Science Essence Journal Vol. 41 No. 2 (2025) | 241-274

Research Article

Development and Implementation of a Smart Single-Station Manual Assembly Cell for an Inexperienced Worker to Enhance Industrial Efficiency in an MSME

Prathamesh Shailesh Shinde[1], Srishti Sudhir Patil[2], Chaitanya Shrikant Poredi[3], Ganesh Suresh Shelke[3], Jahida Javed Subhedar[3], Maneetkumar Rangnath Dhanvijay[4] and Sudhir Madhav Patil[5]*

Received: 7 June 2025
Revised: 16 August 2025
Accepted: 18 August 2025

ABSTRACT

Micro, Small, and Medium Enterprises (MSMEs) often face low efficiency, high error rates, and operator fatigue in manual assembly. High turnover of inexperienced/novice workers worsens these issues. Automation is common in large industries, but affordable smart solutions for MSMEs are limited. This study addresses the gap by converting a Traditional Single-Station Manual Assembly Cell (SSMAC) into a Smart SSMAC i.e. Smart Assembly Table (SAT). The SAT/Smart SSMAC uses smart technologies to improve efficiency, reduce errors, and counter the effects of high attrition among novice workers. A design-based experimental method was used. The upgrade included a Programmable Logic Controller (PLC), a Human-Machine Interface (HMI), sensor-enabled bin racks, and a modular workstation layout. The SAT/Smart SSMAC was tested in an MSME with inexperienced/novice workers. Productivity, error rates, and labor cost efficiency were measured. Real-time monitoring and digital displays guided operators in part selection, placement, and cycle time adherence using video and alarms. Tests with five inexperienced/novice workers over 100 assembly cycles showed significant gains. Cycle time dropped by 22.5%, and operator errors fell by 71.43%. Meeting the target cycle time improved by 34.33%, and delays reduced by 69.69%. The upgrade cost INR 129,988. Labor cost per unit decreased by INR 11.38, giving a 35% reduction. The SAT/Smart SSMAC supports Industry 4.0 goals, enhances lean manufacturing, and retains human involvement. Future upgrades, such as predictive maintenance and augmented reality, could further increase its benefits. The system's flexibility across skill levels and product complexities offers potential for broader application.

Keywords: Industry 4.0, Manual assembly cell, MSME, Real-time monitoring, Smart assembly

[1] Industry 4.0: Automation, Robotics & 3D Manufacturing, Department of Engineering and Sustainable Technology Management, SRH Berlin University of Applied Sciences, Berlin 12059, Germany.

[2] Department of Computer Engineering and Technology, Dr. Vishwanath Karad MIT World Peace University (MIT-WPU), Kothrud, Pune 411038, Maharashtra State, India.

[3] School of Mechatronics Engineering, Symbiosis Skills and Professional University (SSPU), Kiwale, Pimpri-Chinchwad, Pune 412101, Maharashtra State, India.

[4] School of Mechanical and Manufacturing Sciences, JSPM University Pune, Wagholi, Pune 412207, Maharashtra State, India.

[5] Department of Manufacturing Engineering and Industrial Management, COEP Technological University (COEP Tech), Chhatrapati Shivajinagar, Pune 411005, Maharashtra State, India.

* Corresponding author, email: smp.prod@coeptech.ac.in

Introduction

Micro, Small, and Medium Enterprises (MSMEs) are vital components of the global manufacturing landscape, making substantial contributions to both industrial expansion and overall economic progress [1]. Nevertheless, many of these enterprises encounter persistent issues including frequent workforce turnover, varying skill levels among operators, and inefficiencies inherent to manual assembly tasks [2-4]. Traditional Single-Station Manual Assembly Cells (SSMACs) depend significantly on human expertise, which introduces risks such as operational inconsistencies, elevated error rates, and higher production costs [5, 6]. Tackling these concerns is vital for improving operational effectiveness, maintaining product quality, and sustaining competitiveness [7, 8]. The advent of Industry 4.0 technologies offers a promising pathway, where the adoption of intelligent/smart systems within manufacturing environments can effectively address these operational shortcomings [7-9].

Traditional SSMAC faces challenges like space limitations, static designs, and high error rates due to manual operations for diverse products [10, 11]. Additionally, traditional setups lack real-time feedback and adaptability, hindering quick issue resolution and process optimization [12]. The rise of Industry 4.0 has transformed traditional manufacturing through digital integration [13].

Previous research has explored various aspects of SSMAC's efficiency, including automation and ergonomic design [14]. However, many studies have focused on narrow aspects such as robotic automation or specific ergonomic improvements [14, 15], often neglecting a holistic approach that integrates both technological and human factors. Additionally, there is a lack of comprehensive studies that evaluate the real-world implementation and impact of Smart SSMAC in industry.

This study investigates the operational limitations encountered by a specific MSME struggling with high annual attrition rates among inexperienced/novice assembly workers. The frequent turnover resulted in increased training demands, loss of process consistency, and reduced overall productivity. While prior research has explored the adoption of automation and smart technologies in large-scale manufacturing, limited attention has been given to context-specific solutions for MSMEs, particularly those that rely on novice workers for labor-intensive assembly tasks. This study fills that gap by developing and implementing a Smart SSMAC designed to enhance worker support, reduce errors, and improve production efficiency in high-attrition environments common to MSMEs. To mitigate these issues, a traditional SSMAC was upgraded to a Smart SSMAC. The study specifically aimed to resolve inefficiencies, frequent errors, and higher assembly cycle time i.e. low productivity associated with inexperienced/novice workers using traditional assembly methods while addressing gaps identified in existing literature. The study specifically focused on addressing inefficiencies, frequent errors, and prolonged assembly cycle times because these factors directly impacted the MSME's ability to meet production targets, maintain product quality, and remain competitive. These challenges were exacerbated by the reliance on inexperienced/novice workers, leading to inconsistent outputs and increased operational costs. The main goal was to develop a Smart Assembly Table (SAT), functioning as a Smart SSMAC, to minimize reliance on operator expertise by integrating automation, guided interfaces, and error-proofing features. This development aimed to provide consistent assembly performance regardless of worker experience, thereby addressing operational challenges specific to the MSME. It aimed to reduce assembly cycle time and minimize operator errors, leading to better assembly efficiency and accuracy while maintaining the reduced set/target cycle time. The Smart SSMAC was designed to be versatile, adaptable to diverse assembly tasks and environments, and capable of accommodating a range of products. By addressing these challenges, the research contributes to advancements in industrial assembly technologies and aligns with the broader goals of Industry 4.0.

The study's primary goals were: (i) to design and implement a Smart SSMAC incorporating advanced technologies such as real-time monitoring, a Programmable Logic Controller (PLC), and an intuitive Human-Machine Interface (HMI) using an iterative prototyping-based design and experiment methodology guided by the principles of user-centered design and lean manufacturing, (ii) to assess the impact of the Smart SSMAC on assembly cycle time, operator errors, defect rate, and financial benefits while working with inexperienced/novice workers, and (iii) to explore possible enhancements and future research opportunities for Smart SSMAC, focusing on emerging technologies and long-term outcomes.

This paper adds value to the field by offering a holistic approach to smart manual assembly systems. It combines both technological and human factors, details the design and implementation of the smart SSMAC, and provides an in-depth analysis of its performance. The study offers significant insights into the integration of advanced technologies in transforming manual assembly processes and sets the stage for future advancements in this domain.

The structure of the paper is as follows: Section 2 reviews related literature and previous work on automation, smart technologies and improvements in assembly efficiency. Section 3 describes the methodology employed in designing and implementing the Smart SSMAC, including data collection and analysis methods. Section 4 presents the results and evaluates the performance of the Smart SSMAC. It also discusses the implications of the findings, including interpretations, limitations, and recommendations. Finally, Section 5 concludes the paper and suggests potential directions for future research.

The field of assembly efficiency has been extensively studied, with various approaches aiming to enhance accuracy and reduce errors in manual assembly processes. This section reviews relevant literature on traditional assembly methods, automation in SSMAC, smart technologies in assembly systems, overview of assembly efficiency improvements and design approaches of assembly system development.

A. Traditional assembly methods

Enhancing efficiency in Traditional SSMAC typically involves boosting worker productivity and minimizing waste. By optimizing workstation designs ergonomically, operator fatigue and unnecessary movement are reduced, leading to streamlined workflows [16, 17]. Standardizing procedures plays a crucial role in maintaining consistency and quality, while regular maintenance of tools and equipment helps minimize downtime and errors. Cross-training of workers increases operational flexibility, allowing quick responses to varying production needs [18, 19]. The use of visual aids and clear documentation further supports efficient task completion [20]. Continuous monitoring and feedback mechanisms are essential for identifying improvement areas, promoting a culture of ongoing enhancement [21]. These combined efforts result in increased productivity, improved product quality, and reduced operational costs in single-station assembly environments [20-22].

Early research on assembly efficiency often centered on optimizing manual assembly processes through ergonomic and workflow improvements. These studies examined workstation design and task layout to lessen worker strain and decrease cycle times, resulting in enhanced worker comfort and modest reductions in assembly duration. Notably, some studies reported reductions in cycle time due to ergonomic modifications, which also contributed to worker well-being and marginal efficiency gains. However, these improvements were inherently limited by the manual nature and static design of traditional assembly systems, lacking real-time feedback and adaptive capabilities that could have further enhanced efficiency and accuracy.

B. Automation in SSMAC

The introduction of automation in assembly systems aimed to address the limitations of manual processes. Studies investigated the use of robotic arms and automated conveyors to streamline assembly operations. Automation led to significant improvements in speed and consistency. Studies have reported increase in production rates and reduction in error rates due to automated systems [23-25]. A pneumatic PLC-based system was developed to automate the testing of automotive lift gates and door slams, enabling the analysis of the integrity of various system components. The system incorporated a pneumatic circuit and PLC-controlled sequential operations to regulate multiple processes, including determining door opening and closing velocities and executing the required number of continuous cycles [26, 27]. This development exemplifies the transition from a traditional SSMAC to a single-station automated assembly cell (SSAAC), demonstrating the role of PLCs in enhancing automation, improving process efficiency, and ensuring consistent quality in assembly operations.

Automation enhanced speed and precision, reduced the dependency on human operators, and minimized repetitive strain. However, the primary limitations included high initial costs and the inflexibility of automated systems to adapt to varying product types and changes in assembly processes. Automation neglects a holistic approach that integrates both technological and human factors. It overlooks the importance of human involvement in the assembly process.

C. Smart technologies in assembly systems

Numerous studies have investigated the incorporation of smart technologies to improve efficiency and accuracy in assembly processes. A Smart Assembly Data Model was introduced to optimize data integration across different assembly stages, with the goal of enhancing traceability and control [28]. Smart technologies in assembly environments increasingly employ real-time monitoring, sensor-based feedback, and programmable logic control to improve accuracy and reduce variability. Systems integrating vision-based inspection and sensor-assisted error-proofing have demonstrated notable improvements in defect reduction and process repeatability [29]. Additionally, the use of HMI to provide context-aware operator guidance has been shown to decrease assembly time and enhance quality, particularly in setups involving inexperienced/novice workers [30, 31]. Such smart solutions align closely with the objectives of this study, where technology is leveraged to address inefficiencies, reduce errors, and optimize assembly cycle times. A case study introduced a manual assembly station equipped with smart technologies, designed to self-configure based on worker needs and product variety. It demonstrated reduced assembly times and errors compared to traditional workstations [12]. Digital Twin (DT) is being considered as a prominent advanced technology in automation and smart systems [32-34]. A study evaluated the use of a DT in the concept of a smart assembly line to optimize assembly processes, comparing selective assembly and individualized locator adjustments. Results showed that individualized locator adjustments significantly improved geometrical quality compared to selective assembly [35]. A smart assembly system with a self-configurable workstation used smart algorithms. It improved ergonomics, reduced assembly time, and minimized errors. The system adapted efficiently to new products and worker characteristics [36]. An adjustable smart assembly workstation with a motorized table and an adjustable chair improved worker comfort and task performance compared to fixed workstations. It enhanced ergonomics and reduced health risks [37]. An Intelligent Assembly Process Improvement System (IAPIS) using k-means clustering and multi-response Taguchi methods was proposed. It identified critical process parameters and significantly improved Printed Circuit Board Assembly (PCBA) yield performance in a case study [38].

A conceptual framework for Smart Manufacturing in PCB industries was presented, focusing on intelligent systems to enhance PCBA processes [39]. Productivity improvements at assembly stations were explored using work study techniques, with an emphasis on lean methodologies and ergonomic enhancements [40]. A Smart Assembly Line for automotive manufacturing was developed, incorporating Internet of Things (IoT) and machine learning to facilitate adaptive process control and predictive maintenance [41]. The integration of IoT and machine learning in smart assembly systems was further examined, highlighting advances in real-time monitoring and decision-making capabilities [42]. A comprehensive review of smart assembly technologies outlined current applications, challenges, and future developments in the field [43]. An Intelligent Assembly Table for the aerospace industry was designed, focusing on adaptive tooling and real-time feedback to improve precision and efficiency [44]. Additionally, a case study on enhancing assembly line efficiency through smart manufacturing emphasized the role of DTs and predictive analytics in optimizing production processes [45]. Collectively, these studies illustrate the various approaches and technological advancements driving the evolution of smart assembly systems, from augmented reality and adaptive algorithms to IoT integration and predictive analytics [13, 46]. Manufacturers are driven to invest in smart manufacturing by the potential for increased production volumes, enhanced efficiency, and reduced overhead, operational, and capital expenses [46].

Smart technologies offer real-time monitoring, predictive maintenance, and enhanced adaptability, providing a more flexible and responsive assembly environment. Despite these advancements, challenges remain, such as the integration complexity of new technologies and the need for significant upfront investment. Additionally, the effectiveness of these systems can be limited by the quality of data and the ability to accurately interpret and act upon it.

D. Overview of assembly efficiency improvements

Assembly efficiency improvements in smart manual assembly systems, utilizing PLCs, real-time monitoring, and HMIs, focus on enhancing human performance and process control [47]. PLCs ensure precise control of assembly operations, automating guidance for routine tasks and maintaining consistency [47, 48]. Real-time monitoring provides instant feedback on system performance, allowing for quick detection and resolution of issues, thereby minimizing downtime [49]. HMIs facilitate seamless interaction between operators and machinery, displaying critical data and enabling easy adjustments [50]. These systems support detailed tracking of assembly metrics, helping identify inefficiencies and areas for improvement [13, 22, 50].

By optimizing manual processes with these technologies, manufacturers can achieve higher productivity, better quality control, and reduced operational costs without relying on robotics or advanced Artificial Intelligence (AI) systems.

E. Design approaches for assembly system development

Designing effective assembly systems, particularly in low-volume, high-mix environments typical of MSMEs, requires a multidisciplinary approach that integrates ergonomics, cognitive engineering, and lean principles [51, 52]. Traditional design approaches often relied on operator-centered workstations optimized for reachability, visibility, and fatigue reduction, as discussed in the works of Konz and Johnson [53]. Over time, methodologies such as Human-Centered Design (HCD) and User-Centered Design (UCD) have gained prominence for tailoring systems to inexperienced/novice or variable-skill operators, which is highly relevant in the context of high attrition environments [54-56].

Moreover, smart assembly cell development increasingly adopts iterative prototyping frameworks such as the Design Thinking process, which emphasizes empathy-driven problem definition, ideation, rapid prototyping, and user feedback integration [57-59]. Lean Product and Process Development (LPPD) principles have also been applied to minimize waste and improve flexibility in workstation layout and function [60-62].

Modular design strategies, combined with Cyber-Physical System (CPS) principles, have further enabled the integration of programmable controllers, feedback interfaces, and sensor-based decision-making into manual stations. These hybrid approaches allow for enhanced operator guidance, error-proofing (poka-yoke), and dynamic work pacing [63, 64]. Such integrated design methodologies provide a foundation for implementing Smart SSMACs aimed at inexperienced/novice users, as in the current study.

The literature highlights a clear progression from manual assembly improvements to automation and smart technologies. Traditional methods provided foundational improvements but were constrained by their static nature and lack of real-time adaptability. Automation improved efficiency and accuracy, but it had high costs and lacked flexibility. It also failed to adopt a holistic approach that combines technology and human involvement. Smart technologies represent the latest advancement, providing enhanced real-time feedback, predictive maintenance, and adaptability. However, they also introduce new challenges, including integration complexity and data management issues.

The reviewed literature underscores the potential of integrating advanced technologies into assembly systems to address both traditional and automation-related limitations. This paper builds upon these findings by developing and implementing a SAT, a Smart SSMAC, that combines real-time monitoring, programmable automation control by PLC, advanced HMI, and modular design to overcome existing challenges and enhance overall assembly performance with inexperienced/novice worker.

Methodology

This section describes the development and implementation of the Smart SSMAC, including the methodology used for designing, testing, and evaluating the system. It provides a detailed account of the process, including data collection, curation, and analysis. Figure 1 provides the outline of the overall methodology highlighting the three/four major stages: system design, programming, experimentation and evaluation metrics.

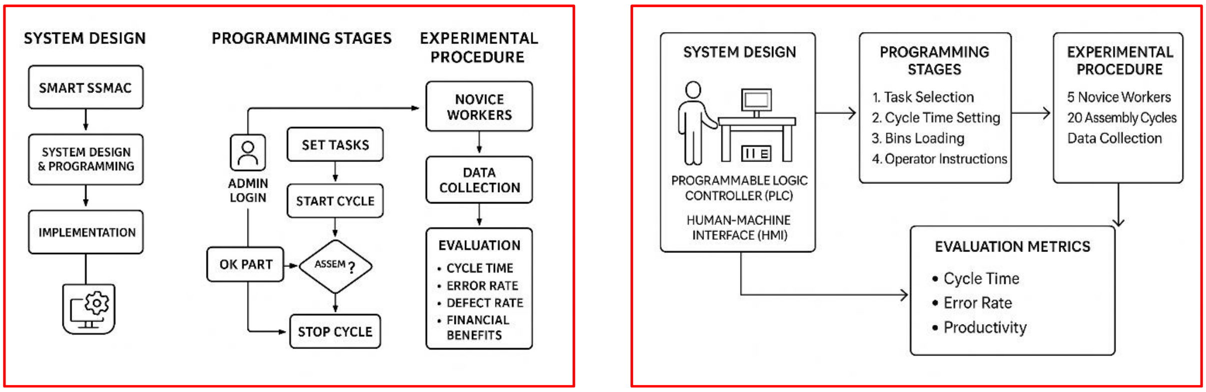


Figure 1 Outline of Methodology.

This study adopted an iterative prototyping-based design and experiment methodology approach rooted in UCD principles to develop the Smart SSMAC. The design process was structured into three main stages: (i) Conceptual Design and Requirement Analysis – Initial requirements were gathered through consultations with the MSME's production supervisors, line operators, and quality control personnel. Key pain points, such as high error rates, inconsistent cycle times, and limited operator experience, were translated into functional and technical specifications. (ii) Prototype Development – The Smart SSMAC was designed to integrate a PLC for process control, sensors for error-proofing, and an HMI for operator guidance. Multiple low-fidelity mock-ups were created, reviewed with stakeholders, and refined into a fully functional prototype. The iterative process allowed feedback-driven refinements to enhance usability and functionality. (iii) System Integration and Pilot Implementation – The finalized prototype (Smart SSMAC) was deployed on the shop floor, replacing a Traditional SSMAC in one assembly station to ensure controlled testing conditions.

Testing Procedure: The Smart SSMAC was evaluated over a four-week period. A total of 5 inexperienced/novice operators with less than six months of assembly experience participated. Each operator performed identical assembly tasks on both the Traditional SSMAC (baseline) and the Smart SSMAC (experimental setup). The testing was conducted under identical work conditions, with standardized work instructions, tools, and material batches to ensure fair comparison.

Evaluation Criteria and Metrics: The system's performance was assessed using quantitative and qualitative measures: (i) Assembly cycle time (seconds) – Measured from task initiation to completion for each product unit. (ii) Error rate (%) – Calculated as the proportion of defective units identified by quality inspection to total units assembled. (iii) Defect types – Categorized into assembly sequence errors, component misplacements, and missed fastenings. (iv) Operator Satisfaction – Assessed through a post-trial subjective survey, covering ease of use, clarity of instructions, and perceived workload reduction. (v) Operational disruption frequency – recorded as the number of stoppages due to assembly errors or uncertainty during task execution. This structured methodology ensured that the design process was transparent, the testing environment was controlled, and the evaluation criteria allowed for rigorous performance assessment.

A. Block diagram of the approach

In a broad sense, the overall system consists of three major sections: input, processing and output. Figure 2 outlines the flow of information across three stages.

Input:

- Bin Sensors: When the operator selects a child part, a video will play on the HMI. This is done using the PLC and SIMATIC WinCC Runtime (RT), a personal computer (PC) -based system from the Totally Integrated Automation (TIA) portal for monitoring and controlling automation tasks.
- Buttons/Switches (Start, Stop, Reset, Cycle Start, Cycle Stop, Emergency Stop): These buttons allow the operator to interact with the system. They can start or stop a process, reset the system, or initiate a cycle.

Central Processing Unit (CPU):

- PLC: The PLC acts as the brain of the system, processing inputs from the sensors and buttons. It makes decisions based on its programming and controls the outputs accordingly.

Output:

- HMI Screen: The HMI screen displays information to the operator, such as system status, visual instructions (video), textual instructions or error messages. The video shows the operator how to assemble the selected part into the product. Additionally, an indicator will flash to show which child part should be picked next. It allows the operator to monitor and interact with the system more effectively.

- Tower Light/Indicators: These visual indicators provide immediate feedback to the operator. They can show the status of the system, such as whether it is running, stopped, or if there is an error.

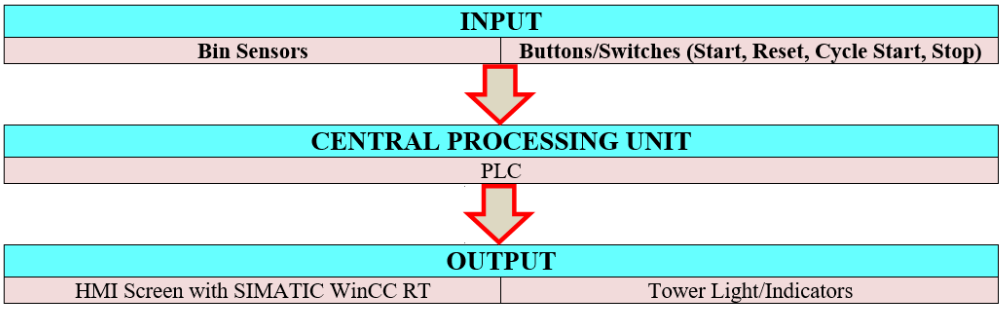


Figure 2 Outline of information flow.

Figure 3 provides an overview of the building blocks of the system. It shows the four major blocks of the system: input component, user interface component, controller component, and output component.

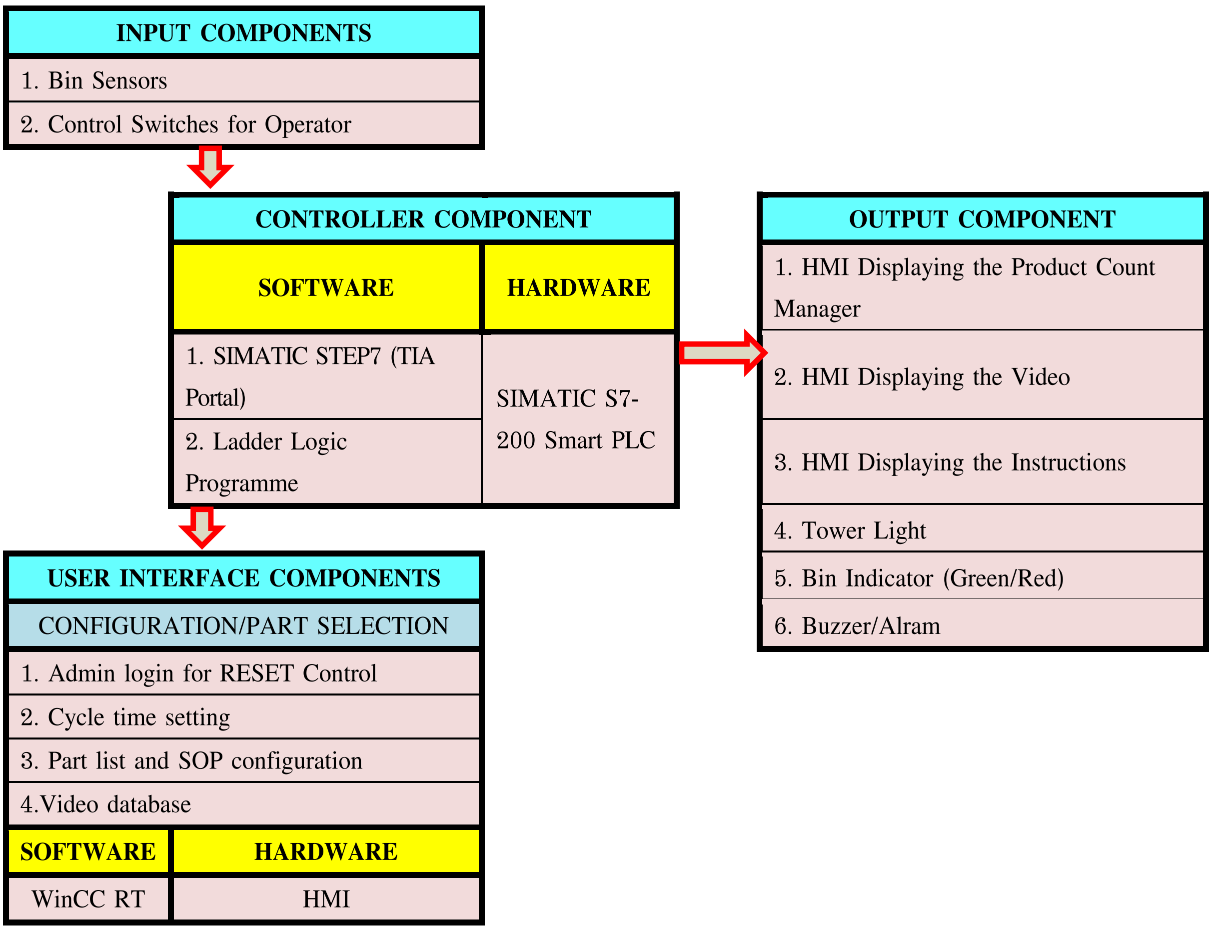


Figure 3 Building blocks of the system.

B. System design and implementation

Design of the SAT/Smart SSMAC:

The SAT integrates several key components like modular workstations, sensors for part identification, a HMI for real-time feedback, and a PLC based control unit for managing assembly processes. The SAT/Smart SSMAC features a modular setup that allows for customizable configurations to suit different assembly tasks. This design facilitates easy adaptation and scalability.

Development, Integration and Implementation of the SAT/Smart SSMAC:

- Development Process: Initial prototypes were developed to test various configurations and functionalities.
- Integration Process: Components were integrated into a cohesive system, ensuring seamless communication between sensors, HMI, and PLC based control units.
- Implementation Process: The prototypes were evaluated for ergonomics, efficiency, and integration capabilities.

C. Data collection

Performance Metrics:

- Cycle Time: The time taken to complete an assembly cycle was recorded to evaluate efficiency improvements.
- Error Rates: The number of errors and failed cycles were monitored to assess the accuracy of the assembly process.
- Adherence to the set/target cycle time: Data on time keeping by the operator was collected for inexperienced/novice operators.

Data Sources:

Data from sensors tracking part placement and cycle time. Real-time logs from the HMI interface providing insights into cycle times, error rates, and part counts. Observations and feedback from operators during testing phases.

D. Data curation

Data Validation:

Raw data was cleaned to remove any anomalies or inaccuracies, ensuring that the data used for analysis was reliable. Data was normalized to facilitate comparisons between different test scenarios for inexperienced/novice operator.

Data Organization:

A database was created to store and manage the collected data, allowing for efficient querying and retrieval. Data was categorized based on performance metrics and assembly configurations.

E. Mechanical details

This sub-section includes the mechanical design and dimensions of the SAT focused on enhancing worker efficiency and reducing errors through a refined, ergonomic layout. Initial concepts underwent multiple iterations to improve functionality and user interaction. Key features include an adjustable control panel, strategically placed bin sensors, and ample leg movement space, ensuring both comfort and precision for operators.

In the initial stages, multiple iterations were developed to refine the concept and enhance the overall functionality of the SAT. Figure 4 illustrates a refined design derived from these iterations, showcasing significant improvements and optimized functionality. This SAT is meticulously engineered to enhance user experience through a well-organized layout, ergonomic features, and advanced control options. Unlike previous versions, this design is more intuitive, facilitating easier user interaction. It is also highly efficient, reducing the time and effort required for assembly tasks. The user-friendly design ensures that operators can work comfortably and with greater precision, leading to a streamlined assembly process. Consequently, productivity is significantly increased, and the quality of outputs is greatly improved. This SAT represents a significant advancement in assembly technology, embodying innovation and excellence in its design and functionality. Table S1 presents the dimensions taken into consideration while preparing iterations and CAD designs for the SAT.

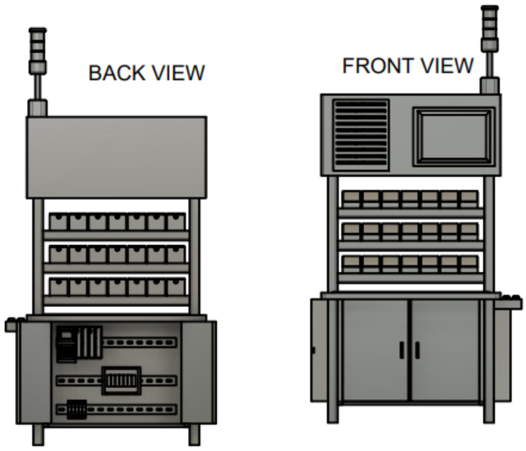


Figure 4 Conceptual design of SAT, a Smart SSMAC.

F. Electrical details

This section deals with the electrical system, focusing on the control panel wiring associated with the SAT. The electrical design plays a crucial role in ensuring the seamless operation of the SAT, integrating various sensors, control units, and feedback mechanisms to enhance efficiency and accuracy in the assembly process.

The control panel is the central hub of the electrical system, housing the wiring and components that manage the SAT's functionality. It involves integration of sensors that detect the correct parts and alert operators to errors, ensuring precision in assembly tasks. The wiring was meticulously planned and implemented to support these functionalities, prioritizing reliability and ease of maintenance. Figure 5 highlights the detailed and complex wiring and connections within the control panel of the SAT system. Prominent components include the Siemens S7 200 Smart PLC with Extension Module Digital 32 (EM DT 32), Trinity Touch Relay Module 8 Channel/4 Channel (Omron Relay), L&T Molded Case Circuit Breaker (MCCB) 10 ampere Double Pole, NHP Switch Mode Power Supply (SMPS) 24V 5A, and Elmex KUT2.5 terminal connector blocks, all of which are precisely arranged and interconnected. On the other hand, the wiring diagram for the control panel of the SAT system illustrates the intricate connections and interactions between various components, ensuring optimal functionality and reliability. Key components include the PLC, which processes and controls the assembly process, connected to sensors and actuators via input and output terminals. The relay module board receives control signals from the PLC to switch high-power devices, while the Miniature Circuit Breaker (MCB) provides overcurrent protection, distributing power to the SMPS and directly to high-power components. The SMPS converts AC to DC, supplying power to the PLC, relay module, and other devices. Connector terminal blocks facilitate secure and organized wiring, with color-coded wires routed neatly to prevent interference. The diagram ensures proper assembly and maintenance by showing clear power distribution, control signal pathways, actuation processes, and safety features, all essential for the efficient and safe operation of the SAT system. Additionally, input/output (I/O) list was prepared to account for some unused inputs and outputs in the control panel.

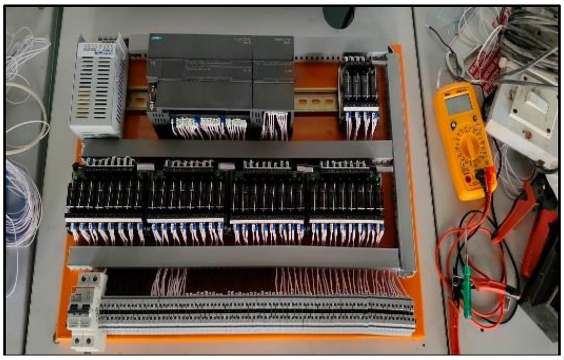


Figure 5 Wiring within control panel.

G. Sensor and indicator mounting

This section addresses the mounting of sensors and indicators on the SAT. The placement and integration of these components are critical for the SAT's functionality, ensuring accurate detection of parts and effective communication of status to operators.

The sensor and indicator mounting process began with careful planning to determine the optimal positions for each component. Sensors were strategically placed to monitor the correct bin selections and assembly steps, providing real-time feedback and error alerts to operators. This positioning helps prevent mistakes and streamlines the assembly process by guiding the operator through each task. Figure 6 shows the mounting of sensors and indicators on the fabricated bin racks.

The Sensor GTB6-P1212, photoelectric sensor made by SICK, was selected for the SAT project due to its high detection accuracy, robust performance, and ease of integration. Its retro reflective sensing capability with a polarization filter ensures reliable detection of objects up to 6 meters away, making it ideal for the various detection needs of the SAT. The sensor's fast response time and high load capacity ensure it can handle real-time detection and control tasks effectively. The compact and durable design, along with flexible mounting options, facilitates easy installation and long-term reliability, making the GTB6-P1212 an excellent choice for enhancing the automation and efficiency of the SAT.

Industrial Light Emitting Diode (LED) 10 mm indicator was selected for the SAT project due to its exceptional durability, visibility, and ease of integration. Featuring a bright surface mount device LED that ensures clear visibility in various lighting conditions, coupled with its IP65 rating for dust and water resistance, the indicator is well-suited for demanding industrial environments. Its wired design simplifies installation and connection to existing systems, enhancing operational efficiency. Moreover, the indicator's robust construction, including fire-retardant and Ultra Violet (UV) -resistant materials, ensures longevity and safety, making it an ideal choice for enhancing the functionality and reliability of the SAT system.

Figure 6 Sensor and indicator mounting.

H. Switches and operational sequence

The EMERGENCY SWITCH integrated on the 6-button panel, alongside the START CYCLE, START, STOP, STOP CYCLE and RESET buttons, is a crucial safety feature for the SAT. This panel ensures efficient control and quick response during assembly operations. The START button initiates the individual assembly cycle as and when required by the operator. STOP button provides signal to stop the ongoing assembly of the product due to (i) erroneous activities done by the operator or (ii) intentional stoppage as per operators will (personal break, shift change etc.). Now, pressing START button resumes the assembly cycle from where it was stopped previously. STOP CYCLE button provides signal for completion of current batch of the product and manager/supervisor is expected to intervene to provide/set instructions for the next product to be assembled through the admin login of the HMI screen. After STOP button, pressing RESET button is used to terminate the ongoing cycle and then pressing

START button initiates a new assembly cycle for the ongoing product. The partially assembled product is to be placed into Not OK bin. The START button initiates the assembly process, the STOP button halts operations as needed, and the RESET button reinitializes the system after a stoppage or error. The EMERGENCY SWITCH, distinctly colored and easily accessible, is designed to immediately cut off power and halt all operations in the event of an emergency. This rapid shutdown capability is essential for protecting workers from potential hazards and preventing damage to equipment. The integration of these six functions into a single panel streamlines operations, enhances worker safety, and ensures a robust response to any situation that may arise during the assembly process. In normal run, there is no need to press START button for every individual assembly cycle, the PLC is programmed to initiate new cycle in loop. After assembling the last child part, the final assembled product is required to be inspected and tested manually by the operator. Based on the manual inspection and testing the final assembled product is placed in OK or Not OK bin and the corresponding product counter increments accordingly.

I. Programming

The programming of the SAT system is carried out to streamline the assembly process and minimize errors through an intuitive workflow and real-time feedback mechanisms. Figure 7 illustrates the system workflow chart, which guides operators through the part selection process with automated prompts and alerts. The manager/supervisor must check whether the type of product for which assembly is to be carried out is available in the product master list. If not, intimate to information technology (IT) team to include the parts list and the sequence of assembly tasks. The master data includes types of products to be assembled, recipes: list of child parts required for respective product along with their part identification number and bin location; the sequence in which assembly task is to be carried out, and standard cycle time required to complete the entire assembly for that one product. Figure 8 present flowcharts illustrating the Stages for the Manager/Supervisor (Figure 8 (a)) and Stages for the Operator (Figure 8 (b)).

Stages for the Manager/Supervisor (Figure 8 (a)):

Before the operator starts working with the SAT, the Manager/Supervisor has to first set the assembly tasks of a particular product for the operator through HMI screen. Before the operator starts working with the SAT, the Manager/Supervisor, through the admin login of the HMI screen, has to first select the type of product for which assembly is to be carried out, secondly to set the product cycle time, and third to instruct the operator to load the bins fully with respective child parts. The product cycle time is the summation of all equal element times corresponding to the individual assembly tasks associated with each child part. For example, if the product requires assembly of 10 child parts and standard cycle time associated with the assembly of product is 30 minutes (1800 seconds), then the permissible element time for completing the assembly of each child part is automatically set to 3 minutes (180 seconds) through the program. The quantity of assembled product (number of OK products) is required to be monitored through the counter monitor display (number of OK parts). Once the required quantity of products is assembled, operator has to intimate the manager/supervisor to provide/set instructions for the next product to be assembled. Manager/supervisor does this through the admin login of the HMI screen.

Stages for the Operator (Figure 8 (b)):

Once the instructions are set by the manager/supervisor, operator has to start working with the workstation and start assembly activity. The stages involved are as below: 1. Press START CYCLE button, 2. Press START button (within 10 seconds otherwise buzzer alerts notify the operator), thereby Green indicator, of a bin containing first child part, turns ON, 3. Operator to pick up the part from the specified bin, 4. Part pick-up activity is detected by the sensor, 5.1 Accordingly the video of the respective assembly process plays on the HMI screen (Operator can choose to skip the video playing. Operator takes help of video only when there is new kind of assembly task. However, with certain number of repetitive activities operator learns or acquires the skill and then may choose to skip displaying the video(s) for further cycles), 5.2 The Green indicator of the bin containing next child part to be picked up for assembly turns ON, 5.3. Timer corresponding to the element time is initiated, 6.1 If the operator takes more than the permissible time to complete the elemental activity then the buzzer alerts notify the operator. The system memorizes this event. When operator completes the assembly and if the assembled product is put in OK bin then failed cycle (delayed cycle time) counter and number of OK products counter get simultaneously incremented, 6.2. If the operator completes all the assembly tasks (elemental activities) within permissible time and if the assembled product is put in OK bin then successfully cycles completed counter and number of OK products counter get simultaneously incremented, 7. After inspection and testing, if the final assembled product is not found OK then the operator places it in Not OK bin and the number of Not OK parts counter gets incremented, 8. After accumulation of required number of OK parts the operator presses STOP CYCLE button, 9. The manager/supervisor sets the instructions for a batch of another product. Number of OK parts displayed is the summation of successfully cycles completed and failed cycles.

The workflow begins with the selection of a child part from a bin. If the selection is correct, the process moves to the next bin. If the selection is incorrect, buzzer alerts notify the operator, prompting them to pick the correct part. The system also includes steps for inspecting parts manually and determining their status, ensuring that only acceptable parts are used in the assembly. This programming approach enhances accuracy and efficiency, significantly improving the overall assembly process.

- The process starts with selecting a child part from a bin.
- If the child part selection from a bin is CORRECT, the process moves to the NEXT BIN.
- If the child part selection from a bin is WRONG, the process triggers BUZZER ALERTS.
- When a wrong bin is selected, a buzzer alerts the operator/assembler and he/she is then prompted to PICK CORRECT PART from the bin.
- The operator inspects the part and determines its status.

- In OK BIN,
  If the final assembled product is OK, it is ACCEPTED.
- In NOT OK BIN,
  If the final assembled product is not OK, it is REJECTED.

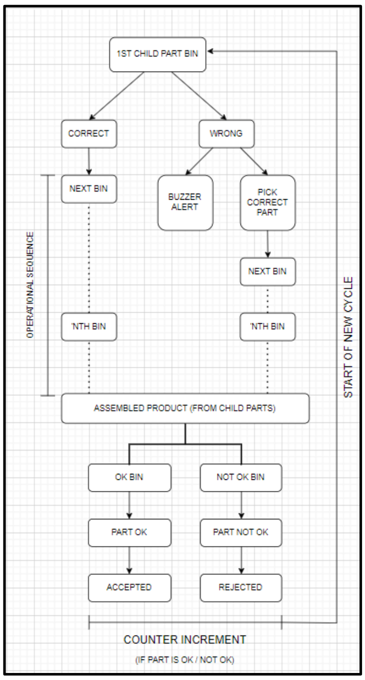
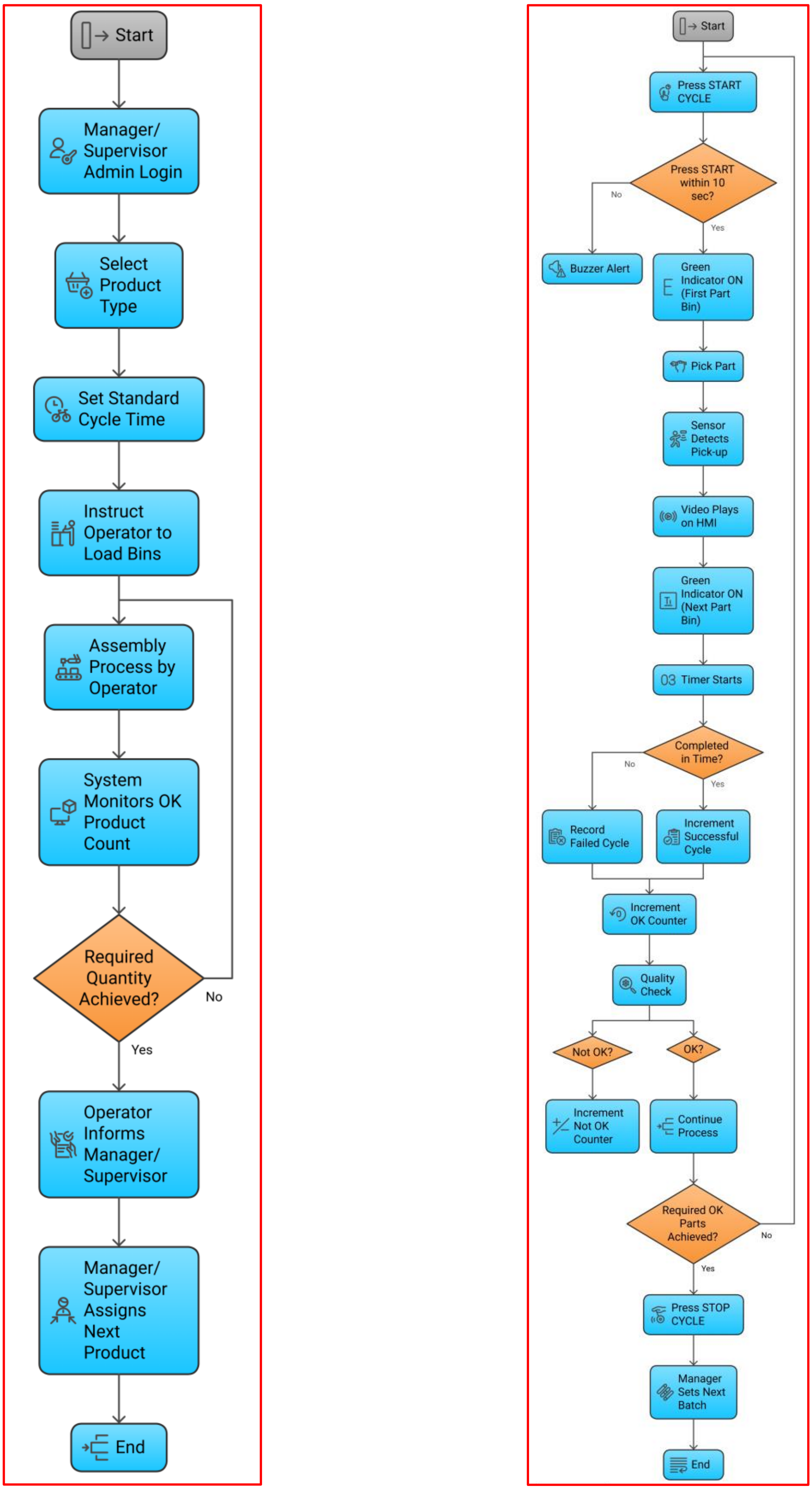


Figure 7 System workflow chart.

J. HMI screen design

Using WinCC RT, the focus was on creating HMI screens that are user-friendly and easy to understand. These screens are designed to be straightforward and intuitive, ensuring that operators and assemblers can effectively use the SAT without confusion. The design prioritizes simplicity in layout and clarity in instructions, guiding users step-by-step through the assembly process. By considering ergonomic factors and ensuring the screens are easy to navigate, the overall efficiency in industrial operations is enhanced. This approach not only reduces the likelihood of errors but also improves productivity by enabling workers to perform tasks more effectively and with greater confidence.



(a) Stages for the Manager/Supervisor (b) Stages for the Operator

Figure 8 Flowcharts illustrating (a) Stages for the Manager/Supervisor, and (b) Stages for the Operator.

K. Experimental procedure

A study was conducted using two types of SSMAC: a Traditional SSMAC and a Smart SSMAC. Both stations perform identical assembly tasks, ensuring a consistent basis for comparison. The Smart SSMAC was equipped with advanced features, including a PLC, HMI screen, sensor-enabled bin racks, and real-time monitoring systems. These enhancements were designed to assist workers with precise part selection, placement, and cycle time adherence.

The assembly stations were operated by five different inexperienced/novice workers with minimal or no prior experience in assembly work. The sample size of five participants was selected based on the exploratory nature of this study, which aimed to evaluate the feasibility and functionality of the Smart SSMAC system rather than to establish definitive statistical generalizations. This participant count aligns with prior early-stage industrial ergonomics and HMI evaluation studies, where small sample, within-subject designs have been shown sufficient for detecting major usability issues and process bottlenecks during initial trials [65–68]. Additionally, a preliminary statistical power analysis was performed assuming a medium effect size (Cohen's d = 0.5) and $\alpha = 0.05$ for paired-sample comparisons. The analysis indicated that a minimum of five participants would provide >80% power to detect significant differences between baseline Traditional SSMAC and Smart SSMAC assembly times. This justified the chosen participant number for this stage. Future work will incorporate larger and more diverse participant groups to validate the findings for broader industrial applicability. The Supporting Information - Statistical power analysis (planning and post-hoc) provides more insights for the justification of chosen participant number.

Each worker was asked to run 20 assembly cycles. A total of one hundred assembly cycles were observed with each type of SSMAC and pertinent data was recorded. Each worker was tasked with completing a series of assembly operations on both the assembly stations for the same product. The chosen methodology of testing both a Traditional SSMAC and a Smart SSMAC using five inexperienced/novice workers across 100 assembly cycles ensures a systematic, unbiased, and representative comparison of the two systems. The following justifications support this approach:

Standardization and Fair Comparison

- Using the same product for assembly across both stations had ensured that differences in performance could be attributed to the assembly system rather than variations in the product.
- The same five workers performing assembly on both stations had eliminated variability due to skill differences, ensuring that the comparison was valid.

Evaluation of Usability for Inexperienced/Novice Workers

- Inexperienced/Novice workers (with minimal or no prior experience) had been intentionally chosen to assess how intuitive and user-friendly each assembly system was.
- The learning curve and ease of operation for inexperienced/novice workers had been critical factors in determining the efficiency of a smart assembly system.

Minimizing Bias and Ensuring Statistical Relevance

- Each worker having performed 20 cycles per station had ensured a sufficient sample size (100 total cycles per station) for meaningful statistical analysis.
- This had reduced the impact of random variations and had enhanced the reliability and reproducibility of the results.

Understanding Performance under Realistic Conditions

- In many industrial settings, new or inexperienced/novice workers had frequently join assembly lines. Testing with novices had helped determine which system required less training and allowed quicker adaptation.
- The performance comparison between Traditional and Smart SSMACs under real-world conditions had provided insights into potential productivity gains and error reduction.

Assessment of Efficiency, Error Rates, and Ergonomics

- Observing 100 cycles per station had allowed for the collection of quantitative and qualitative data, such as assembly time, error rates, worker fatigue, and ergonomic factors.
- This data had been essential for evaluating the effectiveness of the Smart SSMAC in reducing errors, improving efficiency, and enhancing worker comfort.

The historical data from the concerned MSME indicated that the batch quantity for any assembled product ranged from 10 to 20 per setup. The same batch was repeated later with a different quantity. The repetition frequency over a week varied between 2 and 6 times. This posed limitations on learning rate or learning curve analysis due to limited number of cycles per batch and frequent changeovers for different types of products to be assembled.

Studies indicate that learning effects are most pronounced in the first 20-30 cycles of a repetitive assembly task. By 50-100 repetitions, the improvement rate slows down significantly, and the cycle time stabilizes. Beyond 200-300 repetitions, the learning curve flattens, and further reductions in cycle time become minimal [69, 70].

Thus, though the learning rate or learning curve analysis was not conducted for this study, it can be inferred that the limited batch size and low repetition frequency hindered the establishment of a consistent learning pattern. The frequent changeovers and variability in batch quantities likely disrupted any sustained improvement in cycle time. As a result, traditional learning curve models, which rely on continuous repetition and progressive efficiency gains, would not be fully applicable in this context.

To determine the target/set standard cycle time following steps were followed [71]:

1. The assembly process was broken down into work elements requiring approximately equal amount of time.
2. Time study was conducted with five different workers and each worker operating 20 assembly cycles for the same product.
3. The average observed time was calculated.
4. Every worker's speed was assessed relative to standard pace while working on Traditional and Smart SSMAC. The performance ratings of all workers were determined using the

Methods Time Measurement (MTM), the most popular Predetermined Motion Time Standards (PMTS) as it is the oldest one.

5. Subjective feedback was taken from all the workers.
6. The feedback was analysed to identify the reasons for obtaining the same/ different performance ratings by the same worker over the two scenarios.
7. The observed assembly cycle time was adjusted based on the performance rating using the relation as per the equation (1):

$$\text{Normal Time} = (\text{Observed Time}) \times (\text{Performance Rating}) \tag{1}$$

8. A 10% allowance was considered while calculating the standard time as per the equation (2):

$$\text{Standard Time} = \text{Normal Time} \times (1 + \text{Allowance}) \tag{2}$$

9. The standard time was then compared with industry benchmark and historical data and adjusted accordingly.

This methodology ensured an objective, data-driven comparison of both assembly systems (Traditional and Smart SSMAC) under controlled yet realistic conditions. It provided insights into the usability, efficiency, error rates, and learning curve associated with each system, supporting informed decision-making regarding the adoption of smart assembly technologies.

The following metrics were recorded for each task: (i) completion time (cycle time)- the time taken by each worker to complete the entire assembly operation, (ii) operator errors (error rate)- the number of errors made while picking the requisite child part in sequence during the assembly process (but not necessarily result in final assembled defective product, however may result in delayed cycle time), (iii) delayed cycle time instances (cycle time adherence)- the instances which resulted in producing acceptable (OK) final assembled product but cycle time required to complete the assembly is higher than the set cycle time, (iv) operator feedback- subjective feedback from the workers regarding their experience with both assembly stations.

Efficiency was defined as a function of task completion time, error rate, and cycle time adherence. The efficiency of worker group on both assembly stations was calculated and compared to identify trends and differences. The efficiency improvement for the Smart SSMAC was determined by comparing the performance metrics of the workers on the smart station to those on the traditional SSMAC.

Data were recorded for analysis pertaining to Traditional SSMAC and Smart SSMAC. The collected data were analysed to determine the efficiency improvements for inexperienced/novice workers when transitioning from the Traditional to the Smart SSMAC. To understand the financial implications on the organization, data was also recorded to facilitate cost saving per assembled product.

Results and discussion

Figure 9 presents a comparative look at the SSMAC system before and after implementation through photographic evidence. The images visually illustrate significant improvements in system design, workspace layout, and automation enhancements, showcasing the advantages of the upgraded system.

Figure 10 illustrates the HMI screens designed for the SAT/Smart SSMAC, showcasing a comprehensive and user-friendly layout for efficient part assembly and managerial/supervisory control. These screens enabled the Smart SSMAC to remain flexible while accommodating the requirements of soft product variety. The Smart SSMAC can be configured based on the type or variety of the product to be assembled, with its configuration limited by the number of child parts as determined by the hardware/bin setup.

The primary screen provides options for part selection and cycle monitoring, ensuring operators can easily initiate and track the assembly process. Subsequent screens display detailed information on the number of successful and failed cycles, as well as the count of Ok and Nok (Not OK) parts, allowing operators to monitor performance and identify errors in real time. Additionally, the interface includes specific screens for different final assembled product component categories, such as Emergency Switch, Selector Switch, and Metal Lock and Key, each listing corresponding child parts for easy identification and selection. The managerial control screen enables administrators to reset controls and adjust cycle time settings via a user-friendly slider, facilitating precise cycle time management and enhancing overall assembly efficiency. This HMI design aims to streamline the assembly process, reduce errors, and optimize worker productivity by providing intuitive and accessible control options.

The implementation of the SAT/Smart SSMAC has yielded significant positive outcomes across various metrics critical to industrial assembly. The data were recorded during the testing and evaluation phases and further analysed for determination of various performance metrics.

Table S2 presents the actual cycle time recorded for twenty assembly cycles by each of five workers (i.e. one hundred assembly cycles) with Traditional and Smart SSMAC.

Figure 9 SSMAC photographs before (i.e. Traditional) and after (i.e. Smart).

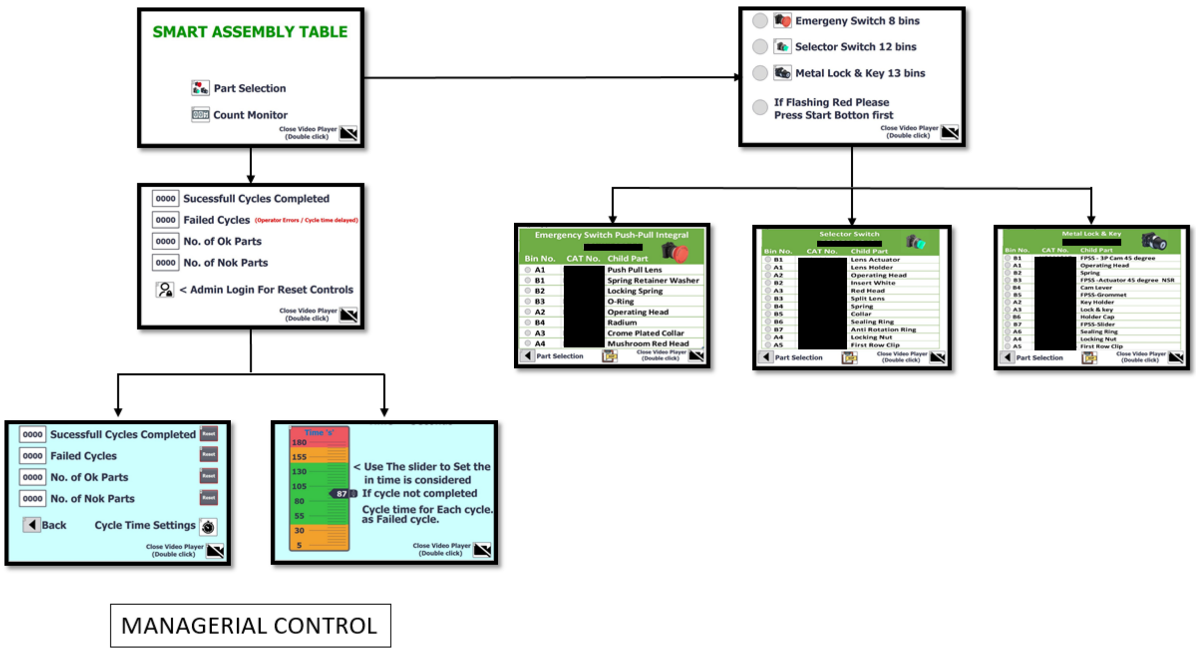


Figure 10 Illustration of HMI screens to cater product variety.

A. Analysis based on Cycle Time and Standard Time

Tables S3 and S4 illustrate the determination of standard assembly cycle time through data analysis for assembly cycles using Traditional and Smart SSMAC, respectively.

Comparative Analysis of Cycle Time and Standard Time

- The data indicated that inexperienced/novice workers exhibited significantly lower cycle times in the Smart SSMAC compared to the Traditional SSMAC. The average cycle time for workers in the Smart SSMAC ranged from 898.55 to 930.95 seconds, whereas in the Traditional SSMAC, it was 1142.65 to 1223.80 seconds. This suggests that the Smart SSMAC facilitated faster task execution, even though all workers were still operating at a pace slower than the standard.
- The calculated Standard Time in the Smart SSMAC was approximately 898.52 to 946.82 seconds, while for the Traditional SSMAC, it was 1194.07 to 1211.56 seconds. The average Standard Time considered for further analysis in the Smart SSMAC was 930 seconds, while for the Traditional SSMAC, it was 1200 seconds. This reduction in Standard Time further confirmed the efficiency-enhancing capabilities of the Smart SSMAC.

Impact of Smart SSMAC on Performance Efficiency

- Despite having performance ratings below 100% (indicating that workers are slower than standard pace in both setups), the cycle times in the Smart SSMAC were consistently lower. This suggests that technological enhancements, better ergonomics, and process guidance in the Smart SSMAC helped mitigate inefficiencies, reducing total assembly time. The percentage reduction in cycle time due to Smart SSMAC implementation ranges from 20% to 26% across different workers. With reference to the average cycle time, 22.5% reduction in cycle time was obtained.

Influence of Worker Speed (Performance Rating) on Cycle Time

- It is interesting to note that the performance rating of two workers (worker 3 and 4) were different and three workers (worker 1, 2 and 5) were same while working with Traditional and Smart SSMAC. Worker 3 demonstrated faster performance rating of 95% while working with Smart SSMAC than that of 90% with Traditional SSMAC. Worker 4 demonstrated slower performance rating of 90% while working with Smart SSMAC than that of 93% with Traditional SSMAC. No change in performance rating was observed for worker 1, 2, and 5 while working with Traditional and Smart SSMAC. The performance rating of all workers was recorded and observed as lower than the standard pace (i.e. lower than 100%) for both Traditional and Smart SSMAC. Subjective feedback was taken from all the workers and analysing the feedback helped to identify the reasons for obtaining the same/different performance ratings by the same worker over the two scenarios.
- Reasons identified for improvement in performance rating while working with Smart than that of Traditional SSMAC (i.e. worker is faster in the Smart setup than in the Traditional setup) are discussed here.
    - Better Ergonomics in Smart SSMAC:
      Smart system has better workstation design, optimized tool positioning, reduction in unnecessary movements and improvement in cycle time. e.g. a pick-to-light system has reduced search time, leading to faster assembly.
    - Assisted Decision-Making:
      The smart system provided step-by-step guidance (video displays, digital work instructions), it reduced mental effort, helping the worker work faster and with fewer errors.
    - Error Prevention & Time Adjustments:
      The chances of violating the sequential pick up of parts has got drastically reduced due to buzzer alerts. Worker was made alert about the excessive elemental time from time-to-time and this helped worker to change the pace at subsequent work elements and provided an opportunity to make up against the excessive time spent at earlier work elements.
    - Real-Time Performance Feedback & Motivation:
      Smart systems often provide real-time performance tracking, which motivated workers to improve their speed by comparing their performance to standard/target.
    - Reduced Stress & Increased Confidence:
      With real-time feedback and structured workflows, the worker felt more confident and less anxious, leading to a smoother and faster performance.
- Reasons identified for greater performance rating while working with Traditional than that of Smart SSMAC (i.e. worker is faster in the Traditional setup than in the Smart setup) are discussed here.

- Learning Curve & Adaptation Issues:
  The worker was more familiar with the traditional setup and took time to adapt to the smart system, leading to initial hesitation or slower performance. The smart system has new digital interfaces (e.g., touch screens, video displays, pick-to-light and buzzer signals), the worker took longer to operate and understand them.
- Increased Cognitive Load in Smart SSMAC:
  Worker felt that, the smart system provided too much information (such as real-time monitoring, alerts, or instructional videos), it slowed down decision-making. The workers were over-reliant on the guidance from the smart system instead of following their intuition, causing delays. The worker was overwhelmed by too much real-time data, alerts, or step-by-step instructions, making them slower as they process information before taking action.
- Automation Bottlenecks:
  The Smart system forced sequential steps (e.g., waiting for verification before proceeding) and this slowed an inexperienced/novice worker who previously worked in non-automated environment.
- Lack of Flexibility in Smart SSMAC:
  Traditional setups allowed workers to improvise (e.g., adjusting part handling methods or doing the same thing in different way). Smart system enforced rigid workflows (e.g., requiring confirmation before proceeding), which slowed down inexperienced/novice workers.
- Lack of Familiarity with Smart System:
  The novice worker struggled to navigate the smart system's digital interfaces, sensors, or automated feedback mechanisms, leading to slower execution.

- Reasons identified for same performance rating while working with Traditional and that of Smart SSMAC (i.e. worker performs at the same speed in both environments) are discussed here.
  - Worker's Adaptation to Both Systems:
    Workers naturally adapted well to both Traditional and Smart systems, showing consistent performance.
  - Minimal Difference in Task Complexity:
    The assembly process was simplified and did not require much decision-making. The smart system did not distract or acted as a cognitive load on the worker, leading to similar performance rating in both setups.
  - Slow Learning Curve in Both Setups:
    The worker was still in the early stages of skill acquisition and has not yet developed speed, making their performance consistently slow across both systems.
- In both setups, the performance rating alone does not fully explain the cycle time reduction in the Smart SSMAC. Even workers with the same rating (e.g., Worker 1 in both setups, rated at

95%) showed substantial improvements in Smart SSMAC. This suggests that process standardization, automation assistance, and cognitive load reduction play a major role in improving efficiency, independent of the worker's manual skill level.

Reduction in Variability of Work Output

- The range of cycle times in the Traditional SSMAC was 81.15 seconds (1223.80 - 1142.65), whereas in the Smart SSMAC, it was 32.40 seconds (930.95 - 898.55). The reduced variability in the Smart SSMAC suggests that the system standardizes assembly processes, making performance more consistent across workers. This reduction in variability indicates that smart assistance compensates for individual differences in skill level, creating a more predictable and controlled work environment.

Efficiency Gains from Smart SSMAC

- The percentage decrease in Standard Time for each worker when shifting from Traditional to Smart SSMAC was significant:
  - Worker 1: 21.3% reduction
    (1200.29s ⟶ 944.31s)
  - Worker 2: 22.9% reduction
    (1195.92s ⟶ 921.64s)
  - Worker 3: 21.8% reduction
    (1211.56s ⟶ 946.82s)
  - Worker 4: 24.8% reduction
    (1194.81s ⟶ 898.52s)
  - Worker 5: 21.4% reduction
    (1194.07s ⟶ 938.98s)
- This confirmed that the Smart SSMAC provided efficiency improvements of approximately 21% to 25%, likely due to better work ergonomics, automated guidance, and improved workflow management.

To evaluate whether the observed reduction in cycle time using the Smart SSMAC compared to the Traditional assembly method was statistically significant, a paired-sample t-test was conducted [31]. The test was chosen because the same participants performed assembly cycles under both conditions, allowing for within-subject comparison. The paired-sample t-test showed that the Smart SSMAC significantly reduced the mean cycle time compared to the traditional method ($t(4) = 35.4587$, $p < 0.0001$, $d = 15.86$). The 95% CI of the difference ([248.1915 s, 290.3605 s]) indicates that the reduction in cycle time is both statistically significant and practically meaningful. These results demonstrate that the observed improvements are highly unlikely to be due to random variation, supporting the conclusion that the Smart SSMAC offers a substantial performance advantage.

A one-way repeated-measures ANOVA was conducted with Method (Traditional vs Smart SSMAC) as the within-subject factor [31]. The F-ratio value is 1257.32109. The p-value is < .00001. The result is significant at $p < .01$. The ANOVA confirms the paired t-test results, showing a very strong and statistically significant effect of method on cycle time.

The convergence of results from parametric (t-test, ANOVA) analyses demonstrates that the performance improvements achieved by Smart SSMAC are statistically significant, practically meaningful, and robust to analytical approach [31].

B. Analysis based on errors and defective products

Tables S6 and S7 present the data recorded pertaining to errors, instances of delayed cycle time and defective products for assembly cycles using Traditional and Smart SSMAC, respectively. The analysis of data from Tables S6 and S7 helped to determine the performance metrics. Table S8 presents the performance metrics indicating better performance by Smart SSMAC over Traditional.

Comparative Analysis of Errors and Defective Products (Nok Parts)

- The transition from a Traditional SSMAC to a Smart SSMAC has led to a significant reduction in operator errors, delayed cycle time instances, and defective products. A comparison of key performance indicators is presented in Table S8.

Reduction in Operator Errors

- In the Smart SSMAC, the total operator errors were reduced from 14 to 4, a 71.4% improvement. Possible reasons for this significant reduction include: (i) Real-time guidance and digital work instructions, minimizing confusion and manual errors, (ii) Cognitive load reduction, allowing workers to focus more on precision rather than memorizing steps.

Improved Adherence to Set Cycle Time

- The Smart SSMAC increased adherence to set cycle time from 67 to 90 instances, an improvement of 34.3%. This improvement suggests: (i) Better process standardization, ensuring workers follow the correct sequence efficiently, (ii) Assisted task execution, reducing hesitation and variation in task completion, (iii) Automation support for repetitive or complex steps, reducing delays.

Reduction in Delayed Cycle Time Instances

- The number of instances where cycle time exceeded the set standard dropped from 33 to 10, a 69.7% improvement. In the Traditional SSMAC, workers faced frequent delays due to: (i) Inefficient task flow (e.g., searching for tools or components), (ii) Errors requiring correction, leading to extended cycle times, (iii) Physical fatigue and lack of process optimization. The Smart SSMAC addressed these issues through: (i) Ergonomically optimized workstations, minimizing unnecessary motion, (ii) Intelligent workflow management, preventing bottlenecks.

Reduction in Defective Products (Nok Parts)

- The number of defective products decreased from 10 to 3, a 70% improvement. Possible reasons for the quality enhancement include: (i) Error-proofing mechanisms, ensuring correct assembly steps are followed, (ii) Digital guidance systems, alerting about defects before they lead to faulty assemblies. (iii) Reduced rework cycles, preventing cumulative defects.

- Table S9 provides comparison of reasons for production of final defective assembled product (Nok Parts) in both the environments. This suggests that though there is substantial reduction in defective products, those cannot be completely eliminated due to certain possible reasons associated with the Smart SSMAC too.

Standardization and Process Control in Smart SSMAC

- The Smart SSMAC minimized variation across workers. In the Traditional SSMAC, some workers (e.g., Worker 3) had higher error rates and more delayed cycle times. In the Smart SSMAC, all workers consistently adhered to set cycle times, with significantly fewer delays and errors. This suggests that automation and digital assistance compensated for skill level differences, ensuring consistent output across all operators.

C. Financial implications

Table S10 presents the data for economic analysis for Traditional and Smart SSMAC based on one hundred cycles.

Productivity Enhancement with Smart SSMAC

- The cycle time per unit is reduced by 22.5% (from 1200 sec to 930 sec), enabling higher production efficiency. The number of units assembled per hour increased by 29% in Smart SSMAC (from 3 to 3.87 units/hour), demonstrating improved operational throughput.

Reduction in Labor Cost per Unit

- The average labor cost per unit decreased by 22.5%, from INR 25 in Traditional SSMAC to INR 19.38 in Smart SSMAC. The total labor cost for 100 good-quality products dropped by INR 1137.58 (35%), making Smart SSMAC a cost-effective alternative.

Impact of Defective Products on Labor Cost

- The defect rate reduced from 10% to 3% in Smart SSMAC, resulting in 70% fewer defective products. Due to this improvement, only 103.09 units were required to produce 100 good-quality products in Smart SSMAC, compared to 111.11 units in Traditional SSMAC. The total labor cost associated with defective products decreased from INR 750 to INR 174.42, marking a 76.7% reduction in rework expenses.

Savings on Rework and Assembly Labor Costs

- Smart SSMAC significantly minimizes rework costs, as defective products undergo additional assembly, disassembly, inspection, and reassembly processes. The average labor cost per unit for good-quality products is INR 21.12 in Smart SSMAC versus INR 32.50 in Traditional SSMAC, leading to a 35% per-unit cost reduction.

Reasons for Cost Reduction in Smart SSMAC

- Process Automation and Digital Assistance
    - Automated guidance systems reduce assembly errors, improving first-pass yield.

  - Faster cycle times lead to increased production output per hour.
  - Real-time monitoring and process control minimize rework requirements.
- Reduced Defects and Rework
  - Smart SSMAC prevents incorrect assembly through error-proofing mechanisms, leading to fewer defective parts.
  - Lower defect rates reduce the need for additional labor costs related to reassembly, inspection, and disassembly.
- Improved Standardization and Operator Efficiency
  - Consistent workflow and guided operations result in less variation between workers.
  - Ergonomically optimized workstations reduce operator fatigue, leading to better productivity.

Table S11 provides the overall comparison of results of Traditional SSMAC and Smart SSMAC.

Conclusion

The observed improvements suggest that SAT/Smart SSMAC effectively addressed the key challenges posed due to the high attrition rate of inexperienced/novice workers while working with the Traditional SSMAC of the MSME. The real-time monitoring and automated features contributed to more precise and efficient operations. The significant reduction in cycle times and errors underscored the potential of advanced technologies to optimize manual processes, enhance accuracy, and streamline workflow. The improved cycle times and reduced error rates implied that manufacturers can achieve higher production rates and better product quality with the SAT/Smart SSMAC. This efficiency can lead to cost savings and improved competitiveness in the market. The cost of upgrading to the Smart SSMAC was justified by the observed performance gains, highlighting the value of advanced technologies in modern manufacturing. The increased efficiency for an inexperienced/novice worker highlighted the Smart SSMAC’s ability to support inexperienced/novice workers. This capability can further reduce the training burden and ensure consistent performance regardless of operator skill.

By reducing the cognitive load on workers through automated alerts and clear digital instructions, the Smart SSMAC contributed to a more focused and efficient workforce. This suggests that smart technologies can enhance human capabilities rather than replace them, fostering a collaborative human-machine environment. The decrease in errors and increase in productivity reflect the Smart SSMAC's capacity to support continuous improvement and lean manufacturing principles, which are essential for maintaining competitive advantage in modern industries. The improved workflow and resource utilization indicated that the Smart SSMAC not only benefits individual workers but also enhances overall production line efficiency. This holistic improvement aligns with the goals of Industry 4.0, which emphasizes interconnected and intelligent production systems.

The adaptability of the Smart SSMAC to various assembly tasks and environments need to be further evaluated for its versatility and potential for widespread adoption across different sectors. The study was conducted in a specific controlled environment, which might not have fully captured the variability of real-world manufacturing conditions. Future research should explore the Smart SSMAC's performance in diverse settings and with different product types. Although the Smart SAMC improved efficiency for inexperienced/novice operators, the extent of improvement varied. Further investigation is needed to understand how the system performs with a broader range of skill levels (highly skilled, moderately skilled and unskilled) and in different operational contexts. The study focused on short-term performance metrics. Long-term reliability and maintenance considerations were not extensively analysed, which should be addressed in future evaluations. Considering the limited batch size and the high frequency of batch repetition, implementing a scheduling system and an optimized scheduling algorithm can further enhance the financial benefits for the MSME. Since the MSME operates based on both internal orders driven by forecasting and external customer orders, there is an opportunity to analyze order sequencing and frequency. By applying a suitable production scheduling technique or algorithm, setup time can be minimized. Additionally, the MSME may plan to expand the number of Smart SSMACs and explore the possibility of a parallel machining environment to improve efficiency [72, 73].

This research contributes to the understanding of how advanced assembly technologies can enhance industrial efficiency and accuracy. The study provides empirical data and insights into the benefits of integrating smart technologies in manufacturing processes. The development and implementation of the Smart SSMAC offer a practical example of how technology can address common challenges in assembly operations. The findings provide a foundation for further research into optimizing assembly processes and exploring additional technological advancements.

The findings from the implementation of the SAT/Smart SSMAC underscore its potential as a transformative tool in the landscape of industrial assembly, particularly in the context of Industry 4.0. The significant improvements in worker efficiency, assembly accuracy, and operational efficiency highlight the effectiveness of integrating advanced technologies into traditional assembly processes.

Acknowledgements

The Smart SSMAC was developed with the support of Esbee ElectroTech LLP, MIDC Bhosari, Pune: 411026, Maharashtra State, India. The authors are grateful to the Esbee ElectroTech LLP team for their contribution. Authors thank Mr. Vijay Chordiya (Designated Partner), Mr. Vikrant Khomne (Head of Operations & General Manager), Mr. Avinash Kulkarni (Maintenance Engineer), and Ms. Shraddha Milke (Manager Executive – Services).

References

1. Vasani S, Abdulkareem AM. MSME market presence and competitiveness in a global economy. Cogent Econ Finance. 2024;12(1):2416992.
2. Maheshkar C, Soni N. Problems faced by Indian micro, small and medium enterprises (MSMEs). SEDME Small Enterp Dev Manag Ext J. 2022; 49(1):1-18.

3. Hansen H, De SK, Rand J, Trifković N. Wage returns to workplace training in Myanmar. Dev Policy Rev. 2022;41(2):e12658.
4. Mishra SK. Labor rights and MSME policy in India: a critical assessment of compliance with international conventions. Rev Bras Desenvolv Inov. Rev Bras Desenvolv Inov [Internet]. 2025;2(3). Available from: https://rbdin.com.br/index.php/revista/article/view/56/55.
5. Saptari A, Leau JX, Mohamad NA. The effect of time pressure, working position, component bin position and gender on human error in manual assembly line. Proceedings of the 2015 International Conference on Industrial Engineering and Operations Management (IEOM); 2015 Mar 3-5; Dubai, United Arab Emirates. Dubai: IEEE; 2015. p. 1-6.
6. Saptari A, Leau JX, Ng PK, Mohamad E. Human error and production rate correlation in assembly process of electronics goods. Proceedings of the Design and Systems Conference; 2014 Sep 17-19; Tokushima City, Japan. 2014;24(2309):1-6.
7. Aly S, Tyrychtr J, Vrana I. Optimizing design of smart workplace through multi-objective programming. Appl Sci. 2021;11(7):3042.
8. Slotwinski JA, Tilove RB. Smart assembly: industry needs and challenges. Proceedings of the 2007 Workshop on Performance Metrics for Intelligent Systems, PerMIS'07; 2007 Aug 28-30; New York, USA. New York: Association for Computing Machinery; 2007. p. 257-62.
9. Hijry H, Naqvi SMR, Javed K, Albalawi OH, Olawoyin R, Varnier C. Real time worker stress prediction in a smart factory assembly line. IEEE Access. 2024;12:116238-49.
10. Petruse RE, Vlad SM. Optimizing manual assembly operations: ergonomics analysis and human-robot collaboration. Acta Univ Cibiniensis. Technical Series. 2023;75(1):1-13.
11. Miqueo A, Torralba M, Yagüe-Fabra JA. Lean manual assembly 4.0: a systematic review. Appl Sci. 2020;10(23):8555.
12. Turk M, Resman M, Herakovič N. The impact of smart technologies: a case study on the efficiency of the manual assembly process. Procedia CIRP. 2021;97:412-7.
13. Javaid M, Haleem A, Singh RP, Suman R, Gonzalez ES. Understanding the adoption of industry 4.0 technologies in improving environmental sustainability. Sustain Oper Comput. 2022;3:203-17.
14. Lorenzini M, Lagomarsino M, Fortini L, Gholami S, Ajoudani A. Ergonomic human-robot collaboration in industry: a review. Front Robot AI. 2023;9:813907.
15. Hasanain B. The role of ergonomic and human factors in sustainable manufacturing: a review. Machines. 2024;12(3):159.
16. Ciccarelli M, Papetti A, Cappelletti F, Brunzini A, Germani M. Combining world class manufacturing system and industry 4.0 technologies to design ergonomic manufacturing equipment. Int J Interact Des M. 2022;16(1):263-79.
17. Alipoor P, Daneshmandi H, Fararuei M, Zamanian Z. Ergonomic design of manual assembly workstation using digital human modeling. Ann Glob Health. 2021;87(1):55.
18. Mor RS, Bhardwaj A, Singh S, Sachdeva A. Productivity gains through standardization-of-work in a manufacturing company. J Manuf Technol Manag. 2018;30*(6)*:899-919.

19. Alrae R. Quality tools, technologies, and techniques: enhancing product and service excellence. In: Zahid Qamar Z, Al-Hinai N, editors. Quality control and quality assurance - techniques and applications. IntechOpen;2024.p.1-31.
20. Sanchez E, Joelsson A, Baumgartner MA, Åkesson K. The impact of visualizing operational deviations on overall quality in assembly lines. Procedia CIRP, 2022;107:46-52.
21. Komandla V. Enhancing product development through continuous feedback integration. ESP Journal of Engineering and Technology Advancements (ESP-JETA). 2022;2(4):105-15.
22. Fletcher SR, Johnson T, Adlon T, Larreina J, Casla P, Parigot L, et al. Adaptive automation assembly: identifying system requirements for technical efficiency and worker satisfaction. Comput Ind Eng. 2020;139:105772.
23. Harrison CS. A review of automation in manufacturing illustrated by a case study on mixed-mode hot forging. Manuf Rev. 2014;1:15.
24. Wen B-J, Liu T-W. Automatic assembly with dual robotic arms based on mutual visual tracking and positioning. Sci Prog. 2023;106(2):003685042311726.
25. Macias-Velasquez S, Medellin-Castillo HI, Garcia-Barrientos A. New-user experience evaluation in a semi-immersive and haptic-enabled virtual reality system for assembly operations. Int J Hum Comput Stud. 2024;190:103312.
26. Dhanvijay M, Kulkarni V, Patil N, Bewoor A. Development of PLC-based system for lift gate slam platform. Proceedings of the International Conference on Materials for Emerging Technologies: ICMET-2021, 18-19 February 2022, Phagwara, India. AIP Conf Proc. 2023;2800(1):020231.
27. Dhanvijay M, Patki R, Ahuja B. Development of PLC-based controller for door slam platform. In: Panchal D, Chatterjee P, Tyagi M, Singh RP, editors. Optimization methods for engineering problems. New York: Apple Academic Press; 2023:17-30.
28. Durão LFCS, Haag S, Anderl R, Schützer K, Zancul E. Development of a smart assembly data model. In: RÍos J, Bernard A, Bouras A, Foufou S, editors. Product lifecycle management and the industry of the future. PLM 2017. IFIP Advances in Information and Communication Technology. Cham: Springer International Publishing. 2017;517:655-66.
29. Da Costa TP, Da Costa DMB, Murphy F. A systematic review of real-time data monitoring and its potential application to support dynamic life cycle inventories. Environ Impact Assess Rev. 2024;105:107416.
30. Gardecki A, Rut J, Klin B, Podpora M, Beniak R. Implementation of a hybrid intelligence system enabling the effectiveness assessment of interaction channels use in HMI. Sensors (Basel). 2023;23(8):3826.
31. Shinde PS, Poredi CS, Shelke GS, Patil SS, Subhedar JJ, Dhanvijay MR, et al. Transforming MSME assembly operations: smart manual assembly table for improved productivity. Int J Basic Appl Sci (IJBAS). 2025;14(1):40-51.
32. Khamkar AD, Patil SM. Digital twin in fluid power: reviewing constituents. Int Res J Multidiscip Scope. 2024;5(1):750-65.

33. Khamkar AD, Patil SM. Digital twin in fluid power: Review-technology trends. Int Res J Multidiscip Scope. 2024;5(2):596-610.
34. Khamkar AD, Patil SM. Digital twin in fluid power: review-uses and outlook. Int Res J Multidiscip Scope. 2024;5(3):79-96.
35. Aderiani AR, Wärmefjord K, Söderberg R. Combining selective assembly and individualized locator adjustments techniques in a smart assembly line. Procedia CIRP. 2021;97:429-34.
36. Turk M, Pipan M, Simic M, Herakovic N. A smart algorithm for personalizing the workstation in the assembly process. Appl Sci. 2020;10(23):8624.
37. Shikdar A, Garbie I, Khadem MMRK. Development of a smart workstation for an assembly task. Proceedings of the 2011 International Conference on Industrial Engineering and Operations Management; 2011 Jan 22-24; Kuala Lumpur, Malaysia. 2011. p. 826-31.
38. Fung VW, Yung KC. An intelligent approach for improving printed circuit board assembly process performance in smart manufacturing. International Journal of Engineering Business Management. 2020;12:184797902094618.
39. Mumtaz J, Zailin G, Rauf M, Yue L, He C, Wang H. A conceptual framework of smart manufacturing for pcb industries. Proceedings of the 48th International Conference on Computers and Industrial Engineering (CIE48); 2018 Dec 2-5; Auckland, New Zealand. 2018. p. 1298-1306.
40. Kamble R, Kulkarni V. productivity improvement at assembly station using work study techniques. Int J Res Eng Technol. 2014;3(9):480-487.
41. Raouf I, Kumar P, Khalid S, Kim HS. Developments, challenges, and opportunities for the health assessment of smart factory. Int J Precis Eng Manuf-Green Technol. 2025;12:1321-38.
42. Visconti P, Rausa G, Del-Valle-Soto C, Velázquez R, Cafagna D, De Fazio R. Machine learning and IoT-based solutions in industrial applications for smart manufacturing: a critical review. Future Internet. 2024;16(11):394.
43. Allagui A, Belhadj I, Plateaux R, Hammadi M, Penas O, Aifaoui N. Towards smart assembly based design. In: Walha L, Jarraya A, Djemal F, Chouchane M, Aifaoui N, Chaari F, et al. editors. Design and Modeling of Mechanical Systems-V. CMSM 2021. Lecture Notes in Mechanical Engineering. Cham: Springer International Publishing. 2022. p. 225-31.
44. Tian W, Ding Y, Du X, Li K, Wang W, Wang C, et al. A review of intelligent assembly technology of small electronic equipment. Micromachines. 2023;14(6):1126.
45. Webb L, Tokhi OM, Alkan B. State of the art and future directions of digital twin-enabled smart assembly automation in discrete manufacturing industries. Int J Comput Integr Manuf. 2025;38(8):1126-60.
46. Alahi MEE, Sukkuea A, Tina FW, Nag A, Kurdthongmee W, Suwannarat,K, et al. Integration of IoT-enabled technologies and artificial intelligence (AI) for smart city scenario: recent advancements and future trends. Sensors. 2023;23(11):5206.

47. Mo F, Querejeta MU, Hellewell J, Rehman HU, Rezabal MI, Chaplin JC, et al. PLC orchestration automation to enhance human–machine integration in adaptive manufacturing systems. J Manuf Syst. 2023;71:172-87.
48. Gnana SOV, Karthikeyan A., Karthikeyan K, Sanjeevikumar P, Thomas SK, Babu A. Critical review of SCADA and PLC in smart buildings and energy sector. Energy Rep. 2024;12:1518-30.
49. Chavhan N, Bhattad R, Khot S, Patil S, Pawar A, Pawar T, et al. APAH: An autonomous IoT driven real-time monitoring system for industrial wastewater. Digit Chem Eng. 2025;14:100217.
50. Bernabei M, Costantino F. Adaptive automation: status of research and future challenges. Robot Comput Integr Manuf. 2024;88:102724.
51. Bortolini M, Botti L, Galizia FG, Mora C. Ergonomic design of an adaptive automation assembly system. Machines. 2023;11(9):898.
52. Botti L, Mora C, Regattieri A. Integrating ergonomics and lean manufacturing principles in a hybrid assembly line. Comput Ind Eng. 2017;111:481-91.
53. Konz SA, Johnson S. Work design: occupational ergonomics. 7th ed. CRC Press: Taylor & Francis Group; 2016.
54. Peruzzini P, Pellicciari M, Gadaleta M. A comparative study on computer-integrated set-ups to design human-centred manufacturing systems. Robot Comput Integr Manuf. 2019;55B:265-78.
55. Velsen Lv, Ludden G, Grünloh C. The limitations of user-and human-centered design in an ehealth context and how to move beyond them. J Med Internet Res. 2022;24(10):e37341.
56. Duffy A, Boroumandzad N, Sherman AL, Christie G, Riadi I, Moreno S. Examining challenges to co-design digital health interventions with end users: systematic review. J Med Internet Res. 2025;27:e50178.
57. Sreenivasan A, Suresh M. Design thinking and artificial intelligence: a systematic literature review exploring synergies. Int J Inno Stud. 2024;8(3):297-312.
58. Kenny U, Regan A, Hearne D, O'Meara C. Empathising, defining and ideating with the farming community to develop a geotagged photo app for smart devices: a design thinking approach. Agric Syst. 2021;194:103248.
59. Seidel VP, Fixson SK. Adopting design thinking in novice multidisciplinary teams: the application and limits of design methods and reflexive practices. J Prod Innov Manage. 2013;30(SI):19-33
60. Khan MS, Al-Ashaab A, Shehab E, Haque B, Ewers P, Sorli M, et al. Towards lean product and process development. Int J Comput Integr Manu. 2011;26(12):1105-16.
61. Nagai RA, Torres Junior AS. Lean product and process development and set-based concurrent engineering in the dining industry: the experience of an american-asian fusion restaurant. Int J Action Res. 2020;16(3):202-24.
62. Gomes M, Correia M, Marques F, Alves AC. Lean product and process development in an automotive company. Preprints. 2023; 2023110303.
63. Dafflon B, Moalla N, Ouzrout Y. The challenges, approaches, and used techniques of CPS for manufacturing in Industry 4.0: a literature review. Int J Adv Manuf Technol. 2021;113:2395-2412.

64. Javaid M, Haleem A, Singh RP, Suman R. An integrated outlook of cyber–physical systems for industry 4.0: topical practices, architecture, and applications. Green Technol Sustain. 2023;1(1):100001.
65. Nielsen J, Landauer TK. A mathematical model of the finding of usability problems. Proceedings of the INTERACT'93 and CHI'93 Conference on Human Factors in Computing Systems; 1993 Apr 24-29; Amsterdam, The Netherlands. Amsterdam: ACM Press; 1993. p. 206-13.
66. Virzi RA. Refining the test phase of usability evaluation: how many subjects is enough? Hum Factors. 1992;34(4):457-68.
67. Sauro J, Lewis JR. Quantifying the user experience practical statistics for user research. Elsevier; 2012.
68. Alroobaea R, Mayhew PJ. How many participants are really enough for usability studies? Proceedings of the 2014 Science and Information Conference; 2014 Aug 27-29; London, UK. London: IEEE; 2014. p. 48-56.
69. Li Y, Yang X, Yang Z. Uncertain learning curve and its application in scheduling. Comput Ind Eng. 2019;131:534-41.
70. Hogan D, Elshaw J, Koschnick C, Ritschel J, Badiru A, Valentine S. Cost estimating using a new learning curve theory for non-constant production rates. Forecasting. 2020;2(4):429-51.
71. Al-Moteri M, Alzahrani AA, Althobiti ES, Plummer V, Sahrah AZ, Alkhaldi MJ, et al. The road to developing standard time for efficient nursing care: a time and motion analysis. Healthcare. 2023;11(15):2216.
72. Patil PS, Patil SS, Patil SM, Dhanvijay MR. Development of MS Excel and Power BI integrated production scheduling system for an MSME. Engineering Access. 2024;10*(2):*124-42.
73. Hajariwala DC, Patil SS, Patil SM. A review of metaheuristic algorithms for job shop scheduling. Engineering Access. 2025;11*(1):*65-91.