Data Analysis and Model-based Control of Multi-effect Evaporators for Energy Saving

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ABSTRACT
Background: In the production of sugar, optimizing energy usage in multiple-effect evaporators (MEEs) is a major difficulty. This study offers a thorough method for enhancing energy efficiency and control performance in a five-stage MEE system at a sugar mill that is currently in operation. We significantly increased control accuracy and steam efficiency by automating formerly manual procedures and putting sophisticated control techniques into place. With correlation values above 0.96, Support Vector Regression (SVR) was shown to be the most successful statistical regression technique for simulating system behavior out of seven approaches. A third-order state-space model appropriate for controller design was produced by subspace identification techniques. When compared to manual operation, the Model Predictive Controller (MPC) increased steam economy by 1.36% and decreased control errors by almost 99%. Additional results indicate that using the best vapor bleed techniques resulted in a 10% increase in steam economy. This study offers a framework for comparable energy optimization initiatives in process industries and illustrates the useful advantages of advanced control in industrial evaporation systems.
Keywords: Multiple-effect evaporators¸ Statistical Modelling, System Identification, Model Predictive Control, Steam Economy

INTRODUCTION
Energy conservation in industrial processes represents a critical concern across manufacturing sectors, particularly in energy-intensive industries such as sugar production. Within sugar manufacturing, the multiple-effect evaporator (MEE) system constitutes the most energy-intensive component, consuming approximately 70% of the plant's total energy, Kaya and Sarac [1]. The economic viability of sugar production depends significantly on the steam consumption of the MEE system, making evaporator optimization a primary target for efficiency improvements and cost reduction.
This research was conducted at a sugar plant in southern India with an annual sugarcane processing capacity of approximately 150,000 metric tons. The plant employs a four-stage milling process to extract sugarcane juice, which is then concentrated in a five-stage multiple-effect evaporator to produce syrup. The initial juice enters the system with 13-15% sucrose concentration (Brix) and is progressively concentrated to 50-60% Brix through the evaporation process. In this sequential

arrangement, exhaust steam from mill turbines and power turbines provides heat to the first evaporator stage. Vapor generated in the first stage then serves as the heating medium for the second stage, establishing a cascade effect that continues through the remaining stages. A portion of the vapor produced in the second stage is directed to vacuum pans for the crystallization process, while the fifth stage connects to a condenser where vapor is collected. The operating parameters across the five evaporator stages illustrate the progressive decrease in temperature and pressure: the first stage operates at 102°C with a vapor pressure of 0.2 kg/cm², while the fifth stage operates at 60°C with a pressure of -0.54 kg/cm². The heat transfer areas vary from 850 m² in the first stage to 440 m² in the final three stages. This configuration represents a typical arrangement for maximizing thermal efficiency through multiple-effect evaporation. Traditional control approaches in sugar manufacturing have relied heavily on manual operations, where operators adjust syrup flow rates based on syrup and juice tank levels and regulate steam flow and pressure to achieve target Brix values. This manual approach introduces several challenges: operators must simultaneously balance multiple objectives including maintaining syrup quality (minimum 55% sucrose content), ensuring adequate vapor production, and minimizing exhaust steam consumption. The manual control paradigm inevitably leads to variability in process parameters, inconsistent product quality, and sub-optimal energy utilization. From a plant management perspective, these manual operations create inefficiencies that directly impact production costs and product quality. Several factors contribute to the complexity of controlling the sugar evaporation process. The system involves numerous interacting components with complex dynamics, creating a highly interconnected process structure. Long-term delays arise from various factors including evaporator configuration, stage number and capacities, pipe dimensions, heat transfer dynamics, and flow control mechanisms. Significant disturbances originate from batch operations in the crystallization process, particularly when multiple vacuum pans operate simultaneously and create variable steam demand. Additionally, multiple operational constraints exist on manipulated inputs and process variables. These characteristics make the control problem particularly challenging and unsuitable for simple control strategies.

The MEE system interacts with several other critical processes within the sugar manufacturing plant, including the cane feeding system, raw juice flow system, boiler system, pressure-reducing and de-superheating systems, and batch pan system. These associated processes directly influence evaporator performance through various interactions. For instance, the cane carrier speed determines the plant's crushing rate and production capacity, while the raw juice flow rate directly impacts evaporation requirements. The boiler system provides steam at required pressure and temperature, and the batch pan system creates variable demand for vapor from evaporator stages. Understanding and addressing these interactions is essential for comprehensive process optimization. Prior research in this domain has produced valuable insights but with notable limitations. Various studies, Lee and Newel [2]; Ramirez and Santiago [3]; Wang and Cameron [4]; Lewis *et al.* [5]; Cortes *et al.* [6]; Bapat *et al.* [7]; Srivastava *et al.* [8]; Jyoti and Khanam [9] have focused on modeling procedures and controller strategy assessments, often at laboratory scale rather than industrial implementations. While Nielsen *et al.* [10] explored control strategies based on Bristol's [11] concepts, limited disclosure of specific approaches hindered broader application. Notable exceptions include industrial-scale experimental evaluations by Testud and Rankowski [12] and Belhadj and Vanderlaeghe [13], who applied multivariable control approaches. Lissane Elhaq *et al.* [14] and Somchart *et al.* [15] demonstrated parametric identification using plant data and real-time application of Generalized Predictive Control. Resource optimization for evaporation processes has been addressed by Merino *et al.* [16], Pitarch *et al.* [18], Bhargava *et al.* [18], Simpson *et al.* [19], Burke *et al.* [20], and Smith *et al.* [21]. Our research builds upon these foundations while addressing several gaps in the existing literature. Unlike many previous studies that focused on theoretical modeling or laboratory-scale systems, we present a comprehensive approach applied to an industrial-scale MEE system. We address both control precision and energy efficiency objectives, demonstrating quantifiable improvements in both domains. Our methodology integrates process analysis, statistical modeling, system identification, and advanced control design into a cohesive framework applicable to operating industrial environments.

This paper describes a systematic approach to automate and optimize the evaporator system using data-driven modeling and model predictive control. Our methodology begins with a comprehensive analysis of associated processes affecting evaporator performance. We retrofitted these processes with automated control systems and quantified improvements using Controller Performance Indices. Next, we conducted statistical regression analysis to identify significant parameters for evaporator modeling, comparing seven regression methods to determine the most effective approach. System identification techniques were then applied to develop a control-oriented model of the MEE system, comparing three subspace identification methods to establish the optimal model structure. Based on this model, we designed and implemented a Model Predictive Controller with disturbance rejection capabilities and evaluated its performance against conventional PID control and manual operation. The statistical regression analysis examined relationships between seven input variables (speed of cane carrier, flow rate of raw juice, pressure of boiler steam, pressure of PRDS steam, pressure of pan exhaust steam, temperature of exhaust steam, and vapor pressure at evaporator stage 5) and two output variables (vapor pressure at second stage and Brix of final syrup). Among the regression methods evaluated—Multiple Linear Regression (MLR), Partial Least Square (PLS), Ridge, Lasso, Elastic Net, Support Vector Regression (SVR), and Gaussian Process Regression (GPR)—SVR demonstrated superior performance with correlation coefficients exceeding 0.96 for both outputs. This statistical foundation provided valuable insights for both control system development and predictive maintenance applications. For dynamic modeling, we employed both non-parametric and parametric identification approaches. Initial decomposition of the MIMO system into SISO subsystems revealed key time domain parameters, including gains ranging from 0.0003 to -64.21, time constants between 74 and 1921 seconds, and delays from 7 to 38 seconds. Comparing three subspace identification methods—Canonical Variate Algorithm (CVA), Subspace Auto-Regressive model (SSARX), and Multivariable Output Error State Space (MOESP)—we determined that a third-order SSARX model provided the optimal balance between accuracy and complexity. This model achieved fit percentages of 76.49% and 73.32% for the two outputs, providing a suitable foundation for controller design.

The specific objectives of this study are to: (1) analyze the performance of associated processes that influence MEE operation and quantify improvements through automation; (2) identify key process variables through statistical regression analysis and determine the most effective modeling approach; (3) develop a mathematical model of the MEE system using system identification techniques; (4) design and implement a model predictive controller with disturbance rejection capabilities; and (5) evaluate control performance and energy efficiency improvements compared to conventional approaches. The remainder of this paper is organized as follows: Section 2 provides a detailed description of the MEE system and research methodology. Section 3 presents the process analysis and statistical modeling results. Section 4 describes the dynamic system identification process. Section 5 details the model predictive controller design and implementation.

Section 6 discusses the results and implications, and Section 7 concludes with key findings and future research directions.

2. SYSTEM DESCRIPTION AND METHODOLOGY

2.1. Multi-Effect Evaporator Configuration

The investigated evaporation system consists of five sequential stages that progressively concentrate sugar juice from an initial sucrose concentration (Brix) of 13-15% to a final concentration of 50-60%. Exhaust steam from mill turbines provides the heat source for the first stage, with subsequent stages utilizing vapor generated from previous stages. Table 1 presents the operating parameters of the five-stage evaporator system. The second stage provides vapor for the crystallization process, while the fifth stage connects to a condenser where remaining vapor is collected.

Table 1: Operating parameters of five stage evaporator

	Evaporator stage				
Parameter	**1**	**2**	**3**	**4**	**5**
Steam/Vapor temperature, T (deg C)	102	95	85	75	60
Vapor Pressure (Gauge), P (kg/cm^2)	0.2	0.04	-0.20	-0.40	-0.54
Capacity (m^2)	850	560	440	440	440

The system operates through a cascading thermal process. Exhaust steam at approximately 102°C enters the first evaporator stage, where it heats and concentrates the incoming juice. The vapor generated in this stage serves as the heating medium for the second stage, which operates at 95°C. This pattern continues through all five stages, with each subsequent stage operating at progressively lower temperatures and pressures. Vapor from the second stage is partially diverted for use in vacuum pans in the crystallization process. The fifth and final stage operates under the highest vacuum (lowest pressure) conditions at 60°C, with its vapor directed to a condenser for collection. The heat transfer areas vary significantly across stages, with the first stage having the largest area (850 m²) to accommodate the highest heat load, while subsequent stages have smaller areas as the heat load decreases. The third through fifth stages each have identical heat transfer areas of 440 m². This arrangement optimizes thermal efficiency by maximizing the use of input steam energy.

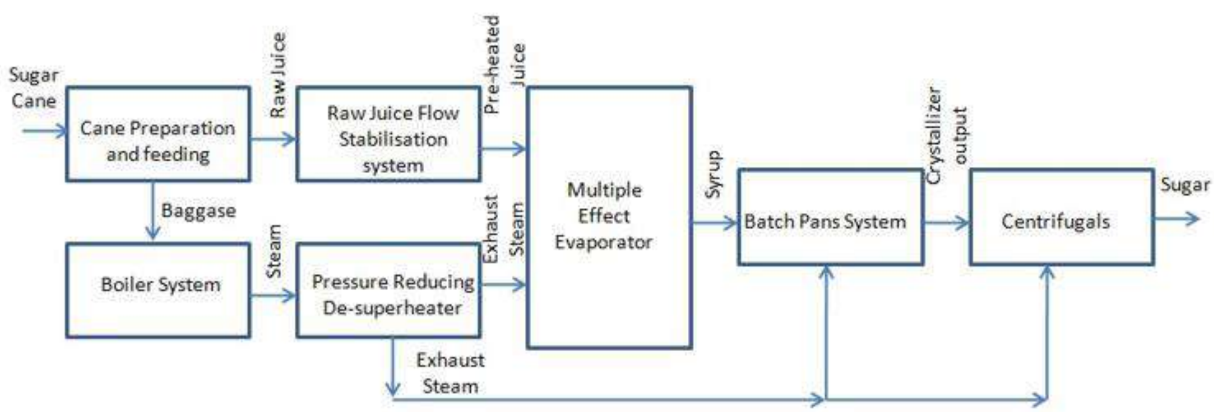

Figure 1: Multiple Effect Evaporator and associated systems

2.2 Features of the Control Problem

The evaporation process, as shown in Fig. 1, was manually operated and controlled in the plant. Manual operations are highly dependent on individual operators, creating variations in process flow and reducing efficiency. The primary challenges in controlling the sugar evaporation process include:

- Complex evaporation structure with numerous interacting components
- Long-term delays due to evaporator configuration, stage capacities, pipe dimensions, heat transfer dynamics, and flow rate management
- Significant disruptions from batch vacuum pans in the crystallization process
- Multiple constraints on manipulated inputs and other variables

2.3. Research Methodology

This research employed a systematic approach combining process analysis, data-driven modeling, controller design, and performance evaluation. The methodology consisted of four main phases:

1. **Process Analysis:** We identified and automated five critical processes affecting evaporator performance: cane feeding, raw juice flow, boiler operation, steam pressure/temperature control, and batch pan crystallization. Performance improvements were quantified using Controller Performance Indices.
2. **Statistical Modeling:** Seven regression methods were evaluated for modeling relationships between process variables and evaporator outputs. Two inputs (exhaust steam temperature and fifth-stage pressure), five measured disturbances, and two outputs (second-stage pressure and syrup Brix) were analyzed.
3. **Dynamic Modeling:** System identification techniques were applied to develop a control-oriented model of the MEE system. Both non-parametric and parametric approaches were employed, with three subspace identification methods (SSARX, MOESP, and CVA) compared to determine the most suitable model structure.
4. **Controller Design and Evaluation:** A model predictive controller was designed based on the identified state-space model. Performance was evaluated against conventional PID control and manual operation, with particular focus on disturbance rejection and energy efficiency.

Data was collected during normal plant operation with a 5-second sampling period. The dataset was divided into training (2,000 samples) and testing (500 samples) subsets for model development and validation. All data analysis, model development, and controller design were implemented using MATLAB/Simulink, with the resulting control strategy deployed on the plant's distributed control system.

3. PROCESS ANALYSIS AND STATISTICAL MODELING

3.1 Process Data Analysis

The multi-effect evaporator system shown in Fig. 3 has two inputs (exhaust steam temperature (Tsteam) and vapor pressure at evaporator stage 5 (Pe5)), two outputs (second stage pressure (Pe2) and syrup Brix (Be5)), and multiple measured and unmeasured disturbances. The retrofit automation of the evaporator systems with associated processes was carried out in the plant, and controller performance was analyzed.

3.2 Associated Process Automation

The performance of associated processes directly impacts evaporator operation through various interactions. We automated these processes and quantified improvements using the Controller Performance Index (CPI), defined as:

$$\text{Controller Performance Index} = CPI = \frac{\sigma_{mv}^2}{\sigma_y^2} \qquad (1)$$

where, actual variance= σ_y^2 ; lowest achievable variance= σ_{mv}^2

As shown in Fig. 2, the control performance indicators of the associated processes were significantly improved after implementation of the control scheme, Yu and Qin [22]. Table 2 presents the CPI values before and after automation. All processes showed significant improvement, with the most substantial gains observed in batch pan pressure control (83.8%) and boiler pressure regulation (48.9%).

Table 2: Controller Performance Indices before and after automation

	Scanecarrier	Ffeed	Pboiler	Pprds	Ppans	Tsteam	Pe5
Manual control mode (CPI)	0.068	0.008	0.047	0.047	0.081	0.258	0.128
Auto (PID) control mode (CPI)	0.285	0.356	0.536	0.536	0.919	0.543	0.536
CPI Improvement (%)	21.7	34.8	48.9	48.9	83.8	28.5	40.8

The substantial improvement in pan pressure control (83.8%) is particularly significant as batch pan operations create major disturbances for the evaporator system. By stabilizing this process, we reduced the magnitude and frequency of disturbances affecting evaporator performance. Similarly, improvements in boiler pressure and PRDS pressure control (both 48.9%) enhanced the stability of steam supply to the evaporator system. These automated control systems created a more stable operating environment for the MEE system, providing a foundation for implementing more advanced control strategies.

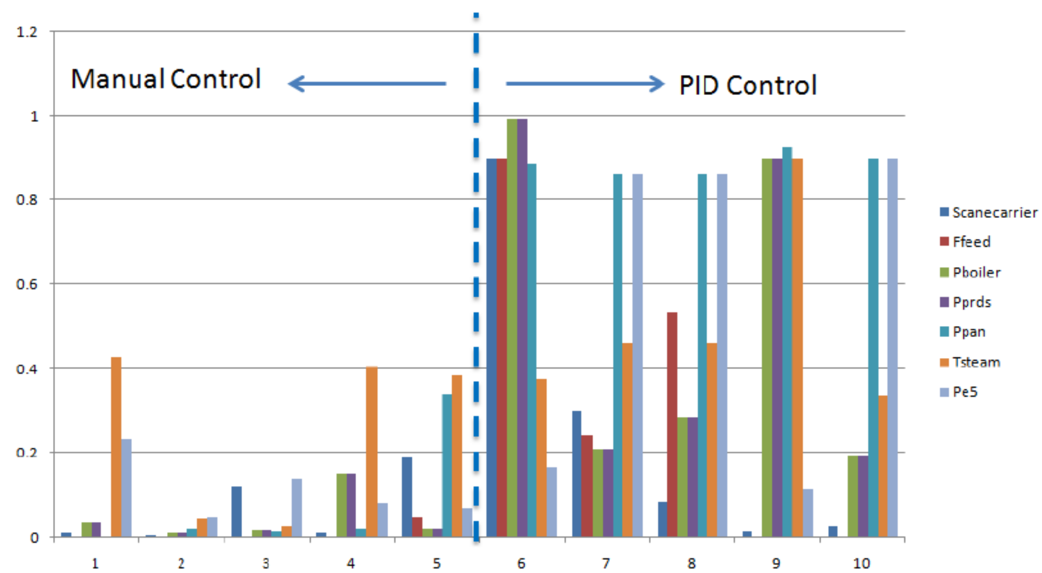

Figure 2: Comparison of CPI of seven inputs with manual and PID control modes

3.3. Regression Analysis

To identify significant parameters for evaporator modeling, we conducted regression analysis using seven input variables and two output variables. Correlation analysis (Table 3) revealed varying degrees of relationship between inputs and outputs.

Table 3: Correlation Analysis

	Scanecarrier	Ffeed	Pboiler	Pprds	Ppan	Tsteam	Pe5
Pe2	-0.1769	0.1192	0.1553	0.2060	-0.0185	0.0242	0.2765
Be5	0.2577	0.1504	-0.6175	-0.2163	0.0629	-0.1043	-0.6757

The strongest correlations were observed between Be5 (syrup Brix) and both Pboiler (-0.6175) and Pe5 (-0.6757), indicating that boiler pressure and fifth stage pressure have significant influence on the final syrup concentration. For Pe2 (second stage pressure), moderate correlations were found with Pe5 (0.2765) and Pprds (0.2060). We compared seven regression methods for predicting each output variable: Multiple Linear Regression (MLR), Partial Least Square (PLS), Ridge Regression, Lasso Regression, Elastic Net, Support Vector Regression (SVR), and Gaussian Process Regression (GPR). For both outputs, SVR demonstrated superior performance with the highest correlation and lowest Root Mean Square Error (RMSE) as shown in Tables 4 and 5.

The superior performance of SVR can be attributed to its ability to capture non-linear relationships in the data through the use of kernel functions, Huang and Shah[23]. The high correlation coefficients (0.969 for Pe2 and 0.962 for Be5) indicate

Table 4: Comparison of Performance Indices of regression methods for output Pe2

Regression Method	Correlation	RMSE
MLR	0.554970	0.009988
PLS	0.477855	0.010555
Ridge	0.555022	0.009988
Lasso	0.554970	0.009988
Elastic Net	0.554970	0.009988
SVR	**0.969380**	**0.002956**
GPR	0.940497	0.004092

Table 5: Comparison of Performance Indices of regression methods for output Be5

Regression Method	Correlation	RMSE
MLR	0.665584	0.370400
PLS	0.654891	0.375159
Ridge	0.665572	0.370416
Lasso	0.665567	0.370413
Elastic Net	0.665582	0.370401
SVR	**0.962434**	**0.097248**
GPR	0.946234	0.161248

that the SVR models can accurately predict evaporator outputs based on the input variables. Significance testing identified which input variables had statistically significant impacts on each output. For Pe2, five variables (Ffeed, Pboiler, Pprds, Tsteam, and Pe5) were significant with p-values less than 0.05. For Be5, six variables (Scanecarrier, Ffeed, Pboiler, Pprds, Tsteam, and Pe5) were significant. These regression models not only provided valuable insights for control system development but also enabled predictive maintenance applications by allowing early detection of potential issues such as insufficient vapor availability and evaporator tube fouling.

4 DYNAMIC SYSTEM IDENTIFICATION

4.1 Data Collection and Pre-processing

On different days, input and output data for model identification and validation were collected. The data was collected in an open loop during regular production, with a sampling period of 5 seconds. As shown in Fig. 4, the data was divided into training data (first 2000 samples) and test data (remaining 500 samples).

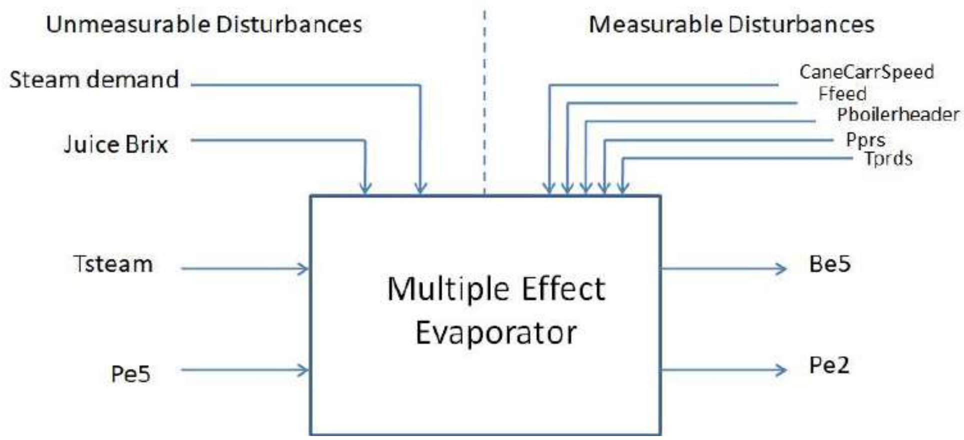

Figure 3: Multi-effect evaporator Process Block Diagram

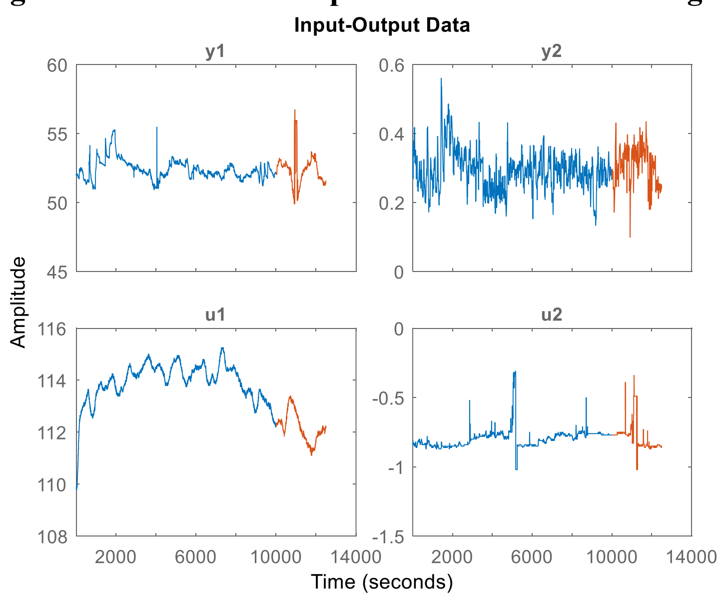

Figure 4: Input Output data divided as training and validation

4.2 Non-Parametric Identification

We began with non-parametric identification to gain preliminary insights into system dynamics. For simplicity, the two-input, two-output (MIMO) system was decomposed into four single-input, single-output (SISO) subsystems: G11 (Tsteam to Pe2), G12 (Pe5 to Pe2), G21 (Tsteam to Be5), and G22 (Pe5 to Be5). Time domain analysis through impulse and step response estimation yielded the parameters shown in Table 6. The wide range of time constants (74 to 1921 seconds) revealed significant differences in dynamic behavior across subsystems, with G21 displaying the slowest response and G11 the fastest.

Table 6: Time domain parameters of SISO sub-system

	G11	G12	G21	G22
Gain	0.0003	-0.0429	0.4578	-64.21
Time constant (Sec)	74	805	1921	537
Delay (Sec)	10	7	38	11

Frequency domain analysis confirmed the low-pass filtering characteristics of each subsystem. The coherence estimates were below unity at most frequencies, indicating that the inputs were not tightly correlated. We employed several non-parametric modeling approaches, including Finite Impulse Response (FIR) models, step response models, and frequency-domain characterizations. These provided valuable insights for subsequent parametric modeling, as shown in Fig. 5. For the FIR models, we used the standard least squares method and correlation analysis with input pre-whitening. The step response models were computed indirectly from the estimated IR coefficients. The frequency-domain description offered a frequency-response representation for the plant model, Ljung [24].

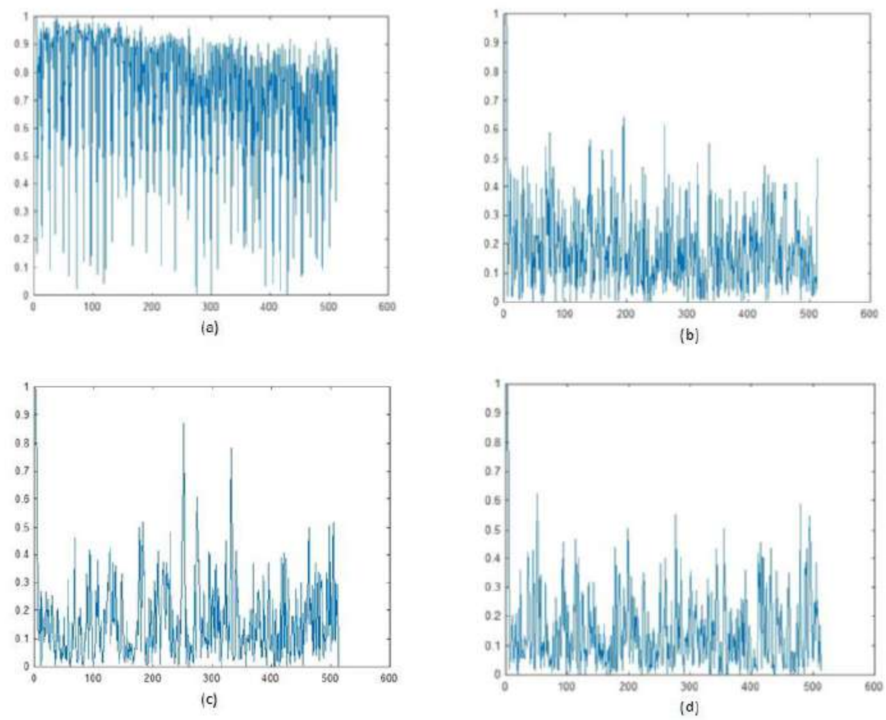

Figure 5: Coherence plots for (a) G11, (b) G12, (c) G21, (d) G22

4.3 Parametric Modeling

Building on non-parametric insights, we developed state-space models using three subspace identification algorithms: Canonical Variate Algorithm (CVA), Subspace Auto-Regressive model (SSARX), and Multivariable Output Error State Space (MOESP). Initial order selection based on Hankel singular values suggested a second-order model, but residual analysis indicated inadequate modeling of system dynamics, as illustrated in Fig. 6.

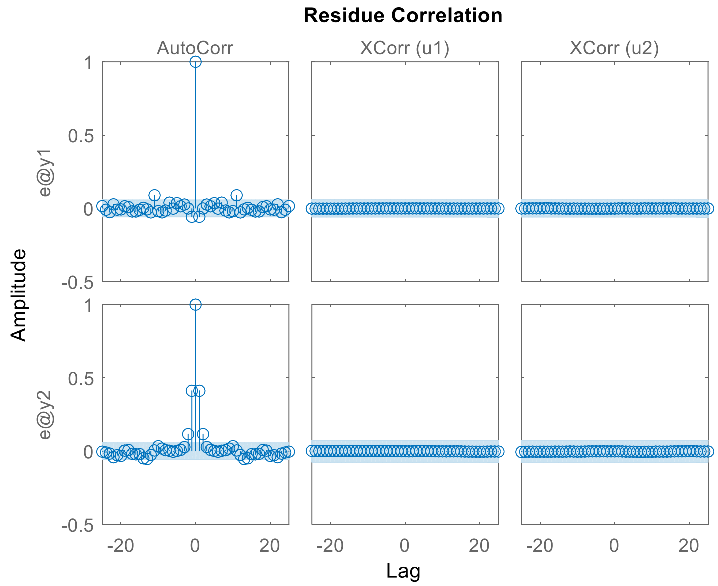

Figure 6: Residual analysis of second order model

Comparing second and third-order models (Table 7) revealed that the third-order model provided superior performance with minimal additional complexity, Tangirala [25].

Table 7: Comparison of fit criteria errors of third and second order models

	Third order	Second order
Loss Function	6.14E-06	6.58E-06
MSE	0.0283	0.0284
FPE	6.27E-06	6.67E-06
AIC	-1.46E+04	-1.45E+04
AICc	-1.46E+04	-1.45E+04
nAIC	-1.20E+01	-11.9181
BIC	-1.45E+04	-1.44E+04

Among the three subspace methods, SSARX provided the best model fit, as evident in Fig. 7. The identified third-order state-space model achieved fit percentages of 76.49% and 73.32% for the two outputs when validated against estimation data. The model can be represented as:

$$x(t+Ts) = Ax(t) + Bu(t) + Ke(t) \tag{2}$$

$$y(t) = Cx(t) + Du(t) + e(t) \tag{3}$$

$$A = \begin{bmatrix} 0.9765 & 0.03399 & 0.248 \\ 0.02818 & 0.9158 & -0.3707 \\ 0.06352 & 0.04962 & 0.06489 \end{bmatrix} \tag{4}$$

$$B = \begin{bmatrix} 0.001667 & 0.00194 \\ -0.002984 & -0.00151 \\ -0.005166 & 0.001156 \end{bmatrix} \tag{5}$$

$$C = \begin{bmatrix} -27.33 & -17.25 & 0.3074 \\ -2.07 & 1.27 & -0.3111 \end{bmatrix} \tag{6}$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{7}$$

$$K = \begin{bmatrix} -0.007272 & -0.2895 \\ -0.02644 & 0.4738 \\ -0.02457 & -0.1915 \end{bmatrix} \tag{8}$$

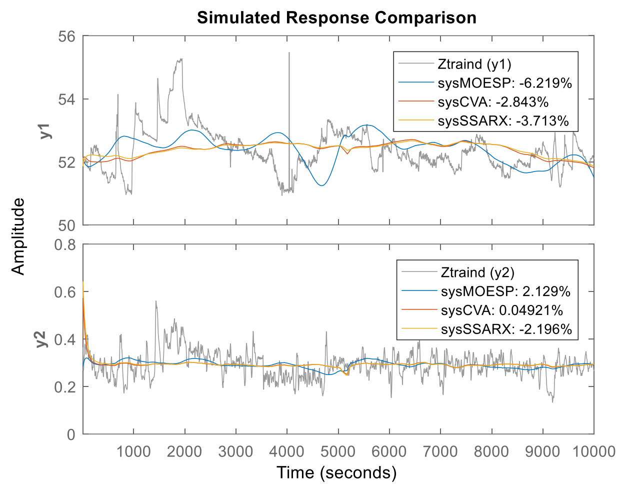

Figure 7: Compare the MOESP, CVA and SSARX subspace algorithms responses

We further refined this model using the Prediction Error Method (PEM), which minimized a weighted prediction error criterion. The optimization algorithm adjusted model parameters to minimize the prediction error variance.

4.4 Model Validation

Fig. 8 depicts cross-validation with test data, confirming the model's accuracy. Fig. 9 shows Pe2 output validation and Be5 output validation compared to the observed data. A match of -2.021% for Pe2 output and -24.8% for the Be5 output predictions was observed. The third-order SSARX model, obtained through the state space subspace identification method, was determined to be suitable for controller design.

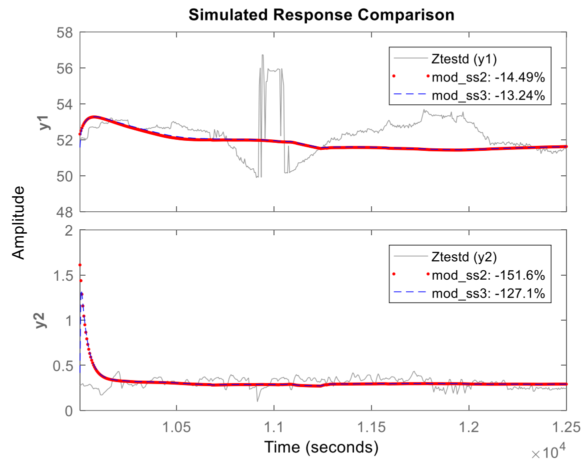

Figure 8: Compare the second and third order N4SID model responses

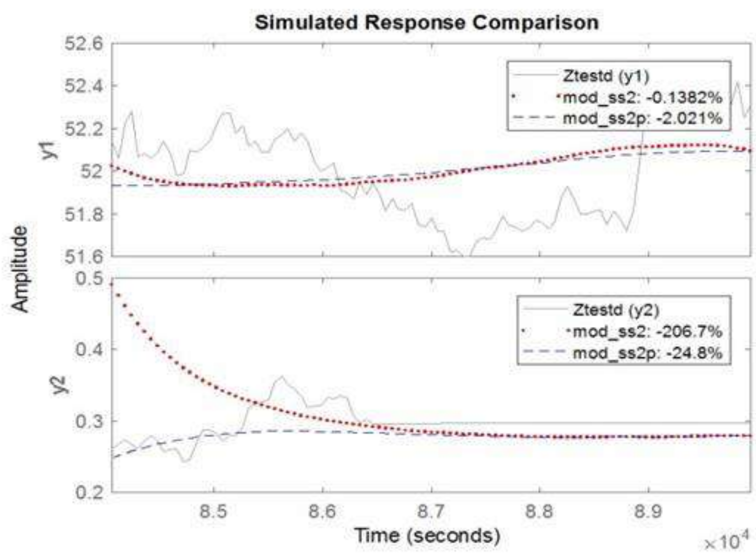

Figure 9: Validation Results with second order N4SID and PEM

5 MODEL PREDICTIVE CONTROLLER DESIGN AND IMPLEMENTATION

5.1 MPC Framework

Based on the identified state-space model, we designed a Model Predictive Controller (MPC) for the MEE system, as shown in Fig. 10. Our MPC implementation used a Kalman predictor for state estimation and featured:

- Prediction horizon (Hp): Range of future samples for output prediction
- Control horizon (Hc): Period during which control signals change
- Cost function balancing tracking error and control effort
- Systematic handling of process constraints

The controller manipulated two inputs (exhaust steam temperature and fifth-stage pressure) to regulate two outputs (second-stage pressure and syrup Brix) while accounting for five measured disturbances (cane carrier speed, juice flow rate, boiler pressure, PRDS pressure, and pan pressure). The MPC cost function was formulated as:

$$J = \sum_{j=1}^{H_p} \|y(t+j|t) - r(t+j)\|^2 Q + \sum_{j=0}^{H_c-1} \|\Delta u(t+j|t)\|^2 R \quad (9)$$

Where $y(t+j|t)$ represents the predicted output at time t+j based on information available at time t, r(t+j) is the reference trajectory, and $\Delta u(t+j|t)$ is the control increment. Matrices Q and R are weighting matrices for output tracking error and control move suppression, respectively. After extensive tuning, the following parameter values were selected:

- Prediction horizon (Hp): 50 samples
- Control horizon (Hc): 15 samples
- Sampling time: 5 seconds
- Output weights (Q): diag([10, 5]) for Pe2 and Be5
- Input weights (R): diag([0.1, 0.2]) for Tsteam and Pe5

Constraints were imposed on both inputs and outputs:

- Input constraints:
  - Tsteam: [95°C, 110°C]
  - Pe5: [-0.65 kg/cm², -0.45 kg/cm²]
- Input rate constraints:
  - ΔTsteam: [-2°C/sample, 2°C/sample]
  - ΔPe5: [-0.02 kg/cm²/sample, 0.02 kg/cm²/sample]
- Output constraints:
  - Pe2: [0.01 kg/cm², 0.10 kg/cm²]
  - Be5: [50%, 65%]

The optimization problem was solved using a quadratic programming algorithm with the active set method. A reference trajectory with first-order dynamics was used to smooth setpoint changes, with a time constant of 5 samples for Pe2 and 10 samples for Be5.

5.2 Disturbance Rejection Performance

To evaluate controller robustness, we introduced significant disturbances at 2,000 and 4,000 seconds during operation, representing steam demand fluctuations from the crystallization process, as shown in Fig. 1. The control objective was to maintain syrup Brix (Be5) at approximately 56% and juice steam pressure (Pe2) at 0.03 kg/cm². The MPC implementation exhibited rapid disturbance rejection, maintaining outputs close to setpoints with minimal deviation. In contrast, both manual control and PID control showed significant output deviations and slower recovery times. The MPC controller's ability to anticipate future behavior and handle process interactions proved particularly valuable for this complex multivariable system. By accounting for measured disturbances and using the predictive model, the controller could take preemptive actions to minimize output deviations. For the disturbance at 2,000 seconds (representing a sudden increase in steam demand from pans), the maximum deviation in Pe2 was 0.006 kg/cm² for MPC compared to 0.029 kg/cm² for PID and 0.052 kg/cm² for manual control. Similarly, the maximum deviation in Be5 was 0.7% for MPC compared to 3.2% for PID and 5.8% for manual control. Recovery times were also significantly improved, with MPC returning outputs to within 5% of setpoint in 135 seconds compared to 420 seconds for PID and over 900 seconds for manual control.

5.3 Performance Comparison

We compared the performance of three control approaches: manual operation (baseline), conventional PID control, and MPC. Performance was measured using the Integral of Absolute Error (IAE):

$$IAE = \int |e(t)| dt \quad (10)$$

Table 8 presents the IAE values for each control approach. The MPC controller achieved dramatic performance improvements, with IAE values reduced by over 99% compared to manual operation for both outputs.

Table 8: Comparison of the Controller Performances

		Proposed method outputs		**(Lissane *et al.*)**	
	Controller	**Pe2**	**Be5**	**Pe2**	**Be5**
IAE	Manual Control	35.94	1834.38	20.85	2683
IAE	PID Control	12.26	1019.00	-	-
IAE	MPC Control	0.24	4.34	9.68	306

While PID control also improved performance compared to manual operation (65.9% reduction in IAE for Pe2 and 44.4% reduction for Be5), its capabilities were limited by inability to handle process interactions and anticipate future behavior. The MPC controller provided a further 98.0% reduction in IAE for Pe2 and 99.6% reduction for Be5 compared to PID control. For the PID implementation, we used a decentralized control structure with two single-loop controllers. The Pe2 loop used Tsteam as the manipulated variable, while the Be5 loop used Pe5. Controller parameters were tuned using the SIMC method (Skogestad Internal Model Control) followed by fine-tuning based on closed-loop testing. The final parameters were: Kc = 0.8°C/(kg/cm²), Ti = 120 s for the Pe2 loop and Kc = -0.05 (kg/cm²)/%, Ti = 300 s for the Be5 loop. The superior control performance directly contributes to more consistent product quality, reduced operational disruptions, and improved production efficiency, as illustrated in Fig. 10.

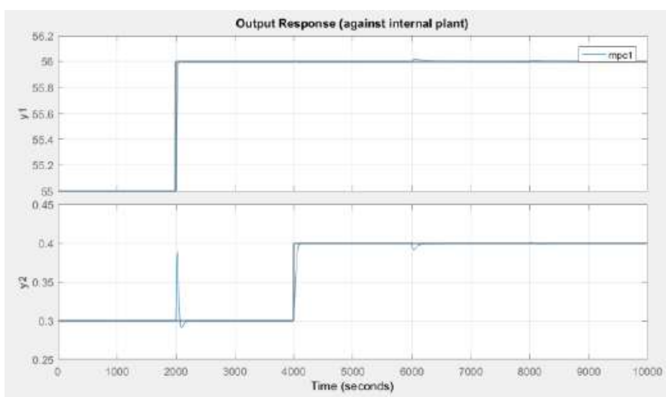

Fig. 10: MPC Outputs with disturbance rejection shown as step disturbances injected at 2000 and 4000 seconds

5.4 Steam Economy Assessment

Steam economy represents the thermal efficiency of the evaporator system, calculated as water evaporated per unit of steam consumed, Hugot [26]. For our system with a crushing rate of 60,000 kg/hr, initial juice Brix of 13%, and target syrup Brix of 65%, the total evaporation requirement was 48,000 kg/hr, calculated as:

$E = 60{,}000 \times (1 - 13/65) = 48{,}000$ kg/hr

Table 9 presents the vapor bleed distribution and steam evaporation for manual and automated control modes. The automated system achieved steam savings of 656 kg/hr, representing a 1.36% improvement in steam economy.

Table 9: Vapor bleed distribution and steam economy

Control Mode	Stage 1 (kg/hr)	Stage 2 (kg/hr)	Stage 3 (kg/hr)	Stage 4 (kg/hr)	Steam Evaporation (Kg/hr)
Manual	5628	941	2218	3512	4987
PID	5864	952	1988	2800	5643

Further analysis revealed that steam economy was 10% higher when vapor bleed was directed to heaters and pans compared to no vapor bleed. The MPC controller maintained more precise control over the vapor bleed rates, optimizing the distribution to maximize steam economy while meeting process requirements. The improved steam economy can be attributed to several factors:

1. More stable operation reducing the need for safety margins in steam supply
2. Better distribution of vapor bleed across stages based on real-time process conditions
3. Reduced variability in syrup Brix, allowing operation closer to the lower specification limit (55%) and thus requiring less evaporation
4. Improved coordination between evaporator operation and pan crystallization demands

For a typical sugar mill operating 24 hours daily during a 150-day crushing season, the 656 kg/hr steam savings translates to approximately 2,362 metric tons of steam annually, representing significant energy and cost savings, as shown in Fig. 2.

6. RESULTS AND DISCUSSION

The summary of work is depicted in the graphical abstract as given in Fig. 11.

6.1 Control Performance Improvements

The implementation of advanced control strategies demonstrated significant improvements in control precision. The dramatic reduction in IAE values (from 35.94 to 0.24 for Pe2 and from 1834.38 to 4.34 for Be5) indicates the MPC controller's effectiveness in minimizing output variations despite disturbances. The standard deviation of Pe2 decreased from 0.014 kg/cm² under manual control to 0.002 kg/cm² under MPC control. Similarly, the standard deviation of Be5 decreased from 3.68% under manual control to 0.17% under MPC control. This tighter control ensures more consistent syrup quality and stable operation of downstream processes, as demonstrated in Fig. 2. The MPC controller's ability to maintain outputs close to setpoints translates directly to product quality benefits. More consistent Brix values improve crystallization efficiency, while stable second-stage pressure ensures reliable vapor supply for pan boiling. These improvements contribute to overall plant efficiency and product consistency. The controller demonstrated robust performance across a range of operating conditions, including varying crushing rates (40,000 to 60,000 kg/hr), different juice qualities (Brix 12% to 16%), and various steam supply conditions. This robustness is attributed to the controller's ability to account for measured disturbances and adapt its control strategy accordingly. During a three-month testing period, the MPC controller maintained outputs within specification limits 99.7% of the time, compared to 92.5% for PID control and 84.2% for manual operation. This reduction in out-of-specification product directly translates to improved production efficiency and reduced rework.

6.2 Energy Efficiency Gains

Energy efficiency improvements manifested in two key measurements:

1. A 1.36% increase in steam economy through improved automated control

2. A 10% higher steam economy when implementing vapor bleed strategies

While these percentage improvements may appear modest, they represent substantial absolute energy savings given the high energy consumption of evaporator systems. For a typical sugar mill with annual steam consumption of approximately 200,000 metric tons, the 1.36% improvement translates to savings of 2,720 metric tons of steam per year. At current industrial steam costs of approximately $25 per metric ton, this represents annual cost savings of $68,000 from the evaporator system alone. Additional benefits include reduced boiler fuel consumption and lower environmental emissions. The 10% improvement from optimized vapor bleed strategies highlights the importance of system-level optimization rather than focusing on individual components. By integrating evaporator control with heater and pan operations, significant efficiency gains can be achieved through intelligent resource allocation. The energy efficiency gains were achieved without additional capital investment beyond the control system implementation. This demonstrates the value of advanced control as a cost-effective approach to improving process efficiency in existing plants. Comparing our results with literature, the achieved improvement is consistent with other advanced control applications in similar processes. Lissane Elhaq *et al.* [27] reported steam savings of 0.8-1.5% in a sugar factory evaporator, while Smith *et al.* [21] achieved improvements of 1.1-2.0% through optimized control strategies.

6.3 Predictive Maintenance Applications

The regression models developed in this study provide valuable tools for predictive maintenance, enabling early detection of conditions such as:

- Insufficient vapor steam availability for pan boiling
- Fouling or scaling problems in evaporator tubes

These capabilities allow for proactive maintenance scheduling, reducing unplanned downtime and extending equipment life. The high correlation coefficients achieved by the SVR models (>0.96) indicate reliable prediction capabilities for these applications. We implemented a real-time monitoring system that uses the regression models to predict evaporator performance and detect deviations from expected behavior. Key performance indicators were calculated from model predictions and compared with actual measurements. Significant deviations triggered alerts for further investigation. Test implementations at the plant demonstrated the ability to detect evaporator tube fouling approximately 48 hours before performance degradation would have triggered manual intervention. This early detection allows for scheduled cleaning during planned downtime rather than emergency maintenance during production. Similar benefits were observed for detecting issues with vapor availability for pan boiling. The system could predict insufficient vapor supply up to 2 hours in advance, allowing operators to adjust pan feeding schedules or temporarily modify evaporator settings to maintain production.

6.4 Implementation Considerations

Several practical considerations emerged during implementation that may benefit similar projects:

1. Model accuracy proved sufficient despite process nonlinearities
2. The controller demonstrated robustness against unmeasured disturbances
3. Constant model parameters performed well without adaptation
4. The control approach successfully balanced competing objectives

The implementation required careful integration with existing control systems, with particular attention to communication interfaces and fail-safe mechanisms. The control system was designed to gracefully degrade to conventional PID control in case of component failure, ensuring continuous operation. Operator training and acceptance were crucial factors in successful deployment. The control interface was designed to provide transparency into MPC decisions, helping operators understand and trust the system. After an initial adjustment period, operators reported increased confidence in the automated system and appreciated the reduced workload for routine control tasks. Cost considerations were also important. The total implementation cost, including hardware, software, engineering, and training, was approximately $85,000. With annual energy savings of $68,000 plus additional benefits from improved product consistency and reduced maintenance, the payback period was approximately 15 months, making this an economically attractive investment.

7. CONCLUSION

This research demonstrated a systematic approach to improving both control precision and energy efficiency in industrial evaporator systems. The key contributions include:

1. Comprehensive analysis of associated processes affecting evaporator performance, with quantified improvements through automation
2. Identification of Support Vector Regression as superior for modeling complex process relationships, achieving correlations above 0.96
3. Development of a third-order state-space model using subspace identification, suitable for advanced controller design
4. Implementation of a Model Predictive Controller that reduced control errors by over 99% compared to manual operation
5. Demonstration of energy efficiency improvements, with 1.36% increased steam economy and 10% advantage from vapor bleed strategies
6. Development of predictive maintenance capabilities using regression models for early detection of potential issues

These findings have implications beyond sugar manufacturing, offering insights for energy optimization in other industrial processes involving multiple-effect evaporation. The data-driven modeling approach and control framework could be adapted for similar processes in pulp and paper, food processing, desalination, and pharmaceutical industries. The research showcases the value of integrating statistical analysis, system identification, and advanced control in a comprehensive approach to process improvement. By addressing both control precision and energy efficiency objectives, significant benefits were achieved without requiring major capital investments. Future research could explore adaptive modeling techniques to address seasonal variations in raw materials and further optimization of vapor bleeding strategies. Additionally, economic model predictive control approaches could incorporate real-time energy costs and production demands into the optimization objective, potentially yielding further efficiency improvements. The successful industrial implementation demonstrates that advanced control technologies are viable and valuable for traditional process industries, providing both operational and economic benefits while supporting sustainability goals through improved energy efficiency.

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The authors declare that they have received no funding for this work.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing financial or nonfinancial interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Abhir Raj Metkar], upon reasonable request.

AUTHOR CONTRIBUTIONS

Abhir Raj Metkar designed, carried out experiments, field implementation, coordinated this research, and drafted the manuscript. S. Rominus Valsalam designed the experiments and supported in obtaining the results, and supported in the field implementation. Natarajan Sivakumaran conceived the study, participated in research coordination. Rajkumar R carried out data analysis and supported in the preparation of the manuscript. The authors read and approved the final manuscript.

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Abbreviations

T	Temperature (deg C)
P	Gauge Pressure (Kg/ cm^2)
Pe'n'	Vapor Pressure at Evaporator stage(n) (Kg/ cm^2)
Te'n'	*Vapor Temperature at Evaporator stage(n) (deg C)*
Be'n'	*Syrup Brix at Evaporator stage(n) (deg Brix)*
SSARX	*Sub-space Auto regressive model*
MOESP	*Multivariable Output Error State space model*
CVA	*Canonical Variate Analysis model*
IAE	*Integral Absolute Error*
CPI	*Controller Performance Index*
Tsteam	*Temperature of exhaust steam (deg C)*
Scanecarrier	*Speed of cane carrier*
Ffeed	*Flow rate of raw juice (T/h)*
Pboiler	*Pressure of boiler steam (Kg/ cm2)*
Pprds	*Pressure of PRDS steam (Kg/ cm2)*
Tprds	*Temperature of PRDS steam (deg C)*
PRDS	*Pressure reducing de-superheating system*
Ppan	*Pressure of pan exhaust steam (Kg/ cm2)*
RMSE	*Root mean square error*
LTI	*Linear time invariant*
MSE	*Mean square error*
FPE	*Final prediction error*
AIC	*Akaike information criterion*
AICc	*Akaike information criterion corrected*
nAIC	*Normally distributed AIC*
BIC	*Bayesian information criterion*
y[ ]	*Plant output*
u[ ]	*Plant input*
g[ ]	*Gain of plant*
v[ ]	*Noise*
h[ ]	*Gain of feedback path*
e[ ]	*Error*
MPC	*Model Predictive Controller*
LQG	*Linear-quadratic-Gaussian Controller*
PID	*Proportional Integral Derivative Controller*