Adopting Shop Floor Digitalization in Indian Manufacturing SMEs—A Transformational Study

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Abstract The objective of this paper is to enumerate a study of the transformation of a brownfield manufacturing facility producing Electro-Mechanical Devices (EMD). Essentially this study can be termed as a testimonial for “Digitalize and Transform” initiative. A Production Digital Twin was developed leveraging the IIoT ready shop floor and adopting appropriate digital technologies. The proven DES model and digital twin methodology can be leveraged for future simulations to support market variability. Discrete Event Simulation (DES) method was deployed to create digital models of the shop floor resources and their interplay to help explore the plant characteristics and optimize its performance. The digital simulation model was integrated with the shop floor IIoT framework in a closed-loop, to run experiments and what-if scenarios with variable input parameters. Using this setup, physical shop floor and the digital simulation model share operational data in a continuous closed-loop to provide decision support for improving plant operations. EDM manufacturer’s target was to set up a re-usable DES model to arrive at actionable insights those can help them improve assembly line performance and get ready for the variable demand and product variants that subsequently would help them in driving business and profitability. Significant improvements were realized across all operational indicators—efficiency, quality, productivity and flexibility. Manufacturing SMEs across India are implementing IIoT and data analytics with the objective of acquiring real-time data thus enabling quick and accurate decision making. The closed-loop discrete event simulation methodology has the potential of enhancing IIoT investments further. Especially in the post-COVID scenario, when manufacturers are challenged with disrupted supply-chain, inconsistent demand and manpower shortages, this methodology can help execute shop-floor plans efficiently with optimum resources.

Keywords Simulation · Digital · IIoT

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R. K. Phanden et al. (eds.), Advances in Industrial and Production Engineering, Lecture Notes in Mechanical Engineering, https://doi.org/10.1007/978-981-33-4320-7_53
1 Introduction

India’s manufacturing SMEs are striving to find its place in the new global order. In its transformational journey, Industry 4.0 is playing a pivotal role. Manufacturing SMEs equipped are aspiring to update their existing older generation assets with IIOT [8] and take advantage of digital technologies like simulation, cloud and data analytics [9]. It is also significant to note that mass customization needs are increasing across industry verticals and the advantage of scale is constantly eroding [34]. Thus, manufacturing SMEs have an opportunity to compete with their larger counterparts, provided they achieve productivity gains, innovate with smarter offerings at competitive cost structure, gain market share and achieve profitability. With digitalization, these gains are not one time, the resulting integration across entire value chains facilitates continuous optimization of processes, resulting in sustainable, lean practices.

The objective of this paper is to enumerate a study of digitalizing an old manufacturing facility producing Electro-Mechanical Devices (EMD) used for controlling electrical transmission. The EMD manufacturing facility that once used to produce industrial control products for the local market has been transformed into a highly efficient digital factory, by implementing a combination of digital technologies, catering to local and global demand of electromechanical devices. This EMD facility emulates two major objectives—firstly, localizing global devices and making them available locally and secondly, to leverage innovation opportunities and deliver low-cost innovative devices for the developing countries to fulfill their electrification needs. Adoption of digitalization helped the manufacturer engage with customers globally and integrate with its supplier value chain more efficiently. In the digitalized manufacturing facility, the products and machines communicate with each other and most processes are IT optimized, resulting in high-quality and reliable output [33].

Essentially, this study can be termed as a testimonial for “Digitalize and Transform” initiative. Adoption of appropriate digital technologies in shop floor processes enables advanced capabilities like production digital twin [24]. This in turn enables EMD facility assets & resources to be connected to the virtual twin of physical assets and systems to help perform variety of simulations in the “what if” scenarios (see Fig. 1). Based on the learnings from this transformational study, this research paper studies how the Industry 4.0 technologies like IIOT, simulation, system integration and methodologies like discrete event, closed-loop and digital twin can be combined to help manufacturers meet their emerging business needs of efficiency, productivity, quality and mass customization.

1.1 EMD Manufacturing—Organizational Brief

EMD Manufacturing (henceforth called EMD) produces low voltage electrical switching devices. Their product portfolio includes protection devices such as circuit
breakers, miniature circuit breakers, residual current protection devices, fuse systems and overvoltage protection devices, switching devices and switch disconnectors. A typical device of this nature provides over and under-voltage protection, safe isolation and local and remote switching. These devices are deployed from homes to industrial installations and therefore, diverse variants of different ratings and sizes are required to fulfill the breadth of demand. A typical device of this nature consists of several static and moving parts, electronic controls, all encompassed in molded casings. A logical flow of assembly sequences based on individual device designs need to be followed to manufacture these devices. Varying batch sizes of device variants are assembled in a defined sequence with assembly operations allocated to automatic, semi-automatic and manual-assisted assembly stations in a line which is equipped with computer-controlled conveyor.

Most stations of the assembly line are automated and equipped with Programmable Logic Controllers (PLC). These PLCs are preprogrammed to carry out specific operations allocated to the workstation of the assembly line. It continuously monitors and receives information from input devices or sensors, processes the information and triggers the connected automation devices to complete the task designated for the specific assembly station in the EMD assembly line. The line PLCs have been integrated to IIOT systems to upgrade legacy automation and allow remote access, data streaming and monitoring. Before digitalization, the EMD line had the capacity to produce more than 70 variants of switchgears manufactured across 3 separate production lines and the intent of the transformation project was to enhance it substantially in order to cater to the increasing market demand for variants.
2 Relevance, Objectives and Challenges

2.1 Literature Survey to Establish Relevance and Gaps

A literature survey was undertaken to understand the practical aspects of adopting digital technologies to upgrade brownfield manufacturing facilities [13], essentially to address the market demands of [32] mass-customized [23] goods, establishing global quality standards and regulations, while continuing to be profitable. This literature survey intended to further understand interventions that can be undertaken in a shop floor, based on data and analytics [4]. Continuous interventions are facilitated by acquisition of real-time manufacturing data [7] from production equipment and workstations, outfitted with IIoT sensors [27] and data gateways [5]. Insights from various simulations [17] can help identify workstations prone to cause bottlenecks [18].

Surveyed research papers established that implementation of IIOT helps data-based [28] decisions [16], especially to address shop-floor issues. There are observations of reluctance on the part of manufacturers to invest [2], as they are not clear how to use insights to intervene and improve the operational metrics [15] of speed, efficiency, quality and flexibility [6]. The literature survey also targeted subjects like closed-loop methodology involving data and analytics driving simulation, validation, optimization and automation [19]. Digital twin is an emerging technology [29] which is changing the way products and processes are continuously validated and optimized. Literature survey included this subject matter to understand both the product digital twin and production digital twin [20] and its elements.

A manufacturing-related research cannot overlook today’s special circumstance of COVID-19. While the operations across geographies are reopening, they need to adapt to a new normal in the post-COVID world [14]. Three focus areas can help navigate their transition from the crisis point to this new normal—employee safety, managing risk and managing performance while ensuring physical distancing [10]. The literature survey highlighted the scarce understanding related to adoption of digital technologies by manufacturing SMEs in the post-COVID scenario to manage this transition and face the new normal.

The literature survey indicates that while past research has extensively addressed benefits and challenges of implementing various digital technologies in companies of different sizes, studies addressing the inter-dependence of technology and processes are few [26]. One area where more research will help the manufacturing fraternity, especially those belonging to small and medium business segment, is to establish how a typical manufacturing facility can leverage digital technologies like IIOT analytics and closed-loop simulation to improve and optimize operations.
2.2 Objectives of Digitalizing the EMD Facility

This study establishes the following set of new digital capabilities for the EMD facility. IIoT and machine networking was implemented in its shop floor complemented with digital product definition in its engineering function. To build upon this investment further, need was to develop an efficient digital factory.

Digital capabilities of the EMD facility are expected to integrate the virtual model of the assembly line with real production assets thus establishing a digital twin framework and perform operational simulations. The data streaming is expected to be bi-directional. In one direction, to acquire feedback from physical EMD assembly line into its virtual model to fine-tune the digital twin using real production data and machine downtimes, i.e., MTTR & MTBF and improve performance using a calibrated digital twin of production with higher level of confidence. In the other direction, to get insights as inputs from virtual model to real assembly line to analyze constraints and critical assets, run simulations for alternative scenarios, perform diagnostics, identify defective assets, perform root-cause triggering predictive maintenance and undertake performance monitoring to continuously improve.

2.3 Identified Improvement Areas

EMD proposed an enhanced digitalization plan to leverage its existing investments of IIoT implementation in its factory floor and digital product definition capability in its engineering function. It was expected that digitalization will help EMD to engage with customers globally and integrate with supplier value chain more efficiently [22]. It was expected that digitalization will make EMD facility scalable and be agile with its capacity to manufacture more device variants and be in tune with dynamic market needs. The improvements to be realized included improved efficiency, quality, flexibility and reduced time-to-market.

3 Digital Twin of the EMD Assembly Line

3.1 Step 1: Discrete Event Simulation (DES)

Discrete-Event Simulation (DES) helps model the functioning of a system as a sequence of discrete events in time. Each event occurs at an instant in time and marks a change of state in the system [30]. It is assumed that between consecutive events, no change in the system state occurs, thus, the simulation time can switch to the time the next event occurs, which is also called next-event time progression, while in real world, time is continuous. For instance, when a component moves
along a conveyor, no leaps in time are observed in real world. On the other hand, a DES model only takes into consideration those events and corresponding points in time that are critical during further course of simulation. For example, it could be a part reaching a station in an assembly line, exiting it, and progressing to the next stage. One major advantage of DES is its speed of simulating performance. Since the simulation model can skip all those moments in time that are not of interest for the experiment, it is possible to simulate years of factory operation in just minutes. This is particularly useful when different configurations of the same system need to be simulated and compared or simulating “what-if” scenarios.

DES was deployed to create digital models of EMD assembly line resources and their interplay to help explore system characteristics and optimize their performance. The digital simulation model enables to run experiments and “what-if” scenarios without disturbing an existing production system [25]. Analysis tools, statistics and dashboards enable evaluation of different manufacturing scenarios and help make fast, reliable decisions in the early stages of production planning [21].

3.1.1 Input Data

In the initial steps, DES captured information like workstation sequence, station-wise operations, conveyor layout, control locations, control logic, routing logics, shift details, failure rates, maintenance schedules, conveyor capacities and buffer strategies [3]. While preparing for the simulation, following operational data was input in the DES program—parts details, sub-assembly details, variants handled in the line, production schedule, batch sizes, number of stations per the variant and station-wise cycle times, conveyor speed, line-side and station buffer sizes, station-wise process and activity times, material flow details with routing and transfer dependencies, routing rules and restrictions including in-process quality checks and station MTBF and MTTR.

3.1.2 DES Deliverables

A DES model was developed by capturing the data points stated above. In addition to the 2D view (see Fig. 2) of DES, models were also created in a 3D virtual environment using computer-aided design (CAD) data of the assembly machines (see Fig. 3). This was done keeping in mind the future automation experiments on the performance digital twin. The result is a 3D virtual model that is synchronized with its 2D counterpart [1] allowing the flexibility to choose the appropriate method of visualization without compromising simulation and analysis needs.

The simulated output of the production line helped validate the station-wise cycle times, current bottlenecks, stage-wise utilizations, line balancing effect, utilization of operators, sequencing and scheduling of variants and impact of layout [21]. It also provided reports like total distance travelled by product and total waiting time of a product. The simulation was performed for varying input parameters like batch size,
cycle time, rejections and tests and results were obtained for resources, throughput, bottleneck locations, machine-wise failure and part sequence times (see Fig. 4).

3.2 Step 2: Closed-Loop Discrete Events Simulation

Closed-loop discrete events simulation together with the digital twin help create, manage and run the simulation between an IIOT ready physical production line [11]
Simulation and bottleneck results for various scenarios and batch sizes and its DES model created in step 1. This connected setup consisting of simulation software, assembly line PLCs on IIOT network and data gateways was used to interface the actual EMD assembly line with the DES model (see Fig. 5):

- to map physical assets and variables of the assets in EMD assembly line to the simulation models thus enabling to define digital twin prototype [21].
- to define experiments for the digital twin prototype of EMD facility. Experiments include all the required settings for the closed-loop discrete event simulation.
- to select and import time-slotted data files from the IIOT ready physical assets through digital twin framework and run the DES model with that data to bring models to life [19].
- to run the model with real asset data to transform the model into a digital twin and all existing DES analytical tools into diagnostic tools for the real production line.

![Fig. 4 Simulation and bottleneck results for various scenarios and batch sizes](image)

![Fig. 5 Integrated digital twin network between assembly line PLCs & simulation tool](image)
thus, insights from the analysis of the closed-loop simulation results can be applied in different use cases, for example, model calibration, design improvement, bottleneck analysis, condition monitoring, diagnostics and predictive maintenance.

3.2.1 Creating the Closed-Loop Between Simulation Model and Physical Facility

Closed-loop is established by creating asset types with similar hierarchy as the DES model built in step 1 (see Fig. 6). The machine properties and its variable information are exported from the simulation model to IIOT ready digital twin framework. The framework is populated with information regarding physical machines constituting the EMD Assembly line [12]. Once the closed-loop is established, feedback is received from physical plant assembly line to DES model to improve production design model accuracy, and feedback from DES model is sent to real production line to replay optimized scenarios, using plant floor data thus creating a bridge between the physical and virtual world [35]. Various analysis and experiments are then performed for the assembly line to help operate at the highest level of efficiencies as explained in the following scenarios.

Scenario 1: Bottleneck Analysis, Using Digital Twin of a Production-Line
Production engineer opens DES model of the EMD assembly line, uploads physical plant data into the model and runs bottleneck analysis. Critical equipment causing the bottleneck is identified and is serviced at a higher priority and gets flagged for the next plant equipment upgrade. This ensures the assembly line is operating at an optimum efficiency and productivity level. The same procedure is followed to validate the next production lot which could be of different variant mix and quantity thus establishing flexibility.
Scenario 2: Diagnostics and Root-Cause Analysis for Reduced Line Throughput
Upon encountering diminished throughput on the EMD assembly line, individual throughputs of each machine in the digital twin is checked to identify the machine responsible and the OEM is informed. OEM analyses and identifies the machine upgrade requirement which delivers the required reliability.

Scenario 3: Preventive Maintenance Followed by Diagnostics Activities
As per the preventive maintenance schedule, OEM sets up a service call with EMD to maintain the target machine and replaces the impacted subsystem. As per service level agreement, OEM also replaces similar sub-systems on other machines as a predictive maintenance measure thus ensuring continuous improvement in asset efficiency and productivity.

4 Results and Discussions
EMD’s organizational target was to set up a re-usable DES model to arrive at actionable insights that can help them improve assembly line performance and get ready for the variable demand and large number of variants that subsequently would help them in driving business and profitability.

Based on DES studies performed, the following listed areas were identified as opportunities for improvement (1) Capacity simulation in the light of varying batch sizes and variant mixes (2) Digital twin methodology supporting input of validated machine parameters to the physical assembly line thus saving precious downtimes (2) Logistics and material flow simulation to reduce shop-floor conflicts arising from material handling (3) Predicting assembly line bottlenecks arising from unbalanced station loads or underperforming machines. (4) Predictive maintenance of stations and machines thus improving machine availability. The model developed, tested and closed-loop with production assembly line is currently used in production planning and forecasting.

4.1 Improvements Achieved
- 3 EMD assembly lines reduced to 1.
- 233% increase in variant types manufactured.
- 43% reduction in average cycle time per variant.
- $3 \times$ improvement in number of quality parameters checked in 1/6th of time.
- $3 \times$ improvement in line performance owing to improved machine availability.
- Local manufacturing of high-tech devices for global markets.
5 Conclusion and Future Scope

India is currently transitioning to an efficiency-driven economy from factor-driven economy. Aspiration would be to elevate to an innovation-driven economy [31]. This indicates that efficiency and innovation are the key drivers for the manufacturing to be a significant contributor to the economy.

Digital twin framework is fast becoming a widely used methodology to simulate, validate, iterate and optimize product, process and performance with the objective of improving efficiency throughout the value chain across various industry verticals. Further, for innovation to be a way of life for a manufacturing organization, continuous experimentation is crucial. It helps in identifying potential faults early while acquiring new knowledge and achieve exponential improvements. Experimentation or using physical prototyping may not be viable owing to economic considerations or paucity of time. Simulating the various scenarios and experimenting with numerous alternatives can quickly give us results and save expensive prototyping.

The transformational study of EMD assembly plant enumerated in this research paper demonstrates how closed-loop discrete event simulation can be deployed to develop a production digital twin. Subsequently, combining simulation studies and continuous feedback data from physical assembly line facilitates real time, operational decision making. These simulation-based decisions have resulted in significant improvements realized across all operational indicators efficiency, quality, productivity and flexibility as demonstrated.

This research paper being based on a transformational study of a manufacturing facility has limitations regarding effects of evolving product designs, its variants and/or upgrades on shop floor operations. Also, automation of lines and workstations has not been included in this research whereas, automation has considerable influence on shop-floor operations. Hence, it is recommended that future research work should include product digital twin methodology in conjunction with production digital twin, to establish deeper understanding of end-to-end value chain consisting of all stages of product design, manufacturing planning, factory automation and customer servicing.

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