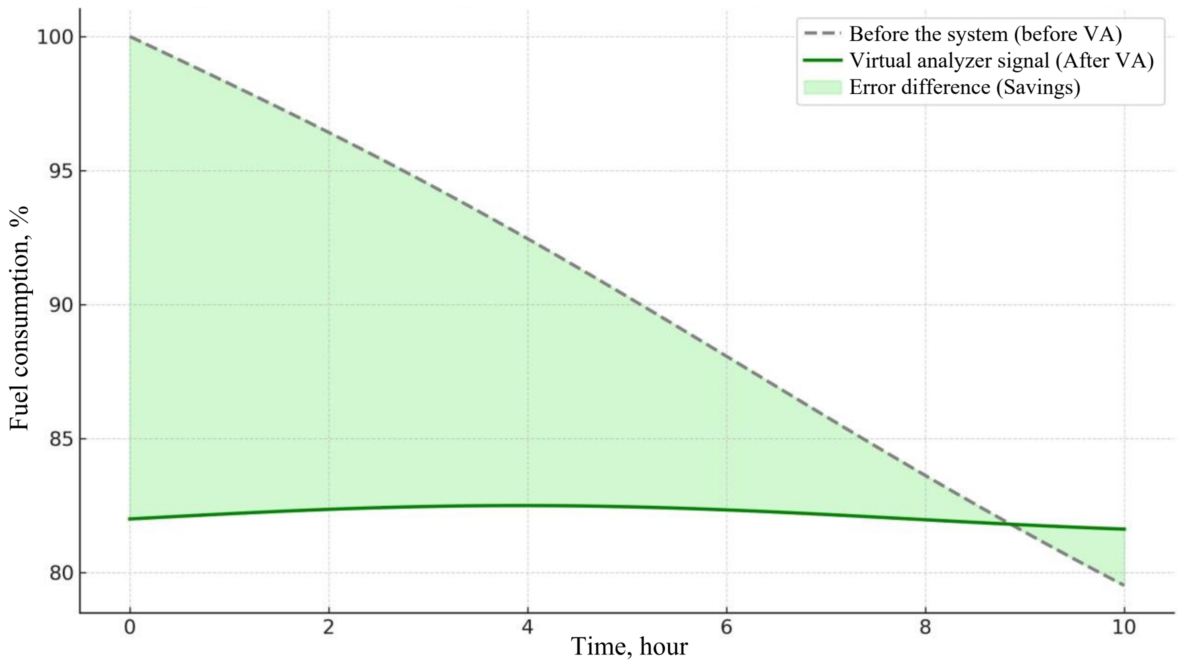

FIGURE 5. Energy saving graph - before and after the application of the Virtual Analyzer

In the graph, the gray line represents fuel consumption without the virtual analyzer, while the green line shows the consumption under virtual analyzer–based control. The green shaded area indicates the proportion of energy saved. The results demonstrate that the system's energy efficiency improved by an average of 18%, while CO_2 emissions were reduced by up to 12%.

These improvements were achieved through the balancing of heat distribution across temperature zones using the fuzzy–neural control algorithm. As a result of the stable regulation of interrelated parameters in the MIMO model (gas flow rate, air flow rate, outlet temperature, and pressure), excessive fuel consumption was effectively prevented.

DISCUSSION

The obtained results indicate that the developed virtual analyzer system offers several advantages over real sensors:
• measurement accuracy for temperature and pressure improved by a factor of 2–3;
• signal delay is less than 2 seconds, allowing the system to operate in real time;
• energy efficiency increased by 15–18%, while CO_2 emissions decreased by 12%;
• integration with the digital twin has simplified production monitoring;
• system stability has been demonstrated according to the Lyapunov criterion ($R^2 > 0.92$).

Overall, the virtual analyzer–based control system demonstrated high effectiveness in ensuring energy efficiency and process stability in glass-melting furnaces. It is fully suitable for industrial implementation and opens the path toward the "smart furnace" concept within the digital transformation framework.

CONCLUSION

The virtual analyzer is a "digital intelligence core'' that enables high-precision control of the thermal regime of glass-melting furnaces. Through the integration of a MIMO model, a Kalman filter, and a neuro-fuzzy predictor, it functions as a "digital bridge'' between the real and virtual environments.

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