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A Hybrid Multi-Layer Digital Twin Framework for Real-Time Control and Optimization of Seamless Pipe Rolling Mills

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ABSTRACT

However, accurate and real-time control of power parameters in seamless pipe rolling mills remains a critical challenge owing to complex thermo-mechanical interactions and changing process conditions. The accuracy and response time of conventional approaches, such as analytical, numerical, and data-driven models, are often insufficient, either in terms of accuracy or response time, to meet industrial requirements. To overcome this limitation, a novel multilayer digital twin (DT) approach has been developed that incorporates analytical models, thermo-mechanical finite element models, and machine learning (ML) models in a single cyber-physical system. Analytical models facilitate rapid evaluation and estimation of rolling force and torque, allowing immediate response and control, whereas thermo-mechanical finite element models facilitate accurate evaluation and analysis of temperature, stress, and deformation fields, providing a deeper understanding of physical processes. In parallel, ML models, such as artificial neural networks (ANN) and XGBoost regressors, are employed to learn complex relationships from industrial sensor data and facilitate adaptive prediction and control. The results indicate that a coefficient of determination (R^2) value of up to 0.98 and prediction errors less than 3% can be obtained, along with improvements in terms of energy efficiency, peak motor load, and scrap rates.

1. INTRODUCTION

Significant changes have been noted in the current state of the manufacturing industry owing to the rapid development of digital technologies and the implementation of Industry 4.0. The Internet of Things, big data analytics, artificial intelligence, and cyber-physical systems have enabled a transition from traditional manufacturing to intelligent, autonomous, and more efficient systems [1]. Seamless rolling mills are an important part of the metal-forming industry, where product quality, energy consumption, equipment life, and plant efficiency are significantly affected by the precise control of power parameters, rolling force, torque, and contact pressure [2]. However, owing to complex thermo-mechanical interactions and varying operating conditions, precise prediction and control of power parameters are considered to be an important challenge [3].

Digital twin (DT) technology has been found to play an important role in resolving the current challenges faced in industrial systems. The term "DT" refers to the creation of a virtual replica of an object or a system, which is used to monitor, predict, and optimize industrial processes [1]. During metal-forming operations, particularly seamless rolling mills, the strong coupling effects of thermal and mechanical phenomena require an adaptive modeling strategy to cope with the rapid changes occurring in the process [2, 3]. Precise prediction of power parameters in multi-stand rolling mills with retained mandrels is considered an important challenge owing to continuous deformation, temperature changes, and complex material properties.

Traditionally, analytical modeling has been extensively employed for parameter estimation in rolling operations, considering factors such as computational efficiency and simplicity. These models offer closed-form expressions that describe deformation zones, flow stress, and contact mechanics at a relatively low computational cost [3, 4]. Although analytical modeling has several advantages, certain limitations exist, including difficulties in simulating nonlinear material behavior, temperature gradients, interstrand stress, and time-dependent frictional conditions. As a result, discrepancies between analytical modeling and real-world metal rolling operations arise under various operating conditions [4, 5].

To overcome some of the above limitations, thermomechanical finite element modeling (FEM) has been employed as an effective tool for simulating metal rolling operations. FEM modeling offers detailed insight into temperature distribution, stress/strain, and contact behavior, enabling a better understanding of material behavior during metal rolling operations. Although FEM modeling offers excellent accuracy, there exist certain limitations, including high computational cost, which renders FEM modeling inappropriate for real-time applications, especially in continuous rolling operations where quick decision-making is required [2, 5].

Machine learning (ML) modeling has attracted considerable research attention in recent times, considering factors such as modeling nonlinear relationships between variables. ML modeling, including artificial neural networks (ANN) and gradient boosting, has been employed to predict rolling parameters, including rolling force, torque, and temperature variation, considering factors such as the large amount of data obtained from industrial IoT devices. These models offer excellent performance, particularly in noisy and dynamic environments, considering factors such as the ability to continuously learn from newly obtained data [6, 7]. Although ML modeling has several advantages, including excellent performance, certain limitations exist, including poor interpretability and data dependence, which render ML modeling inappropriate under unseen conditions [8, 9].

As indicated in the literature review, analytical modeling, FEM simulation, and ML techniques have all made notable contributions to the understanding and prediction of the rolling process. However, the majority of the literature has only considered these techniques in isolation or in partial combinations, rather than integrating them in a unified manner. Specifically, there has been a lack of research in the area of developing a comprehensive multilayer DT architecture specifically designed for seamless pipe rolling mill processes. This has made it challenging to achieve the objectives of simultaneous real-time responsiveness, physical accuracy, and learning capabilities [3, 7, 10]. Additionally, traditional control techniques are unable to effectively address the thermo-mechanical complexities involved in the rolling process, including temperature variations, stress distributions, and deformation evolutions, which necessitate the need for more sophisticated real-time modeling techniques [11].

In recent times, developments in the area of digital manufacturing technologies have demonstrated the capabilities of the hybrid DT architecture, which combines the benefits of physical modeling with data-driven techniques to enhance the accuracy, stability, and efficiency of the rolling processes [12-14]. Such techniques have been successfully demonstrated in various industrial processes, but the application of these techniques in seamless pipe rolling processes, which include the use of retained mandrels, stress evolutions, and dimensional tolerances, has been limited and warrants further investigation.

In this context, this study proposes a novel multilayer DT approach that incorporates analytical modeling, thermomechanical finite element method simulations, and ML into a unified cyber-physical system. The proposed approach is expected to take advantage of the computational power of analytical modeling, high-fidelity results of finite element method simulations, and the adaptive nature of ML to ensure the prediction and control of power parameters for seamless pipe rolling processes with high accuracy and adaptability. The developed DT is expected to ensure a smooth and efficient transition to intelligent and self-optimizing manufacturing systems, as envisioned for Industry 4.0 and its related concepts [15-18].

The novelty of this study is the development of a highly integrated multilayer DT approach for seamless pipe rolling processes. Unlike previous studies, this study proposes a unified approach that incorporates analytical modeling, finite element method simulations, and ML into a unified cyber-physical system for seamless pipe-rolling processes. The integration and synchronization capabilities of the developed DT are expected to ensure a smooth and efficient transition to intelligent and self-optimizing manufacturing systems, as envisioned for Industry 4.0 and its related concepts.

The proposed approach is also novel because it incorporates a hybrid approach that utilizes the high computational power of analytical modeling, high-fidelity results of finite element method simulations, and nonlinear predictive capabilities of ML to ensure high prediction accuracy, high response time, and high adaptability for seamless pipe rolling processes. To the best of the authors' knowledge, such a highly integrated and application-specific DT approach for seamless pipe rolling processes, including real-time control and adaptive ML, is still an unexplored area in the literature.

2. METHODOLOGY

The methodological framework upon which this research study has been conducted is centered on the development of a multi-layer DT architecture, with the aim of improving accuracy, flexibility, and real-time performance in terms of power parameter predictions in seamless pipe rolling mills. The proposed approach will be able to seamlessly integrate analytical modeling, finite element modeling, and ML under one cyber-physical system, considering the complicated thermomechanical interactions that exist during retained mandrel rolling. Table 1 shows a general overview of the structure and interaction between various components, whereas Figure 1 shows how all these components interact with one another.

The analytical modeling component is responsible for making quick predictions concerning the rolling force, torque, and other relevant geometric parameters. The analytical model was developed from classical rolling theory, considering factors such as longitudinal force equilibrium, radial compression, average flow stress, and frictional interactions between the roll, mandrel, and billet. The model will be calibrated using industrial data, including the mandrel contact angle and roll widening, to ensure better accuracy. Although analytical modeling cannot account for temperature gradients and stress development between rolling stands, this approach will be utilized because of its efficiency in real-time decision-making.

To overcome some of the limitations associated with analytical modeling, a high-fidelity finite element modeling approach was employed to simulate the behavior of high-carbon steel billets during rolling. The FEM is capable of simulating temperature-dependent elastoplastic material behavior, realistic friction coefficients between roll and mandrel interfaces, and realistic geometric configurations such as roll speed and mandrel gap. The FEM is capable of simulating the stress, strain, contact pressure, and temperature distribution during the rolling process. Although FEM will be capable of simulating all relevant parameters, it will be limited to offline analysis only, considering the associated computational cost.

ML has been incorporated into the DT framework, providing adaptive and data-driven predictive capabilities for rolling process parameters. The models were trained on industrial datasets obtained from actual industrial processes, such as rolling seamless pipes, using real-time sensor measurements during the seamless pipe rolling processes. The dataset consists of important process parameter values, such as billet temperature, roll speed, rolling torque, elongation coefficients, and contact conditions. However, before training the models, preprocessing was performed on the actual dataset to improve its quality and consistency. This ensured improved quality and consistency in the dataset, allowing for enhanced model performance and accuracy during actual implementation.

Two different ML models were implemented: feed-forward ANN and XGBoost regression models. The ANN model was implemented to predict complex non-linear relationships between different input process parameter values and output values, such as rolling force and torque values, while XGBoost regression models were implemented owing to their robustness and ability to perform effectively when handling structured industrial data.

To improve the accuracy and reliability of the models, adaptive learning strategies were implemented, allowing the models to update and correct their output values based on new data received from actual processes. The implementation of ML models within the DT framework allows corrections to be made to actual analytical and FEM calculations, providing a much more accurate, robust, and responsive system overall.

The integration of various modeling techniques is enabled through a cyber-physical DT concept, where data are continuously synchronized in real time based on data collected directly from PLC systems and IoT devices. This allows for the simultaneous adaptation of parameters such as torque, temperature, rolling speed, and deformation indicators. A hybrid technique for integrating different model predictions, such as analytical, FEM, and ML models, is employed based on the operating conditions and historical performance. In cases where large deviations occur, adaptive retraining is initiated to ensure long-term predictive stability.

The operational mechanism of the proposed DT is based on a closed-loop control strategy, as depicted in Figure 1. In the proposed control strategy, the data obtained from the PLC system and IoT sensors in the rolling mill are transmitted in real time to the DT environment. The data are processed simultaneously in the analytical, finite element, and ML models to produce predictive results regarding the current state of the process.

The results obtained from the analytical, finite element, and ML models were integrated in the central decision layer using a hybrid fusion technique that considers the reliability of the prediction results according to the conditions of operation and historical results. According to the integrated results obtained from the predictive model, control actions are dynamically generated in the rolling mill, allowing real-time control of the process parameters, including the speed of the rolls, the inter-stand tension, and the lubrication conditions.

Through this integrated architecture, it can be seen that the DT can be utilized within a closed-loop control system, thus enabling it to affect parameters such as roll speed, inter-stand tension, and lubrication in real time. In this regard, it can be stated that the hybrid approach ensures computational efficiency and accuracy in predictions, with an inference time of 0.20 seconds for each prediction cycle.

It can be stated here that the proposed concept of a multi-layer DT can be utilized for providing a scalable, flexible, and physically informed platform for real-time optimization and intelligent control of seamless pipe rolling operations. This concept bridges the gap between physics-based and data-based predictions.

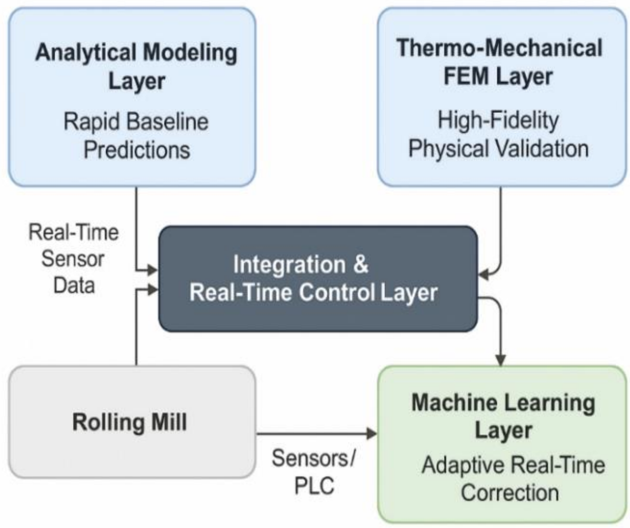

Figure 1. Multilayer digital twin (DT) architecture for seamless pipe rolling mills

Table 1. Summary of the multi-layer digital twin (DT) architecture

Layer	Purpose	Inputs	Outputs	Models / Tools
Analytical Modeling Layer	Fast predictive estimation of rolling force, torque, and deformation behaviour.	Rolling geometry, material properties, and process parameters.	Closed-form predictions: Baseline estimates for FEM validation.	Analytical equations and mechanistic models.
Thermo-Mechanical Finite Element Modeling (FEM) Layer	High-fidelity simulation of the temperature, stress, and strain fields.	Thermal boundary conditions, material constitutive laws, analytical estimates.	Detailed field distributions; process sensitivity analysis.	Coupled FEM solvers and thermomechanical simulation software.
Machine Learning (ML) Layer	Real-time prediction- and adaptive learning based on sensor data.	Historical datasets, live sensor streams, FEM-enhanced features.	Predicted power parameters, anomaly detection, and adaptive process updates.	Neural networks, ensemble models, online learning algorithms.
Integration & Real-Time Control Layer	Synchronizing data flow and enabling closed-loop control adjustments.	Outputs from all layers and real-time measurements.	Control commands, optimized rolling conditions, alerts.	DT platform, IoT middleware, real-time controllers.

3. RESULTS AND DISCUSSION

This section presents the combined outcomes of the analytical layer, thermo-mechanical FEM model, and ML models developed using the proposed multi-layer DT architecture seamless pipe-rolling mills. It was demonstrated that the combination of physics-based and data-driven approaches provides more accurate control of the power parameters in the rolling processes, greater responsiveness in real time, and overall stability. The section is configured without a table and Tables 2-7 placeholders will be occupied later when it is possible to generate words.

3.1 Analytical model results

The analytical modeling component is responsible for providing rapid estimations of the rolling force, torque, and key geometric parameters. The model was developed based on the classical rolling theory, where the rolling force F is related to the average flow stress, deformation geometry, and contact conditions. Therefore, the rolling force can be expressed as:

$$F = \bar{\sigma} \cdot b \cdot L \quad (1)$$

where, $\bar{\sigma}$ represents the average flow stress of the material, b is the width of the deformation zone, and L is the contact length between the roll and billet. The contact length is approximated as:

$$L = \sqrt{(R \cdot \Delta h)} \quad (2)$$

where, R is the roll radius and Δh is the reduction in thickness. The average flow stress was estimated using the strain-hardening relationship

$$\bar{\sigma} = K \cdot \varepsilon^n \quad (3)$$

where, K is the strength coefficient, ε is the effective strain, and n is the strain-hardening exponent.

Based on the estimated rolling force, the rolling torque T can be calculated as:

$$T = F \cdot R \quad (4)$$

These formulations enable fast and reasonably accurate estimation of the power parameters, making the analytical model suitable for real-time prediction and decision-making. The model was further calibrated using industrial data, including the mandrel contact angle and roll widening, to improve the prediction accuracy under realistic operating conditions.

Although the analytical model does not fully capture the temperature gradients and stress evolution between rolling stands, it serves as a computationally efficient foundation for higher-fidelity FEM and ML layers.

From the results obtained using the analytical model, it can be seen that it is an acceptable tool for baseline predictions, with an R^2 value close to 0.91 and a mean absolute percentage error close to 10.8%, as shown in Table 2.

Nevertheless, it was observed that the model underpredicted the rolling force owing to its basic assumptions, especially when dealing with non-uniform temperature distribution and frictional interactions.

Figure 2 shows the von Mises stress distribution along the pipe during rolling. It can be seen that the stress is concentrated within the deformation zone and decreases gradually along the rolling direction. This is in agreement with the predictions of the deformation behavior using the analytical model.

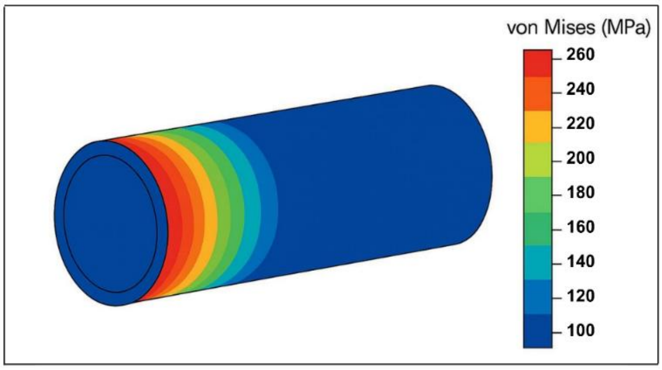

Figure 2. The Von Mises stress distribution along the pipe during the rolling process

3.2 Thermo-mechanical finite element modeling simulation results

The thermo-mechanical behavior of the rolling process was simulated using high-fidelity finite-element simulations. The material of the billet was modeled as a temperature-dependent elastoplastic material, where the flow stress was a function of strain and temperature. Appropriate boundary conditions were applied to the FEM model, including the roll rotation, mandrel position, and billet temperature at the inlet.

The roll-billet and mandrel-billet interfaces were modeled using friction coefficients corresponding to industrial conditions. A refined mesh was applied to discretize the simulation domain to accurately predict the stress, strain, and temperature gradients in the deformation zone.

The main findings of the FEM analysis are summarized in Table 3, where the accuracy of the FEM predictions for the torque in various rolling stands is presented. The accuracy of the FEM predictions is high and close to the measured data, with significantly low prediction errors compared to the analytical model.

Table 2. Comparison of rolling force prediction accuracy

Model Type	RMSE (kN)	MAPE (%)	R^2	Mean Error (%)	Notes
Analytical Model	22.5	10.8	0.91	Underestimates force	Fast but low fidelity
Finite Element Modeling (FEM) Model	14.3	6.2	0.95	Slight overestimation	High accuracy, slower
Artificial Neural Networks (ANN) Model	8.1	3.4	0.97	Good nonlinear capture	Requires training data
XGBoost Model	8.6	3.6	0.96	Strong generalization	Stable performance
Hybrid Digital Twin (DT)	6.8	2.9	0.98	Sub-1% stand error	Best performance overall

Table 3. Torque prediction accuracy (measured vs predicted)

Stand No.	Measured Torque (kN·m)	Analytical (Error %)	Finite Element Modeling (FEM) (Error %)	ANN (Error %)	Hybrid DT (Error %)
1	132	119 (-9.8%)	127 (-3.8%)	130 (-1.5%)	131 (-0.8%)
2	145	132 (-8.9%)	138 (-4.8%)	143 (-1.4%)	144 (-0.7%)
3	150	138 (-8.0%)	143 (-4.6%)	148 (-1.3%)	149 (-0.6%)
4	155	142 (-8.3%)	148 (-4.5%)	153 (-1.2%)	154 (-0.6%)
5	158	148 (-6.3%)	154 (-2.5%)	156 (-1.2%)	157 (-0.6%)

Note: artificial neural networks (ANN); digital twin (DT)

Table 4. Force prediction per stand (measured vs models)

Stand No.	Measured Force (kN)	Analytical	Finite Element Modeling (FEM)	ANN	Hybrid DT
1	1100	980	1040	1085	1092
2	1200	1070	1130	1180	1190
3	1250	1125	1188	1235	1245
4	1280	1150	1210	1260	1273
5	1300	1170	1235	1285	1294

Note: artificial neural networks (ANN); digital twin (DT)

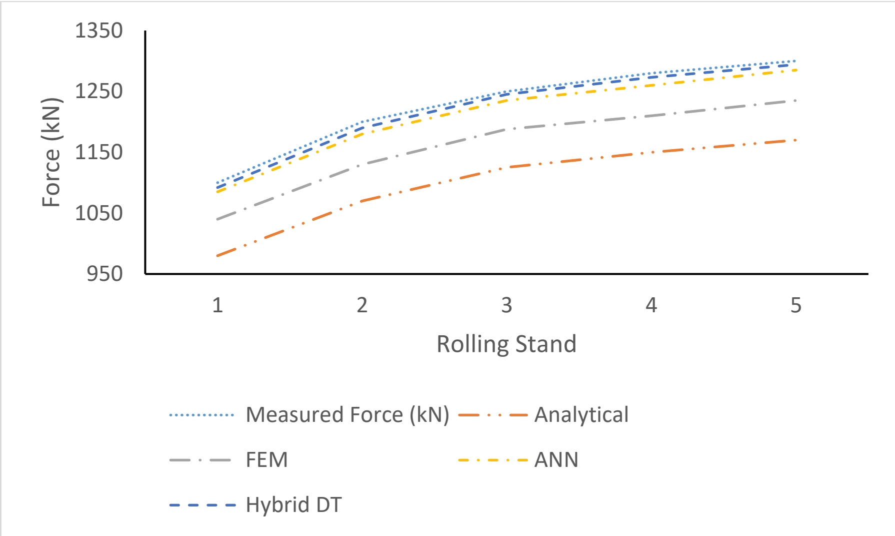

Figure 3. Comparison of rolling force predictions per stand obtained from analytical, finite element modeling (FEM), artificial neural networks (ANN), and hybrid digital twin (DT) models against measured values

The results obtained through the FEM indicate that the errors for the torque are within a range of 2.5 to 4.8%, while the errors obtained through the analytical model are higher, within a range of 6.3 to 9.8%. The hybrid DT model also offers improved prediction accuracy, with errors below 1% for all rolling stands. A significant temperature gradient was observed along the pipe wall, particularly in the deformation zone. These temperature gradients affect the dimensions of the rolled pipe, including changes in ovality and thickness, as shown in Table 4 and Figure 3. Figure 3 shows the variation in the rolling force and dimensional changes obtained in various stands, where better agreement between the FEM and hybrid DT predictions is observed rather than the analytical results.

Figure 4 depicts the temperature distribution along the pipe, where it can be seen that there is an increased temperature at the roll-mandrel interface, followed by a gradual decrease in temperature along the rolling direction. The temperature distribution in Figure 4 confirms the presence of high gradients in the deformation zone, which directly affect the flow stress and deformation resistance of materials, thus validating the importance of thermomechanical coupling in FEM simulations.

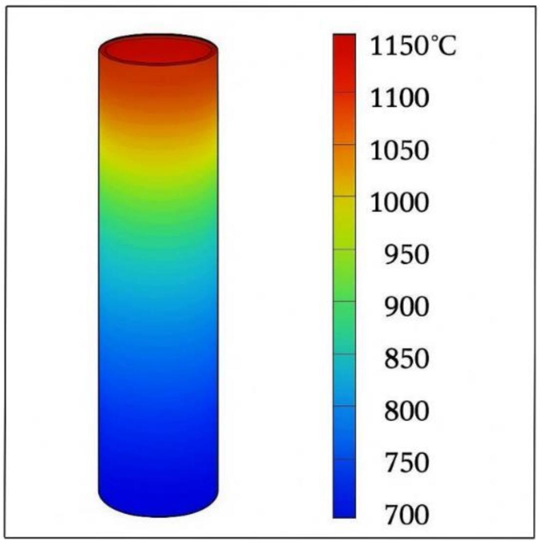

Figure 4. The thermomechanical finite element modeling (FEM) model demonstrates the change in the temperature of the pipe during the rolling process

3.3 Machine learning prediction results

The ML models were capable of making precise predictions of both the rolling force and torque when trained using mill sensor operational datasets. The performance measures (MAE, RMSE, and prediction accuracy) are listed in Table 5. Besides predictive accuracy, another tangible benefit of the DT implementation was an improvement in process efficiency, where the specific energy consumption was reduced from 112 to 102 kWh/ton, that is, an improvement of 8.9%; the peak motor load was reduced from 93% to 85%; and the scrap rate was reduced from 9.10% to 8.40%, as depicted in Table 5.

The results obtained from the experiment show that the ANN model has a better performance, with a validation RMSE of 8.1 and an R^2 value of 0.97, while the XGBoost model has an RMSE value of 8.6 and an R^2 value of 0.96. The proposed hybrid DT model has shown better performance, with the lowest RMSE value of 6.8 and the highest accuracy, with an R^2 value of 0.98. These results confirm that the hybrid DT model outperforms all standalone ML approaches by effectively combining data-driven prediction and physics-based insights.

The ML predictions were close to the FEM reference results, particularly in terms of explaining the nonlinear variations in force and torque with variations in temperature and mechanical conditions. Table 6 shows the comparisons between the predictions of ML and the actual measurements of a factory regarding a typical production batch. This agreement between the ML predictions, FEM results, and experiments verifies the robustness of the proposed framework in simulating process dynamics under changing operational conditions.

In Figure 4, it is evident that the measured rolling force and the force predicted by the hybrid DT conform to each other over time during a standard rolling cycle. The two curves are clustered close enough, which demonstrates that the hybrid model can properly adhere to rapid variations in the force and load in real time. This implies that it is useful for closed-loop control processes. This is clearly shown in Figure 5, where the ability of the hybrid model to accurately track dynamic changes in the rolling force is demonstrated.

3.4 Digital twin synchronization and real-time updating

It is because the three layers, namely the analytical, FEM, and ML layers, have been well synchronized that the DT was able to track the actual rolling mill behavior in real time. The effectiveness of the DT updating mechanism, as far as synchronization and prediction are concerned, is presented in Table 7. From the results, the DT model shows high agreement with the actual parameters, as the deviation is maintained within a narrow band under different conditions. The synchronization error was very small, reflecting the reliability and stability of the real-time updating process.

Table 5. Energy consumption before and after digital twin (DT) optimization

Parameter	Baseline Operation	With Digital Twin	Improvement
Specific Energy (kWh/ton)	112	102	-8.90%
Peak Motor Load (%)	93%	85%	Reduced mechanical stress
Idle Energy Loss (kWh/day)	64	51	-20%
Scrap Rate (%)	9.10%	8.40%	-7%

Table 6. Machine learning (ML) model performance

Model	Training RMSE	Validation RMSE	R^2	Notes
Artificial neural networks (ANN)	7.6	8.1	0.97	Best standalone ML
XGBoost	8	8.6	0.96	Robust generalizer
Random Forest	9.4	10.2	0.94	Slight overfitting
SVR	11.8	12.5	0.89	Limited nonlinear capture
Hybrid Digital Twin (DT)	6.8	6.8	0.98	Best overall performance

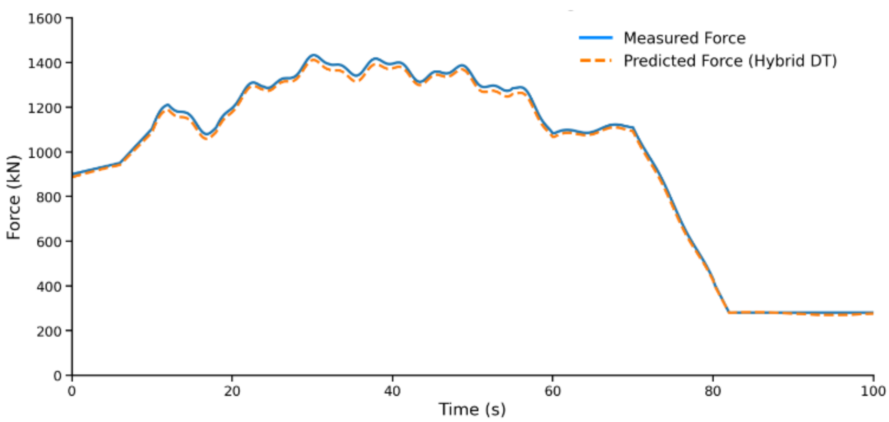

Figure 5. A comparison of the measured rolling force and the predicted rolling force over time as compared to the hybrid digital twin (DT) model indicates that these two are nearly similar and that the model has the ability to trace them even under changing conditions

The hybrid model ensures the continuous generation of predictions using the analytical model, application of corrections using the ML model, and periodic execution of validations using the FEM model, thereby ensuring the long-term accuracy of the DT model. The synchronization of the multiple layers ensures the generation of predictions within a short time, as the prediction updates are performed within an inference time of 0.20 seconds per cycle. The integration of feedback from multiple layers enhances the prediction accuracy and reliability, thus ensuring the reliability of the decision-making process in the real-time control of the rolling process.

Table 7. Geometric regression results (α and W vs μ)

μ	α Measured (°)	α DT Model (°)	W Measured (mm)	W DT Model (mm)
1.2	37	36.8	8.1	8
1.3	34	33.9	7.2	7.1
1.4	31	30.8	6.5	6.4
1.5	29	28.9	6	5.9
1.6	27	27.2	5.6	5.5

3.5 Integrated interpretation

The results show that the hybrid multilayer architecture considerably improves the accuracy and reliability of the predictions. Analytical formulation enables fast initial predictions, as shown in Table 2, whereas FEM simulations provide accurate physical validation of stress, temperature, and deformation, as shown in Tables 3 and 4. ML enables real-time adaptive prediction and correction according to the operational data, as shown in Tables 5 and 6.

In quantitative terms, the proposed hybrid DT architecture yields the highest accuracy in the predictions, as indicated by the value of the R^2 statistic, which reaches 0.98, whereas the prediction error is less than 3%. In comparison, the other modeling approaches are less accurate, that is, the analytical approach yields an accuracy of approximately 0.91, while the FEM and ML approaches yield intermediate accuracy, i.e., 0.95-0.97.

According to the performance metrics of the data synchronization, as shown in Table 7, the integration of the proposed layers in the unified DT environment enables effective real-time control of the rolling process. The high speed of the response, that is, approximately 0.20 seconds per prediction cycle, further supports the suitability of the proposed approach for dynamic conditions in the industry. The results show the effectiveness of the proposed DT architecture in providing a robust solution for improving the performance of the rolling mill.

In addition, the results show an improvement in the energy efficiency, that is, approximately 8.9%, motor load, and scrap rate, which confirms the benefits of the proposed approach in the industry.

3.6 Comprehensive discussion

From the comprehensive evaluation of the developed multi-layer DT framework, it is evident that no specific modeling strategy is sufficient to ensure the accurate and reliable control of power parameters in seamless pipe rolling mills under real-world conditions. This is in accordance with recent findings on digital manufacturing, which emphasize the limitations of analytical, numerical, and data-driven modeling techniques in terms of accuracy and real-time response [5, 9, 19, 20].

Analytical modeling was found to be useful in obtaining quick estimations of the rolling force and torque. However, the observed underestimation of force values is due to the limitations of classical rolling theories, particularly when non-uniform temperature distributions are involved [2, 4, 21, 22]. These theories were also found to be less accurate in simulating the complex frictional interactions occurring in the rolling process. Such limitations are effectively addressed using thermo-mechanical FEM simulations, where accurate insights into stress, strain, and temperature distributions are obtained. As shown in Figures 2 and 3, the stress concentration patterns and temperature gradients are in good agreement with previously reported FEM-based studies on the rolling process [11, 23, 24]. Although FEM-based models are found to be very accurate, they are computationally expensive and are thus unsuitable for real-time responses, as widely reported in the literature on metal-forming processes [12, 25].

ML models also complement these approaches, particularly in terms of capturing complex nonlinear relationships directly from the operational data. The close agreement between ML model predictions, FEM simulations, and experimental measurements validates the efficacy of data-driven models in predicting the rolling force and torque under different operating conditions [26, 27]. However, the data dependency and inability of standalone ML models to extrapolate the importance of incorporating physics-based constraint models into predictive models [3, 28].

The hybrid DT approach presented in this study successfully integrates the advantages of analytical models, FEM, and ML models within a single framework. Recent studies have emphasized the importance of developing hybrid DT models, especially those incorporating physics-based models, to realize reliable, adaptive, and energy-efficient control strategies for complex manufacturing processes, such as metal rolling [13, 17, 29-31]. As depicted in Figure 5, the close agreement between the measured and predicted rolling forces over time validates the ability of the proposed DT framework to effectively track changes in the rolling process under different real-time operating conditions.

From a practical perspective, the reduction in prediction error, energy consumption, and scrap rate also parallels the benefits associated with DT implementation in metal forming processes, such as improved process stability and increased equipment lifespan [18, 32]. Thus, the proposed DT approach, with its multi-layer structure, presents a powerful, scalable, and physics-based solution to enable a paradigm shift toward intelligent and self-optimizing manufacturing processes, especially in line with Industry 4.0 concepts and principles [33].

Despite the high predictive capabilities of the suggested multi-layer DT approach, there are certain uncertainties that can affect the accuracy of the results obtained. Such uncertainties can be caused by a number of factors depending on the layer of the modeling process. In the analytical model, the assumptions made regarding the uniform deformation, friction, and average material characteristics can lead to certain uncertainties in the results obtained. In the FEM simulation, uncertainties can be caused by the discretization of the mesh, definition of the boundary conditions, and temperature-dependent material characteristics. In the ML approach, the results can be affected by data variations, noise in the measurements obtained from the sensors, and possible limitations in the dataset.

The effect of the uncertainties in the results obtained can be seen in the small variations in the results compared to the measured values, particularly under highly dynamic operating conditions. However, the effect of the uncertainties is compensated for in the results obtained from the hybrid approach, which combines the results obtained from the analytical, numerical, and machine-learning approaches. The updating mechanism in the suggested DT approach can improve the stability of the results obtained.

The suggested approach, which combines the results obtained from the analytical, numerical, and ML approaches, can improve the reliability of the results obtained by considering the limitations of the results obtained from the individual approaches, which can lead to certain variations in the results obtained under varying operating conditions.

4. CONCLUSION

This study presents and validates a novel multi-layer DT framework that integrates analytical modeling, thermo-mechanical FEM, and ML to enable accurate real-time control of power parameters in seamless pipe rolling mills. The proposed approach effectively overcomes the limitations of conventional single-model strategies by combining computational efficiency, high-fidelity physical modeling, and adaptive data-driven prediction.

The results demonstrate that the analytical model provides rapid baseline estimations, whereas the FEM model delivers reliable physical insight into the temperature, stress, and deformation behavior. ML models, particularly ANN and XGBoost, successfully capture nonlinear process dynamics and significantly enhance prediction accuracy under varying operating conditions. The hybrid DT framework achieved the best overall performance, reaching a coefficient of determination (R^2) of up to 0.98 and reducing prediction error to less than 3% across rolling stands.

In addition, the integration of the DT within a closed-loop control framework enables real-time process optimization, resulting in measurable improvements in energy efficiency, reduced peak motor load, and lower scrap rates. These findings highlight the capability of the proposed system to enhance process stability and operational performance.

Overall, the developed framework provides a scalable, robust, and physically informed solution that supports the transition toward intelligent and self-optimizing rolling mills in alignment with Industry 4.0 principles.

5. LIMITATIONS AND FUTURE WORK

Although the suggested multilayer DT architecture is promising, certain issues that should be resolved are present. The existing implementation was largely tested on operational data for a given seamless pipe-rolling mill configuration. This may make it difficult to apply trained ML models to mills of various shapes, materials, or rolling schedules. Moreover, thermomechanical finite element simulations are performed offline because they are expensive in terms of computing power and thus cannot be directly incorporated in continuous real-time control loops. The existing model mostly focuses on the power parameters without considering other critical aspects, such as the parameters of the tool wear, quality of the surface, and processes of defect formation, which are not explicitly modeled. The next generation of research focuses on the extension of the DT to more rolling conditions and mill configurations through transfer learning and domain adaptation processes. When wear and damage evolution models and indicators related to quality, such as ovality, surface defects, and microstructural changes, are included in the framework, its prediction capabilities become even more significant. Moreover, physics-based feedback might be accelerated by applying reinforcement learning methods to fully autonomously optimize parameters and deploy reduced-order or surrogate FEM models to bring the DT closer to fully real-time self-optimizing rolling mill processes.

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NOMENCLATURE

DT	Digital Twin
FEM	Finite Element Modeling (specifically Thermo-Mechanical FEM)
ML	Machine Learning
IoT	Internet of Things
PLC	Programmable Logic Controller
ANN	Artificial Neural Networks
XGBoost	eXtreme Gradient Boosting (regression model)
PLC	Programmable Logic Controller
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error