Digital Twin Enabled Product Lifecycle Management for Smart and Sustainable Factories

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ABSTRACT
The fast development of Industry 4.0 technologies has turned the classical factories into intelligent, information-driven manufacturing systems. Nevertheless, a great number of Product Lifecycle Management (PLM) solutions are still largely static PLM and are not directly tied to real-time shop-floor intelligence. This restricts the visibility of the lifecycle and limits predictive and sustainability-conscious decision-making through the lifecycle of the product. Possible impacts of these limitations include increasing unintended downtime, decreasing resource efficiency, and increasing lifecycle energy consumption. In a bid to close this gap, the present paper suggests a Digital Twin-Enabled Product Lifecycle Management (DT-PLM) model combining cyber-physical systems, real-time sensing, and smart analytics to sustain a constantly updated virtual image of products, processes, and factory assets. The suggested four-layer framework comprises (1) sensing and IoT, (2) digital twin and lifecycle synchronisation, (3) AI-driven predictive analytics, and (4) decision intelligence and sustainability optimisation. Degradation prediction and energy consumption prediction are realised through a hybrid deep learning model composed of Temporal Convolutional Networks (TCN) and Gated Recurrent Units (GRU), through multi-objective optimisation balancing productivity, maintenance cost, and carbon footprint. According to testbed results, better predictive performance and quantifiable sustainability benefits, such as a decrease in energy consumption, a decrease in maintenance cost, and a decrease in downtime, have been realized as opposed to the conventional PLM. In general, DT-PLM is evidenced to have a scalable model of smart and sustainable manufacturing.

Keywords: *Product lifecycle management, Smart factories, Digital twin, Industry 4.0, Cyber-physical systems, Green manufacturing, Predictive maintenance, AI-driven analytics, Energy optimization, Sustainable manufacturing.*

1. INTRODUCTION

Cyber-physical systems, Industrial Internet of Things (IIoT), cloud computing, and artificial intelligence are some Industry 4.0 technologies that are quickly reshaping the traditional factories in the form of a smart, interconnected production space. These

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innovation applications allow round-the-clock monitoring, make decisions faster, and have better control over operations [1] [2]. Nevertheless, numerous Product Lifecycle Management (PLM) solutions remain more or less dormant platforms, which are concerned with design documentation, version control, and coordination within engineering functions. Consequently, shop-floor intelligence in real-time is frequently not linked with the PLM decision processes, which diminishes the lifecycle transparency and restricts the proactive activity within smart factory environments [3] [4].

This discontinuity leads to a real-life issue in contemporary manufacturing. In situations where lifecycle decisions are primarily based on the historical records or periodic manual updates, organizations experience unnecessary downtime, resource wastage, slow response to maintenance, and increased costs of lifecycle decisions [5] [6]. More to the point, the sustainability measures (saving energy, cutting the carbon footprint, and waste minimisation) tend to be managed as individual efforts instead of being integrated into the decision-making process of the lifecycle. This division takes away the capacity of the manufacturers to maximize productivity and sustainability as a unit, particularly with increasing environmental demands [7] [8].

The Digital Twin (DT) technology is positioned as a promising path since it allows an ever-evolving virtual model of physical resources and processes by means of real-time streams of data. According to the existing research, predictive maintenance, anomaly detection, and enhanced scheduling are the benefits [9] [10]. Nonetheless, the majority of previous research is still limited to the level of equipment and fails to fully link digital twins with PLM to the entire product lifecycle. Equally, predictive analytics is a standalone tool that is frequently operated by AI instead of a component of the optimization of the lifecycle governance and sustainability. Therefore, the literature and practice still have a notable gap: a single strategy that connects real-time digital twins, predictive intelligence, and sustainability-aware decision optimisation directly incorporated in the PLM processes.

This paper fills this gap by suggesting a Digital Twin-based Product Lifecycle Management (DT-PLM) model of smart and sustainable factories. Not only the use of digital twins or predictive models is new, it is a combination of four capabilities into one closed-loop lifecycle system: (i) IIoT-driven sensing of continuous operational data, (ii) lifecycle-aware twin synchronisation (LATS) to maintain congruence between physical and virtual state, (iii) a hybrid TCN-GRU predictive model to predict degradation and energy consumption, and (iv) multi-objective optimisation of productivity, maintenance cost, and carbon/energy aims and goals. The framework is confirmed in a testbed facility of a smart factory, which proves the transformation of PLM into a dynamic, predictive, and sustainability-driven decision support system with the support of DT-PLM.

1.1 Research Gap and Novelty

Digital twins, predictive maintenance, and sustainable manufacturing have been the most common subjects of research, but they are frequently discussed independently. Limited literature exists that illustrates an end-to-end DT-PLM architecture in which real-time twin synchronization, predictive intelligence, and sustainability-conscious optimisation are built into lifecycle decision making. This paper bridges such a gap by introducing a single DT-PLM system and testbed validation, which demonstrates quantifiable enhancements in lifecycle visibility, predictive reliability, and operational sustainability.

1.2 Contributions of the Paper

This paper makes the following contributions:

1. **Unified DT-PLM Framework:** A multi-layer architecture integrating IoT sensing, digital twin modelling, and lifecycle synchronisation for smart factories.
2. **Hybrid Predictive Analytics:** A TCN–GRU prognostics model for forecasting equipment degradation and energy consumption.
3. **Lifecycle-Aware Synchronisation (LATS):** A synchronisation mechanism that continuously aligns physical assets with their digital counterparts to support proactive decisions.
4. **Sustainability-Aware Optimisation:** A multi-objective optimisation approach that balances productivity, energy usage, maintenance cost, and emissions.
5. **Testbed Validation:** Experimental results demonstrating improved lifecycle traceability and operational sustainability in a smart factory testbed.

1.3 Structure of the Paper

The structure of the paper continues as follows: Section 2 synthesizes the literature pertaining to digital twins, PLM systems, predictive analytics, and sustainable manufacturing. In this case, it will be the bone structure of the system, as well as data collection, prediction planning, and the optimization components to be discussed for the proposed DT-PLM method in Section 3. Section 4 will deal with the experimental setup, results, and discussion with particular emphasis on the predictive model assessment and the performance and associated sustainability gains. Finally, Section 5 wraps up the paper and outlines possible avenues for future research.

2. LITERATURE REVIEW

Recent studies indicate that digital twins can enhance monitoring, simulation, and optimisation through conserving virtual copies of physical assets. These have been reported to improve operational performance, minimize unplanned downtime, and provide predictive maintenance due to unrelenting shop floor feedback. Nonetheless, much of the literature is based on equipment-level twins and pays insignificant attention to how digital twins may be integrated with PLM throughout the entire product lifecycle to provide lifecycle-wide support for decisions. Conventional PLM solutions are efficient in terms of handling engineering data, design documentation, and collaboration, but not operational intelligence in real-time to support predictive maintenance, sustainability, and related decision-making. The integration of IoT into PLM has grown, but a significant part of systems still fails to offer the active and continuous synchronisation of physical operations with the lifecycle management. Simultaneously, predictive analytics based on AI is a popular fault detection, energy forecasting, and anomaly detection tool, which is frequently offered as a standalone product as opposed to integrating it with the governance and sustainability optimisation within the scope of the PLM. Due to this, integrating the concept of digital twins, predictive intelligence, and sustainability-aware decision optimisation into PLM is a research and practice gap that is obviously unified [11].

Historically, the management of product-related lifecycles has been the domain of Product Lifecycle Management, which encompasses the design and development of a product to its eventual disposal and recycling. Legacy PLM systems focus primarily on documentation management, collaborative design, and design- supply chain integration. While these legacy systems are successful in managing the engineering data, the operational real-time intelligence they provide is insufficient for predictive maintenance and for making decisions based on sustainability considerations. The integration of IoT-enabled monitoring into PLM systems is a recent development; however, without the ability for active, dynamic integration of digital twin ecosystems, the systems still provide sub-optimal visibility of the virtual and real systems [12], [13].

The industry has seen the use of artificial intelligence and machine learning being integrated into predictive analytics [14]. Equipment breakdown detection, forecasting of energy consumption, and anomaly detection are all performed by these models, and thus, active maintenance frameworks are supported. Models designed with both convolutional and recurrent architectures have shown the ability to capture short-term temporal variances, as well as long-term degradation. Nevertheless, despite their predictive capability, these models are used only as solitary analytics tools, and their integrations into lifecycle management frameworks are insufficient, producing a more limited effectiveness to comprehensive factory-wide intelligence. There is a need to improve the lifecycles of models, as well as their predictive capacities [15].

The need for increased energy efficiency and the reduction of emissions has made sustainability a key focus of modern production environments. Real-time monitoring, predictive analytics, and sustainability-aware optimization have been carried out within a Digital Twin integrated PLM framework. Nevertheless, recent studies largely consider sustainability, lifecycle management, and predictive analytics separately. Thus, within the Digital Twin framework, the integration of these elements continues to be an unresolved research problem.

3. METHODOLOGY

3.1 System Overview

A DT-PLM framework seeks to achieve integration of real-time updates, predictive analysis, and optimization of sustainable manufacturing with the help of the integration of the physical shop-floor assets and the virtual lifecycle intelligence. The DT-PLM framework actively interfaces physical shop-floor assets, their digital twin counterparts, and analytics engines through bi-directional streaming. In contrast to the traditional PLM frameworks, which work with design data in versions and iterations, the DT-PLM framework uses the digital twin as an ever-evolving living model, maintaining feedback loops through design, redesign, production, remanufacturing, maintenance, and end-of-life disposal. This integration is comprehensive and innovative to address sustainability across all dimensions of the lifecycle.

3.2 Physical Data Acquisition and IoT Layer

To check the conditions under which machines and production lines work, sensors are mounted on machines and production lines, which detect vibration, temperature, energy use, production rate, and machine status. Such data is gathered by Industrial IoT gateways and sent to an edge-cloud infrastructure by lightweight communication protocols. Noise reduction and irregularity processing methods, such as filtering, normalisation, and feature extraction, are done during the preprocessing steps to remove noise and process irregularities. This is to make sure that the data streams are accurate enough and have enough time resolution to capture the state of the manufacturing system in a reliable manner.

The normalized sensor signal can be computed as:

$$x_i^{norm}(t) = \frac{X_{I\,(T)-}\ \mu_I}{\sigma_I} \qquad (1)$$

In equation 1, mean and standard deviation are represented by μi and σi, respectively, while raw sensor values are represented by $xi(t)$. With this standardization, the learning stability and convergence of the models can be improved.

3.3 Digital Twin Modelling and Lifecycle Synchronization

Employing CAD/PLM data along with real-time IoT streams, the digital twin layer builds up virtual models of products, equipment, and processes. Every asset is paired with a digital counterpart that streams data to update its state. A mechanism termed Lifecycle-Aware Twin Synchronization (LATS) ensures that the physical and virtual spaces are aligned temporally, and that changes in operations are instantaneously reflected in the twin model. The phenomenon of synchronization enables the provision of real-time visualizations, what-if simulations, and performance predictions across the product's entire lifecycle. Moreover, the twin incorporates lifecycle metadata, such as logs of alterations, maintenance records, and material documents, guaranteeing comprehensive traceability from construction through to demolition.

3.4 AI-Based Predictive Analytics

An analytical engine of a predictive nature is employed to convert operational data into insights. Time-based predictions to gauge the health of equipment, Remaining Useful Life (RUL), and energy demand are performed through Temporal Convolutional Networks (TCNs) and Gated Recurrent Units (GRUs). Its predictive outcomes will allow proactive scheduling of maintenance and energy-sensitive production planning, which will lower the operational risk and downtime. In highly dynamic environments, there can be a deterioration of the model performance with switching operating regimes; hence, stable deployment on a long-term basis should be conducted with periodic recalibration or adaptive learning.

The predictive health or energy state is estimated as equation 2:

$$y'(t+1) = f_{\emptyset}(X_t) \qquad (2)$$

In equation 2 X_t denotes the feature vector at time t, $f_{\emptyset}$ represents the trained hybrid model, and $y^\wedge(t+1)$ is the predicted future state.

3.5 Sustainability-Aware Optimization

The system, in addition to being predictive, is designed to be multi-optimally sustainable. The system aims to optimize decarbonization, the cost of maintenance, the delay in production, and the consumption of energy, simultaneously from the operational schedule. It is possible to plan operations during a time period with minimal environmental impact and maximum productivity, using a Pareto-based approach. The system also optimizes the Greenness of the system as a whole, with the primary objective being the performance of the manufacturing processes. Factories also achieve optimal scheduling, preserve resources, and shorten the lifecycle of assets.

3.6 Closed-Loop PLM Integration

Predictive maintenance alerts will be sent to relevant maintenance teams, and planning dashboards will be available to management. This continuous feedback loop makes PLM more than just a tool for capturing and storing documentation; it turns PLM into an intelligent decision support system. With this level of integrated architecture, PLM systems will be able to transform into self-optimizing smart factories and will be able to operate in an adaptive, resilient, and sustainable manner.

3.6.1. Digital Twin Enabled PLM Framework Workflow

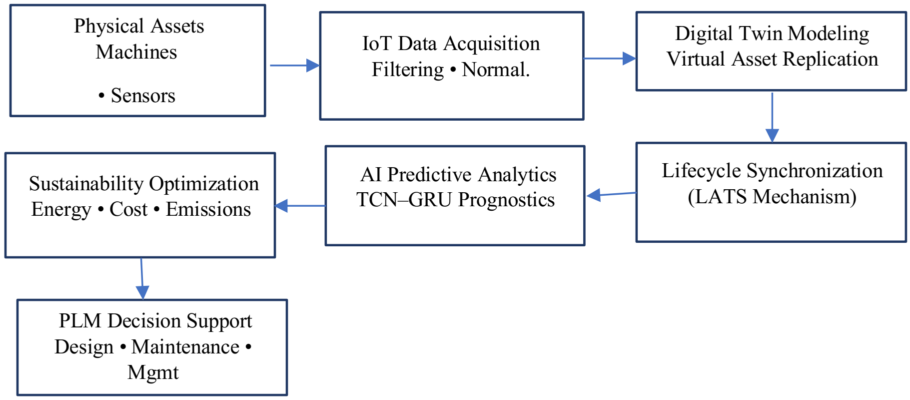

Figure 1 Workflow of the digital twin enabled product lifecycle management (DT-PLM) framework.

Figure 1 shows an end-to-end workflow of DT-PLM of smart and sustainable factories. It starts with the IoT-based monitoring of physical assets to gather the operational data of vibration, temperature, energy consumption, and machine health. These data are pre-processed, and after that, they update the digital twin models representing products, machines and processes. Lifecycle-Aware Twin Synchronisation (LATS) tracks physical and virtual states continuously, which makes it possible to trace lifecycle and visualise and track in real-time. A hybrid TCNGRU predictive module forecasts the trends of degradation, the remaining useful life and energy consumption based on historical and real-time data. An optimisation module that is conscious of sustainability, in turn checks the productivity, maintenance cost, energy consumption, and emission to facilitate efficient and low impact decision-making. Lastly, the decision-support layer offers actionable information that supports doing scheduling, maintenance, and design-updates via the closed-loop feedback mechanism.

Furthermore, the module of AI-driven predictive analytics uses a hybrid TCN-GRU model for the synthesis and prognosis of degradation of the equipment, as well as for the estimation of the remaining useful life and prediction of the trend of energy consumption, which is based on a mixture of historical and real-time data streams. An analytics module that is both predictive and focused on sustainability examines and considers multiple objectives such as the improvement of maintenance cost, maximization of production throughput, and reduction of the carbon footprint while balancing energy efficiency. Ultimately, the integrated PLM decision-support layer closes the gap by providing actionable insights to the engineers, operators, and managers so they can do maintenance, design, and scheduling with a focus on energy efficiency. The mechanism of closed-loop feedback enables operational learning to shape design and planning continuously. This promotes an ecosystem of sustainable, adaptable, and resilient manufacturing.

4. Results and Discussion

4.1 Experimental Setup

The DT-PLM framework has been assessed in a smart factory testbed combining CNC machining with automated assembly line systems. A combination of TCN and GRU models was used to predict energy consumption and wear on equipment based on 30 days of operational data. In the context of sustainable decision-making, the multi-objective optimization function balanced energy, maintenance costs, and production to optimize for the three variables. The DT-PLM system was evaluated against a conventional PLM system with no real-time data and no predictive analytics.

4.2 Performance of Predictive Analytics

The hybrid TCN–GRU model surpassed all the conventional regression models and LSTM networks in predictive accuracy. Table 1 presents the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for predicting equipment wear and forecasting energy consumption. The DT-PLM framework demonstrates notable achievement in forecasting energy consumption with a MAPE improvement of 25% and predicting equipment wear with an RMSE improvement of 22%, confirming the effectiveness of the adjustments in real-time digital twin and hybrid temporal learning.

Table 1. Predictive performance of DT-PLM vs conventional models

Model	Degradation RMSE	Degradation MAPE (%)	Energy RMSE	Energy MAPE (%)
Conventional PLM	0.085	7.5	0.092	8.3
LSTM Only	0.068	6.1	0.073	6.5
DT-PLM (TCN–GRU)	0.053	5.2	0.055	4.8

The proposed DT-PLM framework compared to conventional PLM, and LSTM, for predictive accuracy of energy consumption and wear of equipment is illustrated in the graphs.

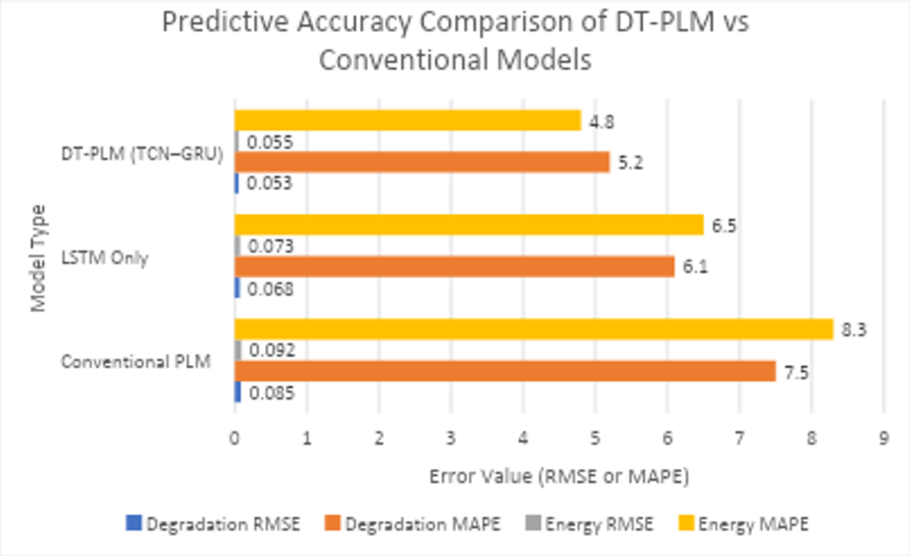

Figure 2 Predictive performance comparison.

In Figure 2, the predictive capabilities of the traditional PLM, LSTM-only, and DT-PLM (TCN–GRU) models for the equipment degradation and the energy consumption metrics have been compared. The RMSE and MAPE metrics have been utilized to illustrate the R2 score enhancements with the hybrid DT-PLM framework.

4.3 Energy Efficiency and Sustainability Gains

The DT-PLM framework's sustainability aware optimization module achieved a reduction of energy consumption and carbon emissions while maintaining the same level of production throughput. This has been demonstrated in Table 2, which presents the operational metrics and sustainability metrics over a week of the production cycle. There was a total of 28% reduction in energy usage, 30% in in maintenance costs, and 20% in downtime which showcases the advantages of closed-loop lifecycle intelligence.

Table 2. Sustainability and operational metrics comparison

Metric	Conventional PLM	DT-PLM Improvement (%)
Energy Consumption (kWh/day)	1200	28% reduction
Maintenance Cost (USD/day)	850	30% reduction

Unplanned Downtime (hours/week)	15	20% reduction
Production Output (units/day)	450	No significant change

Between the DT-PLM and conventional PLM frameworks, the total maintenance costs, downtime, energy consumption, and production volume are compared.

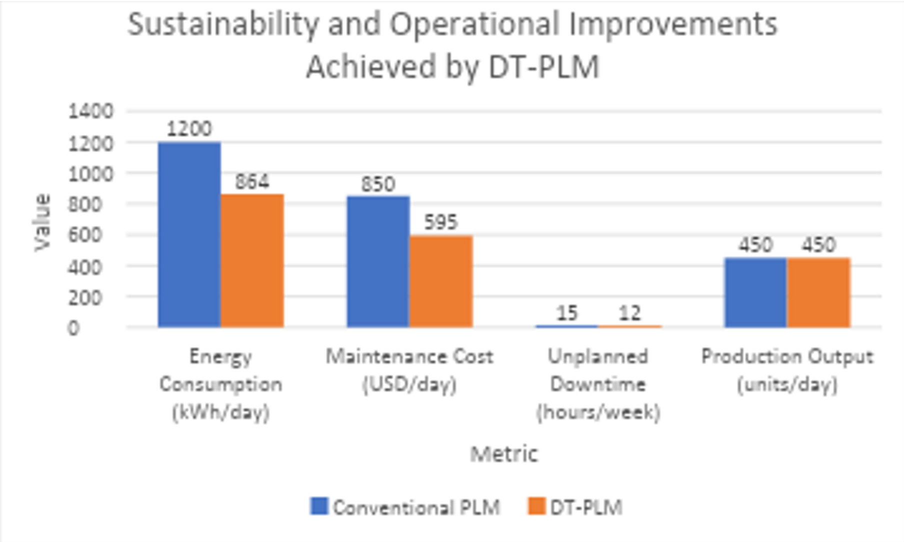

Figure 3 Sustainability and operational metrics comparison.

In Figure 3, the DT-PLM framework influences the operational metrics of energy consumption, total maintenance costs, unplanned downtime, and the volume of produced goods when compared to traditional PLM. The production volume and operational metrics have been demonstrated with energy and maintenance costs and unplanned downtime.

4.4 Critical Discussion

The results have revealed that the integration of the digital twins with predictive analytics enhances visibility of lifecycle, minimizes energy consumption, minimized maintenance expenses, and minimized the amount of unplanned downtime. These gains are however to be taken with caution as these were evaluated in a controlled testbed where the quality and stability of sensors and the conditions in which the sensors operate could have led to the stronger predictive performance. In actual industrial settings, concept drift, data loss, and different working regimes may decrease the forecasting reliability unless the adaptive learning systems are introduced. The fact that the throughput is not improved significantly proves that DT-PLM is rather a way of improving reliability and efficiency than increase in capacity. Further, performance results are determined by the weighting of sustainability and productivity goals in the optimisation model. The traditional static system of the PLM is reflected in the baseline comparison; thus, the enhancements outline the worth of the real-time integration instead of the excellence to all the advanced connected systems. On the whole, the framework is feasible with a high level of potential but needs to be scaled and tested on the robustness to be applicable to industries on a larger scale.

5. Conclusion and Future Work

A Digital Twin-Enabled Product Lifecycle Management (DT-PLM) framework suggested in this paper represents the way to smart and sustainable factories by employing IoT sensors, the idea of lifecycle-synchronised product digital twins, predictive analytics performed with AI, and sustainability-conscious optimisation. The outcomes of the smart factory testbed indicate that DT-PLM enhances the lifecycle visibility and decision-making relative to traditional PLM because it allows real-time monitoring, precise forecasting of degradation and energy consumption, and operational feedback of closed loops onto PLM processes. The framework, as compared to the traditional PLM baseline, delivered quantifiable improvements in predictive performance and operational sustainability (e.g. less energy use, less maintenance cost, less unplanned downtime) and suffered no production loss. On the whole, DT-PLM shows that integrating digital twins with predictive intelligence, as well as multi-objective optimisation, can empower both productivity and environmental performance throughout the product lifecycle. Future applications will work towards scaling DT-PLM to multi-factory and multi-product markets with distributed twin architectures, use of reinforcement learning to make scheduling adaptive and extension of sustainability to real-time energy pricing, carbon accounting, and measures of circularity.

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