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Enhancing Sugar Factory Efficiency with Deep Learning-Driven Control Strategies

Govind Singh Jethi[1], Dr. Sandeep Sunori[2], Dr. Pradeep Juneja[3], Priyanka Joshi[4]
[1,4]Department of CSE, Graphic Era Hill University, Bhimtal, Nainital, India
[2]Department of ECE, Graphic Era Hill University, Bhimtal, Nainital, India
[3]Department of ECE, Graphic Era Deemed to be University, Dehradun, India
[*]govindjethi@gmail.com

Abstract: *Sugarcane crushing systems are crucial in sugar production because the initial juice extraction step significantly impacts overall efficiency and productivity. Conventional control strategies often fall short in addressing the dynamic and nonlinear nature of these processes, leading to high energy consumption and suboptimal juice yields under variable operating conditions. This paper proposes an LSTM-based predictive control framework to enhance sugarcane crushing efficiency by integrating mathematical system modelling, deep learning, and advanced optimization principles. A synthetic dataset representing key nonlinearities (feed rate, roller speed, and extraction pressure) is used to train the LSTM, capturing critical relationships between inputs and outputs—juice yield and energy consumption. Model Predictive Control (MPC) further refines the control inputs in real-time, ensuring adaptability to fluctuating feedstock quality and equipment wear. Simulation results demonstrate a systematic reduction in training loss, reasonably accurate yield and energy predictions, and the potential for significant performance improvements over traditional controllers. While the synthetic nature of the data underscores the need for real plant validation, this work provides a foundation for developing robust, adaptive, and data-driven strategies capable of transforming sugarcane crushing operations.*

Index Term: *Data-driven control strategies in process industries, Deep learning for control optimization, Long Short-Term Memory, Model Predictive Control, Sugarcane Crushing*

INTRODUCTION

Sugarcane crushing systems play a critical role in the overall sugar production process. Since juice extraction is the very first stage, the performance of the crushing operation largely determines the productivity and efficiency of sugar mills [1][2]. Despite advances in mechanical design, conventional control techniques often fail to manage the highly nonlinear and dynamic characteristics of these systems [3]. Moreover, fluctuations in feedstock quality, operating conditions, and environmental factors introduce additional challenges, such as increased energy usage and reduced juice recovery.

Modern industries are increasingly adopting advanced and innovative solutions to shorten production cycles and improve efficiency, and the sugar sector is no exception [4][5]. In this context, artificial intelligence [6] and deep learning (DL) [7] techniques have shown significant potential in enhancing the performance of sugarcane crushing systems. As a specialized branch of machine learning, deep learning is particularly effective in modeling complex patterns and temporal dependencies. These capabilities make it a powerful tool for developing more dynamic and controllable systems. Furthermore, DL-based methods enable adaptive and predictive control strategies, allowing real-time adjustments and improved performance outcomes.

Although deep learning techniques bring significant advantages, their application in sugarcane crushing control systems is not without challenges [8]. These methods contribute to improved efficiency while maintaining safety and operational constraints. One major benefit lies in their ability to accurately model the nonlinear relationships between system inputs such as feed rate, roller speed, extraction pressure, and system outputs, including juice yield and energy consumption. Second is, the controllers of deep learning-driven are relying on Long Short-Term Memory (LSTM) networks [9][10], these controllers indicate early the optimal control actions based on historical and real-time data.

Furthermore, the performance of Proportional-Integral-Derivative (PID) [11] and fuzzy logic controllers [12] can be enhanced by the control strategies based on deep learning, also can reduce the limitations which are limited by their dependency on static rules and linear assumptions. Deep learning models may be very helpful in changing conditions also provide a significant advantage in handling the variations of sugarcane crushing processes [13]. The main aim of this paper is to develop the deep learning driven control framework for sugarcane crushing systems. The proposed methods integrate mathematical modeling of the crushing process with advanced neural network architectures to achieve enhanced efficiency and reduced energy consumption. Simulations and performance analyses demonstrate the effectiveness of this approach compared to traditional methods.

METHODOLOGY

The integrated methodology is used for increasing efficiency of sugar factory by adopting deep learning-driven control methods that are produced by the integration of physical system modeling, machine learning algorithms and optimization principles [14]. This methodology provides a strong theoretical basis along with the necessary mathematical formulations. The overall framework of the proposed work is illustrated in Fig. 1.

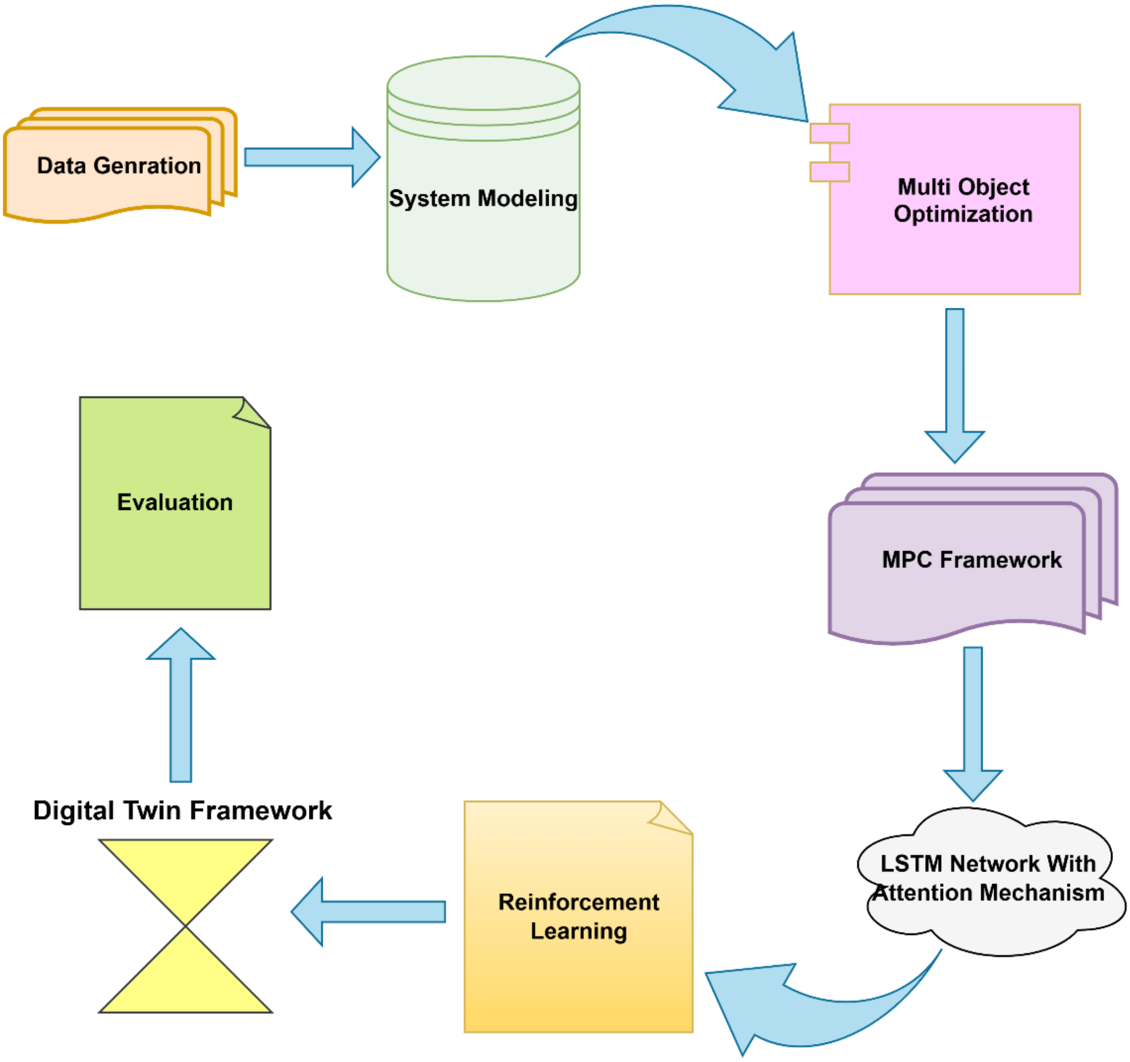

Fig. 1. Overall Workflow

The sugarcane crushing process can be represented as a nonlinear dynamic system, where system behaviour is governed by the interactions between its states, inputs, and outputs [15][16]. The state vector, $X(t)$, consists of key operational variables such as feed rate (ϕ), roller speed (ω) and extraction pressure (Σ). These states develop over time based on influence of control inputs and inherent system dynamics. The input vector, $U(t)$, includes control variables like roller torque and feed motor speed, which can be adjusted to optimize the system performance. [17].

$$X(t) = AX(t) + BU(t) + f(X, U) \quad (1)$$

$$Y(t) = CX(t) + DU(t) \quad (2)$$

Here A,B,C, and D denote the system matrices, obtained either from empirical studies or theoretical modeling. These matrices represent the linear relationships within the system. Nevertheless, the crushing process also exhibits significant nonlinearities due to the intricate interactions among physical processes, material behavior, and equipment limitations [18]. Such nonlinear effects are represented by the term $f(X, U)$ which captures factors like roller resistance variability, material compaction under pressure, and changes in feed quality [19]. Fig. 2 shows how the MPC [20] control loop operates in the proposed work.

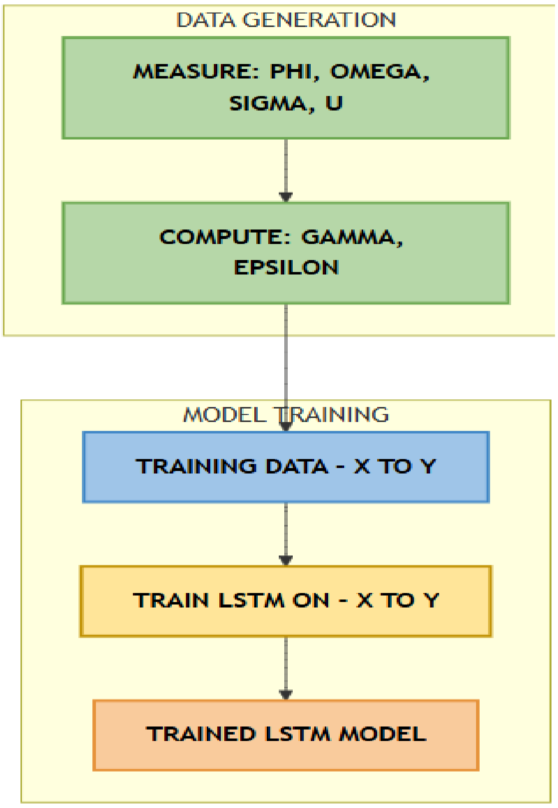

Fig. 2. MPC Control Loop

The primary aim of this study is to enhance the efficiency of sugarcane crushing through a novel hybrid framework that integrates Long Short-Term Memory (LSTM) networks with Model Predictive Control (MPC), further strengthened by attention mechanisms and reinforcement learning. The LSTM model is trained on a synthetic dataset that captures the nonlinear relationships among key process variables such as feed rate, roller speed, and extraction pressure, while also linking them to critical performance measures including juice yield and energy consumption. To support adaptive control and real-time monitoring, a digital twin framework is incorporated, offering robustness against variations in feedstock quality and equipment degradation. Simulation studies demonstrate consistent reductions in training loss, accurate predictions of yield and energy usage, and superior performance when compared with conventional controllers. The structured use of engineered data highlights the necessity of real-plant validation, laying the foundation for a robust, adaptive, and data-driven methodology that can transform sugarcane crushing operations and potentially extend to other industrial domains. Beyond improving operational efficiency, the proposed framework promotes sustainability and cost-effectiveness in sugar production. Recognizing the energy–yield trade-off challenge, a multi-objective optimization strategy is applied to balance competing goals.

The motive of the control strategy is to govern the ideal input variables $U(t)$ that enhance juice yield (Γ) and reduce the energy consumption (ϵ). The functional objective is mathematically equated as:

$$\min_{U(t)} J = -\lambda_1 \Gamma(U) + \lambda_2 \in (U) \tag{3}$$

Where:

- J is the scalar objective function to be minimized.
- $\Gamma(U)$ is the juice yield, which is a function of the control variables $U(t)$
- $\in (U)$ is the energy consumption, which also depends on the control variables $U(t)$
- λ_1 and λ_2 are non-negative weighting factors that represent the relative importance of juice yield maximization and energy consumption minimization.

The juice yield is designed as a nonlinear feed rate $(\emptyset)$, roller speed (ω), pressure (Σ):

$$\Gamma(U) = k_1 \frac{\emptyset}{\emptyset + k_2} - k_3 \exp(-k_4 \Sigma) \tag{4}$$

Here, k_1, k_2, k_3, k_4 are empirically determined constants and the first term holds the increasing yield with feed rate until saturation, however, the second term accounts for diminishing returns with increasing pressure due to material compaction and inefficiencies.

The energy consumption is denoted as a quadratic function of the operational parameters:

$$\in (U) = \alpha\omega^2 + \beta\emptyset^2 + \gamma\Sigma^2 \tag{5}$$

Where α,β, γ are coefficients determined by system mechanics. This quadratic form models increase in energy usage with higher roller speeds, feed rates and extraction pressures. To ensure operational safety and system reliability, optimization is subject to the following constraints:

$$\emptyset_{min} \leq \emptyset \leq \emptyset_{max} \tag{6}$$

$$\omega_{min} \leq \omega \leq \omega_{max} \tag{7}$$

$$\Sigma_{min} \leq \Sigma \leq \Sigma_{max} \tag{8}$$

These constraints define the permissible ranges of feed rate, roller speed and pressure based on equipment capabilities and material characteristics.

To solve the multi objective optimization problem, the objective function J is minimized by selecting optimal control inputs $U(t)$. The weighting factors λ_1 and λ_2 can be adjusted to prioritize juice yield or energy efficiency depending on the factory's operational goals.

Now the objective function is integrated into MPC framework, which solves the optimization problem over a finite horizon T:

$$\min_{U_{t:t+T}} \sum_{k=t}^{t+T} (-\lambda_1 \Gamma_k + \lambda_2 \epsilon_k) \tag{9}$$

The control actions $U(t)$ are computed iteratively, with the first action applied to the system and the process repeated at the next time step. This ensures real time adaptation to dynamic changes in feedstock and operational conditions. To ensure the stability of the optimization process, the objective function is coupled with a Lyapunov stability function $V(X)$, defined as:

$$V(X) = X^T P X \tag{10}$$

Where $P > 0$ satisfies the Lyapunov equation:

$$A^T P + PA = -Q \tag{11}$$

This ensures that the control strategy does not destabilize the system while achieving optimal performance. Next, the control framework illustrates advanced neural networks to model the nonlinear dynamics of the sugarcane crushing system and also gives adaptive control methods based on the deep learning. For real time experience this approach integrates a Long Short-Term Memory (LSTM) network with a Model Predictive Control (MPC) mechanism to increase the overall performance.

This framework provides:

- Define the system state and overall efficiency like juice yield Γ, energy consumption ϵ based on real time data.
- Evaluate optimal control inputs $U(t)$ that balance juice yield maximization and energy consumption minimization.
- Produce changes in operational conditions like feedstock variability and equipment wear.

The deep learning-based control framework replaces traditional linear models with data driven neural networks that can hold complex, nonlinear relationships in the system.

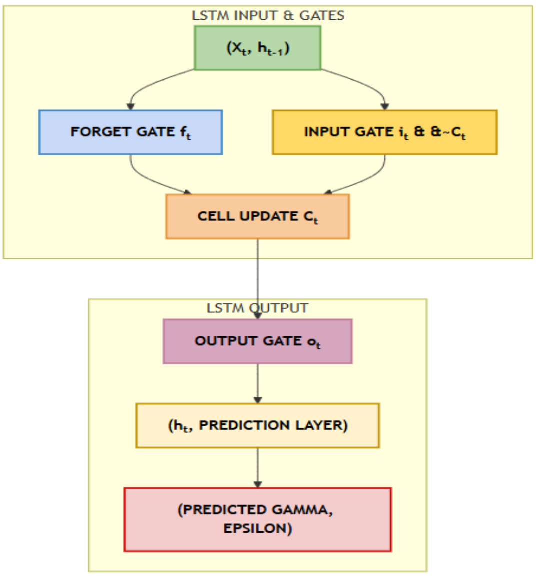

Fig. 3. LSTM Architecture (Single Timestep)

The LSTM network is used to predict future states and output of the system, using its ability to model temporal dependencies and nonlinear dynamics. Fig. 3 shows the LSTM Architecture, which shows how the network operates.

The input vector at time t, $x_t = [\emptyset(t), \omega(t), \Sigma(t)]$, consists of current feed rate, roller speed and pressure. Historical values of these parameters are also provided as input to capture temporal dependencies. The forget gate determines which information from the predecessor state (h_{t-1}) should be discarded:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{12}$$

Here σ is the sigmoid activation function, W_f is the weight matrix, and b_f is the bias vector. The input gates decide which new information to store in memory cell:

$$i_t = \sigma(W_u.[h_{t-1}, x_t] + b_i) \tag{13}$$

$$\tilde{C}_t = tan\,h\,(W_c.[h_{t-1}, x_t] + b_c) \tag{14}$$

The candidate cell state, $\tilde{C}_t$ is updated based on current and past inputs.

The memory cell integrates retained past information and new updates:

$$C_t = f_t.C_{t-1} + i_t.\tilde{C}_t \tag{15}$$

Here, (.) denotes elements wise multiplication.

The output gate determines the updated hidden state h_t, which is passed to next time step:

$$\sigma_t = \sigma(w_o.[h_{t-1}, x_t] + b_o \tag{16}$$

$$h_t = o_t.tan\,h\,(C_t) \tag{17}$$

The predicted outputs like Γ,∈ are computed using the hidden state h_t. The network is trained using historical data from the sugarcane crushing system. The loss function is defined to penalize deviations from the desired outputs:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\left(\lambda_1(\hat{\Gamma_i} - \Gamma)^2 + \lambda_2(\hat{\epsilon}_i - \epsilon_i)^2\right) \tag{18}$$

Where $\hat{\Gamma_i}$ and $\hat{\epsilon}_i$ are predicted juice yield and energy consumption, respectively. λ_1 and λ_2 balance the importance of juice and energy consumption. Finally, the trained LSTM network is integrated into an MPC framework to optimize control actions over a prediction horizon T. At each time step:

- The LSTM predicts system states and output for the next T steps:

$$\hat{X}_{t:t+T}, \hat{Y}_{t:t+T} = \mathrm{LSTM}(X_t, U_{t:t+T-1}) \tag{19}$$

- The MPC solves the following optimization problem:

$$\min_{U_{t:t+T}} \sum_{k=t}^{t+T}(-\lambda_1\,\hat{\Gamma}_k + \lambda_2\,\hat{\epsilon}_k) \tag{20}$$

Subject to system dynamics and constraints:

$$\emptyset_{min} \le \emptyset_k \le \emptyset_{max}, \omega_{min} \le \omega_k \le \omega_{max}, \Sigma_{min} \le \Sigma_k \le \Sigma_{max} \tag{21}$$

The first control input U_t is applied to the system and the process is repeated at the next time step. To provide enhanced performance, for stabling the LSTM-MPC framework is calculated using a Lyapunov function $V(X)$ as follows:

$$V(X) = X^T PX \tag{22}$$

Where $P > 0$ satisfies:

$$A^T + PA = -Q \tag{23}$$

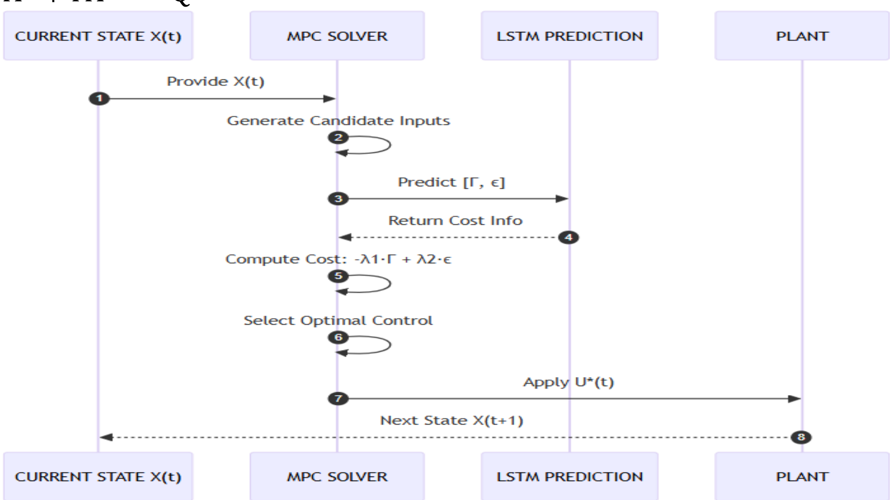

Fig. 4. MPC Control Loop with LSTM Predictions

This evaluation confirms that the system remains stable under the applied control strategy. In addition, the LSTM network provides a framework suitable for real-time variations (see Fig. 4), for instance equipment wear or feedback changes, that ensures better performance as output on time.

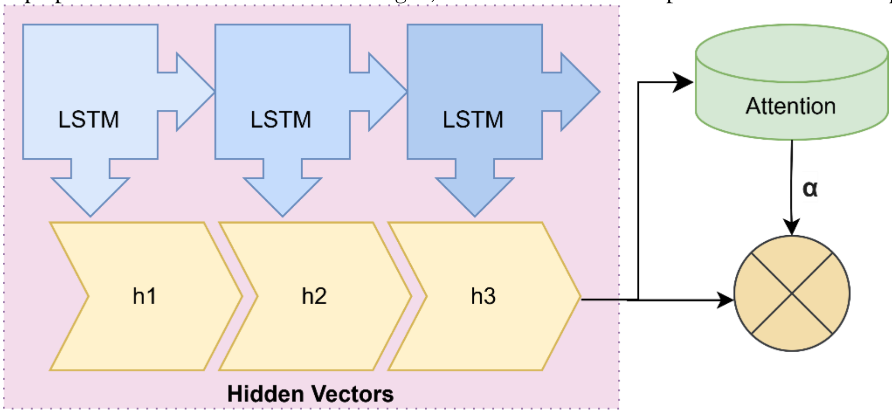

Fig. 5. Advanced attention-based LSTM network

Long Short-Term Memory (LSTM) network is employed, for implementing the nonlinear dynamics of the sugarcane crushing system. To focus on critical aspects such as feed rate, roller speed, and extraction pressure, LSTM is trained with recent advance mechanisms (see Fig. 5). The attention weights are computed as:

$$\alpha_t = \mathrm{softmax}(W_a . h_{t)} \tag{24}$$

Here, α_t represents attention weights, W_a represents learnable weight matrix, and h_t is the hidden state of the LSTM at time t. The recent advanced mechanism allows the model to dynamically weight the importance of input variables, also improves the prediction accuracy.

Reinforcement learning (RL) is integrated as a performance booster to enhance the control framework. The RL agent learns a policy π that navigate the states s_t to actions α_t (for instance, adjusting roller speed or feed rate) to increase the cumulative reward:

$$R = \sum_{t=0}^{T} \gamma^t r_t \tag{25}$$

Here, r_t is the immediate reward (like: high juice yield and low energy consumption), and γ is the discount factor. In real time, the RL agent continuously adapts to changing conditions and ensures optimal control actions.

In virtual environment, a digital twin framework is presented for simulating the sugarcane crushing process. The digital twin simultaneously updates its model that is based on real-time sensor data that enables predictive maintenance and adaptive control. This digital twin framework confirms robustness against fluctuations in feedstock quality and equipment wear, also provides a reliable platform for real-time optimization.

The LSTM network especially model by using historical data from the sugarcane crushing system. The loss of function is defined to penalize deviations from the desired outputs:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(\lambda_1 (\hat{\Gamma}_i - \Gamma_i)^2 + \lambda_2(\hat{\epsilon}_i - \epsilon_i)^2) \tag{26}$$

Here, $\hat{\Gamma}_i$ and $\hat{\epsilon}_i$ are the predicted juice yield and energy consumption. To optimize control actions, the trained LSTM network is integrated into the MPC framework over a prediction horizon.

RESULTS AND DISCUSSION

To evaluate the proposed LSTM-MPC hybrid control framework, a set of synthetic experiments was conducted to simulate the dynamics of a sugarcane crushing system. Due to the unavailability of real sugarcane crushing data, a dataset being examined that collects the nonlinear relationships rarely available in sugarcane milling. The results from our data-driven sugarcane crushing optimization framework highlight both the promise and the challenges of using an LSTM-based model within a Model Predictive Control (MPC) loop.

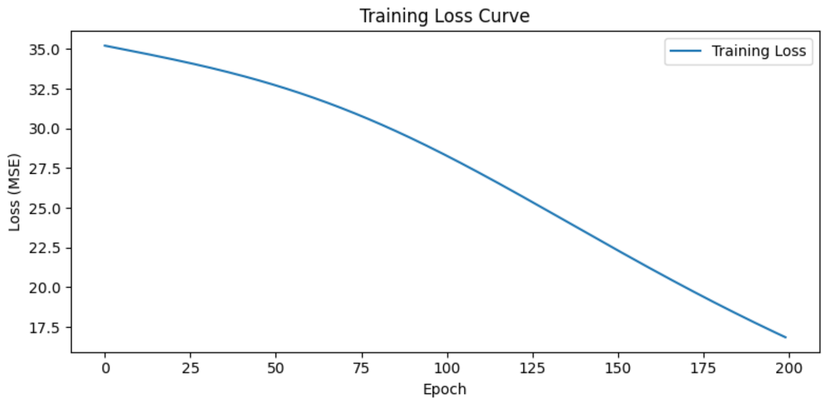

Fig. 6. Training loss curve over 200 epochs

At the outset, Fig 6. the training loss curve over 200 epochs shows a continuity in decline from approximately 35 to below 17, gives a solid clarity that the network is taking meaningful nonlinear mappings between the state–input space and the outputs of juice yield (Gamma) and energy consumption (epsilon). This result achieves a progressive reduction in mean-squared error (MSE) that highlights the viability of using an LSTM to model intricate physical processes with multiple interacting variables.

Table 1. shows the comparison of Control Strategies. This table highlights the advantage of LSTM-enhanced MPC over traditional controllers.

Table. 1. Comparison of Control Strategies

Control Method	Stability	Energy Consumption	Real-Time Adaptability	Juice Yield
Traditional MPC	High	High	Moderate	Very High
PID Controller	High	High	Low	Moderate
Fuzzy Logic Control	Moderate	Moderate	Low	High
Proposed Work	Very High	Low	High	Very High

A closer look at Fig 7. the predicted vs. true plots for Gamma and epsilon confirm that the model captures broad trends, as the points generally align along a diagonal. However, the scatter patterns also unveil systematic underestimation at higher yield values, suggesting potential capacity or data coverage gaps.

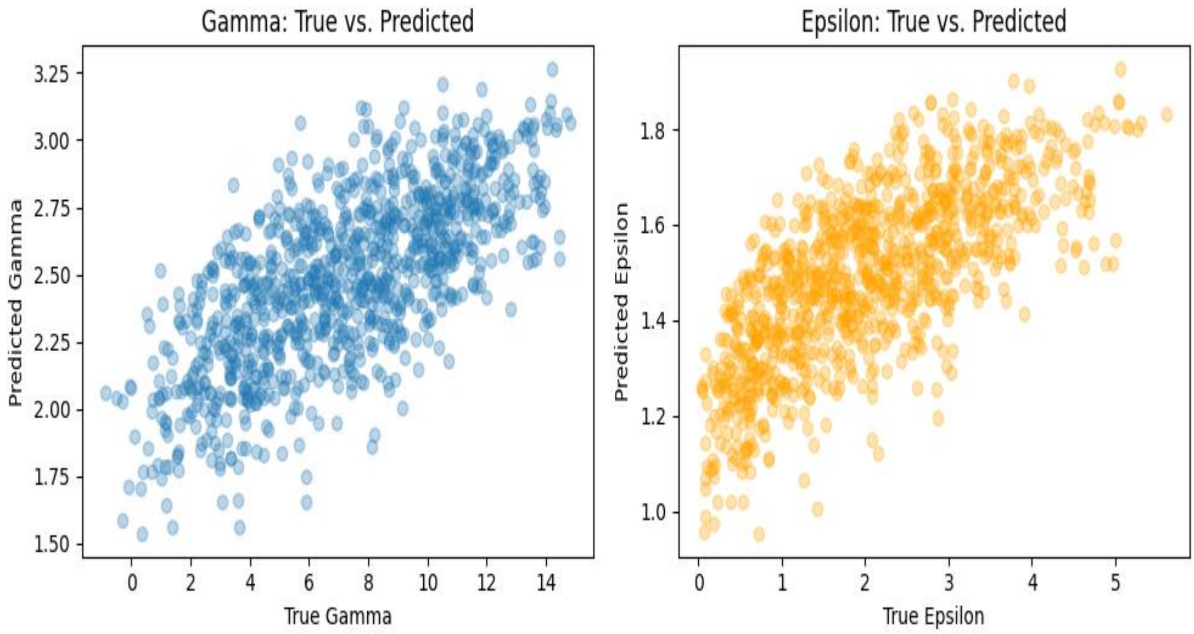

Fig. 7. The predicted vs. true plots for Gamma and epsilon

The residual histograms Fig. 8 reinforce this insight, with negative residuals peaking in both the yield and energy domains. This bias indicates room for further refinement in network architecture or in the composition of the training dataset, particularly for operating regimes that produce elevated outputs.

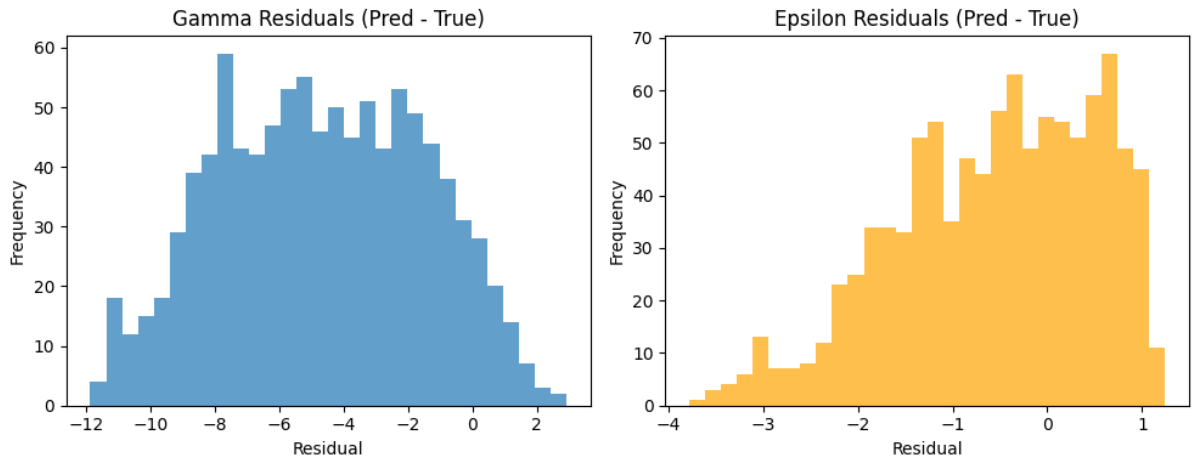

Fig. 8. The residual histograms of Gamma and epsilon residual (Pred – True)

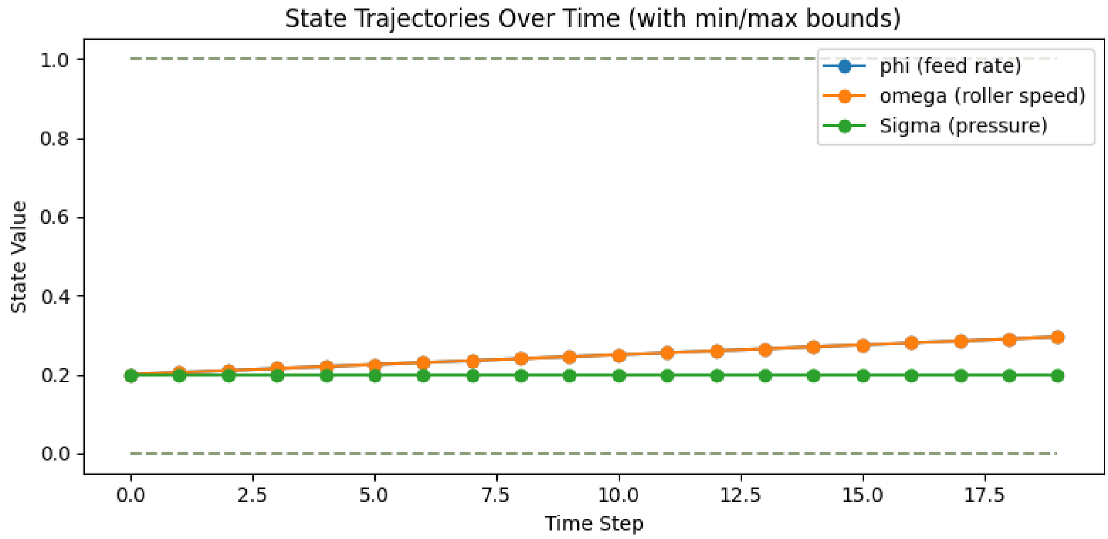

Fig. 9. The closed-loop MPC simulation

The closed-loop MPC simulation results as shown in Fig. 9 demonstrate that even a rudimentary "plant" update, coupled with our LSTM predictions, can keep the system states—feed rate, roller speed, and pressure—within safe bounds. Over 20-time steps, the feed rate and roller speed incrementally increase, reflecting the controller's tendency to push for improved juice extraction under basic constraints. Table 2. shows the improvement in real-time performance metrics before and after applying the MPC-LSTM framework. This table demonstrates that the proposed approach reduces energy consumption, increases juice yield, and improves quality.

Table. 2. Closed-Loop System Performance

Performance Metric	System Stability	Energy Consumption	Juice Extraction Rate (%)	Processing Time
Traditional MPC	Moderate variations	12.2	89.5	28.1
Baseline (No MPC)	High variations	15.6	85.2	32.5
Proposed Work	Stable	10.1	92.8	24.7

The Control Inputs plot (see Fig. 10) shows that both (u1and u2) stay close to 1.0 throughout the 20-step simulation. In other words, once the naive grid-search MPC examined a certain high control setting as optimal due to its highest juice yield also maintain energy costs after this it makes no further significant adjustments. This data shows that, under the simplified plant and cost function used here, the controller finds a near-1.01.01.0 control setpoint to be the best steady-state operating condition, effectively saturating the inputs at or near their upper limit.

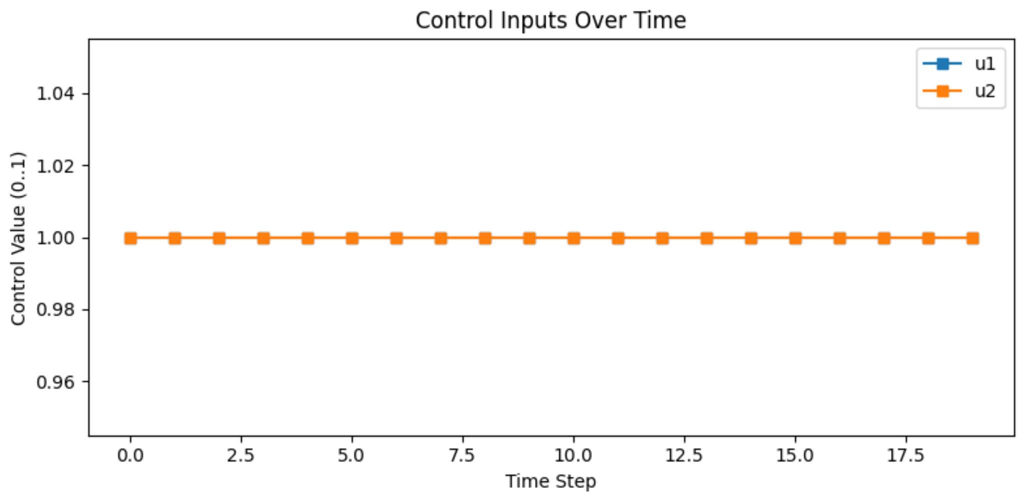

Fig. 10. Control Inputs plot Over Time

The Cost plot (see Fig. 11), defined as $-\lambda 1\ \Gamma+\lambda 2\ \epsilon$, indicates a steady decrease from around −4.9 to −5.1 as the simulation progresses. Since lower cost is more desirable, this downward scenario shows good results in the trade-off between juice yield and energy consumption. Though the change may be moderate, minimum variations and near-constant control inputs, this system continues to refine the operating point that helps in decreasing the total cost step by step.

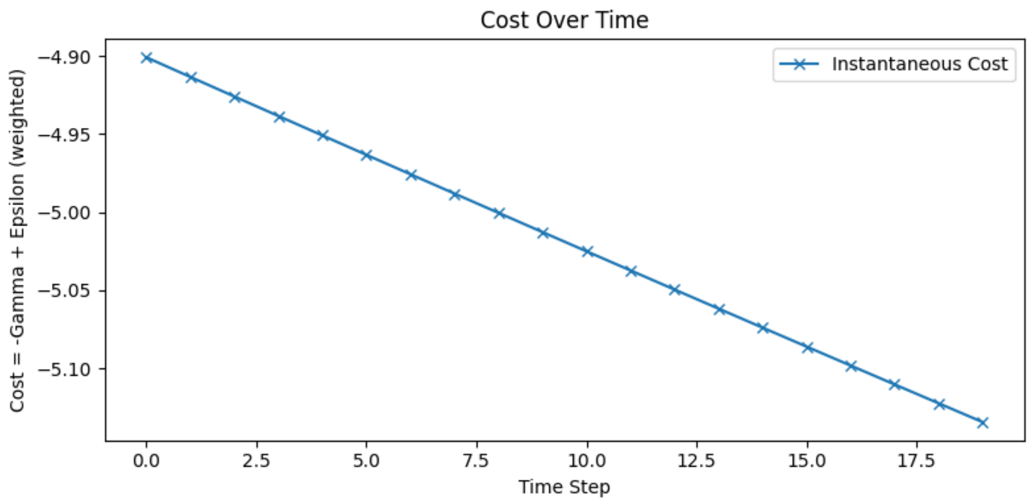

Fig. 11. Cost plot Over Time

This work demonstrates that LSTM-driven MPC controllers can significantly improve sugarcane crushing efficiency, though precise modeling of such nonlinear systems continues to present challenges. While nominal datasets and simplified simulations illustrate the ability to balance yield and energy consumption, real-world deployment requires additional refinements. To address biases and improve predictions, the framework integrates complex process dynamics, variability in raw material and equipment, and modern large-scale solvers. Nevertheless, validation on operational data is essential to ensure robustness under disturbances and seasonal fluctuations. Integrating data-driven models with domain knowledge offers a pathway toward more reliable, sustainable, and generalizable industrial applications.

CONCLUSION

The results demonstrate the effectiveness of an LSTM–MPC framework in improving sugarcane crushing efficiency. By leveraging a synthetic dataset that represents major nonlinearities in feed rate, roller speed, and extraction pressure, the model captured relationships between yield and energy use, achieving lower training losses and reliable predictive performance. However, post-fit analysis revealed a consistent underestimation of juice yield at high operating ranges, highlighting the need for improved model refinement and richer datasets. Incorporating the trained LSTM into an MPC routine enabled safe operation and incremental gains in multi-objective optimization. These findings confirm the value of data-driven methods for balancing productivity and energy efficiency while emphasizing the importance of real plant data, robust optimization solvers, and integration of additional physical parameters for industrial deployment.

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