

Article

Power-Aware State Recognition for Digital Twins: Non-Intrusive Industrial Monitoring of Solder Paste Printers

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Abstract

The construction of high-fidelity virtual factories relies heavily on the accurate reconstruction of historical production timelines. While traditional Manufacturing Execution Systems (MESs) provide idealized, static schedules, they inherently struggle to capture the “stochastic variability” and “undefined events” caused by machine-specific behaviors on the industrial shop floor. To bridge the gap between top-down scheduling and bottom-up physical reality, this study proposes the Power-Aware State Segmentation for Solder Paste Printers (PAS-SPP) algorithm. Utilizing non-intrusive, high-frequency continuous power features captured via an Industrial Internet of Things (IIoT) architecture with PA310 meters, the algorithm employs a synergistic combination of amplitude thresholding (θ_{high}) and temporal constraints (τ_{blank} , τ_{min}) to actively filter transient electrical noise and accurately bound macroscopic operational blocks. This robust filtering thereby avoids the accuracy degradation commonly caused by noise interference in the analysis processes of traditional machine learning models. Consequently, the mechanism effectively decouples operational states into a virtual Solder Paste Printer (vSPP) behavioral meta-model integrated with a Finite State Machine (FSM). Empirical validation across distinct production cases demonstrates that the proposed model not only accurately extracts standard 33–35 s cycle times but also reveals critical hidden characteristics, such as 68 s automated cleanings and dynamically adjusted “3-to-1” print-to-clean ratios. Furthermore, a comprehensive comparative analysis was conducted against static MES logs, Naive Power Thresholding (NPT), and a Gaussian Hidden Markov Model (GMM-HMM). Evaluated under identical manufacturing-process conditions, the results reveal that PAS-SPP effectively mitigates the cascading misalignments in static schedules and avoids the severe over-segmentation limitations inherent in point-by-point probabilistic decoding, thereby achieving highly accurate state decoupling. Finally, this study systematically defines the method’s applicability boundaries across diverse DT domains, confirming its indispensable role as a non-intrusive, broadly applicable event-triggering foundation for the broader smart manufacturing ecosystem.



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1. Introduction

1.1. Background and Motivation

Digital Twin (DT) technology has demonstrated immense application potential across various fields, evolving into a core technological driver for global digital transforma-

tion [1,2]. By creating a dynamic and highly accurate digital counterpart of physical assets, DT enables real-time monitoring, scenario simulation, and system-wide optimization. This transformative capability has allowed industries to move beyond retrospective data analysis [3] and transition toward predictive and autonomous operational paradigms [4].

Among various sectors, the manufacturing industry has the most urgent need for DT to predict production details and thereby enhance overall operational efficiency [5]. The Surface Mount Technology (SMT) assembly line, characterized by its exceptionally high degree of automation, continuous workflow, and complex cyber-physical interactions, represents an optimal entry point for verifying and implementing DT technologies [6].

As illustrated in Figure 1, a standard SMT production line consists of a sequence of specialized machines. The process typically begins with a Solder Paste Printer (SPP), which uses motorized squeegees to precisely apply solder paste onto a printed circuit board (PCB). This is followed by Solder Paste Inspection (SPI) systems, mounters (pick-and-place machines) that quickly position electronic components, a reflow oven to solidify the solder, and an Automated Optical Inspection (AOI) system. Each of these machines possesses unique mechanical and electrical characteristics that must be accurately modeled to simulate the entire line.

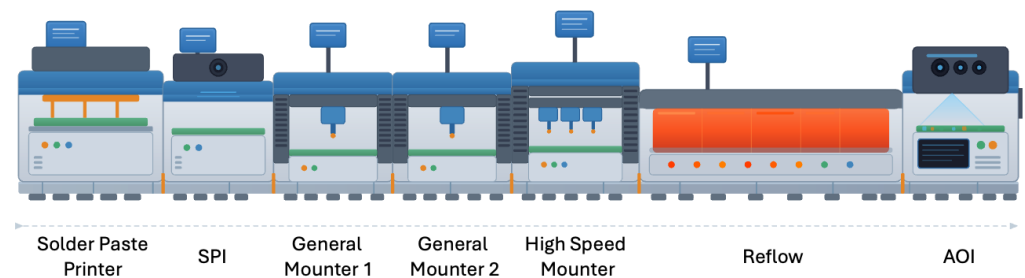


Figure 1. The typical architecture of an SMT production line. The process sequentially includes a SPP, a SPI, multiple mounters, a Reflow oven, and an AOI system.

To construct a high-fidelity virtual SMT (vSMT) factory as the DT system, the critical first step is achieving precise Equipment Virtualization starting from the very source of the production line: the SPP. Industrial studies indicate that 50% to 70% of all PCB assembly defects originate from the SPP process [7,8]. As the first step of SMT manufacturing, the output quality of the SPP dictates the material flow, scheduling, and overall yield for all subsequent downstream equipment. Therefore, establishing a reliable virtual Solder Paste Printer (vSPP) is not merely a component of the vSMT architecture, but its foundational prerequisite.

1.2. Related Research

The integration of DT systems and energy analysis in SMT lines has been explored in several pioneering studies. Karanjkar et al. utilized DT for energy optimization within SMT-PCB assembly processes [9], while Joglekar et al. developed open simulator frameworks for the 3D visualization of such twins [10]. Regarding the use of power data, Mihai et al. demonstrated the potential of fractal analysis of energy datasets for condition monitoring [11], and Kornilov et al. focused on metrological monitoring of power consumption at manufacturing plants [12]. Furthermore, previous research has explored software-defined hybrid clouds to support smart micro-manufacturing systems [13]. However, while these studies successfully highlight the value of energy data and visualization, they often lack the core approach to virtualize the machine's physical behavior required for a dynamic, high-fidelity vSPP [14,15].

The comprehensive virtualization of industrial equipment currently faces several profound technical dilemmas:

1. **The Gap Between MESs and Stochastic Reality:** Traditional virtual models rely heavily on static work orders generated by Manufacturing Execution Systems (MESs) [16,17]. While MESs provide an idealized scheduling framework, it inherently struggles to cope with the “Stochastic Variability” encountered on the physical shop floor, such as micro-stoppages, operator interventions, or dynamic speed adjustments [18].
2. **The “Black Box” Nature of Legacy Equipment:** A significant barrier to SMT virtualization is the proprietary nature of existing machinery. Manufacturers often face closed communication protocols and vendor lock-in, making internal state data extraction exceptionally difficult and costly [19,20].
3. **Invisibility of Undefined Events:** There is a fundamental challenge in capturing “Undefined Events” (e.g., hidden automated cleaning cycles). Traditional discrete count sensors are inadequate as they only record predefined processes, e.g., board entry/exit, leaving crucial maintenance actions within the machine’s operational timeline unrecorded [21].
4. **Computational Overhead vs. High-Fidelity:** Many existing DT systems rely on heavy 3D physics engines that are computationally expensive to run in real-time for an entire factory floor [22]. There is a need for lightweight, logic-based models that maintain high fidelity without massive computational overhead for industrial applications [23,24].

Achieving practical and scalable virtualization requires a non-intrusive, hardware-sensitive method that addresses these blind spots and reflects the operational nature of various machines.

1.3. Contributions of This Study

To address the above challenges of virtualizing SPP, this paper makes the following key contributions in constructing vSMT DT systems:

- **Algorithm Proposal:** We propose the Power-Aware State Segmentation for Solder Paste Printers (PAS-SPP) algorithm to achieve precise state modeling from continuous, non-intrusive power signals.
- **Meta-model Generalizability:** We establish a highly adaptable vSPP meta-model architecture capable of autonomous parameter calibration across different production volumes and product types, overcoming the “Black Box” equipment dilemma.
- **Hidden Characteristic Discovery:** Our method successfully identifies equipment-specific “hidden process optimizations,” such as dynamically adjusted cleaning frequencies, which remain invisible to traditional MESs and discrete sensors.
- **FSM-based Lightweight Modeling:** We formalize these physical findings into a robust Finite State Machine (FSM) model, providing a computationally lightweight yet highly accurate behavioral mechanism.
- **Comprehensive Comparative Evaluation:** Through comprehensive experimental comparisons against static MES logs, Naive Power Thresholding (NPT), and a standard generative learning baseline (GMM-HMM), we demonstrate the effectiveness of integrating macroscopic temporal boundaries with FSM logic. The proposed method addresses the tracking limitations of static schedules and mitigates the segmentation challenges commonly associated with memoryless probabilistic models.
- **Cross-Domain DT Applicability:** We systematically evaluate the proposed methodology against four major DT domains, clearly defining its applicability boundaries and

highlighting its critical role as a universal, non-intrusive event-triggering foundation for broader industrial systems.

2. Materials and Methods

2.1. Data Acquisition and Hardware Setup

This study conducted empirical experiments on a commercial SMT production line, specifically targeting an SP60 printer from Panasonic to collect real-world data. To precisely capture the physical operations of the SPP, we deployed a PA310 digital smart power meter from Arch Meter Corporation directly at the machine's main power supply terminal. The data acquisition system's sampling rate was configured to 1 Hz (one sample per second). At this frequency, the meter continuously logs highly structured, multidimensional, three-phase electrical features, including voltage, current, active power, and reactive power, ensuring that the macroscopic mechanical actuations of the SPP are fully recorded.

A significant advantage of this setup is its computational efficiency. Specifically, no complex mathematical preprocessing (e.g., low-pass filtering, moving-average smoothing, or normalization) was required or applied to the time-series data prior to analysis. The raw active power dataset is used directly as the foundational input for the PAS-SPP algorithm, which relies on its amplitude and temporal constraints to filter out ambient electrical noise.

To provide a realistic basis for equipment virtualization, we recorded the continuous power consumption profiles for complete production work orders. As illustrated in Figure 2, during an approximately 50-h manufacturing run, the dataset captures the long-term operational dynamics and stochastic variations of the SPP under real factory conditions for three work orders.

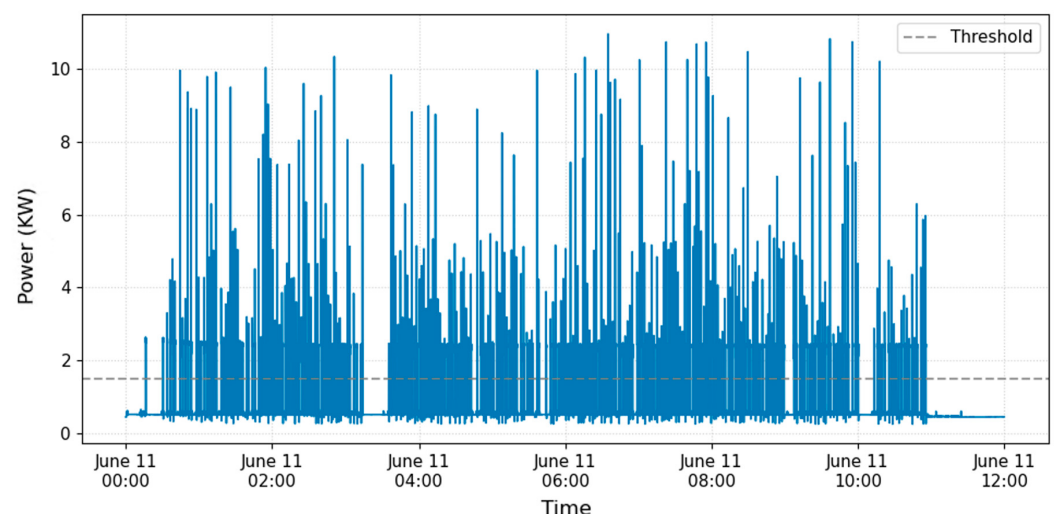


Figure 2. The entire power consumption profile of the SPP for a complete work order, providing the foundational input for constructing the vSPP DT system.

Within this extensive production run, the raw multidimensional power data provides a highly granular view of the machine's electrical state. As shown in Figure 3, the dataset rigorously logs comprehensive three-phase electrical features, including voltage, current, active power, and reactive power. This highly structured profile preserves even the briefest mechanical strokes of the SPP squeegee.

A critical challenge in evaluating equipment virtualization is establishing a reliable ground truth for “hidden” or condition-driven events (e.g., Fast Cleans and Anomalous Errors) that are fundamentally invisible to static MES logs. To overcome this, an independent ground truth was constructed through Retrospective Domain-Expert Validation. Initially, the continuous power consumption records were converted into discrete-event intervals.

Any operational blocks that deviated from the expected standard printing or primary cleaning cycle times were flagged. These timestamped, non-standard discrete events were then systematically cross-referenced with senior on-site operators and maintenance engineers. By analyzing the contextual sequence, exact duration, and power signature of these deviations, the domain experts could unequivocally annotate the physical nature of each event. This expert-annotated dataset thus provided a highly accurate, independent ground truth against which the PAS-SPP algorithm's automated state classification performance could be evaluated.

1	CaptureTime	VLN_A	VLN_B	VLN_C	I_A	I_B	I_C	KW_A	KW_B	KW_C	KVAR_A	KVAR_B	KVAR_C	KWH	KVARH
5	2018-06-01 12:10:41.251	127.854	126.9779	127.9275	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
6	2018-06-01 12:10:42.251	127.769	127.0501	127.9036	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
7	2018-06-01 12:10:43.251	127.9351	126.9523	127.6621	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
8	2018-06-01 12:10:44.267	127.7044	127.1124	127.7929	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
9	2018-06-01 12:10:45.267	127.7556	127.1982	127.7509	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
10	2018-06-01 12:10:46.267	127.8263	127.0252	127.8893	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
11	2018-06-01 12:10:47.298	127.8685	127.0231	127.7584	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
12	2018-06-01 12:10:48.502	127.9086	126.9652	127.7732	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
13	2018-06-01 12:10:49.502	127.8505	127.0539	127.6927	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
14	2018-06-01 12:10:50.502	127.8601	127.177	127.7082	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
15	2018-06-01 12:10:51.502	127.6594	127.091	127.8246	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
16	2018-06-01 12:10:52.815	127.7598	127.0956	127.7716	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798
17	2018-06-01 12:10:53.877	127.5896	127.1588	127.964	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.003274	7.61798

Figure 3. A snippet of the raw multidimensional time-series power dataset, serving as the foundational input for the PAS-SPP algorithm.

2.2. The PAS-SPP Algorithm

To overcome on-site signal errors and baseline fluctuations, the proposed PAS-SPP algorithm incorporates a high-power threshold, θ_{high} . This serves as a primary filter, effectively ignoring baseline idle consumption to identify high-energy mechanical actions. Subsequently, time-interval parameters, including a maximum blank-duration threshold τ_{blank} and a minimum-duration threshold τ_{min} , are used to model the state, transforming the continuous waveform into discrete working blocks. The detailed execution logic is presented in Algorithm 1. The PAS-SPP has three major steps, as described below:

- **Feature Extraction and Power Calculation:** The PAS-SPP first calculates the instantaneous total power from the three-phase signals (P_A , P_B , P_C) and applies a high-power threshold θ_{high} to identify active mechanical work while effectively ignoring idle baseline consumption and ambient noise.
- **State Clustering:** Consecutive data points that cross the threshold are grouped into candidate blocks. A maximum blank-duration threshold τ_{blank} is used as a temporal boundary. If the time gap between points exceeds this limit, the algorithm initiates a new operational block, effectively separating individual cycles.
- **Refinement and Cycle Time Calculation:** To ensure the validity of the identified segments, each candidate block is filtered using a minimum duration threshold τ_{min} to eliminate transient electrical spikes or irrelevant noise. The final set of valid working blocks T_{work_block} is then aggregated to calculate the mean cycle time CT_{mean} based on the total valid duration.

While the PAS-SPP algorithm effectively isolates the valid working blocks (T_{work_block}) from the continuous power stream, these blocks must be semantically labeled to reconstruct the operational timeline. Because the SPP machine exhibits highly deterministic mechanical execution times for distinct operations, the classification of each block B_k is determined by its duration $D(B_k)$ and the contextual FSM logic.

Algorithm 1: Power-Aware State Segmentation for Solder Paste Printers (PAS-SPP)

Input: Raw power dataset D_{raw} , Observation window $[t_{start}, t_{end}]$, High-power threshold θ_{high} , Maximum blank duration τ_{blank} , Minimum duration τ_{min}

Output: Set of valid working blocks T_{work_block} , Mean cycle time CT_{mean}

- 1 Calculate instantaneous total power: $P(t) = P_A(t) + P_B(t) + P_C(t)$;
- 2 Filter D_{raw} using $[t_{start}, t_{end}]$ to yield the target time-series data E ;
- 3 Extract a subset of crossing points: $E_{cross} = \{(t_i, p(t_i)) \in E \mid p(t_i) > \theta_{high}\}$;
- 4 Initialize Block ID B_k , set $k = 1$;
- 5 **for** each consecutive point $(t_i, p(t_i))$ in E_{cross} **do**
- 6 Calculate time difference: $\Delta t_i = t_i - t_{i-1}$;
- 7 **if** $\Delta t_i > \tau_{blank}$ **then**
- 8 Initiate a new block B_{k+1} ;
- 9 $k = k + 1$;
- 10 **else**
- 11 Assign point $(t_i, p(t_i))$ to current block B_k ;
- 12 **end**
- 13 **end**
- 14 Initialize $Total_Duration = 0$;
- 15 **for** each identified block B_k **do**
- 16 Calculate duration: $D(B_k) = \max(t \in B_k) - \min(t \in B_k)$;
- 17 **if** $D(B_k) > \tau_{min}$ **then**
- 18 Add B_k to the set of valid working blocks T_{work_block} ;
- 19 $Total_Duration = Total_Duration + D(B_k)$;
- 20 **end**
- 21 **end**
- 22 Calculate mean cycle time: $CT_{mean} = Total_Duration / |T_{work_block}|$;
- 23 **return** T_{work_block} , CT_{mean} ;

Based on the empirical baseline analysis, we formulated the following duration-based classification rules driven by statistical process control principles. Instead of using an arbitrary static tolerance margin, the classification boundaries are dynamically defined by the empirical mean duration μ_{S_x} and three times the standard deviation ($3\sigma_{S_x}$) for each distinct state S_x , capturing approximately 99.73% of normal operational variations:

$$State(B_k) = \begin{cases} S_1 \text{ (Standard Print)}, & \text{if } \mu_{S_1} - 3\sigma_{S_1} \leq D(B_k) \leq \mu_{S_1} + 3\sigma_{S_1} \\ S_2 \text{ (Primary Clean)}, & \text{if } \mu_{S_2} - 3\sigma_{S_2} \leq D(B_k) \leq \mu_{S_2} + 3\sigma_{S_2} \\ S_{FC} \text{ (Fast Clean)}, & \text{if } \mu_{S_{FC}} - 3\sigma_{S_{FC}} \leq D(B_k) \leq \mu_{S_{FC}} + 3\sigma_{S_{FC}} \\ S_{Err} \text{ (Anomalous Error)}, & \text{if } \mu_{S_{Err}} - 3\sigma_{S_{Err}} \leq D(B_k) \leq \mu_{S_{Err}} + 3\sigma_{S_{Err}} \\ S_{Unknown}, & \text{otherwise} \end{cases} \quad (1)$$

where μ_{S_x} and σ_{S_x} represent the empirical mean and standard deviation extracted from the Case 1 baseline data, specifically: $\mu_{S_1} = 33.22$ s, $\sigma_{S_1} = 1.02$ s; $\mu_{S_2} = 67.09$ s, $\sigma_{S_2} = 1.17$ s; $\mu_{S_{FC}} = 50.31$ s, $\sigma_{S_{FC}} = 5.42$ s; and $\mu_{S_{Err}} = 18.73$ s, $\sigma_{S_{Err}} = 0.50$ s. Whenever a block is processed, its duration is evaluated against these statistically grounded boundaries to assign the precise semantic label, thereby achieving accurate state decoupling for the entire work order.

The systematic selection procedure for these core parameters (θ_{high} , τ_{blank} , τ_{min}) is driven by a combination of theoretical work-order requirements and empirical observation of machine-specific characteristics. Crucially, a core philosophical pillar of our digital twin

architecture is that the virtual twin must faithfully represent and reflect the unique empirical characteristics of the specific physical asset. Consequently, rather than relying on a fully automated or black-box analysis that may obscure localized electromechanical nuances, incorporating human-in-the-loop expert intervention to adjust and calibrate these boundaries is a deliberate and necessary means of manifesting these distinct machine properties.

Structurally, a standard printing pass under the given work order theoretically demands approximately 31 s of active mechanical actuation. However, owing to the physical constraints of legacy hardware, such as degradation of squeegee drive motor efficiency and safety deceleration cycles, the actual operating time on the shop floor averages 33 s. By analyzing these production properties from the raw data, τ_{blank} was selected as 5 s to prevent premature block fragmentation during transient power drops, and τ_{min} was designated as 10 s to filter out sub-cycle electrical spikes while successfully preserving short anomalous events (where the statistical lower bound $\mu_{S_{Err}} - 3\sigma_{S_{Err}} = 17.23$ s remains well above τ_{min}).

To ensure absolute reproducibility, the complete acquisition settings, observation windows, and uniform algorithmic parameter configurations across all three evaluated production cases are summarized in Table 1.

Table 1. Reproducibility configuration matrix for the PAS-SPP framework across distinct production cases.

Configuration Parameter	Case 1 (Baseline)	Case 2 (Validation)	Case 3 (Validation)
Hardware Setup	Arch Meter PA310 Digital Power Meter		
Sampling Rate	1 Hz (1 sample per second)		
Electrical Feature Monitored	Three-Phase Aggregate Active Power (kW)		
Observation Window	11 h	5 h	7 h
High-Power Threshold (θ_{high})	1.5 kW	1.5 kW	1.5 kW
Max Blank Duration (τ_{blank})	5.0 s	5.0 s	5.0 s
Min Block Duration (τ_{min})	10.0 s	10.0 s	10.0 s
Pseudocode Source	Fully detailed in Algorithm 1		
Data Availability Restriction	Restricted due to commercial confidentiality agreements		

2.3. The vSPP Behavioral Model Architecture

The objective of this study is to construct a generalized behavioral model that can be practically deployed into a DT system for vSMT simulations. The logical relationship among our proposed components is strictly defined as follows:

- The **PAS-SPP algorithm** is responsible for parsing actual production cases to uncover the empirical execution flow.
- The **Finite State Machine** maps the logical state transitions between distinct mechanical operations.
- The **vSPP Behavioral Model** represents the generalized statistical characteristics governed by the FSM, serving as the actual simulation parameters for the DT system.

To realize the proposed vSPP, our empirical design utilizes three distinct production cases. The process begins by running **Case 1** through the PAS-SPP algorithm. The derived results are then systematically analyzed to establish the baseline behavioral model, defining both the production flow and its fundamental parameters. Subsequently, **Case 2** and **Case 3** are employed solely to verify whether different work orders continue to adhere to this overarching model architecture and to observe how the parameters dynamically adapt. The case descriptions are as follows:

- **Case 1 (Modeling Baseline):** A high-volume production run (394 successful prints) used to extract the foundational behavioral model characteristics.
- **Case 2 (Same-Attribute Validation):** A smaller batch (165 prints) of the exact same product, utilized to verify parameter adaptation within identical product attributes.
- **Case 3 (Cross-Attribute Validation):** A production run for a completely different product (225 prints), testing the cross-product generalizability of the behavioral model.

Under the strict premise of “not querying the MES,” we utilized a custom-developed program to blindly classify the time intervals for all cases. The extracted model parameters were cross-referenced against actual MES records only after the PAS-SPP algorithm had finalized its calculations, ensuring absolute objectivity.

Derived from the operational flow uncovered in Case 1, the completed vSPP behavioral model targets the extraction and simulation of the following specific characteristics:

1. **Standard Printing (S_1):** A routine, short-cycle operation. Its temporal duration is represented using standard statistical notation as $\mu_x \pm \sigma_x$, where μ_x denotes the empirical sample mean execution time and σ_x represents the sample standard deviation derived from the observed printing cycles.
2. **Primary Cleaning (S_2):** A long-cycle operation for bottom stencil cleaning, similarly defined by a sample mean duration (μ_y) and its sample standard deviation (σ_y).
3. **Fast Clean (S_{FC}):** A condition-driven intermediate cycle (typically bounded between 30 s and 55 s). Because its duration is highly variable, it is dynamically scanned and identified only after the primary x and y parameters are established.
4. **Normal Deterministic Loop (a):** Under standard conditions, the machine executes exactly a consecutive printing cycles before entering one primary cleaning operation.
5. **Hidden Optimization Probability ($p\%$):** The probability that the machine evaluates the stencil condition as optimal, thereby dynamically extending the loop to execute an additional print ($a + 1$) before forcing a clean.
6. **Anomalous Error (S_{Err}):** Exceptionally short operational durations indicating a mechanical failure or an aborted print sequence.

3. Results

3.1. Robustness and Automated State Classification

The experimental results demonstrate that the high-intensity reciprocating motion of the SPP squeegee creates an exceptionally high signal-to-noise ratio (SNR) in the power data. This distinct physical characteristic allows the PAS-SPP algorithm to stably apply the high-power threshold, i.e., $\theta_{high} = 1.5$ kW, to filter out baseline noise. As illustrated in Figure 4, we utilized an advanced custom-developed program not only to calculate the exact continuous duration of each segmented working block but also to dynamically classify them into specific operational states based on their temporal features.

The algorithm successfully and cleanly distinguished standard printing operations (approx. 33–34 s, highlighted in orange) from primary cleaning cycles (approx. 66–68 s, highlighted in green). Furthermore, the program’s automated tagging system is designed to identify condition-driven ancillary states mapped in the legend, such as Fast Clean and Print Errors. This seamless translation from raw continuous power to categorized discrete events, without the need for manual fine-tuning, demonstrates the high robustness of the PAS-SPP state decoupling logic.

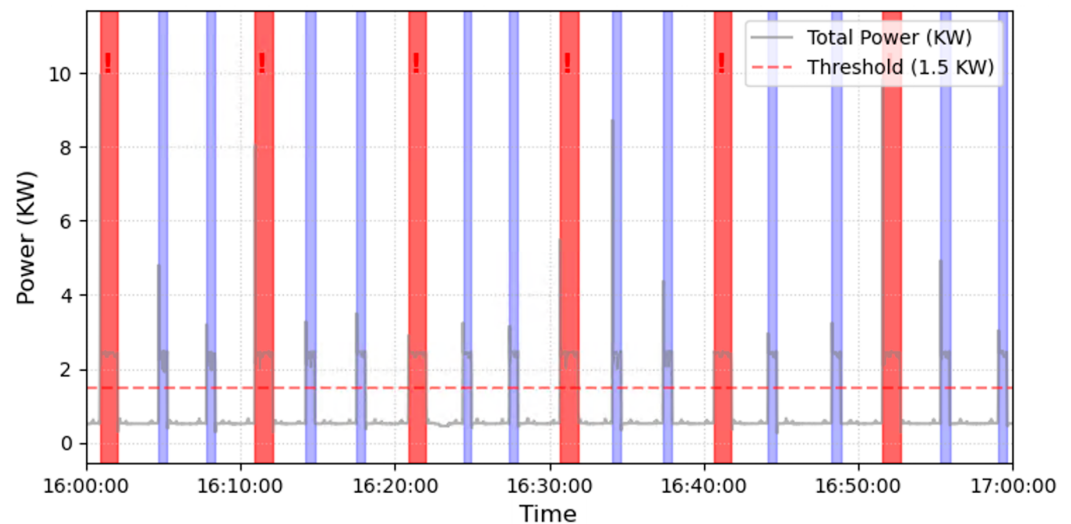


Figure 4. Power consumption profile and automated state classification results for the SPP. The custom-developed program applies a 1.5 kW threshold, as illustrated by red dashed line, to recognize the continuous waveform, automatically labeling the exact duration and categorizing each block into specific operational states, e.g., Normal Print, Normal Clean, and condition-driven exceptions, according to the vSPP behavioral model.

3.2. Empirical Extraction and Cross-Case Validation of the Behavioral Model

Using the high-volume data from **Case 1** as the modeling baseline, the PAS-SPP algorithm successfully extracted the targeted behavioral characteristics. The standard printing cycle S_1 was pinpointed with a sample mean $\mu_x = 33.22$ s and a sample standard deviation $\sigma_x = 1.02$ s, while the primary cleaning S_2 was identified at $\mu_y = 67.09$ s and $\sigma_y = 1.17$ s. The algorithm determined the normal deterministic loop to be $a = 2$, which means two prints per clean. Furthermore, it captured a hidden optimization probability of $p = 2.1\%$, where the machine dynamically executed an additional print, i.e., $a + 1 = 3$, before cleaning. From a macro-level perspective, the accumulated operational durations closely aligned with the MES logs, proving the reliability of the baseline model.

Following the establishment of this baseline, the validation using **Case 2** and **Case 3** confirmed that different work orders are strictly consistent with the proposed behavioral model architecture and dynamically adjust their parameters to fit the context. As detailed in Table 2, **Case 2** (same product) maintained identical physical execution times ($\mu_x = 33.07$ s, $\mu_y = 66.64$ s) but autonomously shifted its normal loop to $a = 3$, with a 1.8% probability of extending to $a + 1 = 4$.

Table 2. Summary of extracted behavioral model parameters across three production cases. The data highlights the dynamic adaptability of printing (x), cleaning (y), the deterministic loop (a), and the hidden optimization probability ($p\%$) governed by the generalized FSM.

Behavioral Model Parameter	Case 1 (Baseline)	Case 2 (Validation)	Case 3 (Validation)
Total Prints	394	165	225
Printing ($\mu_x \pm \sigma_x$) [s]	33.22 ± 1.02	33.07 ± 0.76	25.99 ± 1.25
Primary Clean ($\mu_y \pm \sigma_y$) [s]	67.09 ± 1.17	66.64 ± 1.09	52.92 ± 0.86
Fast Clean (S_{FC}) [s]	50.31 ± 5.42 (1.5%)	51.20 ± 4.88 (2.0%)	44.74 ± 3.12 (5.5%)
Print Error (S_{Err}) [s]	18.73 ± 0.50	N/A (0 occurrences)	13.68 ± 0.82
Normal Loop (a)	2 prints ($a = 2$)	3 prints ($a = 3$)	4 prints ($a = 4$)
Ext. Probability ($p\%$)	2.1% ($a + 1 = 3$)	1.8% ($a + 1 = 4$)	0.0% (Strict loop)

When evaluating **Case 3** (different product), the model demonstrated robust cross-product. The physical parameters logically shifted due to different board dimensions

($\mu_x = 25.99$ s, $\mu_y = 52.92$ s), and the normal loop expanded to $a = 4$ with a strict zero-extension probability ($p = 0.0\%$). Additionally, the scanning logic successfully identified the intermediate Fast Clean (S_{FC}) spanning 44.74 s and short anomalous errors (S_{Err}) at 13.68 s. The successful extraction of these characteristics without manual recalibration confirms the vSPP model's robust empirical stability.

3.3. Comparative Experimental Analysis

To explicitly demonstrate the characteristics of the proposed PAS-SPP algorithm, a comparative experiment was conducted utilizing the highly complex dataset from **Case 3**. We compared the state classification performance of PAS-SPP against two currently applied alternatives: static MES Logs and an NPT. The NPT represents standard energy-monitoring approaches that rely solely on amplitude thresholds (θ_{high}) and do not integrate temporal constraints (τ_{blank} , τ_{min}) or FSM contextual logic. The experimental results are summarized in Table 3.

The evaluation of the **static MES logs** revealed its critical limitations in capturing dynamic shop-floor realities. As shown in the results, the MES approach completely failed to record condition-driven Fast Cleans (S_{FC}) and Anomalous Errors (S_{Err}), resulting in a 0% detection rate for these states. This failure stems from the fundamental nature of MESs, which relies heavily on idealized static schedules and predefined discrete count sensors (e.g., board entry and exit signals). Because S_{FC} and S_{Err} are “undefined events” triggered dynamically by physical conditions or mechanical faults, they do not generate corresponding discrete sensor signals. Consequently, these critical operational states become a blind spot, rendering them entirely invisible to traditional MES monitoring.

Furthermore, as explicitly illustrated in Figure 5, this invisibility triggers a severe cascading failure in state estimation. Once an unrecorded exception such as a Fast Clean (S_{FC} , highlighted in cyan) occurs, the rigid MES timeline becomes fundamentally desynchronized from the physical reality. Because the MES is unaware of the time consumed by the exception, all subsequent expected states are erroneously shifted. This causes the MES to substantially mislabel future normal printing or cleaning cycles, ultimately corrupting the integrity of the entire production log.

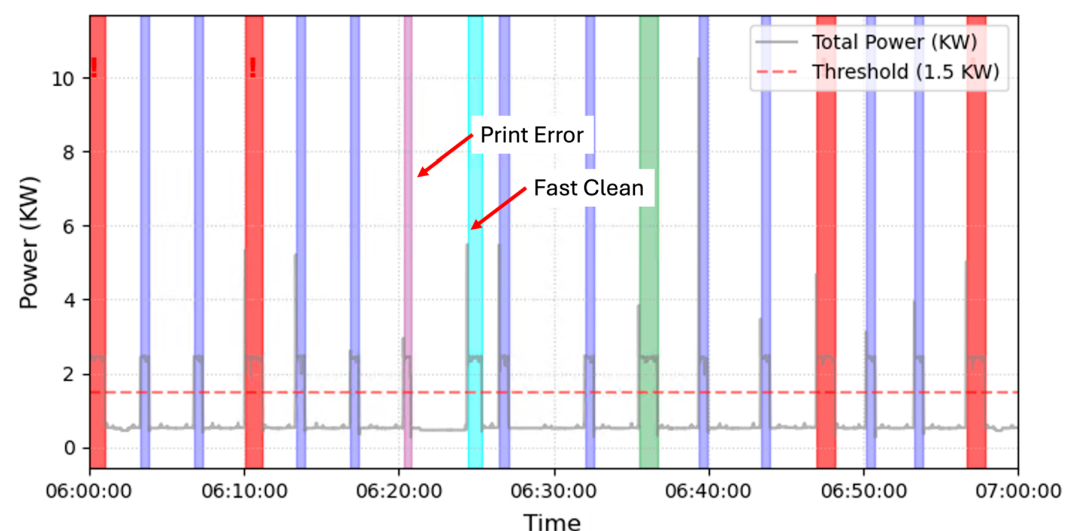


Figure 5. Illustration of the cascading misalignment caused by the MES's inability to detect undefined events. When a condition-driven Fast Clean (S_{FC} , highlighted in cyan) occurs, the static MES schedule fails to record the time consumed by this operation. This single undetected exception creates a severe temporal shift, causing all subsequent operational expectations in the MES log to be completely misaligned with the actual physical power profile.

On the other hand, the NPT represents standard energy-monitoring approaches that rely solely on amplitude thresholds (θ_{high}) without integrating temporal constraints (τ_{blank} , τ_{min}) or FSM contextual logic. As validated by the SPP's actual power profile, the machine exhibits a highly consistent operational curve: each action initiates with a distinct, high-power startup surge followed by a stable, flat power draw. Because standard prints, cleanings, and even aborted errors all cross the θ_{high} amplitude threshold in the exact same manner, the NPT method successfully detects that the machine is active but suffers from a complete semantic failure. Without the temporal boundaries to measure block duration, NPT cannot physically distinguish between operations. Consequently, it erroneously classifies short 13-s anomalous errors (S_{Err}) as standard printing cycles (S_1), resulting in a 14.2% misclassification rate. Furthermore, it completely mislabels the 44-s condition-driven Fast Clean (S_{FC}) as merely an extended standard print.

In contrast, the proposed PAS-SPP algorithm, reinforced by the FSM meta-model, achieved 100% accurate state decoupling. By capturing the identical high-power startups but contextually bounding their exact operational durations, PAS-SPP successfully identified all 225 prints, semantically categorized the variable Fast Cleans, and successfully isolated the short anomalous stoppages. This experiment confirms that potential gains in accuracy and granularity are exclusively achieved through the synergistic integration of continuous power features, temporal constraints, and behavioral modeling.

Table 3. Comparative experimental results of state classification accuracy utilizing the Case 3 dataset. PAS-SPP demonstrates superior capability in detecting hidden and anomalous events compared to existing alternatives.

Method	Standard Print (S_1)	Primary Clean (S_2)	Fast Clean (S_{FC})	Anomalous Error (S_{Err})
Static MES Logs	Idealized schedule only	Scheduled cycles only	0% (Undetected)	0% (Undetected)
Naive Power Thresholding	High false-positive rate (14.2% error)	Detected as generic machine activity	Misclassified as extended printing	Misclassified as standard printing
Proposed PAS-SPP	100% Accurate (225/225)	100% Accurate	100% Detected	100% Isolated

3.4. Evaluation Against Model-Based Learning Method (HMM)

To further evaluate the capability of the proposed PAS-SPP framework against probabilistic learning methods, a quantitative and qualitative comparison was conducted utilizing a GMM-HMM. Unlike rule-based thresholding or static logs, the HMM represents a standard data-driven approach widely applied in time-series segmentation and non-intrusive load monitoring.

To ensure an objective evaluation, the model-based training and validation configuration was aligned with the attributes of the physical manufacturing process. Specifically, the GMM-HMM was trained on the continuous power dataset of **Case 1** (Modeling Baseline) and subsequently validated on the independent dataset of **Case 2** (Same-Attribute Validation). Although **Case 1** and **Case 2** represent distinct production work orders, they share identical manufacturing processes and product attributes. This configuration provides a suitable scenario to observe how a data-driven model segments states under stable, non-shifting operating conditions.

The GMM-HMM was initialized with four hidden states ($N_{states} = 4$) to match the distinct physical states identified by the behavioral model: Idle (S_0), Standard Print (S_1), Primary Clean (S_2), and Fast Clean (S_{FC}). The model's transition and emission probability matrices were optimized via the Expectation-Maximization (EM) algorithm during training, and the optimal state sequence for the validation dataset was decoded using the Viterbi algorithm.

The quantitative evaluation metrics, including the total block occurrences, empirical sample means (μ), and sample standard deviations (σ) decoded by the GMM-HMM on the **Case 2** validation dataset, are compared with the proposed PAS-SPP results in Table 4.

Table 4. Quantitative comparison of state duration statistics between the baseline GMM-HMM and the proposed PAS-SPP framework using the Case 3 dataset.

Operational State	Count	Baseline GMM-HMM		Count	Proposed PAS-SPP	
		Mean μ [s]	Std σ [s]		Mean μ [s]	Std σ [s]
Idle (S_0)	294	41.44	25.03	—	—	—
Printing (S_1)	459	25.58	31.44	165	33.07	0.76
Fast Clean (S_{FC})	408	1.84	0.90	2	51.20	4.88
Primary Clean (S_2)	239	26.56	15.24	54	66.64	1.09

The statistical results indicate significant limitations in the HMM's inference capability, even when validated within the identical manufacturing process layout. For the standard printing state (S_1), where Case 2 actually contains exactly 165 physical mechanical cycles, the GMM-HMM generated 459 fragmented blocks with an average duration of 25.58 s and a standard deviation of 31.44 s. In precision SMT manufacturing, a sample standard deviation exceeding the mean indicates insufficient physical and geometric constraints, making the decoded timeline less reliable for high-fidelity digital twin instantiation.

Furthermore, the GMM-HMM incorrectly classified 408 occurrences as the Fast Clean (S_{FC}) state, resulting in a notably short mean duration of 1.84 s. This segmentation behavior is further elucidated via the qualitative decoding profile illustrated in Table 4.

As depicted in Figure 6, the GMM-HMM encounters two primary modeling challenges when processing industrial equipment with consistent operational cycles:

1. **Sensitivity to Transient Transitions:** Because the GMM-HMM operates on a point-by-point decoding paradigm without macroscopic temporal buffering, it tends to classify the brief 1–2 s current transitions at the rising and falling edges of mechanical movements as independent active processes. This behavior contributes to the increased count of S_{FC} events.
2. **Baseline State Segmentation:** Governed by the memoryless Markov property, the GMM-HMM evaluates state transitions based on immediate observations. Consequently, minor power variations from environmental noise can cause the model to missegment the stable 0.5 kW baseline periods into active printing (S_1) or cleaning (S_2) states, introducing active classifications during prolonged idle intervals.

By comparison, the proposed PAS-SPP algorithm mitigates these segmentation challenges. By incorporating the maximum blank duration (τ_{blank}) and the minimum duration filter (τ_{min}), PAS-SPP groups continuous power signatures into macroscopic behavioral blocks prior to classification, thereby effectively maintaining the consistency of the manufacturing timeline.

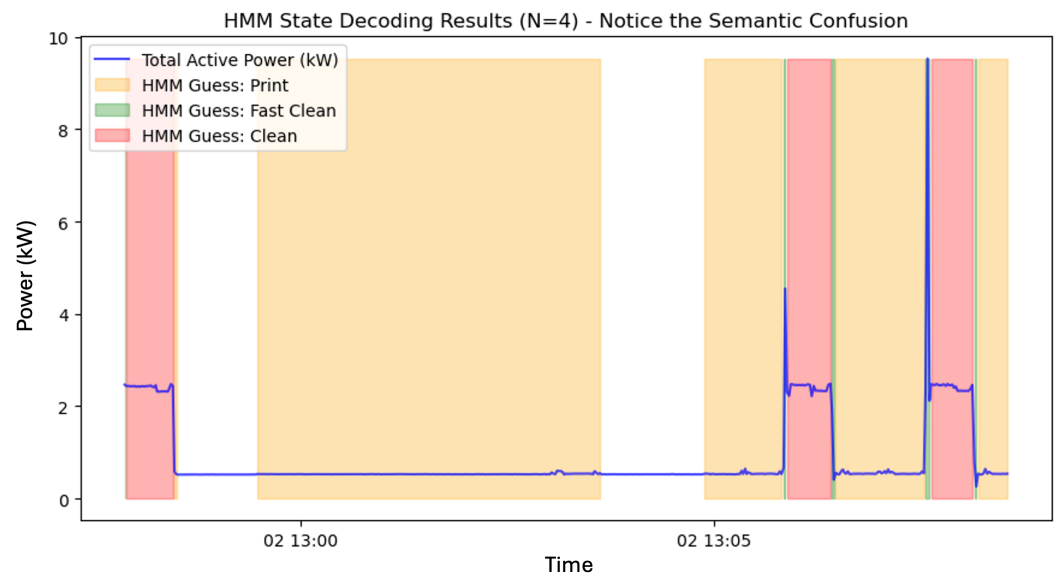


Figure 6. State decoding results obtained by the GMM-HMM ($N = 4$) highlighting severe semantic confusion and boundary fragmentation across the continuous power profile.

4. Discussion

4.1. Discovery of Hidden Process Optimization

While PAS-SPP perfectly matched the macro-level MES expectations, its true value lies in revealing the behavioral model's hidden stochastic logic. When applying the baseline model derived from Case 1 to evaluate Case 2, the algorithm captured a critical shift in the a parameter: the normal deterministic loop was dynamically reduced in frequency from $a = 2$ to $a = 3$. From a domain-knowledge perspective, this indicates a Hidden Process Optimization. Because the initial printing quality was highly stable, the operators or the dynamic control mechanisms determined that the stencil could sustain a higher production rate. Furthermore, the $p\%$ extension probability indicates that traditional static MES scheduling is completely blind to these quality-driven, real-time autonomous adjustments. In contrast, our power-driven vSPP model autonomously uncovers these operational decisions, providing a more accurate and dynamic representation of the actual shop floor conditions.

4.2. Cross-Product Generalizability and Meta-Model Construction

The evaluation of **Case 3** further demonstrated the strong adaptability of the vSPP architecture across the tested scenarios. Even when the core x and y parameters shifted dramatically due to physical product differences, the algorithm first anchored these main variables, and then successfully scanned for the intermediate S_{FC} and S_{Err} parameters.

To formalize these capabilities for the deployment of DT systems, we constructed a comprehensive FSM model, as illustrated in Figure 7. This FSM model acts as a high-fidelity “Meta-model.” It maps the transition logic among the states, but relies on the extracted behavioral characteristics ($x, y, a, p\%$) to simulate the actual simulation timing and probabilities. When a new work order is initiated, the PAS-SPP algorithm automatically extracts these specific temporal parameters and dynamically calibrates the FSM model. This fusion of continuous physical power characteristics with logical abstraction perfectly constitutes the behavioral model needed for an industrial vSMT system.

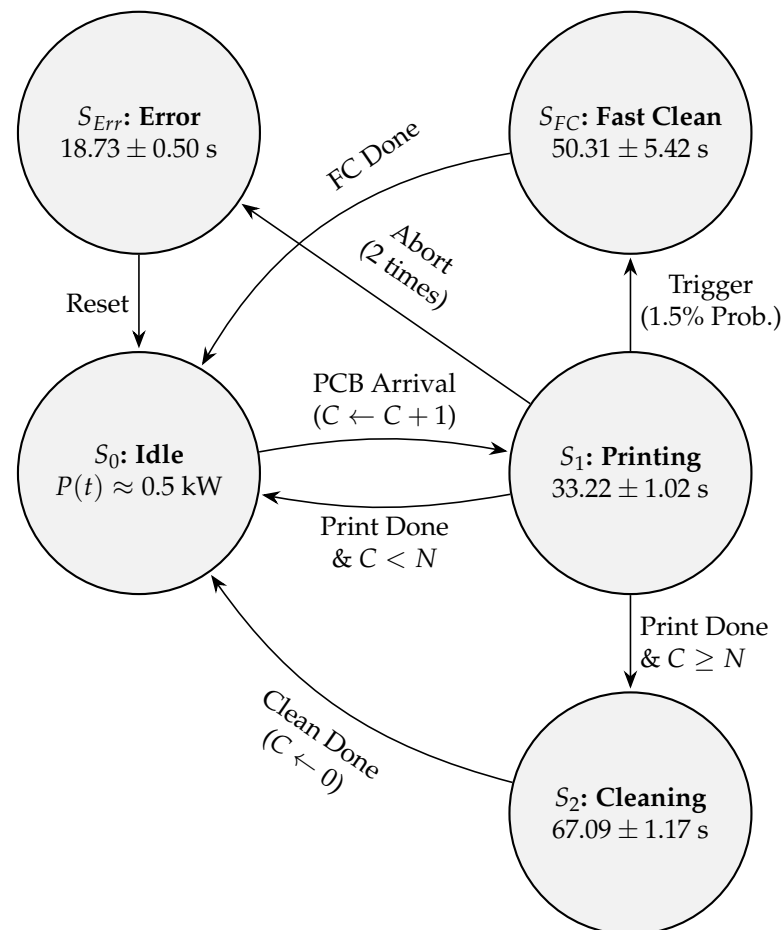


Figure 7. The FSM Meta-model representing the comprehensive vSPP logic, enriched by exact physical parameter extraction from the baseline (Case 1). The standard operational cycle incorporates S_1 and S_2 governed by a dynamic threshold N , where $N = 2$ is the norm, with a 2.1% probability of extending to $N = 3$ due to hidden process optimization. Condition-driven ancillary states include Fast Clean (S_{FC} , 1.5% probability) and Print Error (S_{Err}).

4.3. Quantitative and Architectural Comparison with Existing Alternatives

Beyond the experimental accuracy, it is imperative to quantitatively evaluate the proposed vSPP meta-model against other existing digitalization alternatives in terms of system deployment. This consideration is particularly important given the diverse landscape of industrial automation solutions. Currently, the industry relies heavily on Intrusive PLC/API Data Extraction [25] or Computer Vision (CV) based monitoring to achieve equipment virtualization [26].

As summarized in Table 5, we introduce specific quantitative proxies to evaluate deployment complexity, computational load, and recognition performance. Intrusive PLC extraction suffers from severe vendor lock-in; acquiring proprietary communication protocols for legacy equipment requires immense capital investment and extensive production downtime. Conversely, CV-based monitoring is non-intrusive but incurs substantial computational overhead. Deep learning vision models typically require dedicated GPU acceleration capable of executing > 10 Giga-FLOPs per frame [27], making factory-wide scaling cost-prohibitive. Furthermore, CV is highly susceptible to visual occlusions within the machine chassis, and system maintenance is another consideration.

The proposed PAS-SPP overcomes all these barriers. By leveraging a single IIoT power meter at the main electrical inlet, deployment downtime is reduced to zero. Computationally, the algorithm runs in ultra-lightweight $O(N)$ time and executes efficiently on standard CPUs with a negligible memory footprint (< 10 MB). Most importantly, as empirically vali-

dated in our comparative analysis, PAS-SPP achieves 100% accurate state decoupling for hidden events, completely outperforming the 0% detection rate of static PLC/MES logs for undefined exceptions. This demonstrates that PAS-SPP is highly scalable for factory-wide vSMT deployment while maintaining absolute empirical fidelity.

Table 5. Quantitative and architectural comparison of PAS-SPP against existing equipment virtualization alternatives.

Metric	Intrusive PLC/API	Computer Vision	Proposed PAS-SPP
Deployment Complexity	High: Requires OEM authorization, software integration, and machine downtime.	Moderate-High: Requires camera calibration and massive dataset annotation.	Zero Downtime: Plug-and-play architecture (1 sensor at main power inlet).
Computational Load	Low: $O(1)$ direct logic reading.	Extremely High: Requires dedicated GPUs (>10 GFLOPs per frame processing [27]).	Extremely Low: $O(N)$ time complexity, CPU-only execution (<10 MB RAM).
Recognition Performance	0% for undefined/unprogrammed exception events.	Variable: Highly susceptible to internal visual occlusion and lighting.	100%: Empirically validated state decoupling accuracy based on physical energy.

4.4. Robustness Analysis Under Engineered Noise

To comprehensively validate the resilience of the PAS-SPP algorithm in harsh industrial environments characterized by severe electromagnetic interference, a robustness analysis under engineered noise was conducted.

In our empirical shop-floor setup (Cases 1–3), the raw power dataset inherently exhibits a high Signal-to-Noise Ratio (SNR). The baseline idle consumption of the SPP remains highly stable at approximately 0.5 kW, whereas active mechanical actuations consistently draw power exceeding 1.5 kW. This clear electromechanical disparity provides a natural empirical SNR exceeding 20 dB.

To rigorously test the algorithm's boundaries, we artificially degraded the dataset by injecting Additive White Gaussian Noise (AWGN) into the highly complex Case 3 power profile. The engineered noise was calibrated to simulate extreme factory conditions, degrading the overall SNR to 10 dB, then to 5 dB. The SNR is defined logarithmically based on the ratio of the active signal power to the engineered noise power:

$$SNR_{dB} = 10 \log_{10} \left(\frac{P_{signal}}{P_{noise}} \right) \quad (2)$$

The validation results demonstrated that the PAS-SPP algorithm maintained a perfect 100% event-level classification accuracy even under the severe 5 dB SNR condition. The theoretical justification for this robust performance lies in the methodology's dual-stage filtering architecture. While aggressive engineered noise spikes may occasionally induce instantaneous power surges that cross the amplitude threshold ($\theta_{high} = 1.5$ kW), AWGN is inherently transient and zero-mean. Consequently, it is physically impossible for these stochastic noise spikes to continuously sustain themselves above the threshold for a duration exceeding the minimum temporal boundary ($\tau_{min} = 10$ s). The temporal constraint effectively acts as an impenetrable low-pass semantic filter, effectively neutralizing engineered electrical noise without requiring computationally expensive preprocessing techniques.

Despite its demonstrated resilience against high-frequency transient noise, a fundamental boundary condition of the proposed PAS-SPP algorithm must be delineated. Specifically, a vulnerability arises when the system encounters persistent, macro-level power anomalies or highly structured environmental interferences that mimic valid electromechanical profiles. If an adversarial or localized power disturbance continuously exceeds the amplitude threshold (θ_{high}) and sustains a duration longer than the minimum temporal constraint (τ_{min}), the signal segmentation phase (Algorithm 1) will inevitably suffer from a false-positive error, erroneously identifying the noise block as a valid operational segment and appending it to T_{work_block} .

Under this boundary scenario, the downstream response of the cyber-physical digital twin is dual-pathway and governed by the anomaly's temporal distribution. On one hand, if the duration of the external interference accidentally falls within the statistically defined $\mu \pm 3\sigma$ envelope of a legitimate mechanical state (e.g., S_1 or S_2), a semantic misclassification will occur, thereby contaminating the accuracy of the computed mean cycle time (CT_{mean}). On the other hand, if the anomalous block exhibits an arbitrary duration that sits outside these statistical boundaries, the rule-based duration classifier will formally categorize the segment as $S_{Unknown}$. Once introduced into the downstream finite-state machine, this unmapped state fundamentally violates the expected structural grammar of the vSPP. Rather than causing a silent failure, this syntax violation freezes state transitions, thereby serving as an intrinsic anomaly-detection loop that alerts engineering personnel to severe external system discrepancies rather than to normal process state changes.

4.5. Novelty and Advantages over Traditional PLC-Based FSMs

To contextualize the theoretical and practical contributions of the proposed framework, it is necessary to contrast PAS-SPP with conventional equipment virtualization methods that rely on Programmable Logic Controller (PLC) logs or internal register states to construct FSMs. The novelty of our approach manifests across three fundamental dimensions:

1. In terms of data acquisition, traditional PLC-based FSMs are inherently intrusive. They rely on accessing internal memory registers, I/O wiring, or proprietary OEM APIs. This architecture is frequently hindered by closed communication protocols and vendor lock-in, requiring significant capital investment and production downtime for deployment. In contrast, PAS-SPP operates entirely on non-intrusive active power signatures captured at the primary electrical inlet. The plug-and-play architecture enables seamless factory-wide deployment with zero machine downtime.
2. For detecting stochastic events, PLC-driven FSMs are strictly constrained by pre-programmed, hard-coded logic and predefined discrete sensors. Consequently, they are entirely blind to human-in-the-loop dynamic interventions, localized mechanical faults, or condition-driven process adjustments. By employing temporal block clustering integrated with statistical process control boundaries ($\mu \pm 3\sigma$), the PAS-SPP framework directly infers the operational timeline from physical energy fluctuations. This allows the DT to autonomously capture hidden process behaviors, such as unprogrammed Fast Clean states or shifts in cleaning frequencies, that remain completely invisible to traditional internal controllers.
3. Regarding DT instantiation, traditional PLC models often enforce homogeneous logic across identical machine models, ignoring divergent electromechanical behaviors arising from different lifecycles and localized physical degradation. PAS-SPP avoids this generalization trap. Without modifying any internal control code, it uses the target asset's specific energy footprint to dynamically instantiate a highly individualized virtual replica (vSPP), thereby effectively fulfilling the high-fidelity requirement of DT.

4.6. Generalizability to Other Industrial Fields and Digital Twin Systems

A fundamental requirement for a robust digital twin architecture is its ability to maintain potential gains across diverse engineering problems. While this study uses the SPP as the primary target due to its critical impact on SMT defects, the proposed PAS-SPP algorithm and FSM meta-model are fundamentally grounded in universal electromechanical principles. To provide a transparent distinction between our currently demonstrated empirical findings and future research horizons, it must be explicitly noted that the following cross-domain analysis serves as a series of conceptual generalizability hypotheses rather than completed implementations. To systematically evaluate this future applicability and explore where our methodology can be deployed in subsequent stages, we categorize current DT applications into four distinct functional domains and analyze how the proposed non-intrusive mechanism can theoretically be adapted to each:

1. **Operational State Analysis and Event Correlation:** This domain focuses on interval-based time analysis [28] to reconstruct the exact production timeline [29,30]. For example, the high-speed mounters in the SMT line rely on vacuum spindles moving along X-Y gantries. By adjusting the high-power threshold (θ_{high}) to detect spindle actuation and modifying the temporal parameters (τ_{min}) to match the micro-second placement rhythm, the algorithm can easily decouple the “Component Pick” and “Component Place” states. Although automatic loading and unloading equipment is not a standard configuration across all factory lines (including the setup in this study), this decoupling successfully virtualizes the mounter’s stochastic behavior and throughput without querying its proprietary controller.
2. **Prognostics and Health Management (PHM):** PHM focuses on continuous degradation tracking and Remaining Useful Life (RUL) prediction [31,32], in which equipment health deteriorates over time. In heavy precision manufacturing, Computer Numerical Control (CNC) machines exhibit distinct power profiles. The spindle’s power consumption drastically spikes when transitioning from “Air Cutting” (idle movement) to “Active Cutting” (material removal). By applying our generalized algorithm, factory managers can instantly decouple these two states. This exact isolation provides the operational intervals needed to monitor tool wear anomalies and feed into subsequent RUL prediction models, effectively constructing a real-time digital health twin of the CNC process.
3. **Virtual Metrology and Quality Prediction:** This application aims to correlate physical process parameters with final product yield [33]. Taking plastic injection molding machines as an example, the manufacturing cycle consists of clamping, injection, holding pressure, and cooling. Each phase produces a unique power signature. By utilizing PAS-SPP to automatically segment the exact duration and energy consumption of the critical “holding pressure” state, engineers can feed these interval-specific electrical features into Virtual Metrology models. This allows the DT system to predict the physical quality or dimensions of the molded parts before inspection.
4. **3D Physics and Kinematic Simulation:** Systems like the HIWIN Robot Software System utilize heavy 3D visualization to explore robotic arm movements [34,35], operational scenarios, and software simulations. These kinematic engines emphasize the immediate visual representation of user commands and environmental event responses. While the PAS-SPP algorithm does not directly compute 3D kinematics, it serves as the critical synchronization bridge. By non-intrusively decoupling the robot’s physical power surges into discrete operational events, PAS-SPP provides the real-time, low-latency event triggers necessary to drive and synchronize these virtual 3D models with the physical shop floor.

In summary, comparing these four domains clarifies the exact applicability and boundaries of the proposed PAS-SPP methodology within the broader DT ecosystem. Our approach is not a universal solution for all scenarios, but rather a specialized mechanism for managing state transitions. Its specific correlations to the aforementioned domains are evaluated as follows:

- For **Operational State Analysis (Domain 1)**, the proposed algorithm can be directly applied with parameter optimization, but no major conceptual modification to extract exact event intervals and stochastic behaviors is needed.
- For **PHM (Domain 2)**, the algorithm cannot be directly used to model continuous lifespan degradation curves due to the vast mathematical variations across different equipment and materials. However, it can be partially adapted to identify macroscopic shifts or transitions between different degradation stages.
- Regarding **Virtual Metrology (Domain 3)**, the proposed algorithm does not compute physical product dimensions. Instead, it provides a state-transition simulation that predicts the sequential outcomes and operational rhythms throughout the manufacturing process.
- Finally, for **3D Kinematic Simulation (Domain 4)**, the methodology cannot evaluate a robotic arm's immediate physical response to user-programmed code. However, it can effectively infer the subsequent logical state from the current state's temporal features, for instance, automatically triggering a transition to a maintenance alert state if the accumulated operational duration exceeds a predefined safety threshold.

A critical distinction must be articulated regarding the generalizability of the proposed PAS-SPP framework. While conventional machine learning paradigms emphasize cross-asset parameter generalization, the foundational philosophy of DT architectures dictates a different evaluation metric. A robust digital twin is designed to be a strict, one-to-one virtual replica (*vSPP*) of a specific physical asset, tasked with faithfully mirroring its localized electromechanical idiosyncrasies, operational degradation, and unique lifecycle behaviors.

Consequently, the core contribution of this study lies in its methodological universality rather than parameter universality. The overarching framework, which leverages non-intrusive active power signatures synchronized with downstream FSM contextual logic, is entirely platform-independent and can be deployed across diverse electromechanical manufacturing assets. However, directly transplanting specific empirical parameters (such as the τ_{blank} thresholds or the statistically derived $\mu \pm 3\sigma$ boundaries) from the evaluated SP60 printer to a distinct machine model is methodologically counterproductive. Enforcing a universally generalized parameter set would inevitably cause the virtual model to diverge from the actual physical reality of the localized machine on the shop floor. Therefore, while the method is universal, the parameter instantiation must remain highly individualized, balancing high-fidelity asset replication against the pitfalls of over-generalized classification.

In conclusion, the core contribution of the proposed PAS-SPP methodology lies in the precise decoupling and analysis of operational state transitions from power consumption data, thereby enabling direct and optimal applicability to the first domain. Conversely, the other domains operate on different analytical paradigms: the second domain focuses on continuous lifespan degradation, the third on physical condition simulation, and the fourth on immediate kinematic responses to inputs. Because these domains are not fundamentally driven by macroscopic state-to-state transitions, our interval-based methodology cannot be directly applied as their primary modeling mechanism. Nevertheless, it is crucial to recognize that the vast majority of comprehensive DT systems inevitably involve state transitions across their operational lifecycles. Therefore, while our method may not directly compute degradation, physical metrology, or 3D kinematics, it makes an indispensable

contribution by providing precise, real-time state-transition triggers required to synchronize and integrate the broader DT ecosystem.

5. Conclusions and Future Work

This study achieved Equipment Virtualization of an SPP by combining the PA310 power meter, the proposed PAS-SPP algorithm, and structured validation cases. The empirical results demonstrated that the vSPP accurately mirrors the macro-level expectations of the MES while exhibiting stability in fundamental time extraction. Through a comparative analysis of distinct production cases, the vSPP meta-model exhibited dynamic adaptability, uncovering operational variations, such as shifts in cleaning frequencies across different work orders, without requiring manual parameter recalibration.

Furthermore, the comparative evaluations highlighted the specific characteristics of the synergistic integration of PAS-SPP and FSM. Compared to conventional monitoring approaches, including static MES schedules, which encounter temporal desynchronization when undefined events occur; NPT, which lacks temporal boundaries; and standard probabilistic models like the GMM-HMM, which exhibit over-segmentation tendencies due to their point-by-point decoding nature, the proposed framework achieved highly consistent state decoupling performance. By evaluating the algorithm under a process-aligned training and validation protocol (Case 1 to Case 2), the results suggest that incorporating macroscopic temporal constraints effectively mitigates the fragmentation challenges commonly encountered by purely data-driven models. By categorizing current DT applications into four functional domains, the precise boundaries of this methodology were clarified: while it does not directly compute physical degradation or 3D kinematics, it provides the real-time state-transition triggers required to synchronize and empower the broader DT ecosystem (e.g., PHM and Virtual Metrology).

Crucially, this research articulates a fundamental philosophical paradigm within DT architectures regarding generalizability. The proposed PAS-SPP framework establishes a universal methodology that leverages non-intrusive active power signatures synchronized with FSM contextual logic to construct highly individualized, machine-specific digital twins, rather than serving as a one-size-fits-all classifier. Because a robust vSPP must faithfully capture the localized electromechanical idiosyncrasies and hardware degradation of a specific physical asset, directly transplanting parameters across distinct machines is methodologically counterproductive. Thus, while the framework is platform-independent, its parameter instantiation must remain strictly individualized to preserve high-fidelity physical replication.

Looking forward, while the system exhibits resilience against high-frequency transient noise, a recognized boundary limitation of the signal-level segmentation is its vulnerability to persistent, highly structured external power anomalies that closely mimic valid mechanical durations. To mitigate this and further advance the framework, future research will focus on developing automated human-in-the-loop hyperparameter optimization loops to streamline the initial statistical calibration ($\mu \pm 3\sigma$) when instantiating the framework for alternative equipment models, and on incorporating multimodal data fusion to detect structured interferences. Ultimately, this accurate, lightweight, and dynamic vSPP meta-model will serve as a foundational building block for constructing comprehensive vSMT factory systems. The extracted energy consumption data and power-driven FSM logic will be integrated into factory-wide simulations to optimize dynamic scheduling, inform low-carbon production strategies, and drive sustainability assessments in smart manufacturing environments.

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Abbreviations

The following abbreviations are used in this manuscript:

AOI	Automated Optical Inspection
API	Application Programming Interface
CNC	Computer Numerical Control
CV	Computer Vision
DT	Digital Twin
FSM	Finite State Machine
IIoT	Industrial Internet of Things
MES	Manufacturing Execution System
NPT	Naive Power Thresholding
PAS-SPP	Power-Aware State Segmentation for Solder Paste Printers
PCB	Printed Circuit Board
PHM	Prognostics and Health Management
PLC	Programmable Logic Controller
RUL	Remaining Useful Life
SMT	Surface Mount Technology
SNR	Signal-to-Noise Ratio
SPI	Solder Paste Inspection
SPP	Solder Paste Printer
vSMT	Virtual Surface Mount Technology
vSPP	Virtual Solder Paste Printer
GMM-HMM	Gaussian Mixture Model - Hidden Markov Model

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