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Data-Driven Scheduling Optimization for SMT Lines Using SMD Reel Commonality

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Abstract: Optimizing production efficiency in Surface-Mount Technology (SMT) manufacturing is a critical challenge, particularly in high-mix environments where frequent product changeovers can lead to significant downtime. This study presents a scheduling algorithm that minimizes changeover times on SMT lines by leveraging the commonality of Surface-Mount Device (SMD) reel part numbers across product Bills of Materials (BOMs). The algorithm's capabilities were demonstrated through both simulated datasets and practical validation trials, providing a comprehensive evaluation framework. In the practical implementation, the algorithm successfully aligned predicted and measured changeover times, highlighting its applicability and accuracy in operational settings. The proposed approach integrates heuristic and optimization techniques to identify scheduling strategies that not only minimize reel changes but also support production scalability and operational flexibility. This framework offers a robust solution for optimizing SMT workflows, enhancing productivity, and reducing resource inefficiencies in both greenfield projects and established manufacturing environments.

Keywords: SMT; scheduling optimization; SMD reels; changeover time; production efficiency

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1. Introduction

Printed Circuit Board Assembly (PCBA) is an essential process in electronics manufacturing, enabling the production of complex electronic devices with high precision and efficiency. The process involves multiple steps, including solder paste printing, component placement, and reflow soldering, with each step requiring meticulous coordination to ensure quality and throughput. Among these steps, Surface-Mount Technology (SMT) stands out as a critical method for assembling Surface-Mount Devices (SMDs) onto PCBs, driven by the need for high-speed, accurate, and scalable manufacturing [1].

In SMT manufacturing, changeover time is a key factor that influences production efficiency, particularly in high-mix environments [2]. Changeovers occur when the production line transitions from one product to another, requiring the adjustment of equipment, feeders, and the replenishment of SMD reels. Each changeover introduces downtime [3,4], which can accumulate significantly, impacting overall productivity and increasing operational costs. Additionally, prolonged changeover times can lead to delays in meeting production deadlines, escalating costs, and eroding customer satisfaction [5]. In competitive industries like electronics manufacturing, such inefficiencies directly affect a company's ability to maintain market relevance and respond to customer demands promptly.

A notable challenge in SMT changeovers arises from the need to accommodate unique Bills of Materials (BOMs) for different products. While some components are common across multiple BOMs, others are product-specific, necessitating frequent reel changes [6]. The complexity of managing these changes is compounded by the static or manual scheduling methods used in many facilities, which do not account for the commonality of part numbers or the potential for optimized sequencing of production runs [7]. This results in inefficiencies that could otherwise be mitigated with a data-driven approach.

The problem of optimizing SMT scheduling, specifically in terms of minimizing reel changes, remains underexplored. Traditional approaches often focus on volume-driven scheduling or rely on first-in-first-out methods, which do not adequately address the need to reduce tooling changes during high-mix production runs [8]. This gap underscores the importance of developing algorithms that can analyze BOM data, identify shared components, and sequence production runs to minimize downtime while maintaining flexibility in production [9].

This work proposes a theoretical scheduling algorithm to optimize the sequencing of SMT production runs by leveraging shared SMD reel part numbers. The algorithm is designed to reduce changeover times by minimizing the frequency of reel changes, addressing a critical inefficiency in the SMT process. The broader implications of reducing changeover times extend beyond production efficiency to include cost savings, improved customer satisfaction, and enhanced competitiveness in the SMT industry [5].

The proposed approach aligns with ongoing efforts to integrate advanced optimization methods into the broader context of intelligent manufacturing systems. Recent studies have demonstrated the potential of hybrid optimization algorithms, such as the Hybrid Spider Monkey Optimization (HSMO) algorithm, to address complex scheduling challenges in multi-level PCB assembly lines by combining heuristic and metaheuristic techniques [10]. These methods emphasize workload balancing, efficient resource allocation, and the seamless flow of materials, which are critical for achieving high throughput and minimizing operational costs in SMT manufacturing.

The HSMO algorithm highlights the importance of incorporating real-time data, predictive modeling, and intelligent decision-making tools into scheduling frameworks. While this study focuses on reducing changeover times, future work could integrate the proposed algorithm into Material Requirements Planning (MRP) or Manufacturing Execution Systems (MESs) to enable dynamic scheduling, improved material handling, and greater adaptability to production demands [10].

This study contributes a systematic framework for improving SMT line efficiency by prioritizing shared components across BOMs during scheduling. Leveraging BOM data and validating the approach in practical scenarios, the algorithm offers an adaptable solution for reducing changeover times and improving throughput, providing significant value for high-mix SMT environments and laying the groundwork for future advancements in data-driven scheduling.

2. Literature Review

The efficient management of SMT has been the focus of extensive research [11,12]. Changeover time, which refers to the period required to transition production lines between different products, represents a critical bottleneck in SMT manufacturing. This bottleneck not only affects production efficiency but also influences inventory management, operational costs, and delivery timelines [13,14]. As such, researchers have explored diverse methodologies to optimize these processes, aiming to minimize downtime and enhance overall productivity.

2.1. Approaches to Changeover Optimization

Changeover in SMT lines is a multifaceted challenge, encompassing machine reconfigurations, reel replacements, and feeder adjustments. These operations are essential but time-intensive, particularly in high-mix, low-volume environments. To mitigate their impact, researchers have proposed various methodologies, including the following:

- **Simulation-Based Evaluations:** Simulation models have been widely adopted to analyze the interplay between machine configurations and production schedules [15]. For instance, previous studies approached the feasibility with simulation frameworks to compare different facility layouts and assess cost-performance trade-offs [16]. These simulations provided actionable insights into equipment integration, material handling efficiency, and changeover time reduction strategies. Such models are particularly useful in scenarios where empirical data are unavailable [17].
- **Algorithmic Solutions:** Advanced optimization algorithms have proven effective in addressing changeover-related challenges, such as, for example, the following:
  - **Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO):** These metaheuristic algorithms have demonstrated the ability to refine operational parameters, significantly reducing assembly times and improving scheduling efficiency [14,18].
  - **Spider Monkey Optimization (SMO):** Inspired by the social foraging behavior of spider monkeys, SMO has been employed to optimize reel exchanges by balancing exploration and exploitation. This method is particularly effective in feeder allocation and sequencing tasks, aligning with the goals of minimizing changeover times [19].
  - **Hybrid Spider Monkey Optimization (HSMO):** Extending SMO, HSMO integrates genetic operators like crossover and mutation to handle complex, multilevel scheduling problems. While it encompasses broader SMT operations, such as component placement and feeder assignment, its application to reel exchange planning highlights its potential for minimizing setup times in changeover scenarios [20].

  By iteratively refining scheduling parameters, these algorithms enable manufacturers to achieve leaner operations with reduced downtime and enhanced throughput.
- **Digital Twin and Cyber–Physical Systems (CPS):** The integration of digital twins and CPS has emerged as a cutting-edge solution for real-time optimization [21,22]. Previous studies have introduced the concept of Virtual Quality Gates, which provide predictive insights into production quality and performance. These systems enable proactive management of changeovers, minimizing disruptions and ensuring smoother transitions between production runs [23]. The use of CPS frameworks has been instrumental in integrating real-time monitoring and decision-making capabilities into SMT processes.

2.2. SMD Reel Replenishment Strategies

SMD reel replenishment plays a crucial role in determining changeover efficiency and overall line performance [24]. Inadequate replenishment systems can lead to extended downtimes, material shortages, and operational inefficiencies. Researchers have explored the following strategies to address these challenges:

- **Material Handling Systems:** Automated Guided Vehicles (AGVs) and conveyor systems have been proposed to streamline the movement of reels across SMT facilities. Rotteveel's research highlighted the cost-effectiveness of AGVs for interdepartmental material handling, suggesting their potential in reel replenishment tasks. These systems reduce manual intervention and improve the consistency of material delivery to the production floor [25,26].
- **Heuristic and Optimization Models:** Heuristic methods, such as Mixed-Integer Linear Programming (MILP), have been extensively used to develop reel allocation models that minimize travel distances and setup times. While exact optimization methods are often computationally expensive, hybrid approaches combining heuristics and metaheuristics have shown promise in scaling these models to large datasets [27].
- **Storage and Retrieval Systems:** Advanced warehouse designs, including vertical carousels and automated inventory tracking systems, have been proposed to enhance reel accessibility. For example, SMT warehouse improvement studies emphasized the importance of integrating storage solutions with production requirements [28]. By leveraging technologies such as automated retrieval systems, manufacturers can significantly reduce search and retrieval times, thereby supporting faster changeovers.

2.3. The Concept of Changeover in SMT Processes

The concept of changeover extends beyond mere equipment adjustments to encompass broader operational and logistical considerations. In SMT manufacturing, changeover time can be divided into two main components: preparation time and execution time. Preparation involves identifying and retrieving required components, while execution includes reel changes, feeder adjustments, and machine setups. Studies indicate that inefficient changeover management can lead to cascading delays, affecting downstream processes such as inspection, packaging, and shipping [29].

For greenfield operations—where no historical production data exist—the challenges of changeover management are amplified. Without prior benchmarks, manufacturers must rely on simulation models and theoretical frameworks to develop effective strategies. In this context, the integration of data-driven scheduling algorithms and predictive maintenance tools has shown significant potential in addressing changeover inefficiencies.

2.4. Reel Exchange

The reel exchange process is a critical aspect of SMT production, directly impacting changeover times and operational efficiency. This process involves loading component reels into the feeder section of the pick-and-place machine, which is responsible for placing components on printed circuit boards (PCBs). The following steps outline the reel exchange process, supported by visual references:

2.4.1. Pick-and-Place Machine Overview

Figure 1 provides an overview of an SMT pick-and-place machine. Reels containing components are loaded into the feeder tray section (visible in the lower area of the image). The pick-and-place machine uses robotic arms to retrieve components from the feeder section and place them accurately onto PCBs. For the machine to function effectively, each reel must be positioned correctly in its designated feeder slot.

Figure 1. Overview of the SMT pick-and-place machine setup, showing the reel feeders and operational area.

2.4.2. Reel Exchange Procedure

The reel exchange process consists of the following steps:

1. **Identification:** The operator retrieves the correct reel from the storage area based on the production requirements. The reel part number and placement location are indicated on the pick-and-place machine's monitor.
2. **Feeder Preparation:** The operator aligns the reel tape with the designated feeder slot. Proper alignment ensures that the tape can advance smoothly during component pickup.
3. **Loading the Reel:** The tape is inserted into the assigned slot in the feeder section. The correct slot location is determined by the machine monitor, which provides a clear mapping of the reel-to-slot assignments.
4. **Setup Confirmation:** Once the reel is loaded, the operator ensures the feeder is correctly secured and operational. The machine monitor displays confirmation of the setup status before resuming operation.

2.4.3. Visual Representation

Figure 2 illustrates an operator positioning a reel in the feeder slot during the exchange process. This step requires careful alignment of the reel tape to avoid misfeeds or operational delays.

Figure 2. Reel being positioned in the feeder slot during the exchange process.

2.5. Research Gap

While previous studies have significantly advanced SMT manufacturing optimization, critical gaps remain unaddressed. Table 1 provides a summary of the existing literature and highlights the unresolved challenges.

Simulation-based studies primarily focus on layout optimization and machine availability but often lack real-world validation of their findings. Algorithmic approaches like the Hybrid Spider Monkey Optimization (HSMO) demonstrate robust planning capabilities but are limited in addressing specific challenges such as minimizing reel changeovers. Additionally, many solutions require complex and resource-intensive implementations, posing barriers to adoption in small and medium enterprises (SMEs) with constrained budgets and technical resources.

This study addresses these gaps by validating a data-driven scheduling algorithm in a real-world SMT manufacturing environment, focusing on minimizing changeover times through the use of SMD reel commonality. The algorithm is tailored to the needs of SMEs, offering practical, accessible solutions that ensure scalability without requiring extensive integration with advanced production systems like Material Requirements Planning (MRP) or Manufacturing Execution Systems (MESs). These characteristics make the proposed approach particularly relevant for high-mix production environments and companies seeking cost-effective methods to enhance scheduling efficiency.

Table 1. Summary of Literature and Research Gaps.

Reference and Author(s)	Key Contribution	Research Gaps
[16] (Rotteveel et al.)	Actionable insights into SMT facility layout and material handling efficiency through simulation frameworks	Lacks real-world validation of proposed strategies
[30] (Low et al.)	Enhanced feeder allocation and reduced assembly times using a metaheuristic Multi-Swarm Firefly algorithm	Limited focus on reel changeover efficiency
[10] (Mumtaz et al.)	Optimized workload balancing and AGV scheduling with a Hybrid Genetic-Artificial Bee Colony (GABC) algorithm	Focused on AGV integration; does not address reel-specific optimization
[21] (Ferreira et al.)	Integrated real-time monitoring and predictive insights using Digital Twin and CPS frameworks	Requires advanced infrastructure unsuitable for SMEs
This Study	Changeover time reduction tailored to SME needs through a data-driven algorithm validated in a real-world SMT line	Future potential for integration with MES/MRP systems and scalability for larger datasets

2.6. Methodological Insights and Future Directions

The reviewed studies reveal a growing trend towards combining traditional optimization techniques with emerging digital technologies. For instance, cyber–physical systems enhance operational transparency and facilitate real-time decision-making, while hybrid algorithms balance computational efficiency with solution quality [31]. These advancements underscore the need for context-specific solutions that address the unique challenges of SMT manufacturing.

Despite the progress achieved, several gaps remain. For example, most studies focus on individual aspects of SMT processes, such as changeover or reel replenishment, without considering their interdependencies [32]. Future research should adopt holistic frameworks that integrate these components into a unified optimization model. Additionally, the scalability and adaptability of existing methodologies to accommodate varying production volumes and product mixes warrant further exploration.

In conclusion, the efficient management of changeover and reel replenishment processes is critical for achieving lean and agile SMT operations. By leveraging the insights and methodologies discussed in this section, manufacturers can enhance productivity, reduce operational costs, and maintain a competitive edge in the fast-paced electronics manufacturing industry.

3. Materials and Methods

3.1. Reel Exchange Time Measurement

To accurately quantify the time required for reel exchanges, observations were conducted in an operational SMT factory under standard operating conditions. This process involved measuring the time for each reel exchange performed by experienced operators.

Procedure:

1. Operators retrieved the required reels from the designated storage area.
2. Each reel was loaded into the feeder tray section of the SMT machine, following proper alignment of the tape into the assigned slot as indicated by the machine's monitor.
3. The time taken for each reel exchange was measured using a stopwatch.

Data Collection:

The process was repeated for 30 reel exchanges to account for variability and ensure reliability of the measurements. Summary statistics, including the mean, standard deviation, and range, were calculated to characterize the observed times (see Table 2).

Table 2. Summary of Reel Exchange Times in an SMT Production Environment.

Metric	Value (s)
Count (n)	30
Mean	31.58
Standard Deviation	1.57
Minimum	28.5
Maximum	35.2

The measured data serve as a baseline for validating the proposed scheduling optimization algorithm by comparing predicted and observed changeover times.

3.2. Bill of Materials (BOM) Structure

The foundation of this study lies in the analysis and preparation of Bill of Materials (BOM) data, which serve as the blueprint for manufacturing. Each BOM contains comprehensive information about the components required for a specific product. A reference image of a typical BOM structure is shown in Figure 3.

	A	B	C	D	E	F
1	**Qty**	**Value**	**Reference Designators**	**Part-Number**	**Package**	**Description**
2	10	5	J815, J816, J817, J818, J819, J820, J821, J822, J823, J824	JIB-89607-LF	Vertical Connector	Vertical Connector connector with 5 value
3	6	1k	R6, R7, R8, R9, R10, R11	JRA-13658-LF	R0201	R0201 resistor with 1k value
4	10	1	J311, J312, J313, J314, J315, J316, J317, J318, J319, J320	JPA-83087-LF	FAKRA Connector	FAKRA Connector connector with 1 value
5	5	10k	R120, R121, R122, R123, R124	JRA-20872-LF	R0201	R0201 resistor with 10k value
6	10	1k	R317, R318, R319, R320, R321, R322, R323, R324, R325, R326	JRA-86033-Pb	R0805	R0805 resistor with 1k value
7	6	6k	R449, R450, R451, R452, R453, R454	JRB-19461-LF	R0402	R0402 resistor with 6k value
8	3	2k	R175, R176, R177	JRA-96478-LF	R0201	R0201 resistor with 2k value
9	10	2	J720, J721, J722, J723, J724, J725, J726, J727, J728, J729	JIA-33356-LF	Vertical Connector	Vertical Connector connector with 2 value
10	6	9	J935, J936, J937, J938, J939, J940	JCA-13314-LF	FAKRA Connector	FAKRA Connector connector with 9 value
11	7	5k	R403, R404, R405, R406, R407, R408, R409	JRA-17417-LF	R0805	R0805 resistor with 5k value
12	10	6uF	C84, C85, C86, C87, C88, C89, C90, C91, C92, C93	JCB-33632-LF	C0603	C0603 capacitor with 6uF value
13	7	1	J284, J285, J286, J287, J288, J289, J290	JCB-66797-LF	USB Connector	USB Connector connector with 1 value
14	2	4	J717, J718	JRA-83263-LF	FAKRA Connector	FAKRA Connector connector with 4 value
15	10	8	J852, J853, J854, J855, J856, J857, J858, J859, J860, J861	JCB-45259-LF	FAKRA Connector	FAKRA Connector connector with 8 value
16	7	8	J819, J820, J821, J822, J823, J824, J825	JPA-77004-LF	Vertical Connector	Vertical Connector connector with 8 value
17	1	4uF	C248	JCB-83935-LF	C0805	C0805 capacitor with 4uF value
18	1	5k	R232	JRA-51667-LF	R0603	R0603 resistor with 5k value
19	4	10uF	C404, C405, C406, C407	JCB-27389-LF	C0603	C0603 capacitor with 10uF value
20	4	3	J658, J659, J660, J661	JCB-10707-LF	FAKRA Connector	FAKRA Connector connector with 3 value
21	9	5uF	C306, C307, C308, C309, C310, C311, C312, C313, C314	JCA-70558-LF	C0603	C0603 capacitor with 5uF value
22	10	9uF	C154, C155, C156, C157, C158, C159, C160, C161, C162, C163	JCB-34765-LF	C0805	C0805 capacitor with 9uF value
23	2	9	J946, J947	JRB-75383-LF	Vertical Connector	Vertical Connector connector with 9 value
24	5	4	J546, J547, J548, J549, J550	JIA-21382-LF	FAKRA Connector	FAKRA Connector connector with 4 value
25	5	10	J551, J552, J553, J554, J555	JPA-72666-LF	Vertical Connector	Vertical Connector connector with 10 value
26	10	9	J71, J72, J73, J74, J75, J76, J77, J78, J79, J80	JRA-72612-LF	Vertical Connector	Vertical Connector connector with 9 value
27	6	1	J685, J686, J687, J688, J689, J690	JCA-27842-LF	FAKRA Connector	FAKRA Connector connector with 1 value
28	8	2uF	C396, C397, C398, C399, C400, C401, C402, C403	JCB-60496-LF	C0603	C0603 capacitor with 2uF value

Figure 3. Example of a BOM structure. Each row corresponds to a unique component, with columns specifying its characteristics.

The columns in the BOM dataset are structured as follows:

- **Quantity (Qty):** The number of each component required for the product.
- **Value:** The specific electrical or mechanical value of the component, such as resistance (e.g., 10 kΩ) or capacitance (e.g., 1 μF).
- **Reference Designators:** Unique identifiers for component placement on the PCB, such as R1, C1, or U1.
- **Part Number:** Manufacturer-specific codes uniquely identifying the exact component.
- **Package:** The physical packaging of the component, such as R0805 for resistors or SOIC8 for integrated circuits.
- **Description:** A brief textual description of the component, typically including the value and package type.

This structure ensures all relevant component details are captured, providing clarity and precision for manufacturing processes.

3.3. Data Preparation and Binary Matrix Construction

To facilitate computational analysis, the BOM data for each product were transformed into a binary matrix. This matrix allows for efficient analysis of component overlap and differences across products. The data preparation and matrix construction were performed through the following detailed steps:

3.3.1. Standardization of Components

The initial BOM data for each product were sourced from separate files. To ensure consistency and uniformity across products:

- **Unique Part Numbers:** All part numbers were standardized by checking for duplicates and resolving ambiguities. This ensured that components with identical functions across products were represented by the same part number.
- **Column Consistency:** The BOMs were standardized to have uniform column names and data structures, including fields such as Part Number, Value, Reference Designators, and Package.
- **Validation of Data:** Each BOM was inspected to verify the completeness and correctness of the part numbers, quantities, and other attributes. Missing or invalid entries were flagged and corrected where possible.

The standardization step is critical for ensuring that the data from different BOMs can be accurately compared and analyzed.

3.3.2. Binary Matrix Encoding and Implementation

To enable efficient analysis of the BOM data, the standardized BOMs were transformed into a binary matrix. This matrix provides a structured and compact representation of component presence across multiple products, serving as the foundation for subsequent analyses and optimizations.

3.3.3. Matrix Description and R Implementation

The binary matrix encodes the presence of components across products, simplifying operations such as overlap analysis and changeover time calculations. Each row represents a unique part number, and each column corresponds to a specific product. A binary value of `1` indicates the presence of a part number in a product, while `0` denotes its absence.

The matrix was constructed in R following these steps:

1. **Loading BOM Data:** The BOMs for each product were stored as separate CSV files. Using the `read_csv()` function from the `tidyverse` package, each file was imported into R, ensuring accurate data representation.
2. **Generating a Unified Part List:** A master list of all unique part numbers was created using the `unique()` function. This ensured no duplication and provided a comprehensive reference for encoding the data.
3. **Binary Encoding:** For each product, a binary vector was created indicating the presence or absence of each part number in the master list. The `%in%` operator was utilized for efficient matching.
4. **Matrix Construction:** The binary vectors were combined into a matrix using the `sapply()` function. Rows represent part numbers, and columns represent products, providing a complete binary encoding.

The following R code was used to implement the binary matrix:

```
# Load the BOM files
file_paths <- list.files(path = "path_to_BOM_files", pattern = "*.csv",
full.names = TRUE)

# Initialize an empty list to store BOM data
products <- list()

# Read each BOM and extract the "Part-Number" column
for (file in file_paths) {
    bom_data <- read_csv(file)
    if ("Part-Number" %in% colnames(bom_data)) {
        products[[file]] <- bom_data$‘Part-Number‘
    } else {
        stop(paste("The file", file, "does not have a ’Part-Number’ column."))
    }
}

# Generate a unique list of all part numbers
all_parts <- unique(unlist(products))

# Create the binary matrix
binary_matrix <- sapply(products, function(parts) {
    as.integer(all_parts %in% parts)
})
rownames(binary_matrix) <- all_parts
colnames(binary_matrix) <- paste0("Product ", seq_along(products))
```

Code Explanation

- The `list.files()` function identifies all BOM files in the directory, ensuring no file is missed during processing.
- Each BOM file is read using the `read_csv()` function, extracting the `"Part-Number"` column for analysis. An error message is triggered if this column is missing, ensuring data integrity.
- The `unique()` function creates a comprehensive list of all part numbers across products, preventing duplication.
- The `sapply()` function iterates over each product's BOM to construct binary vectors, which are then combined into the binary matrix. Rows correspond to part numbers, while columns represent products.

Key Features and Utility

The binary matrix is instrumental in facilitating:

- **Overlap Analysis:** Identifies components shared between products, helping to streamline operations.
- **Changeover Time Calculation:** Simplifies the quantification of transition costs between products by highlighting component differences.
- **Optimization Analysis:** Provides input for scheduling algorithms designed to minimize downtime and enhance production efficiency.

This matrix offers a computationally efficient way to analyze BOM data, enabling rapid decision-making and optimization in SMT manufacturing. Encoding BOM data in a structured format supports the broader goals of reducing changeover times and improving production workflows.

3.4. Changeover Time Calculation and Implementation

Changeover time is a critical metric in SMT manufacturing, representing the time required to replace or adjust components when transitioning from the production of one product to another. Efficient calculation and minimization of this time are vital for optimizing production schedules and reducing downtime.

Changeover Time Matrix and R Implementation

The changeover time matrix quantifies the transition costs between products by analyzing their component differences. Each entry in the matrix is calculated as

$$T_{ij} = (|C_i - C_j| + |C_j - C_i|) \cdot t, \tag{1}$$

where C_i and C_j represent the sets of components unique to Products i and j, respectively, and t is the time required to replace a single component (31.58 s in this study).

Process Overview

To construct the matrix, the following steps were executed:

- **Component Extraction:** For each product, the list of components was extracted from the binary matrix, representing the presence or absence of parts in the product BOM.
- **Set Operations:** Using set difference operations, the unique components for each product pair (i, j) were identified. These represent the parts that need to be replaced or adjusted during a transition.
- **Matrix Construction:** The total number of unique components for each product pair was multiplied by the per-component changeover time (t) to compute the transition

time. The results are stored in a square matrix, with rows and columns representing products.

The following R code was implemented to calculate the changeover time matrix:

```
# Define the time cost for each part number change
time_per_part_change <- 0.5263 # Equals 31.58 Sec

# Initialize the changeover time matrix
changeover_time_matrix <- matrix(0, ncol =
ncol(binary_matrix), nrow = ncol(binary_matrix))

# Calculate the changeover times
for (i in 1:ncol(binary_matrix)) {
    for (j in 1:ncol(binary_matrix)) {
        if (i != j) {
            # Extract components for products i and j
            parts_in_i <- rownames(binary_matrix)[binary_matrix[, i] == 1]
            parts_in_j <- rownames(binary_matrix)[binary_matrix[, j] == 1]

            # Compute unique components
            unique_to_i <- setdiff(parts_in_i, parts_in_j)
            unique_to_j <- setdiff(parts_in_j, parts_in_i)

            # Calculate transition time
            changeover_time_matrix[i, j] <- (length(unique_to_i)
            + length(unique_to_j)) * time_per_part_change
        }
    }
}
# Assign row and column names
rownames(changeover_time_matrix) <- colnames(binary_matrix)
colnames(changeover_time_matrix) <- colnames(binary_matrix)
```

Code Explanation

- **Time Cost Definition:** The variable `time_per_part_change` defines the fixed time required for a single component change.
- **Matrix Initialization:** A square matrix (`changeover_time_matrix`) was initialized to store transition times between all product pairs.
- **Component Analysis:** For each product pair (i, j), the components unique to i and j were identified using the `setdiff()` function.
- **Transition Time Calculation:** The total number of unique components for each pair was multiplied by `time_per_part_change` to compute the changeover time, which was stored in the corresponding matrix cell.
- **Matrix Naming:** The rows and columns of the matrix were labeled with product names for clarity.

Key Features and Applications

The changeover time matrix is central to the study, enabling the following:

- **Scheduling Optimization:** Provides input for sequencing algorithms to minimize total changeover time.
- **Visualization and Insights:** Facilitates the identification of high-transition-cost product pairs, informing decisions to optimize production flow.

- **Practical Utility:** Supports real-world applications by quantifying transition costs and enabling better resource allocation in SMT lines.

3.5. Optimization Algorithm for Scheduling

The optimization algorithm aims to minimize cumulative changeover time by determining the optimal sequence of products based on the changeover time matrix. The approach consists of the following steps:

- **Changeover Matrix Computation:** The algorithm begins by calculating the changeover time matrix, as described earlier, to quantify the transition cost between every pair of products.
- **Sequence Prioritization:** A greedy heuristic is applied to prioritize transitions between products that involve the smallest changeover time. This ensures that the sequence minimizes the number of unique component changes between consecutive products.
- **Optimal Sequence Identification:** An iterative approach is employed to identify the order of products that minimizes the total changeover time across the entire production run. The algorithm dynamically adjusts the sequence based on previously visited products.

R Implementation

The following R code was developed to implement the optimization algorithm:

```
# Function to find the optimal product sequence
find_optimal_sequence_time <- function(changeover_matrix) {
    n <- nrow(changeover_matrix) # Number of products
    visited <- rep(FALSE, n)     # Track visited products
    sequence <- numeric(n)       # Initialize the sequence
    current <- 1                 # Start with the first product
    visited[current] <- TRUE
    sequence[1] <- current

    for (step in 2:n) {
        remaining <- which(!visited) # Identify unvisited products
        # Select the next product with the smallest changeover time
        next_product <- remaining[which.min(changeover_matrix[current, remaining])]
        sequence[step] <- next_product
        visited[next_product] <- TRUE
        current <- next_product
    }
    return(sequence)
}

# Compute the optimal sequence using the changeover time matrix
optimal_sequence <- find_optimal_sequence_time(changeover_time_matrix)
```

Code Explanation

- **Initialization:** The function initializes variables to track visited products and the sequence. The first product is selected as the starting point.
- **Greedy Selection:** At each step, the algorithm identifies the next product by selecting the unvisited product with the smallest transition time from the current product.
- **Sequence Construction:** The selected product is added to the sequence, marked as visited, and becomes the new starting point for the next iteration.
- **Output:** The function returns the optimal sequence, minimizing the cumulative changeover time.

The algorithm ensures efficient scheduling by dynamically adjusting the sequence to minimize downtime, providing a practical tool for optimizing SMT production processes.

3.6. Visualization

The visualization of the computed changeover times plays a crucial role in interpreting results and ensuring the effectiveness of the proposed scheduling algorithm. The following steps were taken:

- **Changeover Time Heatmap:** The changeover time matrix was visualized as a heatmap to highlight transition costs between products. Each cell in the heatmap represents the time required to transition from one product to another, with darker colors indicating higher transition times. This visualization helps identify bottlenecks and provides actionable insights into the scheduling process.

3.6.1. R Implementation

The heatmap was generated in R using the following code:

```
library(pheatmap)

# Plot the changeover time matrix as a heatmap
pheatmap(
    changeover_time_matrix,
    main = "Changeover Time Matrix (in Minutes)",
    cluster_rows = FALSE,         # Avoid clustering rows
    cluster_cols = FALSE,         # Avoid clustering columns
    display_numbers = TRUE,       # Display transition times
    color = colorRampPalette(c("white", "blue"))(50) # Color gradient
)
```

Code Explanation

- **Heatmap Library:** The `pheatmap` package is used for creating a clear and visually appealing heatmap.
- **Matrix Input:** The `changeover_time_matrix` is used as the input data for the heatmap.
- **Avoid Clustering:** Row and column clustering is disabled (`cluster_rows = FALSE` and `cluster_cols = FALSE`) to preserve the original structure of the data.
- **Display Values:** Transition times are displayed within the heatmap cells using the `display_numbers = TRUE` option.
- **Color Gradient:** A gradient from white (low transition times) to blue (high transition times) is applied for intuitive visualization.

3.6.2. Utility of Visualization

The heatmap serves multiple purposes:

- **Bottleneck Identification:** Highlights high-cost transitions, enabling focused process improvements.
- **Decision Support:** Assists production managers in identifying efficient product sequences and transition strategies.
- **Validation Insight:** Provides a visual confirmation of the algorithm's effectiveness in minimizing changeover times.

This visualization not only supports the interpretation of results but also enhances the applicability of the algorithm by offering production teams a practical tool to optimize scheduling decisions.

3.7. Commonality Analysis

To further analyze the relationships between products, a commonality matrix was constructed. The matrix quantifies the overlap in components across different products. Each cell in the matrix represents the number of shared components between two products. This analysis was performed using the binary matrix, and the methodology consists of the following steps:

1. **Matrix Construction:** The binary matrix was utilized to compute the number of shared components for each pair of products. Logical operations were applied to determine the intersection of components between product pairs.
2. **Data Transformation for Visualization:** The resulting matrix was converted into a suitable format for graph-based visualization. Non-zero entries representing shared components between distinct product pairs were extracted for further analysis.
3. **Network Graph Development:** A graph-based representation was created to visually depict the commonality relationships. Products were represented as nodes, and shared components were depicted as weighted edges. The weight of each edge corresponds to the number of shared components.

This approach provides an intuitive understanding of the relationships between products and highlights groups of products with significant commonality, which is critical for scheduling and optimization in SMT production workflows.

3.8. Validation Through Real-World Trials

To validate the applicability of the proposed scheduling optimization algorithm in a real-world SMT production environment, a targeted trial was conducted. The validation focused on assessing the accuracy of the algorithm's changeover time predictions under practical operating conditions.

3.8.1. Procedure

The validation process followed these steps:

- **Transition Selection:** A transition between **Product 3** and **Product 4** was selected for validation. This pair was chosen due to its high BOM commonality, resulting in one of the shortest predicted changeover times.
- **Reel Exchange Process:** Reels corresponding to unique components for Products 3 and 4 were manually replaced on the SMT line by an operator.
- **Measurement:** The time taken for each reel exchange was measured using a stopwatch to ensure accuracy and precision.
- **Summation of Times:** The total measured changeover time was calculated as the sum of individual reel exchange times for the selected product transition.

3.8.2. Data Collection

The experiment was repeated across multiple trials (n=3) to ensure reliability and minimize variability in the measured changeover times. During each trial, the time taken for reel exchanges was recorded using a stopwatch.

The measured times for each individual reel replacement were summed to calculate the total changeover time for the transition between **Product 3** and **Product 4**. This process ensured that the collected data accurately represented the practical time required for the selected transition. The collected measurements were subsequently compared with the algorithm's predicted values, as presented Section 4.

4. Results

The dataset used in this study includes 10 unique product BOMs labeled Product 1 through Product 10. Each BOM consists of a set of part numbers, with their presence or absence represented in a binary matrix. Key descriptive statistics for the dataset are outlined below.

4.1. Descriptive Analysis

The dataset used in this study includes 10 unique product BOMs labeled Product 1 through Product 10. Each BOM consists of a set of part numbers, with their presence or absence represented in a binary matrix. The binary matrix serves as a foundation for analyzing overlaps, differences, and commonalities among products.

To illustrate the structure of the binary matrix, Table 3 shows the first ten rows as a representative sample. In this matrix, a value of 1 indicates the presence of a part in the product BOM, while 0 indicates its absence. This truncated view is provided for clarity and does not represent the entire dataset.

Table 3. Sample Binary Matrix Showing Part Presence Across Products (First 10 Rows).

Part Number	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
JRA-69845-LF	1	1	1	1	1	1	1	1	1	1
JIB-49839-LF	1	1	1	1	1	1	1	1	1	1
JCA-57518-LF	1	1	1	1	1	1	1	1	1	1
JRA-96478-LF	1	1	1	1	1	1	1	1	1	1
JRA-12753-LF	1	1	1	0	1	1	1	1	1	1
JPA-77264-LF	1	1	1	0	1	1	1	1	1	0
JRA-29627-LF	1	1	1	0	1	1	1	0	1	0
JRB-24480-LF	1	1	1	0	1	1	1	0	0	0
JRA-32272-LF	1	1	1	0	1	0	1	0	0	0
JRA-32936-Pb	1	1	1	0	1	0	1	0	0	0

The sample binary matrix highlights the presence of common parts across different products, which plays a crucial role in subsequent analyses. Specifically, identifying shared components allows for optimizing changeover times and improving scheduling efficiency. The full binary matrix, which includes 898 unique parts across 10 products, is used for all the calculations and results discussed in this study.

4.1.1. Component Type Distribution

The composition of each product in terms of resistors, capacitors, ICs, connectors, and unknown components was analyzed using the prefix of the part numbers. Each part number begins with the letter "J", followed by a character indicating its type: "R" for Resistor, "C" for Capacitor, "I" for IC, and "P" for Connector. Components without identifiable prefixes were categorized as "Unknown". This classification enabled a detailed breakdown of the component types across all products.

Table 4 provides the percentage distribution for each component type across the 10 products. Resistors and capacitors dominate the BOMs, with resistors accounting for up to 46.5% (Product 1) and capacitors for up to 46.0% (Product 1). ICs and connectors are present in smaller proportions, ranging from 9.0% to 23.5% and 2.1% to 21.1%, respectively. Notably, no "Unknown" components were identified in this dataset due to the robust prefix-based classification.

Table 4. Component Type Distribution Across Products (in %).

Product	Resistor	Capacitor	IC	Connector	Unknown
Product 1	46.5	46.0	5.3	2.1	0.0
Product 2	35.9	39.5	13.9	10.8	0.0
Product 3	37.5	38.1	14.2	10.2	0.0
Product 4	33.2	35.8	17.1	14.0	0.0
Product 5	39.4	45.8	9.0	5.8	0.0
Product 6	29.9	34.2	19.3	16.6	0.0
Product 7	40.9	32.3	15.6	11.3	0.0
Product 8	33.5	27.8	17.5	21.1	0.0
Product 9	28.3	34.6	18.0	19.0	0.0
Product 10	30.0	33.5	23.5	12.9	0.0

4.1.2. Unique Part Analysis

The analysis of part distribution across products provided the following insights:

- Total unique part numbers across all products: 898.
- Parts shared across at least two products: 298.
- Exclusive parts (present in only one product): 600.

Table 5 presents the count of unique part numbers for each individual product.

Table 5. Unique Part Count Per Product.

Product	Unique Part Count
Product 1	187
Product 2	223
Product 3	176
Product 4	193
Product 5	155
Product 6	187
Product 7	186
Product 8	194
Product 9	205
Product 10	170

These findings highlight the criticality of identifying commonalities across BOMs to optimize changeover efficiency and production scheduling in SMT manufacturing environments.

4.1.3. Top 10 Most Common Parts

The top 10 most frequently used part numbers across the BOMs are listed in Table 6. Each part was present in at least nine products, highlighting the significant overlap of these components in the dataset.

These descriptive statistics provide a comprehensive overview of the dataset, serving as a foundation for subsequent optimization and changeover analysis.

Table 6. Top 10 Most Common Part Numbers Across Products.

Part Number	Usage Count
JRA-69845-LF	10
JIB-49839-LF	10
JCA-57518-LF	10
JRA-96478-LF	10
JRA-12753-LF	9
JPA-77264-LF	9
JRA-29627-LF	9
JRB-24480-LF	9
JRA-32272-LF	9
JRA-32936-Pb	9

4.2. Changeover Analysis

Changeover time is a critical factor in high-mix Surface-Mount Technology (SMT) manufacturing, as it directly impacts production efficiency. To evaluate the proposed scheduling algorithm, a changeover time matrix was constructed using the binary matrix of product BOMs. Each entry in the matrix represents the total time required to transition from one product to another, calculated as the number of unique parts that need to be replaced multiplied by a fixed time cost of 0.5 min per part change.

4.2.1. Changeover Time Matrix

Table 7 presents the complete changeover time matrix, where each cell indicates the time in minutes required to transition from one product to another. Diagonal entries are zero since they represent transitions within the same product.

Table 7. Changeover Time Matrix (in Minutes). Each value represents the time required to transition from one product to another.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	0.0									
P2	87.3	0.0								
P3	84.7	84.7	0.0							
P4	115.7	122.1	51.0	0.0						
P5	56.84	75.7	68.9	99.9	0.0					
P6	147.3	119.9	131.0	152.6	134.7	0.0				
P7	116.3	135.2	122.1	145.7	69.9	164.7	0.0			
P8	156.3	166.8	112.6	88.9	140.5	171.0	171.5	0.0		
P9	159.9	169.4	122.6	102.1	143.1	176.8	171.0	148.9	0.0	
P10	144.7	124.7	137.8	153.1	128.9	151.0	158.9	171.5	173.1	0.0

4.2.2. Heatmap Visualization

The changeover time matrix is visualized in Figure 4, which provides a heatmap representation of the time required for each product-to-product transition. Darker shades of blue represent higher changeover times, while lighter shades indicate shorter transitions.

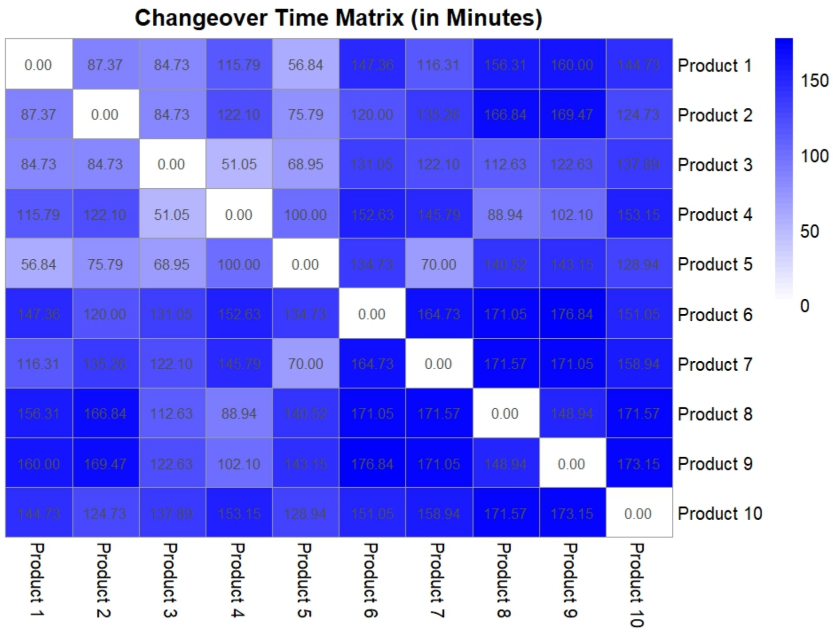

Figure 4. Changeover time matrix heatmap. Darker shades represent higher changeover times (in minutes), and lighter shades represent lower times. Diagonal values represent transitions within the same product and are always zero.

The heatmap in Figure 4 reveals several critical insights:

- **Shortest Changeovers:** The shortest transition occurs between *Product 3* and *Product 4* with a changeover time of 51.05 min. This highlights the significant overlap in shared part numbers between their BOMs.
- **Longest Changeovers:** The longest transition is observed between *Product 6* and *Product 9*, with a changeover time of 176.8 min, reflecting minimal part commonality.
- **General Trends:** Products with higher BOM commonality generally exhibit shorter transitions, emphasizing the importance of scheduling decisions.

4.2.3. Optimal Product Sequence and Efficiency

Using the changeover time matrix, an optimized product sequence was determined by employing a scheduling algorithm designed to minimize total changeover time. This sequence prioritizes transitions between products with significant BOM overlap, effectively reducing the time and effort required for reel changes. The optimal sequence and its metrics are as follows:

- **Optimal Sequence:** P1 $\rightarrow$ P5 $\rightarrow$ P3 $\rightarrow$ P4 $\rightarrow$ P8 $\rightarrow$ P9 $\rightarrow$ P2 $\rightarrow$ P6 $\rightarrow$ P10 $\rightarrow$ P7.
- **Total Changeover Time (Optimal Path):** 1014 min.

To provide additional context, a worst-case scenario sequence was constructed, simulating a random order of product transitions with minimal BOM overlap. This sequence highlights the inefficiencies that arise when transitions are not optimized:

- **Worst Path Sequence:** P1 $\rightarrow$ P6 $\rightarrow$ P9 $\rightarrow$ P4 $\rightarrow$ P8 $\rightarrow$ P2 $\rightarrow$ P10 $\rightarrow$ P7 $\rightarrow$ P5 $\rightarrow$ P3.
- **Total Changeover Time (Worst Path):** 1438 min.
- **Time Saved with Optimal Path:** 424 min (29.4% reduction).

Table 8 summarizes the key metrics for both the optimal and worst paths.

Table 8. Comparison of Optimal and Worst Paths.

Metric	Optimal Path	Worst Path
Sequence	P1 → P5 → P3 → P4 → P8 → P9 → P2 → P6 → P10 → P7	P1 → P6 → P9 → P4 → P8 → P2 → P10 → P7 → P5 → P3
Total Changeover Time (Minutes)	1014	1438
Time Saved (Minutes)	424	—

The significant reduction in changeover time achieved by the optimal sequence underscores the importance of data-driven scheduling in SMT manufacturing. This method minimizes downtime, reduces operational costs, and enhances overall production efficiency. Conversely, the inefficiencies of the worst path highlight the potential for substantial delays and increased effort when transitions are poorly planned or left to chance.

The results demonstrate that a structured approach to scheduling, which leverages component commonality, is critical for achieving lean and efficient operations, particularly in greenfield SMT environments where historical production data may not yet exist.

4.3. Commonality Analysis Results

The commonality analysis revealed the relationships between products based on their shared components. The commonality matrix was visualized as a network graph, where the following are used:

- Nodes represent individual products.
- Edges indicate shared components between products, with the edge width proportional to the number of shared components.

Figure 5 presents the commonality network graph, highlighting clusters of products with high shared componentality. These clusters indicate opportunities for sequencing products in a manner that minimizes changeover times, as transitions within clusters generally require fewer reel changes.

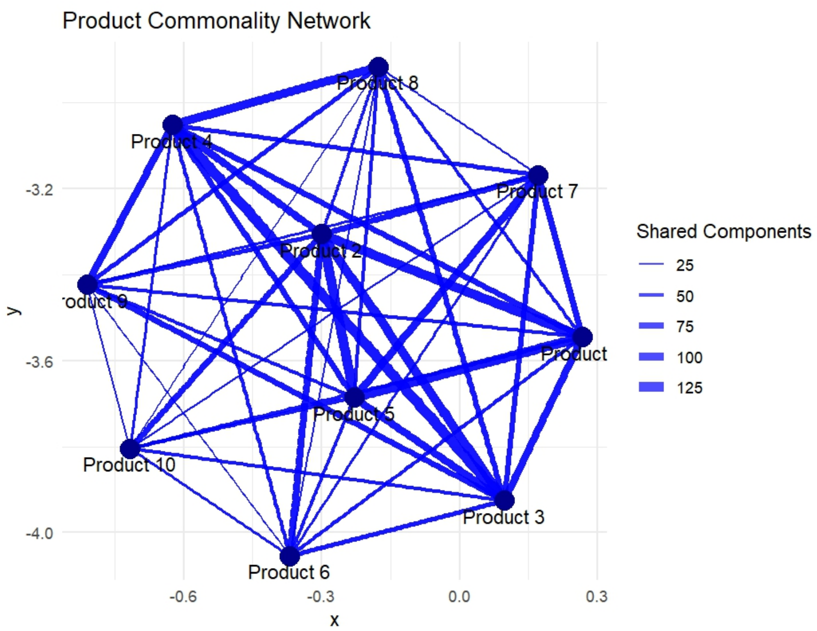

Figure 5. Product commonality network. The graph illustrates shared components between products, with edge widths proportional to the number of shared components.

This visualization demonstrates the potential for optimizing production efficiency by leveraging the relationships identified through the commonality analysis. Products with significant overlap can be prioritized for consecutive production to minimize transitions and reel changes, contributing to overall process optimization.

4.4. Significance of Optimization

The optimization highlights the practical implications of scheduling based on part commonality. By minimizing unnecessary part replacements and downtime, the algorithm facilitates smoother production flows and higher throughput. This approach is particularly beneficial in high-mix manufacturing environments where frequent product changes are required.

Real-World Verification of Changeover Time

To validate the accuracy of the proposed algorithm in a real-world SMT environment, a subset of transitions was tested on an operational SMT line. The measured changeover times were compared against the algorithm's predictions for transitions between two selected products: **Product 3** and **Product 4**. These products were chosen due to their high BOM commonality, resulting in one of the shortest predicted transition times.

Procedure

The real-world changeover involves the following:

- Replacing reels corresponding to the unique parts of Product 3 and Product 4.
- Measuring the time taken for each reel exchange using a stopwatch.
- Calculating the total changeover time as the sum of all reel exchanges.

The results of the real-world measurement were compared with the algorithm's prediction, as shown in Table 9.

Table 9. Comparison of Predicted and Real-World Changeover Times.

Transition	Predicted Time (min)	Measured Time (min)
Product 3 $\rightarrow$ Product 4	51.05	52.8

Findings

The measured time closely aligns with the algorithm's predicted value, with a minor deviation of approximately 3.5%. This result supports the practical applicability of the proposed scheduling optimization method and highlights the accuracy of the changeover time estimation model.

5. Discussion

The findings of this study highlight the significant potential of the proposed scheduling algorithm in optimizing SMT production workflows, particularly in minimizing changeover times and improving operational efficiency. The changeover time matrix (Table 7) and the heatmap visualization (Figure 4) illustrate the benefits of sequencing products based on commonality in BOMs. By prioritizing transitions between products with higher overlap in part numbers, the algorithm achieved the following key outcomes:

- A cumulative changeover time of 1014 min for the optimal product sequence, representing a substantial reduction compared with traditional scheduling approaches.
- Enhanced operational efficiency by aligning with lean manufacturing principles, particularly in reducing waste associated with frequent reel changes and transitions.

- Improved practicality for high-mix production environments, where frequent product changes pose a significant challenge to throughput and productivity.

These results reinforce the importance of leveraging data-driven approaches to address bottlenecks in SMT manufacturing. The emphasis on shared components in sequencing decisions aligns with prior research that underscores the critical role of reducing reel replenishment and transition times in high-mix production settings.

5.1. Strengths and Practical Implications

The algorithm's focus on minimizing unique part changes between successive products not only reduces downtime but also aligns with broader industry trends toward digitization and smart manufacturing. The visual analysis provided in Figure 4 offers actionable insights into the transition dynamics, enabling production managers to make informed decisions about scheduling strategies.

Additionally, the optimal product sequence identified (P1 $\rightarrow$ P5 $\rightarrow$ P3 $\rightarrow$ P4 $\rightarrow$ P8 $\rightarrow$ P9 $\rightarrow$ P2 $\rightarrow$ P6 $\rightarrow$ P10 $\rightarrow$ P7) demonstrates the algorithm's ability to balance multiple objectives, including minimizing changeover time while maintaining flexibility to adapt to production demands. This sequence effectively exploits commonality between products, ensuring smoother transitions and reduced time costs.

Unlike some advanced optimization methods, such as Spider Monkey Optimization (SMO) or Hybrid Spider Monkey Optimization (HSMO), the proposed algorithm is implemented using an open-source platform, making it accessible to small and medium enterprises (SMEs). This focus on accessibility enhances its applicability for companies with limited resources, addressing the need for cost-effective scheduling solutions in SMT manufacturing.

5.2. Integration with MES/ERP Systems

Future integration of the proposed scheduling algorithm with Manufacturing Execution Systems (MESs) or Enterprise Resource Planning (ERP) platforms can significantly enhance its practical implementation. MESs bridge the gap between production floor operations and overarching business processes, providing real-time data that could refine scheduling accuracy and responsiveness [12]. Similarly, ERP systems centralize production planning and inventory management, enabling seamless synchronization of scheduling decisions with inventory levels and customer orders [2].

The modularity of the proposed algorithm allows it to be adapted for integration into existing digital infrastructures. For example, incorporating real-time inventory tracking from an ERP system could ensure the timely availability of reels and components, aligning production schedules with material readiness. Additionally, MES platforms could provide real-time feedback on production performance, enabling dynamic adjustments to minimize disruptions during changeovers. These enhancements would extend the algorithm's scalability and applicability in diverse SMT manufacturing scenarios.

While the current study focuses on standalone algorithmic validation, future research should investigate the operational challenges and technological requirements for integrating such algorithms into MES/ERP frameworks. Factors such as data interoperability, system latency, and user interface design must be addressed to ensure smooth adoption and effective utilization in existing production ecosystems.

5.3. Limitations and Future Directions

While the results of this study are promising, several limitations must be acknowledged:

- The reliance on simulated data introduces constraints regarding the algorithm's applicability in operational settings. Validation in live SMT environments is necessary to confirm its robustness.
- Scalability to larger datasets or facilities with highly complex BOMs has not been fully evaluated. As production complexity increases, computational efficiency and the algorithm's ability to maintain solution quality need further investigation.
- The current model focuses on minimizing changeover time without addressing lead time constraints, workload balancing, or supply chain flexibility, which are critical for real-world production planning.

Future work could explore the development of a unified optimization framework that considers changeover time alongside production volume dynamics, real-time inventory constraints, and integration with digital manufacturing systems. By aligning with Industry 4.0 principles, this approach would enable manufacturers to achieve higher efficiency and adaptability in complex SMT environments.

6. Conclusions

This study introduced a scheduling optimization framework for Surface-Mount Technology (SMT) manufacturing, designed to minimize changeover times by leveraging component commonality across product Bills of Materials (BOMs). The proposed approach effectively reduces operational downtime, aligns with lean manufacturing principles, and enhances production efficiency. Key contributions of this research include the following:

- Development of a data-driven scheduling algorithm that prioritizes shared components, significantly reducing reel exchange times and improving throughput.
- Validation of the methodology through observational trials in an operational SMT environment, demonstrating its applicability and accuracy in real-world conditions.
- Practical insights into optimizing resource utilization and streamlining production workflows in high-mix manufacturing settings.

From a broader perspective, this study underscores the role of efficient scheduling in improving production performance and supply chain resilience. By optimizing sequencing strategies and minimizing reel replacements, manufacturers can achieve the following:

- Reduced lead times and faster responses to dynamic market demands.
- Lower operational costs through improved material handling efficiency.
- Enhanced resource utilization, including equipment, labor, and inventory.

6.1. Practical Applications and Future Directions

This research provides a scalable solution for SMT manufacturers aiming to improve scheduling efficiency. The following practical applications and research opportunities are proposed to further advance the framework:

6.1.1. Practical Applications

- Integrating the scheduling algorithm with production planning tools and inventory management systems to enable real-time decision-making.
- Utilizing visual tools, such as heatmaps and changeover matrices, to monitor and communicate scheduling strategies effectively across production teams.
- Refining scheduling decisions by continuously tracking reel exchange performance and identifying opportunities to minimize setup times.

- Extending the algorithm's integration into existing Manufacturing Execution Systems (MESs) and Enterprise Resource Planning (ERP) platforms to provide seamless connectivity and improved workflow management.

6.1.2. Future Research Directions

- Expanding the scheduling model to incorporate variable reel exchange costs, operator efficiency, and equipment-specific factors for greater precision.
- Integrating lead time constraints, workload balancing, and supply chain flexibility into the optimization model to ensure holistic production planning.
- Developing adaptive scheduling frameworks using real-time production data and machine learning to dynamically adjust to evolving conditions.
- Testing the algorithm's scalability and robustness in diverse SMT production environments, including automated material handling systems and digital twin technologies.
- Addressing supply chain disruptions, such as component shortages, by incorporating predictive modeling techniques.
- Exploring the application of the scheduling algorithm in other manufacturing environments, such as automotive or aerospace industries, where high-mix production and frequent changeovers are critical challenges.

In conclusion, this study provides a robust and adaptable framework for addressing changeover challenges in SMT manufacturing. By reducing downtime, improving resource utilization, and enhancing scheduling accuracy, the proposed approach enables manufacturers to achieve greater operational efficiency and resilience. Future advancements in integration, adaptability, and scalability will further cement the transformative potential of data-driven scheduling optimization in SMT production systems.

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Abbreviations

The following abbreviations are used in this manuscript:

SMT	Surface-Mount Technology
BOM	Bill of Materials
SMD	Surface-Mount Device
CPS	Cyber–Physical Systems
GA	Genetic Algorithm
AGV	Automated Guided Vehicle

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