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Towards Interpretable Digital Twins for Self-Aware Industrial Machines

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***Abstract*— In this research, we introduce a methodology that combines digital twins and Particle Swarm Optimization (PSO) to improve real-time adaptability and interpretability in industrial systems. Using an industrial DC motor simulation as a case study, our approach involves creating a digital twin, performing online parameter estimation via PSO, and identifying unknown system components. The results, especially from scenarios like armature resistance degradation and unbalanced shaft conditions, highlight the digital twin's accuracy and adaptability. This work showcases the potential of our method for real-time monitoring and proactive maintenance in industrial applications.**

I. Background

The industrial domain has transitioned from manual operations to advanced automated systems since the third industrial revolution [1]. Effective control of dynamic systems necessitates understanding their dynamics [2]. However, real-world systems present challenges due to unpredictable factors, potentially leading to operational failures [3]. While adaptive models aim to enhance adaptability, they face complexities and require special instrumentation [4]. Digital Twins provide virtual representations of physical systems for various applications [5], [6]. Updated with real-time data, they offer more accurate predictions, enhancing machine self-awareness [6]. Particle Swarm Optimization (PSO) further augments this awareness by estimating model parameters [7]. The ability to interpret system models is crucial in the industrial domain for safety and efficiency [5] estimating non-instrumented parameters and adapting models using real-time data addresses system adaptability challenges [8]. PSO stands out for its efficiency in parameter estimation [7]. Hence, the aim of this work is to propose a methodology that enhances the interpretability and adaptability of Digital Twins using PSO.

II. Proposed Methodology

The proposed methodology seeks to establish an interpretable Digital Twin that integrates online parameter estimation and unknown components discovery using Particle Swarm Optimization (PSO). The methodology comprises three primary steps:

First, modeling the physical system: creating the digital twin based on mathematical equations that capture the system's physical components, ensuring accurate representation and interpretability [10]. It emphasizes interpretability, parameterizability, and modularity.

Second, employing the Particle Swarm Optimization (PSO) approach for online parameter estimation: by leveraging acquired data to optimize the model's accuracy, focusing on minimizing the root mean square error (RMSE) between the model's predictions and the actual system outputs [9].

Third, utilizing PSO to identify unknown system components: addresses the discrepancy between the real system and the model by identifying and integrating unknown components through meta-models, typical mathematical models that impact system outputs. It aligns the model more closely with the real system by selecting an appropriate combination of these meta-models to complement the original model.

The final Self-Aware Digital Twin model combines the initial model with the added meta-models and parameters estimation, yielding a comprehensive representation that can adaptively mirror the real system's behavior.

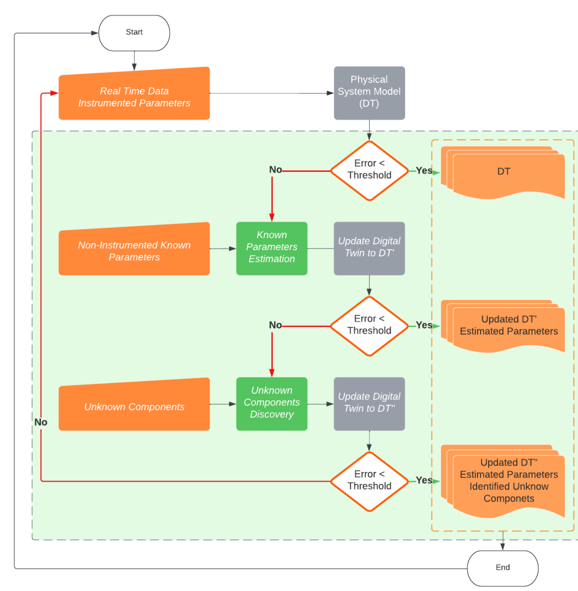

Fig. 1. Detailed flowchart of the proposed methodology

III. Current Results

The methodology has been examined through its application to an industrial DC motor simulation. This motor was defined by initial parameters: armature resistance $R_a = 6.5\Omega$, inductance $L_a = 0.673H$, moment of inertia $J = 0.001171\text{kg} \cdot \text{m}^2$, back electromotive force constant $K_e = 0.038\text{V} \cdot \text{s/rad}$, torque constant $K_t = 0.038\text{N} \cdot \text{m/A}$ and

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damping coefficient $D = 0.00143\text{N} \cdot \text{m/s} \cdot \text{rad}$, reflecting its wide usage in various industrial processes [9].

For optimization, the PSO technique from the 'pymoo' library [11] was employed with defining parameters: a swarm size of 15, a maximum iteration limit of 1000, an inertia weight of 0.9, and both cognitive and social parameters set at 2.0.

In the Armature Resistance Degradation scenario, R_a is decreased along time from 6.5Ω to about 5.6Ω using an exponential decay $-0.044 * \exp(0.003 * t) + 0.044$ each time step initiating at $160s$. In this case, there was a pronounced alignment between the Digital Twins' predictions and the simulated data. This congruence is clearly visualized in Figure 2 which shows the model's estimation percentage error.

To simulate an Unbalanced Shaft, deviations are introduced to the rotor speed. A sinusoidal error is added to the speed calculation at each time step. The amplitude of the error is set as $5rad/s^2$ which is multiplied by the simulation sample time. The frequency is chosen to be fixed at $10rad/s$. In this case, the parameter estimation is not enough to guarantee the model prediction performance as shown in Figure 3. Once the unknown components discovery takes place, the updated model is capable of better predicting and representing the plant behavior. Figure 4 depicts the model prediction and the prediction error of the new updated model for a $2s$ estimation time window. It shows that the maximum absolute error is reduced from $0.5rad/s$ to less than $0.02rad/s$.

The results underscore the robustness of the proposed methodology, especially Steps 2 (Parameter Estimation and Digital Twin Update) and 3 (Unknown Components Discovery). By leveraging these steps, the digital twin not only mirrored the real system's behavior but also demonstrated the ability to adapt to deviations and anomalies. The methodology's emphasis is on real-time parameter estimation and adaptability. It showcases a model that is not only accurate but also self-aware, capable of identifying and rectifying discrepancies in real time. These positions are crucial for industries, ensuring system reliability.

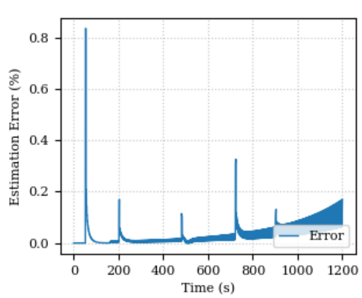

Fig. 2. Estimated percentage error for the Armature Resistance.

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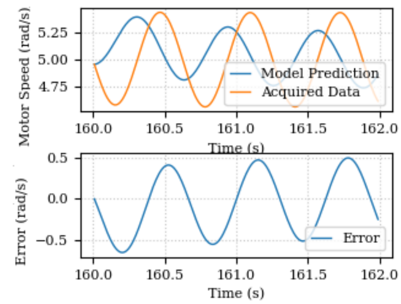

Fig. 3. Predicted and acquired data for output speed before Unknown Components Discovery

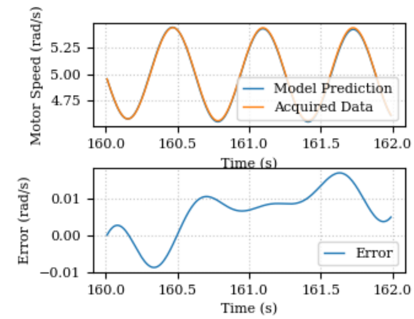

Fig. 4. Predicted and acquired data for output speed after Unknown Components Discovery

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