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Digital Twin-Based Machinery Condition Monitoring: Implications for Improved Sustainable Maintenance Management Practices in Papua New Guinea

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ABSTRACT-
This paper enables real-time, virtual representation of physical assets to enhance operational efficiency and predictive maintenance. It integrates sensor data, system behavior, and machine dynamics to simulate and assess equipment conditions continuously. Existing traditional condition monitoring approaches often face challenges such as limited accuracy, inability to adapt to evolving system behavior, and poor generalization under varying operational conditions. To address these issues, this paper proposes a Hybrid Physics-Based and Data Driven Modeling (HP-DDM) framework that synergistically combines physical modeling of machinery dynamics with machine learning techniques (MLT) for robust and adaptive monitoring. The hybrid framework uses real-time sensor inputs and historical data to continuously update the digital twin, allowing it to detect anomalies, predict failures, and support informed maintenance decisions. This methodology is applied to rotating equipment in power plants, demonstrating how the digital twin adapts to operational variations and environmental conditions. The proposed HP-DDM framework enhances fault detection accuracy, reduces false alarms, and supports predictive maintenance strategies, leading to extended machinery lifespan and reduced downtime. Experimental results validate that the hybrid approach outperforms conventional methods in terms of precision, adaptability, and real-time decision support. The findings of this research will pave path for industries in Papua New Guinea to enhance their machinery failure predication rate that will ultimately lead to improved maintenance management practices and improved productivity.

Keywords: Digital Twin, Condition Monitoring, Hybrid Modeling, Predictive Maintenance, Machinery Health, Rotating Equipment

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I. Introduction

Machinery condition monitoring is crucial for operational productivity, minimizing downtimes, and prolonging longevity of equipment in automation systems and predictive maintenance [1]. Some general limitations of condition monitoring systems include inability to simulate sophisticated dynamic operating conditions, the absence of real-time data amalgamation, and passive fault localization. These weaknesses can incur premature mechanical failures, exorbitant maintenance expenses, and resource squandering. What this research seeks to achieve is a faster, smarter, and more adaptive mode for monitoring using novel digital technologies [3]. Thus, for these all-present problems this research focuses on implementing Digital Twin (DT) technology to systems for state monitoring [4]. A digital twin can stand for an actual counterpart such as an object and be utilized for its simulation, predicting, and receiving real-time data through interfaces with sensors and computer intelligence models [5]. Through this research, these gaps will be bridged by developing an end-to-end DT-based framework that enhances predictive maintenance through anomaly detection, failure forecasting, and real-time diagnosis [6]. Through consideration of these issues, the research helps to improve intelligent maintenance practices [7] and results in the achievement of completely autonomous industrial systems that can adjust to new conditions and optimize operating efficiency with little or no human intervention [8].

Various traditional and sophisticated methods have been used in machinery condition monitoring to identify malfunctions and forecast the time when equipment will fail [9]. Substantive machine health information can be derived from traditional methods such as vibration analysis, thermal imaging, acoustic emission testing, and oil analysis [10]. Although these techniques have their applications, they are reactive and not predictive and often require human interpretation [11]. Emergent developments have introduced data-based techniques like ML and DL algorithms, which analyze gigantic databases of sensors to find trends and failure prognoses [12]. Moreover, Internet-of-Things-based systems enabled distant monitoring through collecting information in real-time by way of networks of sensors [13]. Nonetheless, several hurdles are present. When presented with heterogeneous data from various machine types and manufacturers, such systems often experience integration issues and limited scalability [14]. A lot of ML/DL-based training methods require large labeled data sets, which might not be available in some industrial applications [15]. Finally, existing monitoring systems are not good enough to simulate and estimate how equipment would behave in various operating conditions in real time. Due to these limitations, the system is less flexible and less capable of making anticipatory decisions. DT technology, which offers a virtual representation that mirrors the physical equipment in real-time, promises to address several of these issues. However, there are some challenges to implementing DT as well, such as intricate data synchronization, high processing requirements, and the need for domain-specific modeling expertise [16]. Hence, solutions based on DT attempt to overcome the essential demand for a harmonized, extensible, and intelligent system despite conventional methods retaining core competencies.

Problem statement: For most instances, traditional methods of machinery condition monitoring are not sufficient in identifying anomalies and predicting failures against the backdrop of changing operating conditions. They tend to be highly prone to false alarms, lack generalizability, and rest on static models or stand-alone data-driven techniques. On top of that, they don't understand how to physically merge data from sensors in real time with the known dynamics of the system. Timely maintenance decisions and operating efficiency are both adversely affected by this poor measure. Therefore, to enhance reliability and support predictive maintenance techniques, a clever, responsive, and continuously developing condition monitoring system that combines physical system knowledge with data-driven knowledge is necessary.

Motivation: Conventional system monitoring techniques are insufficient for industrial systems, especially the dynamic and constantly evolving behavior of power plant rotating equipment. The emergence of digital twin technology has presented a revolutionary chance to enhance condition monitoring by real-time prediction and simulation. Through the integration of physics-based models with machine learning techniques, a hybrid method can describe both the fundamental behaviours of the system and data-driven patterns. The objective of this research is to design a trustworthy monitoring system that can adapt to changing conditions, reduce the occurrence of false alarms, and yield valuable information. By taking data-driven maintenance actions at appropriate times, equipment performance is optimized, downtime reduced, and the lifespan of machines increased.

Contribution: The research introduces a new DT monitoring framework for machinery conditions named HP-DDM. The platform continuously updates and optimizes the digital twin based on real-time sensor data as well as past records by blending physical modeling of machine dynamics with machine learning techniques. The methodology is very efficient if used to operate rotating machinery for power plants and eliminate false alarms, change their sensitivity with ambient conditions, and precisely diagnose faults. In this research work, contribution comes through designing, implementing, and experimentally demonstrating the HP-DDM approach; the proposed methodology allows for predictive maintenance and offers real-time decision-making support that surpasses the limitations possible with earlier strategies.

The following is included in this section, which organizes the structure of the research paper: The Digital Twin-Based Machinery Condition Monitoring project is the subject of the section II of this research. The section III of this dissertation will devote its attention to a comprehensive discussion of HP-DDM. Detailed examination, a comparison to earlier approaches, and an analysis of the consequences are all included in Section IV of the report's findings. Section V contains a complete examination of the outcomes that were taken into consideration.

II. Related works

Through predictive maintenance and enhanced operational effectiveness, technologies such as Digital Twin (DT) and Condition Monitoring (CM) are rapidly transforming industries. Fault diagnosis of complex environments, tool condition monitoring (TCM), and bearing life-cycle monitoring can all be significantly benefited by data-driven modeling, real-time data flow, and physical-virtual system interactions.

The application of condition monitoring (CM) and Digital Twin (DT) technology for predictive maintenance is suggested in a systematic review by Liu, H. et al [17]. The research draws DT's involvement regarding the historical overview, significant technologies, and the steps of execution, which enhances data assistance, capability, and maintenance approach. This analysis contributes auxiliary insights concerning DT-guided CM challenges relating to rigidity of the framework, granularity of data models, spatial-uncertainty quantification, and uncertainty quantification.

A framework for digital twin-based real-time anomaly detection during tool condition monitoring (TCM) in analogy machining has been developed by Liu Z et al. [18]. This work incorporates the numerical controller (NC) data and vibration signals to implement a physical virtual system with real-time data streaming. To model tool wear, frequency-based model features (MFFs) and data-driven modeling is applied in real-time. Field studies confirm that the dynamic TCM for complex, intelligent manufacturing systems achieves greater accuracy in anomaly detection.

Guo L et al. [19] present a new BLDT model, an integrated dynamic model comprising a bearing, defect evolution simulation, and neural network degradation model. This technique provides direct real-time data from physical and virtual interfaces which captures the variability of defect size and structural deflection stiffness. The evaluation of the BLDT model with experimental signals showed very good accuracy for the prediction for bearing performance loss. This shows that the method can facilitate condition monitoring throughout the entire operational life of the bearing. Nejad, A. R. et al. [20] trace the origin and application of condition monitoring in ship propulsion systems by noting the more recent performance monitoring changes to digital twin based approaches. They address polar operations and other legal, environmental, and policy issues as well as onboard practices. The proposed technique is based on the application of digital twins for real-time health assessments to enable failure diagnosis at advanced stages. Results show that the use of digital twins in marine environments helped in reduced costs of maintenance, increased reliability, and clearly showed the advantages and limitations of such an approach. Bofill et al. [21] propose the combination of Predictive Fault Monitoring (PFM) and Digital Twin (DT) technologies for increased system reliability across various industries. Digital Transformation (DT) refers to the process of precise virtualization of physical assets using real time data, machine learning, and advanced analytics. This strategy improves maintenance, understanding of systems, and identification of the defects. In healthcare, energy, and manufacturing industries, DT brings improved efficiency, reduced downtime, and better data driven decision making.

Table:1 Summarization of the above existing methods

Authors	**Proposed method**	**Outcomes**
Liu, H. et al.	Systematic review of Digital Twin (DT)-guided Condition Monitoring (CM) predictive maintenance	Highlights DT’s role in enhancing data support, maintenance capabilities;
Liu, Z. et al.	Real-time anomaly identification framework for Tool Condition Monitoring (TCM) using DT, based on NC data and vibration signals with model frequency features (MFFs)	Achieves improved anomaly detection accuracy; enables intelligent TCM in dynamic, complex manufacturing environments
Guo, L. et al.	Bearing Life-Cycle Digital Twin (BLDT) model with defect evolution simulation and neural network-based degradation analysis	High accuracy in forecasting bearing performance degradation; enables effective, real-time lifetime condition monitoring
Nejad, A. R. et al.	DT-enabled real-time condition monitoring system for ship propulsion systems, considering harsh environments and legal compliance	Reduced maintenance cost, enhanced system reliability; addresses challenges in polar operations and highlights DT’s practical strengths and weaknesses
Bofill et al.	Integration of DT with predictive Fault Monitoring (FM) across various industries using real-time data, machine learning, and analytics	Improved reliability, proactive maintenance, reduced downtime; supports data-driven decision

		making across industries like healthcare, energy, and manufacturing

Superior to traditional and other existing approaches in terms of precision and system robustness, the HP-DDM method is the most efficient technique among those listed to enhance fault detection precision, flexibility, and real-time decision-making.

III. Proposed method

To enhance in-real-time physical asset monitoring, this research develops a hybrid physics based dynamics model and machine learning framework. It enables adaptive digital twin systems of high accuracy to be used in operational decision support, predictive maintenance, and defect detection.

3.1. Integration of Hybrid Modeling Architecture

To develop a unified digital twin architecture, the approach combines machine learning techniques with physical modeling of machinery dynamics. Through the application of domain knowledge and data-driven insights, the hybrid approach enables precise modeling of system behavior under various operating and environmental conditions.

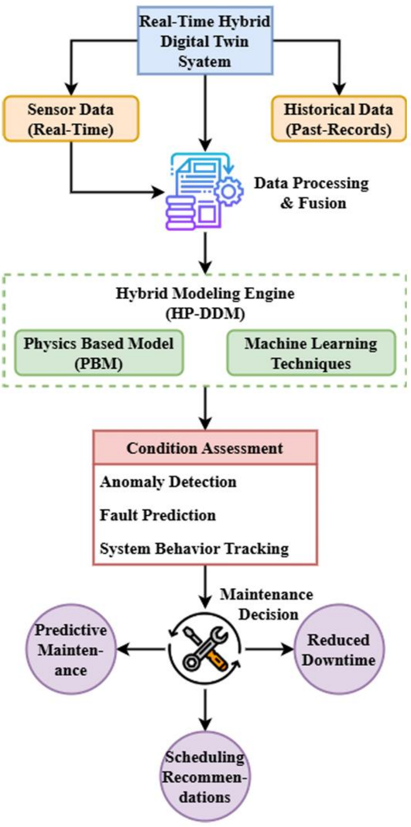

Figure 1: Architecture of the Proposed Real-Time Hybrid Digital Twin System

Figure 1 depicts the architecture of the proposed HP-DDM framework for predictive maintenance and real-time condition monitoring. The technology generates a hybrid digital twin model by combining historical and real-time sensor data. Since Combining Machine Learning Techniques (MLT) that acquire knowledge from patterns in data and system behavior, with a Physics-Based Model (PBM) that captures machinery dynamics, the model Combining both disciplines assists in measuring condition accurately and sensitively. The layer of condition assessment continually monitors equipment state, hence facilitating early defect detection and prevention. This analysis enables the system to yield beneficial insights upon which maintenance planning is supported in predictive maintenance plans, unplanned downtime is minimized, and schedule decisions are made better. This entire strategy ensures that the digital twin adapts to operational conditions, hence ensuring robust decision-making support for planning maintenance and enhancing overall equipment reliability in industrial operations such as in power plants.

$$\frac{\Delta Q_0}{Q_0} = \frac{\Delta c_0}{c_0} + \frac{c_+}{\cos y_+} - \text{const}\, q(t,\tau)\, p(t,\tau) \tag{1}$$

Equation (1) shows a link $(t,)$ between changes in system characteristics, such as compliance $(\Delta Q0/Q0)$, along with dynamic emotional elements $\left(\frac{\Delta c_0}{c_0} + \frac{c_+}{\cos y_+}\right)$ and time-dependent engagement terms $const\ q(t,\tau)$. This equation in the identified HP-DDM architecture describes the interaction between physical movement and data-driven factors.

$$\frac{|\Delta W_0|}{c_0} = 1 \,|\, \Delta y \,| \approx \forall + \frac{d(a)}{\cos y(a)} * G(w,t,t_+) + G(w,t,t_-) \tag{2}$$

Equation (2) describes the normalized evolution in work $|\Delta W0|/c0$ as the function of displaced variation $\left(1 \,|\, \Delta y \,| \approx \forall + \frac{d(a)}{\cos y(a)}\right)$, adjusted from system-specific parameters $G(w,t,t+)$ along with temporal reactions functions $G(w,t,t-)$. It improves predictive maintenance by letting the system record minute changes in mechanical behavior connected to possible defects.

$$\delta+\left(\frac{pd}{p+c}\right)=u-\int_{+t}^{t}\frac{dt'}{d\left(t'\right)}+C+\left(\frac{B}{B_{+}}\right)+\frac{1}{2}\beta-\frac{1}{2}\alpha \tag{3}$$

δ is defined by equation (3) as the divergence between a reference state $\delta+\left(\frac{pd}{p+c}\right)$ and a combined integral expression comprising time-dependent deterioration $\int_{+t}^{t}\frac{dt'}{d\left(t'\right)}$, pressure compliance metrics $\frac{1}{2}\beta-\frac{1}{2}\alpha$, and system stiffness $C+\left(\frac{B}{B_{+}}\right)$. Reflecting both immediate and cumulative system pressures helps the digital twin adapt to shifting forecasts and maintenance notifications.

$$G\exp=U_{w}+\left\{-\int_{s+}^{s}\alpha'\left(w,t'\right)dt'\right\}+\left(\alpha'+\frac{kw}{d}\right) \tag{4}$$

Equation (4) specifies Gexp as a function blending shown by the integral of Uw with real-time dynamic components, including scaling stiffness $-\int_{s+}^{s}\alpha'\left(w,t'\right)dt'$ alongside external inputs $\left(\alpha'+\frac{kw}{d}\right)$. This helps the digital representation to more precisely and facilitate adaptive fault estimation under different running conditions.

$$\forall t+t\left(u,\tau_{w}\right)=d_{0}+\varphi_{v}\leq\left(\frac{\partial}{\forall}\forall_{w}\right)Q+p(x,y) \tag{5}$$

Equation (5) links a combination of the beginning displacement $\forall t$ + $(u,\ \tau w)$, velocity-induced distortion $d0+\varphi v$, and the spatial-temporal impact of loading represented by $\left(\frac{\partial}{\forall}\forall_{w}\right)$, to the entire system development over time $p(x,y)$. It improves the capacity of the digital twin to replicate complicated load exchanges and forecast condition changes with spatial accuracy and real-time flexibility.

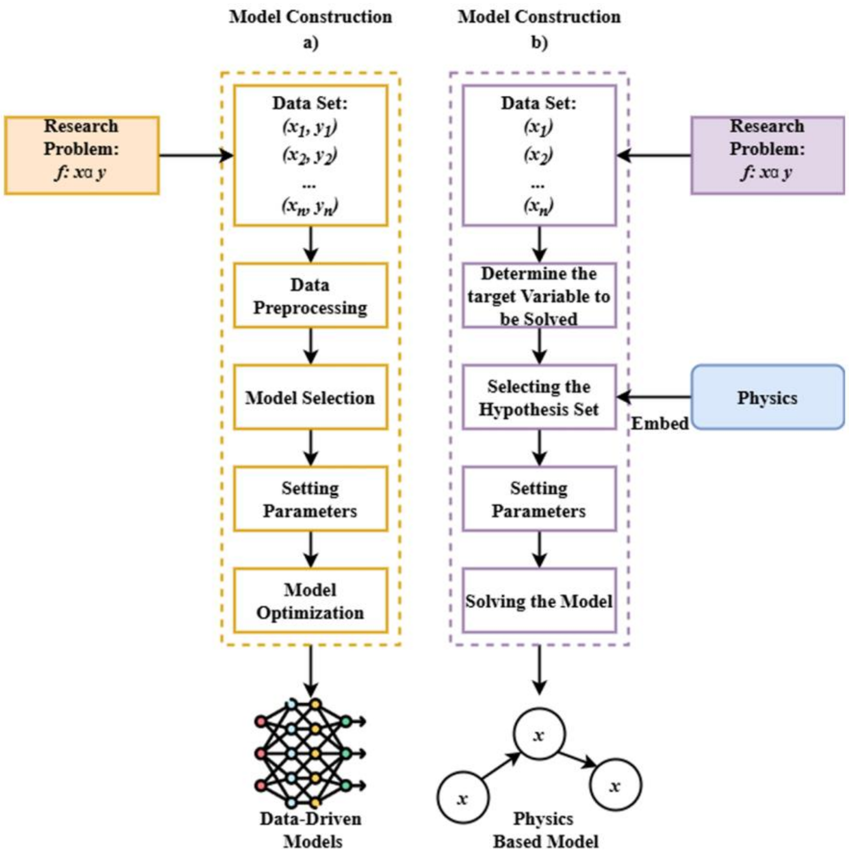

Figure 2: Traditional Data-Driven and Hybrid Physics-Based Data-Driven Modeling Approaches

The proposed hybrid physics-based and data-driven modeling (HP-DDM) framework and conventional data-driven modeling are shown in Figure 2 in a comparison process. Usually resulting in problems like overfitting, poor generalization, and lack of physical interpretability, the conventional method on the left depends only on historical data to transfer input characteristics to output predictions using machine learning models. The hybrid approach introduces yet another level of physics-based modeling. The hybrid method enhances robustness and interpretability by incorporating domain-specific physical principles into the modeling process, thus enriching machine learning predictions with physics-informed constraints. This combination allows the hybrid model to leverage both empirical observations and theoretical concepts, thus maximizing performance for tasks such as predictive maintenance and condition monitoring. The figure highlights how the hybrid method ensures improved prediction accuracy, reduced model uncertainty, and greater real-world applicability for intricate industrial systems by better handling evolving operating conditions than purely data-driven methods.

$$w_h = \frac{dt'}{d_h\left(t', \tau_w\right)} + \frac{1}{u_h} + \frac{1}{u_w} \approx \left(c_0 + \frac{B\forall}{p_c} Q\right) \tag{6}$$

Equation (6) describes wh as a product-integral including inverse degradation dynamics $\left(c_0 + \frac{B\forall}{p_c} Q\right)$, control factors $\frac{1}{u_h} + \frac{1}{u_w}$, and approximates it through system parameters and stress displacement terms $\frac{dt'}{d_h\left(t', \tau_w\right)}$. It supports the ability of the digital twin to measure equipment condition, therefore allowing accuracy in predictive maintenance and proactive corrections.

$$\partial_w N = \beta^3\left(t', t_+\right)dt' + Q_+(\tau w) + \alpha + R + \tau_w q + \left(\tau_w\right) \tag{7}$$

Equation (7) states the derivative of the system's efficiency ∂wN as a mixture of time-evolving stresses $Q+(\tau w)+\alpha$, delayed response $\beta 3(t', t+)dt'$, system constants $\tau wq+(\tau w)$and load interaction. It lets the digital twin foresee performance declines and modify prediction models for better dependability and decision-making.

$$\partial t \cong \int_m^0 \frac{dt'}{c_0\left(t'\right)} - Q_+\left(\tau_w\right) \iint \frac{\alpha}{P_c}\left(t, \tau_w\right)\tau_w - \left.\frac{\delta r'}{\delta t}\right|_t + \left.\frac{\delta r}{\delta s}\right|_{\tau_w} \tag{8}$$

Equation (8) resembles temporal variation ∂t as an integral involving $Q+(\tau w)$ opposite compliance $\frac{dt'}{c_0\left(t'\right)}$, reduced by stress-energy contributions to $\left.\frac{\delta r'}{\delta t}\right|_t + \left.\frac{\delta r}{\delta s}\right|_{\tau_w}$, together with differential terms collecting shifts $\int_m^0 - \iint \frac{\alpha}{P_c}\left(t, \tau_w\right)$ in system behavior. This equation captures in the HP-DDM paradigm time-dependent compliance, material drowsiness and spatial temporal stress.

$$Qp_0 = \exp\left\{k\varepsilon\theta\left(u - \frac{y}{d}\right) - \alpha' y\right\} + \left.\frac{\delta r}{\delta s}\right|_\theta + \left.\frac{\delta r'}{\delta s}\right|_{\tau_w} - \frac{\beta}{p_1 D u_k} \tag{9}$$

Equation (9) represents the effectiveness metric $Qp0$ as a function of time driven by the strain energy relationship $\exp\left\{k\varepsilon\theta\left(u - \frac{y}{d}\right) - \alpha' y\right\}$ and anxiety decay $\left.\frac{\delta r}{\delta s}\right|_\theta + \left.\frac{\delta r'}{\delta s}\right|_{\tau_w}$, mixed with geographical rate changes $\frac{\beta}{p_1 D u_k}$ degradation penalty term. Through degradation patterns, performance loss initiates, and predictive maintenance.

3.2. Real-Time Implementation and Adaptive Monitoring

To keep the digital twin up to date, the architecture integrates real-time sensor inputs and historical data. In response to changes in system behavior, this adaptive approach enhances fault detection capabilities, accurately identifies anomalies, and provides consistent predictive maintenance alarms.

For predictive maintenance and condition monitoring, Figure 3 depicts the end-to- end functional flow of the proposed Real-Time Hybrid Digital Twin system. The process begins with the physical asset and the sensor network attached to it that captures operating data in real time. Preprocessing of this raw data serves to remove noise and enhance quality such that appropriate analysis may ensue. The filtered data is input to a simulation and analytics module that combines machine learning with physics-based modeling to analyze system behavior. Fault diagnosis and prognostics are subsequently performed using this hybrid simulation, allowing for early anomaly detection and failure prediction. A maintenance decision support system inputs these findings to assist in planning corrective measures, scheduling interventions, and optimal utilization of maintenance resources. In dynamic industrial environments, the system ensures an ongoing feedback cycle between asset behavior and decision-making, thus facilitating data-driven maintenance practices that minimize downtime, enhance system reliability, and extend asset lifespan.

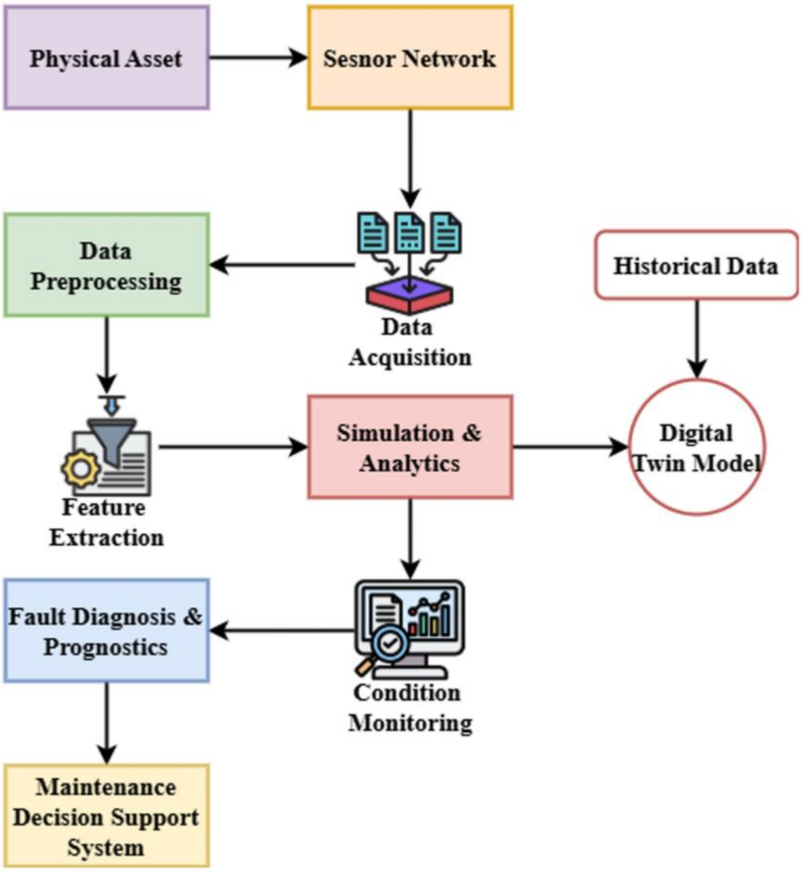

Figure 3: Proposed Real-Time Maintenance Decision Support Framework

$$Cq_{+} = (\tau_w) - \frac{\varphi}{ps^2 Cu_h} + \frac{c'}{c} Q - CQ(\tau_w) + \left.\frac{\delta r'}{\delta t}\right|_s \tag{10}$$

Equation (10) describes $Cq+$ as a mixture of stress-dependent variables, including a deformation measure $(\tau_w) - \frac{\varphi}{ps^2 Cu_h}$, the pace of destruction $\frac{c'}{c} Q - CQ(\tau_w)$, and temporal alongside spatial alterations in system behavior $\left.\frac{\delta r'}{\delta t}\right|_S$. Connecting real-time data and breakdown procedures for improved predictive maintenance and problem detection helps the digital twin.

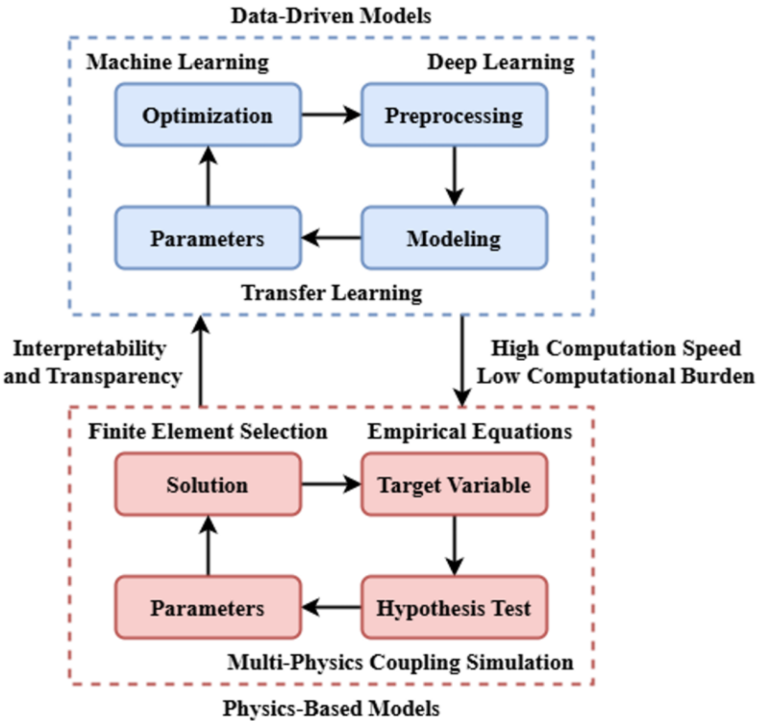

Figure 4: Functional Components of the Proposed Hybrid Modeling Framework

Figure 4 highlights the key functional components involved in developing and evaluating the hybrid physics-based and data-driven modeling (HP-DDM) approach. Including optimization, preprocessing, parameter selection, and modeling, the upper section indicates the model development phase. These activities ensure effective combination of physics-based understanding with machine learning, thus enabling accurate representation of equipment behavior. Whereas preprocessing cleans input data to enhance learning results, optimization ensures that the model can achieve optimal performance. The process of model evaluation that includes solution verification, target variable testing, parameter tuning, and hypothesis testing, is outlined in the lower part. Apply these techniques to check the accuracy, generalizability, and interpretability of the model. These factors provide a structured foundation to construct a resilient digital twin framework covering predictive maintenance and real-time fault detection. This figure describes how the technique achieves a balance between empirical confirmation and theoretical vigor and leads to enhanced decision-making in industrial applications.

3.3. Performance Evaluation on Industrial Equipment

Large-scale rotating equipment in power plants tests verify the effectiveness of the system. Enabling real-world deployment for predictive maintenance and operational efficiency, performance results indicate increased accuracy, reduced false alarms, and increased flexibility compared to traditional monitoring systems.

Using physics-informed loss functions, Figure 5 shows how the proposed Hybrid Physics Based and Data-Driven Modeling (HP-DDM) architecture uses simulation results and monitoring data to improve model learning. Monitoring signals allows one to record equipment activity; simulation models provide synthetic outputs reflecting theoretical system dynamics. These two data sources are fed into a machine learning environment that uses physical constraints—represented here as physics-informed loss functions—to guide the training process. By embedding domain-specific physics into the learning objective, the framework improves prediction accuracy, model reliability, and generalization, especially in data-scarce or variable operational conditions. This integration guarantees that the machine learning model follows the rules of physics controlling the equipment and does not depend only on data patterns. For condition assessment, problem detection, and predictive maintenance in complex industrial systems, the hybrid framework generates hence more strong and understandable results.

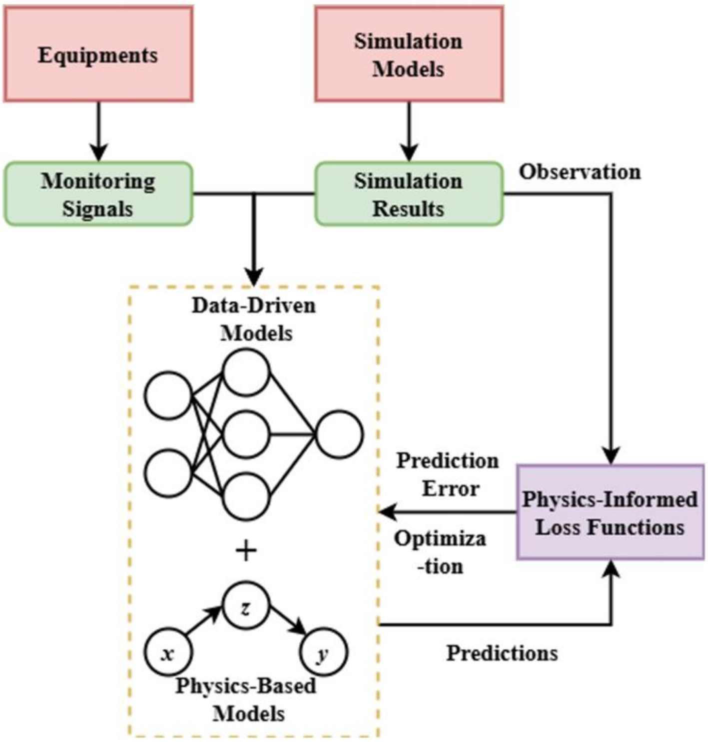

Figure 5: Integration of Simulation and Physics-Informed Learning in the Hybrid Modeling Framework

The integration of physical modeling and machine learning in the hybrid physics-based and data-driven modeling (HP-DDM) framework enhances digital twins. When applied to rotating machinery, it offers greater accuracy, flexibility, and decision support compared to traditional monitoring systems in challenging operating conditions.

IV. Results and Discussion

The accuracy of problem detection, real-time monitoring capability, scalability, physical virtual integration, and maintenance optimization are five essential performance criteria that are examined in this comparative analysis of predictive maintenance systems based on DT. This research shows how DT technologies have changed the inclined by comparing and contrasting HP-DDM, which is based on hybrid physics and classical machine learning techniques, with MLT. The datasets are chosen from the link [22].

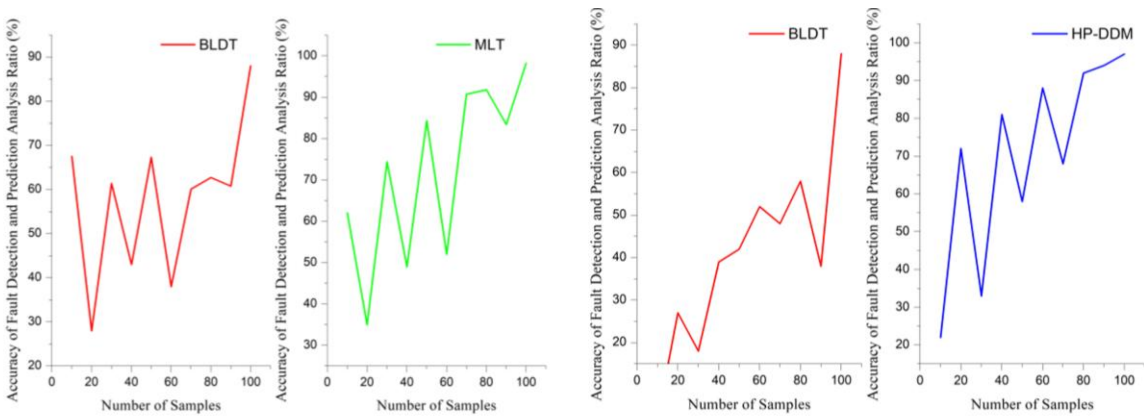

Figure 6. Accuracy of Fault Detection and Prediction Analysis

Figure 6 shows how different DT and CM systems rank in terms of fault detection and prediction. The most accurate methods, as one can observe from the graph, are hybrid ones, and more precisely, those using data-driven methodologies coupled with physics-based modeling HP-DDM. In the aim of being able to identify and predict early-stage defects, the models use machine learning techniques, past system behavior, and real-time data. Note that the BLDT and TCM models surpass traditional monitoring methods in terms of prediction accuracy, with significant improvements. To provide timely maintenance responses and system reliability in general, the research shows that DT-enhanced prediction models greatly minimize false alarms and masked faults. Figure 6(a) shows that when compared to MLT, the accuracy of defect identification and prediction analysis is moderate, with occasional discrepancies. Figure 6(b) shows that the HP-DDM greatly improves accuracy, which guarantees consistent and accurate fault prediction under various conditions.

$$Ww_z(a), = \{W_x(Y), 0\} + \{w_a(u), 0, 0\} + c\sin\frac{Y}{w_y} + c\cos y \tag{11}$$

Combining spatially dependent components $W(a)$, displacement-based terms $\{Wx(Y),0\}$, and sinusoidal stress-response variables $\{wa(u),0,0\}$, equation (11) reflects a composite function $c\sin\frac{Y}{w_y} + c\cos y$. It improves the accuracy of anomaly detection and makes the digital twin more able to replicate and forecast the accuracy of fault detection and prediction analysis.

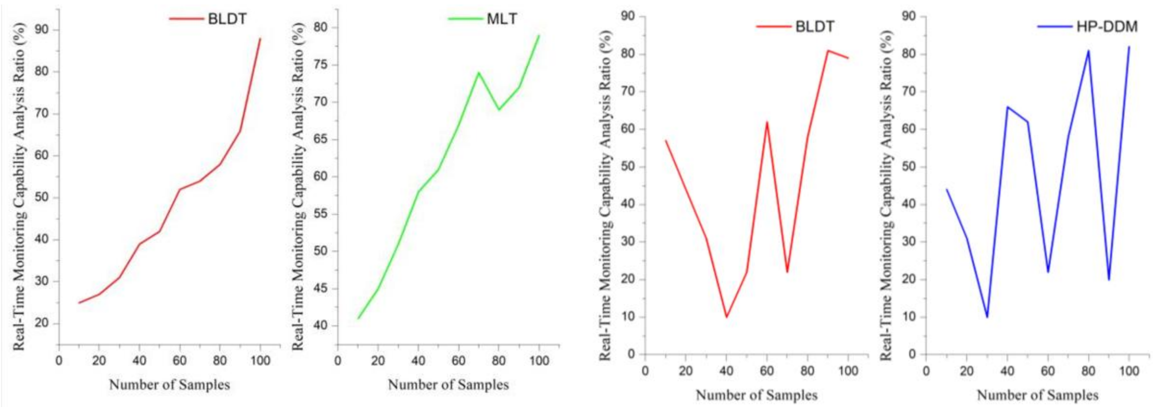

Figure 7. Real-Time Monitoring Capability Analysis is compared with MLT and HP-DDM

Figure 7 illustrates the performance of various Digital Twin (DT) frameworks with respect to real-time monitoring based on their responsiveness and data processing capacity. Improved monitoring capability is provided by systems that enable real-time data exchange between physical and virtual entities. The ability to continually monitor system behavior is enabled through high-frequency inputs from numerical sensors and controllers. This facilitates rapid anomaly detection and status changes. Low latency and precise representation of operational states are provided by physical-virtual synchronized frameworks. The study establishes that real-time monitoring is significantly enhanced through DT ecosystem's real-time analytics, dynamic virtual model adjustments, and smooth data integration. Figure 7(a) compares the real time monitoring capabilities of MLT, highlighting processing speed restrictions and occasional delays under dynamic situations. Figure 7(b) shows that HP-DDM, improves real-time monitoring by processing data more quickly and accurately. In complicated situations, this enables efficient and rapid surveillance.

$$\tan\varnothing = \frac{U_{gy}}{U_{ga}} + \frac{\beta - \frac{B}{B_A}}{\cos x + \text{ const}} * \frac{\varphi}{ps^2 Cu_h} \tag{12}$$

Equation (12) specifies, with system stiffness ratio $\frac{\varphi}{ps^2 Cu_h}$, the angle $\beta - \frac{B}{B_A}$ as a function about inputs and outputs ratios $\cos x + const$, stress adjusting terms $tan\emptyset$, and oxidation factors $\frac{U_{gy}}{U_{ga}}$. Its performance under different settings, hence permitting more precise forecasts of failure and best maintenance scheduling.

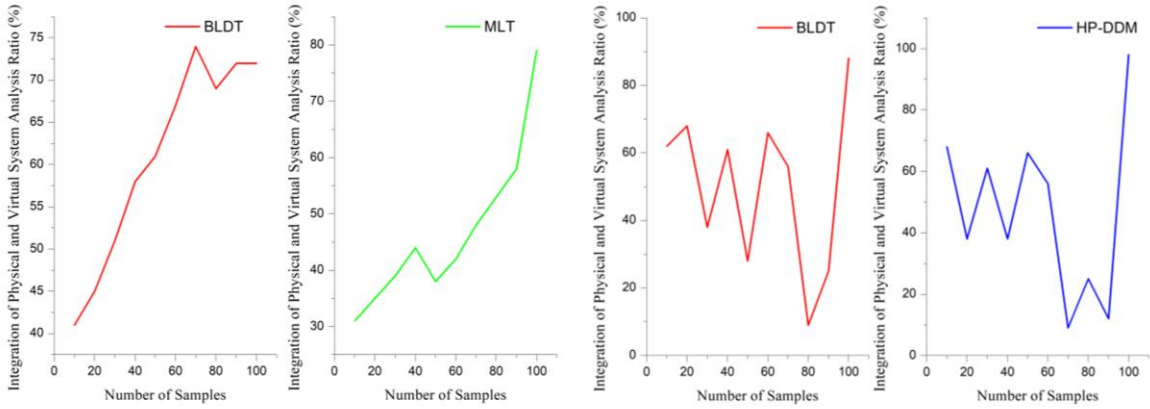

Figure 8. Integration of Physical and Virtual System Analysis is compared with MLT and HP-DDM

Figure 8 shows the result of a survey of how far some DT infrastructures allow digital and physical systems to integrate. Successful integration is characterized by high model fidelity, bidirectional streaming of data, and real-time synchronization. Horizontal feedback loops between the virtual models and the real equipment, as well as reliable copying of the behavioral behavior, signify well-integrated systems. Discrepancies arise during complicated system operations due to the limited synergy between physical data and virtual modeling, as shown in Figure 8(a), which contrasts the integration of physical and virtual systems utilizing MLT. By integrating real-time sensor data with virtual models, as shown in Figure 8(b), HP-DDM allows for a more precise and seamless synchronization of physical and virtual components, thereby integrating physical and virtual systems. Predictive insights and timely responses to anomalies or performance tuning are facilitated by such close coupling. Improved system awareness, operational transparency, and effective deployment of DTs in intricate industrial environments are all dependent on robust physical-virtual coupling.

$$D_a = B_a U \cos y \cdot \sin y + (\alpha - \alpha_w) - \left(\frac{\gamma}{pc^2}\right) 1/(\cos y \cdot \sin y) \tag{13}$$

Equation (13) specifies Da as a BaUcos$y$,sin$y$ function of mechanical labor 1/(cos$y$.sin$y$), important constants ($\alpha - \alpha w$), and one stress-deformation term ($\gamma/pc2$). It helps the digital twin understand and forecast complicated interactions among forces, and integration of physical and virtual system analysis.

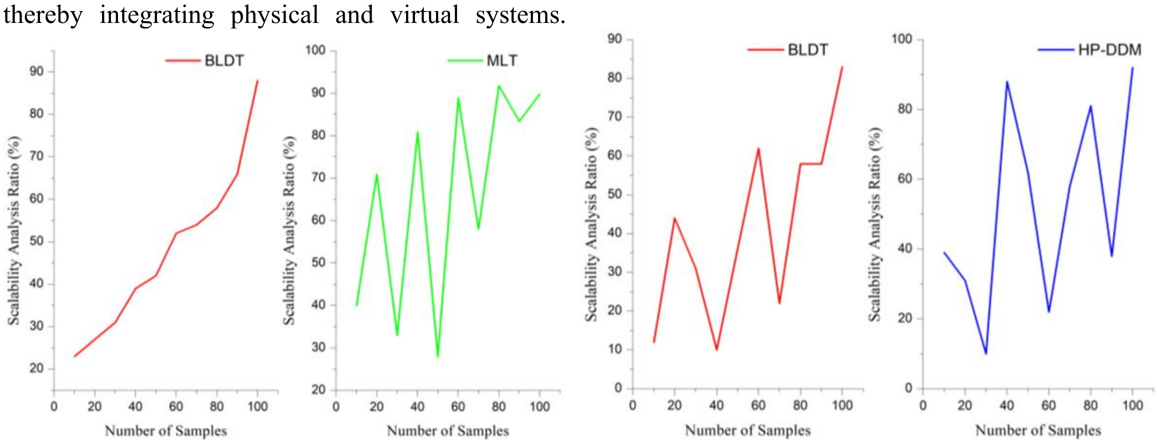

Figure 9. Scalability Analysis is compared with MLT and HP-DDM

Figure 9 illustrates how various industrial applications can be helped by Digital Twin (DT) implementations regarding scalability. The ability of a system to handle increasing amounts of data, bring together disparate assets, and adjust to varying operational scopes without degrading performance is how scalability is measured. Studies indicate that adaptive data processing frameworks, cloud-based infrastructure, and modular architecture all work to create scalable DT models. These traits make DTs particularly suitable for large industrial ecosystems on a mass scale since they enable effective replication across many units and facilities. The figure identifies highly scalable systems as crucial for digital transformation that is both pragmatic and cost-effective in the long term. Scalability analysis utilizing MLT is shown in Figure 9(a). It shows that there are issues when it comes to responding to different system complexities and data quantities, which often means that models need to be retrained a lot. Scalability analysis utilizing HP-DDM is shown in Figure 9(b). The results show that HP-DDM is very adaptable and performs well at different operational scales because of its modular and flexible architecture.

$$q(y,\tau) = \frac{1dN}{dx} * Cq' + c'q - \left(d + w_m\right) * \frac{C}{D}\cos y \tag{14}$$

Equation (14) expresses $q(y,\tau)$ as a mix of rate of change in system state $1dN/dx$, destruction term $Cq' + c'q$, material response ($d + wm$), and other dynamic elements involving $\frac{C}{D}\cos y$. It supports more exact anomaly identification and maintenance scheduling by helping the digital twin monitor by scalability analysis.

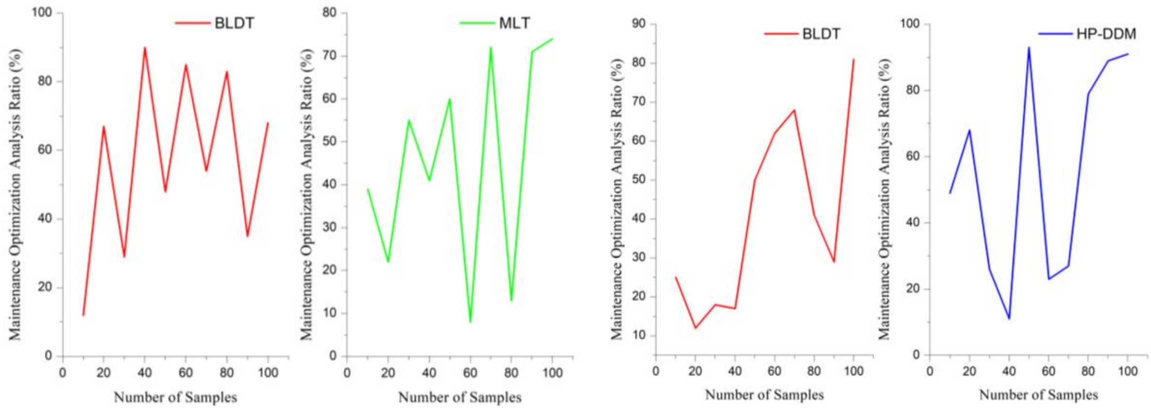

Figure 10. Maintenance Optimization Analysis is compared with MLT and HP-DDM

A review of maintenance optimization that was achieved by embedding Digital Twin (DT) technology is presented in Figure 10. The ability of DT systems to reduce overall maintenance expenses, extend equipment life, and reduce unplanned downtimes is the main emphasis of the study. The image illustrates how DT-enabled systems can analyze operational data in real-time and forecast faults prior to their occurrence, thus significantly supporting decision-making. Maintenance tasks are better planned, resources utilized more optimally, and operations less frequently disrupted by virtue of this forward-looking approach. The analysis emphasizes the key contribution of DT towards creating reliable and economical servicing plans. In Figure 10(a), the results of a maintenance optimization analysis that made use of MLT. This analysis indicates how the lack of contextual system awareness leads to less predictive precision and more reactive maintenance tendencies. Improved maintenance schedule, less downtime, and proactive fault mitigation through accurate modeling of system behavior are shown in Figure 10(b) of the maintenance optimization analysis with HP-DDM.

$$Eu_{ha} = \left.\frac{\delta r'}{\delta s}\right|_{\text{ray}} + DC\sin x + B_a D\sin y * \frac{w}{c}\Delta y(1+N)^3 \tag{15}$$

Equation (15) specifies $Euha$ as a mix of spatial rate modifications $\frac{\delta r'}{\delta s}$, dynamic stress alterations $\Big|_{ray} + DC\sin x$, and material along with operational terms including BaD sin$y$, $\frac{w}{c}\Delta y(1+N)^3$. It offering a better understanding of equipment condition and helps with more exact preservation and failure prediction by maintenance optimization analysis. The results show that HP-DDM is always better than MLT, and that DT is a crucial component of smart, scalable industrial solutions because it improves accuracy, responsiveness, integration integrity, flexibility, and maintenance efficiency.

V. Implications for Sustainable Maintenance Management Practices in Papua New Guinea

The use of a Digital Twin-based Hybrid Physics-Based and Data-Driven Modelling (HP-DDM) framework for monitoring the condition of machinery has big effects on improving sustainable maintenance management in Papua New Guinea's industrial sector.

1. Better capability for predictive maintenance: The HP-DDM framework gives better failure predictions for important assets like rotating equipment in power plants by using both physical models and machine learning approaches. This level of accuracy cuts down on unplanned downtime, which lets businesses in PNG plan maintenance ahead of time and use spare parts and personnel more efficiently.

2. Extending the life of assets: Continuous real-time monitoring and adaptive fault detection assist find small problems before they turn into big ones. This means that expensive machine parts don't need to be replaced as often, which is in line with sustainable practices because it saves money and resources.

3. Better Use of Resources: Fewer false alarms and better decision-making mean that maintenance work is only done when it is really needed. This optimisation cuts down on unnecessary shutdowns, too much material use, and operational disruptions. This is especially critical at PNG's remote industrial sites, where logistics and spare parts availability are hard to come by.

4. Support for building skills and capacity o To use digital twin technologies, local maintenance workers need to learn more about data analytics, machine learning, and sensor integration. This helps build a qualified workforce that can run and maintain advanced monitoring systems, which helps PNG reach its long-term goals for industrial sustainability.

5. Alignment with Environmental Sustainability Goals: More efficient machines use less energy and produce less greenhouse gas emissions. For PNG's energy-intensive industries, this is in line with both the country's goals for sustainability and its promises to fight climate change.

6. Being able to handle tough operational and environmental conditions: The HP-DDM framework is adaptable, which means it can accurately monitor conditions even when the operational loads and environmental changes are frequent in PNG's industrial settings. This ensures constant performance and reliability.

7. Facilitation of Data-Driven Maintenance Culture o The adoption of the digital twin paradigm encourages a shift in culture from reactive to predictive and condition-based maintenance methods. Over time, this leads to data-driven decision-making becoming the norm, which makes it possible for maintenance policies and procedures to get better all the time.

To sum up, the HP-DDM-enabled digital twin method could change how Papua New Guinea manages maintenance in a more sustainable way by lowering costs, improving asset reliability, saving resources, and boosting technical skills. This not only helps the economy work better, but it also helps the environment and makes the region's industries more resilient.

VI. Conclusion:

This research has proposed a framework for condition monitoring of machinery through digital twins, focusing on an HP-DDM method that is physics-data combined. The proposed architecture has enhanced fault detection accuracy, improved adaptability to operational variations, and reduced false alarms by integrating physical models with machine learning methods and real-time sensor information. The ability of the framework to enable predictive maintenance and extend equipment life through informed decision-making has been established by its use in power plant rotating equipment. The future of the HP-DDM framework remains doubtful, despite ongoing studies examining its applicability across various sectors such as manufacturing, aerospace, and automotive. Autonomous diagnosis and real-time processing will get an upgrade by virtue of the adoption of cloud-edge computing systems and state-of-the-art AI techniques. Another promising field of further widening Digital Twin implementations is the employment of augmented reality (AR) to enable interactive visualization and training in maintenance. Even though there are certain advantages of this research, there are certain limitations correspondingly. Development of accurate physical models is a time-consuming process and requires domain expertise. Moreover, in an industrial environment, sensor data quality and consistency may vary and affect the performance of the framework. Enhancement of the method and its usability in realistic scenarios will rely upon addressing these constraints.

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