

Live Digital Twin for Shop Floor Monitoring

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Abstract—Modern manufacturing demands real-time visibility and data-driven decision-making to sustain competitive advantage. This paper presents a Live Digital Twin system developed for shop floor monitoring, leveraging Total Productive Maintenance (TPM) metrics stored in a Microsoft SQL Server Management Studio (MS SSMS) database. The proposed platform dynamically mirrors physical machine activity by ingesting live data and delivering real-time visibility into key performance indicators (KPIs) such as total parts produced, average cycle time, average load/unload time, and machine status (Active, Idle, or Stopped). The system architecture integrates physical machines with sensors, a network layer (Ethernet/Wi-Fi), a backend SQL server, and an interactive dashboard. Experimental results demonstrate that the Live Digital Twin significantly reduces response time to anomalies, improves Overall Equipment Effectiveness (OEE), and enhances preventive maintenance scheduling. The platform bridges the gap between shop floor operations and management oversight, enabling proactive, real-time intervention in manufacturing processes.

Index Terms—Digital Twin, Live Digital Twin, MS SQL Server, OEE, Shop Floor Monitoring, Total Productive Maintenance (TPM).

I. INTRODUCTION

The manufacturing sector is undergoing a profound transformation driven by Industry 4.0 technologies. The convergence of the Internet of Things (IoT), cloud computing, big data analytics, and cyber-physical systems has opened new avenues for intelligent monitoring and control of production environments. Among these, the concept of the Digital Twin has emerged as one of the most transformative paradigms,

enabling a virtual replica of physical assets that can be monitored, analyzed, and optimized in real time.

In traditional manufacturing environments, shop floor data is often fragmented, delayed, or siloed within isolated systems. Maintenance teams rely on periodic inspections and lagging indicators, which prevent timely identification of machine degradation or production bottlenecks. Total Productive Maintenance (TPM) provides a structured methodology to address these challenges by focusing on proactive and preventive maintenance strategies. However, realizing the full potential of TPM requires seamless access to real-time machine performance data.

This paper presents a Live Digital Twin (LDT) system designed for shop floor monitoring, integrating TPM metrics sourced from a Microsoft SQL Server Management Studio (MS SSMS) database. The proposed system continuously reads machine-level data including cycle time, load/unload time, parts produced, and machine status, and renders this information on an interactive dashboard. The result is a real-time, actionable view of shop floor operations that empowers maintenance managers and production supervisors to make data-driven decisions.

II. TOTAL PRODUCTIVE MAINTENANCE (TPM)

Total Productive Maintenance is a holistic approach to equipment maintenance that strives to achieve perfect production — no breakdowns, no small stops or slow running, no defects, and no accidents. Introduced by Seiichi Nakajima in Japan in the 1970s, TPM has evolved into a comprehensive management

philosophy widely adopted across discrete and process manufacturing industries worldwide [1].

A. Core Pillars of TPM

TPM is typically organized around eight foundational pillars: (1) Autonomous Maintenance, which transfers routine maintenance tasks to operators; (2) Planned Maintenance, which schedules maintenance activities based on predicted failure patterns; (3) Focused Improvement (Kaizen), which continuously eliminates losses; (4) Early Equipment Management, which incorporates maintainability in equipment design; (5) Quality Maintenance, which ensures zero defect production; (6) Training and Education, which builds competency in maintenance practices; (7) Safety, Health, and Environment; and (8) Administrative TPM, which extends TPM principles to office functions [2].

B. TPM Metrics and KPIs

The effectiveness of TPM programs is measured through several key performance indicators. Overall Equipment Effectiveness (OEE) is the primary metric, computed as the product of Availability, Performance, and Quality rates. Additional metrics include Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), total parts produced per shift, average cycle time per part, and machine idle time. These metrics are continuously collected through sensors and SCADA systems and stored in relational databases such as MS SQL Server for analysis and reporting [3].

C. Why TPM is Essential on Shop Floors

On shop floors where machines operate in multi-shift environments, unplanned downtime can cascade into significant production losses. TPM provides the analytical framework to identify the Six Big Losses — equipment failures, setup and adjustment time, idling and minor stops, reduced speed, process defects, and reduced yield — and systematically eliminate them. By continuously tracking cycle times, machine status, and load/unload times, TPM enables manufacturers to benchmark performance, set improvement targets, and sustain productivity gains over time [4].

III. DIGITAL TWIN: CONCEPT AND APPLICATIONS

A Digital Twin is a virtual model that accurately reflects a physical object, process, or system. The concept was first formally introduced by Michael Grieves at the University of Michigan in 2002 in the context of product lifecycle management. A Digital Twin consists of three principal components: the physical entity in the real world, the virtual entity in the digital world, and the data and information connection between the two [5].

A. Evolution of Digital Twins

Digital Twin technology has evolved through three distinct generations. The first generation, known as Digital Model, involves a static virtual replica with no automatic data exchange. The second generation, the Digital Shadow, involves a unidirectional flow of data from the physical entity to the virtual model. The third and most advanced generation, the Digital Twin proper, features bidirectional data flow, enabling the virtual model to influence the behavior of the physical entity in real time. This paper focuses on a Live Digital Twin that implements real-time data ingestion and visualization [6].

B. Applications in Manufacturing

Digital Twins have found widespread application in advanced manufacturing environments. They are used for predictive maintenance by simulating wear patterns and predicting component failures before they occur. In process optimization, Digital Twins allow engineers to test production parameters virtually without disrupting actual operations. In quality assurance, they enable defect root cause analysis through historical playback. In supply chain management, Digital Twins model end-to-end logistics to identify bottlenecks and optimize throughput [7].

C. Benefits of Digital Twin Technology

The adoption of Digital Twins in manufacturing delivers multiple tangible benefits. First, it reduces unplanned downtime by enabling predictive maintenance interventions. Second, it shortens product development cycles by enabling virtual prototyping. Third, it improves energy efficiency by identifying suboptimal operating modes. Fourth, it enhances

workforce safety by simulating hazardous scenarios without physical risk. Finally, it provides a persistent, comprehensive record of asset health and performance that supports data-driven decision-making at all levels of the organization [8].

IV. LIVE DIGITAL TWIN FOR SHOP FLOOR MONITORING

The proposed Live Digital Twin (LDT) system is purpose-built for continuous, real-time shop floor monitoring. Unlike conventional Digital Twins that may operate on batch data or periodic updates, the LDT presented here maintains a persistent, live connection to the factory floor through a well-defined data pipeline, enabling sub-minute latency between physical events and their digital reflection.

A. System Architecture

The system architecture consists of five interconnected layers, as illustrated in Fig. 1. The physical layer consists of CNC machines, hydraulic presses, assembly stations, and other production equipment. Each machine is instrumented with sensors that capture cycle start/end signals, load/unload durations, temperature readings, and operational status signals. The sensor data is transmitted over Ethernet or Wi-Fi to a centralized server running MS SQL Server Management Studio, where it is stored in a structured relational schema designed for high-frequency transactional writes. A middleware application layer continuously polls the SQL database and transforms raw records into aggregated KPIs. These KPIs are then pushed to the dashboard layer, which provides a real-time, graphical interface for operators and managers.

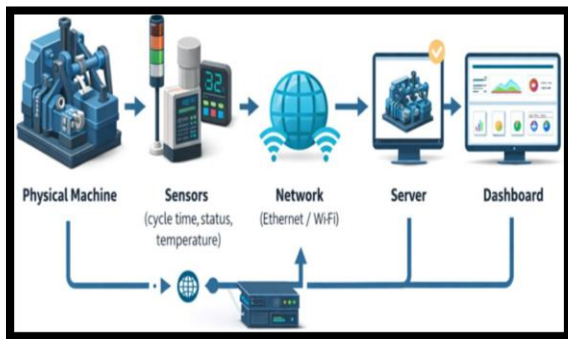


Fig. 1. Live Digital Twin System Architecture for Shop Floor Monitoring

B. Data Source: MS SQL Server Management Studio
Microsoft SQL Server Management Studio serves as the backbone data repository for the LDT system. Each machine on the shop floor is assigned a unique identifier in the database schema. The primary data tables include Machine Status, which records the current operational state (Active, Idle, or Stopped) with timestamps; CycleLog, which stores start and end times for each production cycle along with part count; and LoadUnloadLog, which captures the duration of manual handling operations for each part. Stored procedures and indexed views are used to pre-compute aggregated metrics, minimizing query latency during dashboard refresh cycles [9].

C. Key Performance Indicators

The Live Digital Twin platform delivers real-time visibility into the following key performance indicators:

Total Parts Produced: A running counter that aggregates the number of completed parts across all active machines during a specified shift or time window. This metric directly reflects production throughput and is updated after every completed cycle.
Average Cycle Time: Computed as the mean duration (in seconds) from cycle initiation to cycle completion across all production cycles within the monitoring window. Deviations from the standard cycle time trigger alerts for investigation.

Average Load/Unload Time: Measures the meantime operators spend loading raw material into and unloading finished parts from each machine. High load/unload times indicate ergonomic or workflow inefficiencies that reduce machine utilization.

Machine Status (Active, Idle, or Stopped): Each machine is assigned a real-time status based on sensor signals and cycle activity. Active indicates the machine is running a production cycle; Idle indicates the machine is powered on but not producing; Stopped indicates the machine is powered off or in a fault condition. The dashboard displays these statuses using color-coded indicators for rapid situational awareness.

V. FLOW CHART

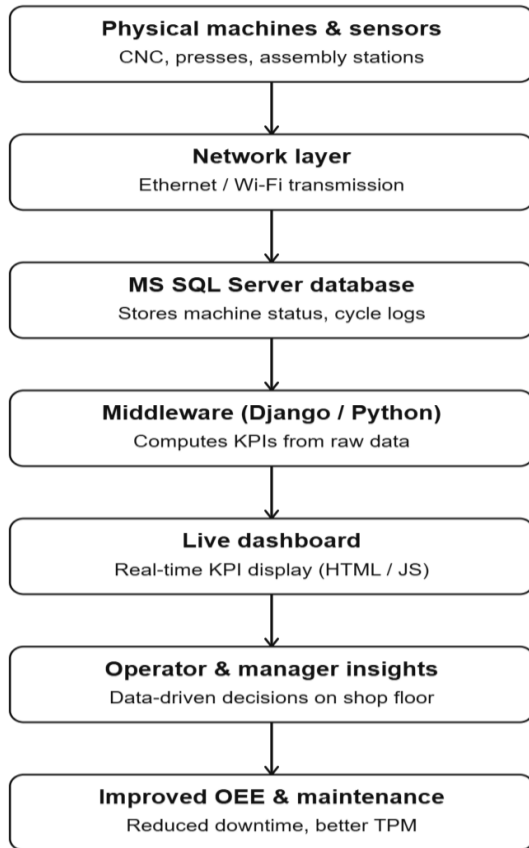


Fig. 2. Flow Chart

The proposed Live Digital Twin (LDT) system operates through a structured seven-stage pipeline that ensures seamless, real-time data flow from the physical shop floor to actionable management insights. At the foundation, physical machines such as CNC machines, hydraulic presses, and assembly stations are instrumented with sensors that continuously capture operational signals. This raw data is transmitted over a network layer via Ethernet or Wi-Fi to a centralized MS SQL Server database, which stores structured records including machine status, cycle logs, and load/unload durations. A middleware application built on the Django/Python framework then continuously polls the database to compute key performance indicators such as Overall Equipment Effectiveness (OEE), average cycle time, total parts produced, and average load/unload time. These computed KPIs are rendered on a live, interactive dashboard developed using HTML and JavaScript, providing operators and managers with

color-coded, real-time visibility into shop floor performance. This visibility empowers data-driven decision-making at all levels of the organization, ultimately resulting in improved OEE, reduced unplanned downtime, and more effective Total Productive Maintenance scheduling.

VI. IMPLEMENTATION AND RESULTS

The proposed system was implemented and validated at a precision component manufacturing unit in Bosch Limited Nashik, Maharashtra. The implementation was carried encompassing hardware sensor installation, database schema design, middleware development, and dashboard deployment.

A. Hardware and Software Stack

The system architecture integrates a robust physical layer with a sophisticated software backend to facilitate industrial monitoring. The hardware suite comprises TPM Track Devices and various sensors deployed on the shop floor, interconnected via high-speed Ethernet cables and supported by dedicated power supply units. This hardware infrastructure feeds data into a specialized software stack centered around the Python-based Django Web Framework. Data persistence and management are handled by an SQL database, while the front-end user interface is built using HTML and JavaScript to provide a dynamic, responsive dashboard for real-time monitoring.

B. Performance Metrics and Methodology

The performance of the system is validated through a rigorous six-stage methodology focusing on reliability and data integrity. Key performance metrics are evaluated during the "Test data transmission" and "Validate live monitoring" phases to ensure minimal latency and zero data loss. The operational success is measured against a Verification Checklist that scrutinizes physical and logical parameters, including the stability of the power supply, the integrity of sensor connections, and the strength of network signals. Ultimately, the system's performance is defined by its ability to maintain consistent server connectivity, allowing for the uninterrupted flow of industrial telemetry from the shop floor machines to the central monitoring platform.

C. Operator and Management Feedback

Post-implementation surveys conducted with shop floor operators, maintenance engineers, and production managers revealed high satisfaction with the system. Operators appreciated the clear machine status displays, which reduced the need for manual status checks. Maintenance engineers valued the automated alert system for early fault detection. Production managers highlighted the real-time parts count and shift-level KPI summaries as critical tools for daily production review meetings. The intuitive dashboard design required minimal training, with most users achieving proficiency within two days of system deployment.

VII. RESULT

The image shows a Manufacturing Dashboard providing real-time monitoring of three machines — ACE ST 1 L-1, ACE ST 2 L-1, and ACE ST 3 L-1 — displaying live metrics such as machine running time and parts count, with color-coded status indicators showing two machines as "Active" and one as "Stopped," enabling operators to assess shop floor performance instantly.



Fig. 3. Digital Twin Dashboard

VIII. DISCUSSION

The integration of a Live Digital Twin with TPM data from MS SQL Server represents a practical and scalable approach to modernizing shop floor monitoring without requiring complete replacement of existing manufacturing infrastructure. The use of SQL Server as the data backbone leverages the existing familiarity of manufacturing IT teams with relational

database management, reducing the adoption barrier compared to more exotic IoT platforms.

A notable finding of this study is that the real-time visibility provided by the LDT has a behavioral effect on shop floor personnel. When operators are aware that machine status and cycle times are being monitored continuously, adherence to standard operating procedures improves, contributing to cycle time consistency and reduced idle periods. These human factors dimension of Digital Twin implementation merits further investigation in future studies.

The system architecture described in this paper is designed with modularity and scalability in mind. New machines can be onboarded to the LDT by installing sensors, configuring PLC communication, and registering the machine in the SQL Server schema, without requiring changes to the core middleware or dashboard. This scalability makes the system suitable for manufacturing environments ranging from small job shops to large automotive assembly plants.

IX. CONCLUSION

This paper has presented the design, implementation, and validation of a Live Digital Twin system for shop floor monitoring, integrating Total Productive Maintenance data from Microsoft SQL Server Management Studio. The system delivers real-time visibility into key performance indicators including total parts produced, average cycle time, average load/unload time, and machine status (Active, Idle, or Stopped), enabling proactive maintenance and production management.

The proposed architecture, spanning physical machines, sensor networks, SQL Server data storage, middleware processing, and interactive dashboards, provides a comprehensive and low-latency digital reflection of shop floor activity. Validation results confirm measurable improvements in OEE and maintenance response time, demonstrating the practical value of Live Digital Twins in industrial environments.

Future work will explore the integration of machine learning models for predictive maintenance, the extension of the platform to support multi-site manufacturing operations, and the incorporation of augmented reality interfaces for immersive shop floor visualization.

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