An Integrated Stochastic Optimization and Simulation Approach to SERU vs. Assembly Line Manufacturing Systems

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This research compares SERU manufacturing systems to traditional assembly lines, focusing on the impact of uncertainty in task processing time on production output. The study considers worker skill levels and team identity, using a stochastic mixed integer linear programming approach to model uncertainty and optimize workforce allocation. Discrete event simulation is then integrated to evaluate performance using five key performance indicators (KPIs). Results show that SERU systems outperform traditional lines in terms of throughput when uncertainty is considered. The integrated approach provides more reliable performance data than deterministic optimization alone. The study also highlights the advantages of SERU systems when worker skill levels and team identity are factored in. This research fills a gap in the literature by proposing a stochastic optimization approach that considers uncertainty and worker skill levels, and by integrating stochastic optimization with simulation for comprehensive analysis. This approach provides valuable guidance for production managers in optimizing production systems.

Keywords: cellular manufacturing, assembly lines, skilled workers, optimization, discrete event simulation, production systems

INTRODUCTION

SERU is a type of manufacturing system design that aims to optimize the use of resources and improve production efficiency. In a SERU system, workers are assigned multiple or all of the tasks involved in making a product, rather than having each worker specialize in one task as in a traditional assembly line. In the Japanese industry, the SERU manufacturing system is a revolutionary approach to production (Süer et al., 2019; Zhang et al., 2017). It involves breaking away from traditional assembly line systems and replacing them with smaller, cellular units known as SERU (Singh 2017). These units consist of equipment and one or more workers responsible for producing one or more products. The SERU production system was first explored by companies in the electronics industry, such as Fujitsu NEC, Canon, Panasonic, Casio, Olympus, Pioneer, and Sony, mainly in the assembly of printers, digital cameras, digital video cameras, and module parts for digital electronics (Singh 2017, Abdullah 2018). The implementation of the SERU production system can be challenging for products with complex processes and heavy manufacturing requirements. However, it is widely accepted among those who use SERU that it is best suited for situations where there is a low demand volume but a high variety of products (Villa 2013, Abdullah 2018).

The SERU system is a human-centered method with a focus on cross-trained workers and low automation (Suer 2019). The system replaces a single, long production line with many short ones, with movable workstations and light equipment contributing to the quick configuration for multiple product types. The SERU System is distinguished from the other systems by configurable workstations that are not fixed, and it is known for its flexible nature, which allows for not just production but also assembly, packaging, and testing of products (Yin et al., 2017). The flexibility of the SERU system comes from the grouping of similar parts or products into a single cell. The equipment is grouped based on similarities in products rather than the functions of the machines. Instead of treating each product as a separate job, the SERU system groups similar parts or products into a product family based on similarities in their characteristics and manufacturing methods (Villa 2013).

SERU configurations can take on different shapes, including U-shaped, L-shaped, and I-shaped lines, which are commonly seen in practice (Villa 2013). Three types of SERU have been proposed in literature: divisional, rotating, and Yatai. A divisional SERU is similar to a traditional conveyor assembly line, but with workers taking on a larger number of tasks. In a rotating SERU, multiple workers with multiple skills move from station to station following a fixed order to complete tasks. A Yatai SERU is a special form of rotating SERU, where a single worker is responsible for assembling the entire product from start to finish, without moving between workstations (Yu et al., 2013). SERU is a combination of Lean and Agile production principles in manufacturing processes and layout design. Its implementation in Japanese companies has shown to be more efficient than traditional assembly lines in terms of reduced workforce and maintained productivity levels (Yin et al., 2017). The three key characteristics of SERU are Kanketsu, meaning all tasks are completed within a SERU cell system, Majime, meaning all resources are kept close to the workbench to reduce non-value-added movements, and Jiritsu, meaning self-management and learning organization (Singh, 2017).

The benefits of the SERU system include its high level of flexibility, quick turnaround time, low inventory levels, and positive impact on worker morale. It leads to decreased lead time, setup time, WIP and finished product inventories, cost and workplace space, resulting in increased productivity and competitiveness. However, there are limitations to the size of each SERU unit, and there is a large investment required in training workers to become multi-skilled (Treville et al. 2017, Poon and Chan 2016). There may also be an increase in variable production costs for things like equipment and logistics. The transition to SERU can be challenging as it requires replacing large, automated machines with smaller general-purpose machines in each cell and investing in training multi-skilled workers. Additionally, the system puts a lot of pressure on workers. This is because the system requires workers to be responsible for the entire production process, which can be demanding and increase pressure. Also, the increased variability of the work process and the requirement for quick response times may also contribute to the pressure on workers in the SERU manufacturing system. However, numerous research studies over several decades have shown that SERU can significantly improve productivity compared to traditional assembly lines, with a focus on reducing makespan, manpower, and training cost (Yu & Tang, 2019).

Specific contributions made in this paper towards its primary goal are as follows. This study proposes an integrated stochastic mixed integer nonlinear optimization and simulation approach to compare SERU vs. traditional assembly line considering processing time uncertainty and worker skill levels. Secondly, five key performance indicators (KPIs) are used to provide a comprehensive evaluation of SERU vs. traditional assembly line manufacturing system’s performance, namely: throughput, cycle time, WIP, waiting time and capacity utilization. Thirdly, a new worker skill-level scale is proposed and proposed stochastic optimization approach is experimented on five workforce team types, namely: newbie, beginner, intermediate, good and great team. Fourthly, the research contributes to the literature by proposing an integrated stochastic optimization and discrete event simulation framework, providing guidance to production managers for designing and optimizing their production systems using a SERU layout.

The remainder of this paper is organized as follows. Section 2 presents a detailed literature review on SERU. Section 3 provides the mathematical formulation of the stochastic mixed integer non-linear programming model. Section 4 discusses case study development and Section 5 provides framework results for our selected problem on our generated case study. Finally, Section 6 presents conclusions and discusses limitations of the paper.

LITERATURE REVIEW

SERU production systems have gained significant attention in recent years due to their potential for improving productivity and reducing lead times in manufacturing settings. To better understand the benefits and challenges of SERU systems, numerous studies have been conducted to optimize or simulate these systems under either stochastic or deterministic conditions. A comprehensive review of SERU production systems, including a thorough comparison with other production models and practical implementations, are provided in (C. Liu et al., 2014; Yin et al., 2017; Yu & Tang, 2019; X. L. Zhang et al., 2017).

Table 1 presents a brief overview and comparison of the recent and relevant literature on SERU systems considering the following attributes: the type of solution method, how processing times are modeled, and the objective(s) of the proposed models. We had a couple of key findings which necessitated to conduct our study. First of all, while SERU systems are majorly used in labor intensive manufacturing settings, task processing times are predominantly considered deterministic in the literature, except a handful of works (e.g., Aboelfotoh et al., 2018, Zhang et al. 2023). In reality, worker skills critically impact the task processing time and depending on the experience (skill level) of the worker, which makes it critical to model task processing times stochastic considering uncertainty (e.g., standard deviation of task processing time).

It was found that majority of the studies primarily focused on developing a single or bi-objective optimization approach, while the predominant objective function was minimizing makespan and/or cycle time. However, it is noteworthy to state that certain critical performance indicators such as work-in-process (WIP), waiting time, and capacity utilization have not received adequate attention in the reviewed literature, in contrast these KPIs are heavily used in production systems' design and management. This is mostly due to the limitations of implementing optimization approaches. While optimization models, whether it's a mathematical or heuristic optimization, critically address the workforce allocation problem, the limits of objective function hinder the validation of findings. In this context, simulation approaches could potentially address these limitations by providing a more comprehensive assessment of production system performance considering other KPIs. As shown in Table 1, while many recent studies aim to enhance production efficiency and resource allocation in SERU production systems through optimization and heuristic techniques, the use of simulation techniques stayed relatively limited. We were able to track two works that employed simulation in SERUs (Deepak et al., 2017 and Zwierzynski & Ahmad 2018), where the solution approach solely consists of simulation.

TABLE 1
SUMMARY OF RECENT RELEVANT LITERATURE ON SERU

Literature	Solution Method	Processing Times	Objective(s)
C. Liu et al., 2013	Optimization (Three-stage heuristic algorithm)	Deterministic	Minimize total training costs and balance processing times
Ying & Tsai, 2017	Optimization (SAIG)	Deterministic	Minimize training cost and balance cost
Deepak et al. 2017	Simulation	Stochastic	Minimize cycle time
Yu et al., 2017	Optimization (Exact Solution and variable-length encoding algorithm)	Deterministic	Minimize number of workers without increasing makespan
Aboelfotoh et al., 2018	Neural Network	Stochastic	Minimize cycle time
Lian et al. 2018	Optimization (NSGA-II)	Deterministic	Minimize deviations from average workload of SERUs
Wu et al. 2018	Optimization	Deterministic	Maximize throughput and balance workload
Zwierzynski & Ahmad 2018	Simulation	Stochastic	Maximize productions and worker utilization while minimizing cost and waiting time
Yılmaz, 2019	Optimization (Exact Solution and NSGA-II)	Deterministic	Minimize makespan and reduce workload imbalance among workers
Sun et al., 2019	Optimization (cooperative coevolution algorithm)	Deterministic	Minimize makespan
Ayough et al., 2020	Optimization (invasive weed optimization algorithm)	Deterministic	Minimizing flow time and workforce allocation
Yılmaz, 2020	Optimization (Genetic algorithm)	Deterministic	Minimize makespan
F. Liu et al., 2021	Optimization (K-means-based NSGA-II)	Deterministic	Minimize makespan and balance the workers' workload
Jiang et al., 2021	Optimization (Exact Solution)	Deterministic	Minimize total waiting time, total absolute differences in waiting time, and total load
Fujita et al. 2022	Optimization (Monte Carlo)	Deterministic	Maximize expected profit
Zhang, Song et al. 2022	Optimization (Hybrid genetic algorithm)	Deterministic	Minimize total completion time of all jobs

Zhang, Wang et al. 2022	Optimization (Improved genetic-simulated annealing algorithm)	Deterministic	Maximize expected profit
Zeng et al., 2022	Optimization (epsilon-constraint method, NSGA-II, SPEA2)	Deterministic	Minimize total labor hours and workload unfairness for multi-skilled worker assignment problem
Shan, 2022	Optimization (Simulated Annealing NSGA-II, and entropy-weighted TOPSIS)	Deterministic	Minimize makespan and maximize workers' expenditure
Gai et al., 2022	Optimization (Exact Solution)	Deterministic	Minimize makespan
Zhang et al. 2023	Optimization (Hybrid genetic-simulated annealing algorithm)	Stochastic	Minimize expected makespan

In this section, we will examine various optimization and simulation techniques used in recent studies to solve SERU production problems and review their objectives in improving system performance. We summarize the studies based on their research focus, including worker skill levels, stochastic models, comparison with the traditional systems, and learning effect.

The productivity of labor-intensive cells is directly influenced by the performance of the workers. (Süer et al., 2019) propose a preliminary approach that takes into account the product life cycle stages and worker skill level to implement SERU production systems. The authors highlight that these factors are often neglected and can have a significant impact on the overall performance of the system. The proposed approach involves dividing the product life cycle into four stages (introduction, growth, maturity, and decline) and assigning different tasks to workers based on their skill level and the stage of the product life cycle.

Several studies address the deterministic problem of multi-skilled worker assignment in SERU systems (C. Liu et al., 2013) (Ying & Tsai, 2017) (Wu et al., 2018) (Lian et al., 2018) (Aboelfotoh et al., 2018) (F. Liu et al., 2021) (Zeng et al., 2022) and (Shan, 2022). (C. Liu et al., 2013) formulate a mathematical model with multiple objectives to minimize total training costs and balance processing times among workers. Different mathematical models, heuristic algorithms, and solution approaches have been proposed to optimize worker assignments, minimize costs, enhance throughput, and balance workload distribution among workers. The authors propose a three-stage heuristic algorithm to solve the model and validate the model and algorithm's performance through computational cases. (Ying & Tsai, 2017) investigate the multiskilled worker training and assignment problem in SERU production systems. The focus is on minimizing the total cost by considering workers' training cost and the balance cost of processing times. The paper presents a two-phase heuristic algorithm (SAIG) to solve the problem effectively.

Wu et al., (2018) study the cross-trained worker assignment problem for two different types of SERUs: divisional and rotating SERU. The authors propose a model to maximize the throughput of SERU while balancing the workload of workers under considering skill levels. The models consider various factors such as task time, available working time, skill levels of workers, and the required number of workers. The results shows that the proposed approaches enhance throughput and workload balance. (Lian et al., 2018) model the multi-skilled worker assignment problem as a bi-objective mathematical model to improve the inter-SERU workload balance and the inter-worker workload balance. They develop a meta-heuristic algorithm based on NSGA-II to solve the proposed problem. (Sun et al., 2019) present a cooperative coevolution algorithm for SERU production, aiming to minimize the makespan by simultaneously solving the SERU formation and SERU scheduling problems. The algorithm combines a genetic algorithm with local search for SERU formation and an ant colony optimization algorithm for improved SERU scheduling.

(Zeng et al., 2022) introduce a bi-objective mixed-integer nonlinear programming model for a similar problem in SERU production systems. The proposed model aims to minimize total labor hours and workload unfairness. The authors present three solution approaches, including the epsilon-constraint method, non-dominated sorting genetic algorithm 2 (NSGA-II), and improved strength Pareto evolutionary algorithm (SPEA2), to solve the problem. They emphasize the need to balance production efficiency and fairness in SERU. When efficiency measures are prioritized without considering the workload distribution among workers, it can be undesirable for highly skilled workers who may end up shouldering a disproportionate workload.(F. Liu et al., 2021) focus on the assignment of cross-trained workers in a hybrid SERU production system, which combines divisional and rotating SERU types. A bi-objective mathematical model is developed to minimize the makespan and balance the workers' workload in each SERU. For large-scale instances, an NSGA-II-based memetic algorithm and two K-means-based NSGA-II algorithms are proposed. (Shan, 2022) investigate an application of converting assembly lines to SERU production in a Chinese electronics assembly company during the transition to a customer-to-manufacturer business model. It proposes a production line improvement scheme and presents a mathematical model for optimizing the makespan and workers' expenditure. The Simulated Annealing NSGA-II algorithm and entropy-weighted TOPSIS approach are used to determine solutions. The study finds that SERU production and multiskilled workers align well with the customer-to-manufacturer model, and effective worker allocation strategies can reduce the number of employees and makespan in SERUs. (Gai et al., 2022) consider a SERU loading problem to minimize a production batch's makespan through a SERU system. They propose a min-max integer optimization model to obtain the optimal allocation. The method is extended to rotating SERUs, addressing the allocation of items to minimize makespan.

Some recent studies have focused on the scheduling and allocation problems in stochastic SERU production systems (Fujita et al., 2022) (Z. Zhang, Wang, et al., 2022) and (Z. Zhang et al., 2023). (Fujita et al., 2022) study a worker and production allocation problem in SERU production systems under uncertain demand. The approach uses the Monte Carlo technique and formulates the optimization problem as a bi-level mixed-integer linear programming problem. The first step involves solving a worker allocation problem before the demand is realized, and the second step involves allocating the production quantity based on the observed demand realization. The paper demonstrates the effectiveness of the proposed method through several numerical problems. (Z. Zhang, Wang, et al., 2022) study a SERU loading problem system with a downward substitution and random product demands and yields, where the objective is to maximize an expected profit. The SERU loading problem involves assigning workers to workstations to perform tasks in a given sequence, while the downward substitution means that a lower skilled worker can replace a higher skilled worker in a specific task. The authors propose an improved genetic-simulated annealing algorithm for the SERU loading problem under uncertainty in product demand. (Z. Zhang et al., 2023) develop a hybrid genetic-simulated annealing algorithm to solve the stochastic rotating SERU scheduling problem with resource allocation, job deterioration, learning effect, and setup time. The objective of the study is to minimize the expected makespan where the scheduling problem contains 3 SERUs and 10 orders. In the study, the processing times are randomly generated using normal distribution and uniform distribution ranging from 5 to 40. The performance of the proposed hybrid genetic-simulated annealing algorithm is tested on the developed instances and compared with genetic algorithm (GA) and particle swarm optimization (PSO) algorithm. The results show that the hybrid algorithm proposed in this paper is more suitable to solve the stochastic SERU scheduling problem considering dynamic resource allocation, job deterioration, learning effect and setup time than GA and PSO.

In addition to optimization studies, a handful of researchers studied SERU production with simulation. (Deepak et al., 2017) conducted a simulation study in a heavy-duty manufacturing industry by converting a fixed-worker-assembly-line into a SERU system. They found that the proposed SERU system offers better resource utilization by reducing cycle time and improving productivity. Furthermore, Zwierzyński & Ahmad (2018) conducted a simple simulation experiment comparing the efficiency of traditional assembly line production with shorter assembly lines and different configurations of SERU cells. In the experiment, the traditional assembly line produced 753 pieces of the finished product. Then, the assembly line was converted into two shorter assembly lines, where each employee performed two assembly operations. After that, the assembly process was converted into three SERU cells, with two employees performing three assembly operations. Finally, the assembly process was converted into six SERU cells, with one employee performing six assembly operations. The goal was to determine which system would be more efficient. The experiment was limited to the assembly process of a single product and did not take into account many other complex factors.

Several studies conducted a comparison between the SERU system and the traditional assembly line system to showcase the improvements offered by the SERU system. (Yu et al., 2017) focus on line-SERU conversion in manufacturing, aiming to reduce the number of workers without increasing the makespan. Two exact algorithms search the solution space in different directions, while a variable-length encoding heuristic algorithm is designed for large-scale instances. (Aboelfotoh et al., 2018) focus on selecting either Classical Assembly Line or SERU based on the higher output rate for a set of product operations. A neural network model is developed to predict the preferred strategy by considering worker skill level variation and inputs such as the number of tasks, product flexibility, and task processing time variation. The aim is to create a decision support tool that helps decision makers select the manufacturing strategy without the need for complex mathematical models. The neural network model achieved an 89.4% accuracy in predicting the preferred strategy. (Yılmaz, 2019) address the bi-objective workforce scheduling problem in a SERU production system by considering interSERU worker transfer. The study focuses on two objectives: minimizing the makespan and reducing workload imbalance among workers. A non-dominated sorting genetic algorithm-II (NSGA-II) is employed to solve large-sized problems. The results show that allowing worker transfer leads to better outcomes. (Yılmaz, 2020) addresses the workforce scheduling problem to minimize the makespan by considering interSERU worker transfer in the SERU production environment. The proposed problem is examined through experimental design, with several scenarios considered. The results demonstrate that allowing interSERU worker transfer leads to a significant reduction in the makespan. (Ayough et al., 2020) integrate job rotation scheduling and line-cell conversion problems. A nonlinear integer programming model called SERU-JRSP is introduced to address this integrated problem. To solve the SERU-JRSP, an invasive weed optimization algorithm is developed. The computational results demonstrate that job rotation scheduling leads to shorter flow time and fewer assigned operators in the SERU system.

In addition to the aforementioned aspects of SERUs, some works took into account learning effect. The consideration of DeJong’s learning effect in the SERU system is receiving increased attention in the recent literature. (Jiang et al., 2021) focus on a yatai SERU scheduling problem that consider past-sequence-dependent setup time and DeJong’s learning effect. The proposed problem aims to minimize total waiting time, total absolute differences in waiting time, and total load. The study proposes a general exact solution method by transforming SERU scheduling problems into assignment problems, which can be solved in polynomial time. (Z. Zhang, Song, et al., 2022) present a scheduling problem in SERU production system, taking into consideration DeJong’s learning effect and job splitting with the objective of the total completion time of all jobs. A non-linear integer programming problem is provided, and they propose a branch and bound algorithm and a local-search based hybrid genetic algorithm for solving small size and large size instances, respectively. They conduct numerical experiments to compare randomly generated scenarios and evaluate the effectiveness of their approach.

Overall, these studies highlight the potential benefits of using SERU production systems in various manufacturing systems and address different optimization problems related to production design and control aspects of SERUs. The current literature on the SERU production system mainly focuses on optimization problems, including scheduling, worker allocation, and product loading, under various uncertainties. However, the impact of workers’ skill levels in task processing time was not addressed considering uncertainty in task completion times. Secondly, traditional assembly lines were argued to have better performance against SERU but the literature does not distinguish the applications of SERUs between labor intensive and machine intensive systems, which could critically change the selection of the better production design alternative. Moreover, some systems use both labor and machine as a hybrid fashion. Thus, it is critical to compare SERUs against traditional assembly lines under uncertain task processing times in a labor-intensive setting, since machine intensive manufacturing systems typically favor the assembly lines and don't have much of a significant task processing time variation compared to human work force. Thirdly, while it is critical to solve SERUs or assembly line optimization problems with analytical models, these models do not provide a comprehensive understanding about the production system performance due to the limitation of setting a solo or dual objective functions, while production system performance is typically monitored by using multiple key performance indicators (KPIs) such as throughput, Work-in-process (WIP), waiting times, and system usage (resource utilization). Most of the literature approach the SERU system design with optimization approaches, which often necessitates a simulation approach to investigate the aforementioned KPIs. The state of art lacks studies where optimization and simulation approaches are employed back-to-back to provide a complete understanding of KPIs.

To address these important gaps, this study contributes to the state of art in the following aspects. First, worker skills can critically impact production system performance in labor intensive systems. Therefore, this study proposes a stochastic optimization approach to model the worker skill level and task processing time relationship considering the uncertainty in task performance. Second, this paper provides a comprehensive investigation of the impact of workers' skill levels by comparing the SERUs against the traditional assembly line. This can significantly help managers to design workstations and systems that can accommodate workers with different skill levels and uncertain task processing times. Third, the production system performance of SERUs is assessed by coupling discrete event simulation (DES) with the stochastic optimization model's results with a focus on throughput, WIP, waiting times, and capacity utilization. This provides a comprehensive evaluation of the system's performance. Fourth, we propose an integrated stochastic optimization and discrete event simulation framework. The modeling approach and results can provide a guidance to the production managers to make informed decisions, when designing and optimizing their production systems on a SERU layout.

METHODOLOGY

The methodology of this paper consists of integrated stochastic optimization and discrete simulation models. The stochastic optimization model is used to find worker and task allocation problem in the assembly line, where task times are probabilistic and derived based on the skill level. Thus, a mixed integer linear programming model with a stochastic chance constraint was built, and explained in the following sub section.

Stochastic Mixed Integer Linear Programming (SMILP) Model

In this section, a mixed integer non-linear programming model is introduced. This objective is to minimize cycle time such that optimal worker-task allocation is carried out where there is a single product, unidirectional (flow shop) process flow with multiple process steps. Each process step could be performed by any worker; however, process times are worker dependent and considered to be stochastic.

Indices

i:	task index
j:	workstation index
k:	worker index
M:	cycle time
n:	number of tasks
m:	number of workstations,
w:	number of workers
α:	Risk threshold
μ_{ijk}:	mean operation time of task i in workstation j by worker k

σ_{ijk}: standard deviation of operation time of task i in workstation j by worker k
E_i: earliest station for task i that can be assigned to, given the precedence relations
L_i: latest station for task i that can be assigned to, given the precedence relations

Decision Variables
X_{ijk}: 1, if task i is assigned in workstation j to worker k; 0, otherwise
Y_{jk}: 1, if worker k is assigned in workstation j; 0, otherwise

Minimize Z = M (1)

Subject to

$$\sum_{j=1}^{m}\sum_{k=1}^{w} X_{ijk} = 1 \text{(for i = 1, 2, …, n)} \quad (2)$$

$$p\left(Z_j \leq \frac{(\sum_{i=1}^{n}\sum_{k=1}^{w} \mu_{ijk} * X_{ijk} - M)}{\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{w} \sigma_{ijk} * X_{ijk}}}\right) \geq (1-\alpha) \text{ for } j = 1, 2, \ldots, m \quad (3)$$

$$X_{ijk} \leq Y_{jk} \text{ (for i = 1, 2, …, n; for j = 1, 2, …, m; for k = 1, 2, …, w)} \quad (4)$$

$$\sum_{j=1}^{m} y_{jk} = 1 \text{ (for k = 1, 2, …, w)} \quad (5)$$

$$\sum_{k=1}^{w} y_{jk} = 1 \text{ (for j = 1, 2, …, m)} \quad (6)$$

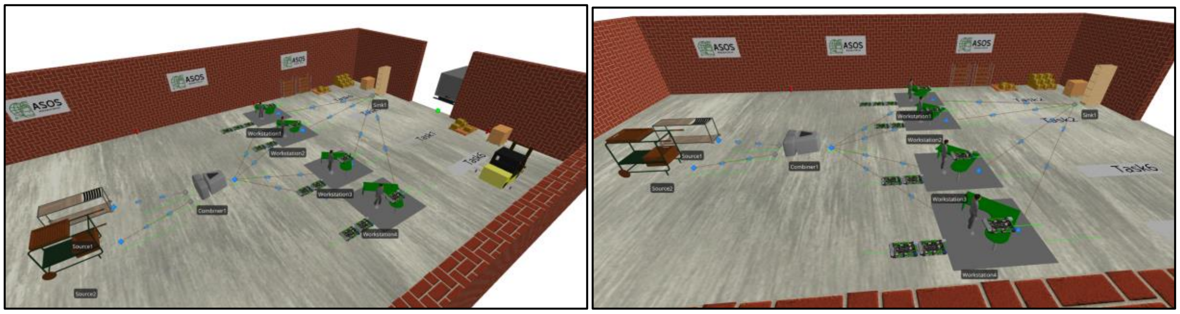
$$\sum_{m=Ea}^{La} X_{ijk} \leq \sum_{m=Eb}^{Lb} X_{ijk} \quad (7)$$

Equation (1) is the objective function, which aims to reduce the cycle time. Cycle time is the bottleneck workstation total process time. Equation (2) is developed to ensure that each task is assigned to a workstation and a worker. Equation (3) is the stochastic constraint. It is developed to ensure that each station's total process time does not exceed the cycle time based on a risk threshold of$\propto$ which ranges between 0 and 1. Equation (4) ensures that all tasks are assigned to an open workstation, which should have at least 1 worker assigned. Equations (5) and (6) ensure that every worker is assigned to a workstation, and each workstation is assigned to a worker, respectively. Finally, equation (7) ensures that precedence relationships between the consecutive tasks are not violated, where 'b' is an immediate follower of 'a'.

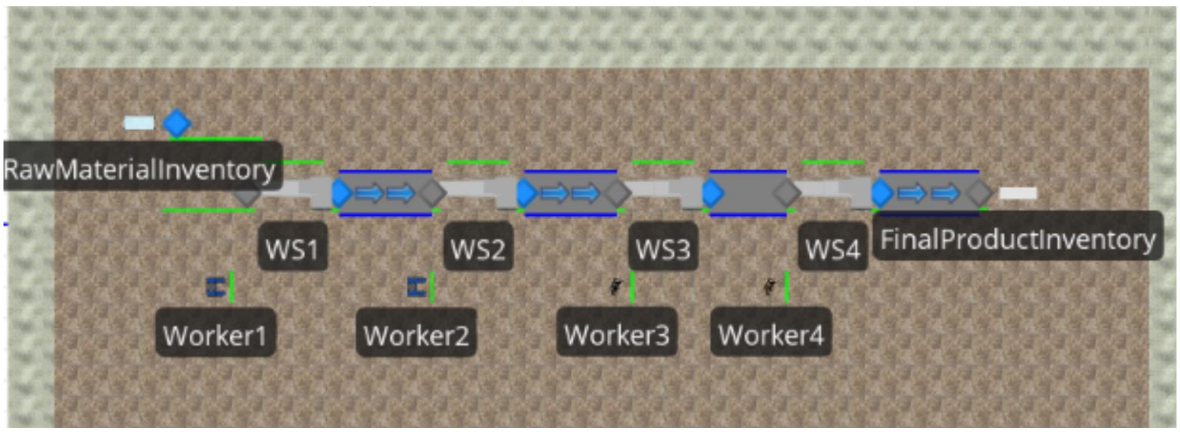
Simulation Model Integration

Simulation models for assembly line and SERU shops were built with Simio simulation software (See Fig. 1). During the simulation experiments, 1000 replications and 1 day run were used as the experimentation parameters to be able to compare with Abdullah (2018)'s results and the proposed stochastic optimization approach's results. The optimized worker to station allocations were taken from optimization model's and SERU and assembly line workstations were created as shown in the screenshots of simulation models (See Fig. 1a and 1b).

FIGURE 1
SCREENSHOTS OF SIMULATION MODELS



a. SERU System Layout



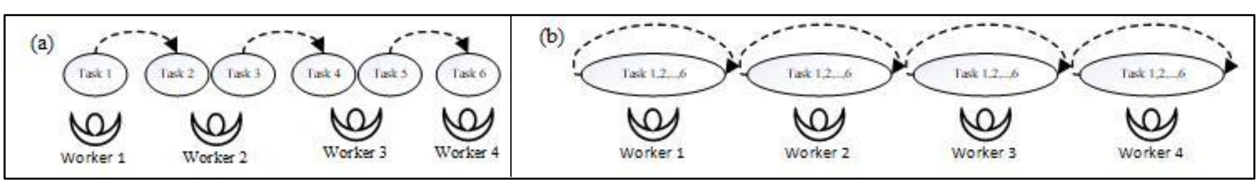
b. Assembly line layout

Case Study

Assembly Line vs. SERU Manufacturing Shops

The schematic provided in figure 1 presents an assembly line (left side) and a yatai SERU system (right side). In figure 1a, the precedence flow of tasks carried out to produce the given example product make up the assembly line. In this assembly line (figure 2a), the product is being produced over six succeeding tasks, which are completed on four workstations. Each workstation has one worker. For instance, worker 1 carries out task 1, worker 2 carries out tasks 2 and 3, and so on. As shown in Fig. 2b, there are four yatai SERUs. Each worker is responsible to carry out all the six tasks to assemble a complete product.

FIGURE 2
(a) ASSEMBLY LINE AND (b) YATAI SERU



The Relationship Between Skill Levels and Task Processing Times

A skill level scale ranging from 1 to 7 in a deterministic mixed integer linear programming model was first introduced by Abdullah (2018), then used by (Abdullah & Süer, 2019), skill level 1 representing the worst performing and 7 representing the best performing worker as shown in Table 1. However, Abdullah (2018) only considered the mean processing time (mPT), in other words expected value of processing time, using a deterministic optimization model and did not account for the variability in task processing time (variance or standard deviation). As a contribution of this study, we propose the skill-level-based processing times as a normally distributed random variable to incorporate both the mean processing time (mPT) and the standard deviation of processing time (sPT). Unlike Abdullah (2018), this addition allows us to capture the performance of workers from both an average performance and variability perspectives, accounting for factors such as inexperience and task-dependent variations. For example, the worst performer (WP), assumed as an inexperienced worker, is expected to exhibit high mPT and sPT values. Their performance may vary significantly across tasks and even within repetitive tasks due to their lack of experience. Conversely, the excellent performer (EP) is expected to have the shortest mPT and sPT. By considering the inherent uncertainty in task processing times, our approach provides a more comprehensive understanding and formulation of worker performance. Table 1 presents both the mean and standard deviation of task processing times, complementing the previous focus solely on mean processing times. Modeling task processing times as normally distributed random variable necessitates a stochastic optimization approach.

TABLE 2
SKILL LEVELS AND PROBABILISTIC TASK TIMES (IN MINUTES)

Skill level	Mean Task Processing Time (mPT)	St. Dev. of Task Processing Time (sPT)	Worker Type
1	μ+3σ	3σ	Worst Performer (WP)
2	μ+2σ	2σ	Very Poor Performer (VPP)
3	μ+1σ	1.5σ	Poor Performer (PP)
4	μ	1σ	Average Performer (AP)
5	μ-1σ	0.666667σ	Good Performer (GP)
6	μ-2σ	0.5σ	Very Good Performer (VGP)
7	μ-3σ	0.3333σ	Excellent Performer (EP)

In Table 2 (Abdullah, 2018; Abdullah & Süer, 2019; Khalafallah & Egilmez, 2021) an example of normally distributed processing times for an average worker (AP) is presented for six tasks involved in the assembly of a product. The table displays the standard mean and standard deviation of task processing time, where the standard deviation is set to 15% of the mean task time.

TABLE 3
MEAN AND STANDARD DEVIATION OF TASK PROCESSING TIME FOR AP

	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Mean (μ)	10	8	5	7	3	9
St dev (σ = 0.15*μ)	1.5	1.2	0.75	1.05	0.45	1.35

To provide a clearer understanding of how the mean and standard deviation processing times from Table 1, and the standard average worker task times from Table 2, are utilized, we present an example scenario with a newbie team of inexperienced workers in Table 3. This newbie team consists of four workers, with one worker classified as an excellent performer (skill level 7) and the remaining workers as inexperienced worst performers (skill level 1). Table 3 showcases the relationship between worker skill level and the corresponding mean and standard deviation of task processing times, which are incorporated into the stochastic mixed integer linear programming model. In Table 4, the calculated skill levels for the example newbie team are presented alongside their respective mean and standard deviation processing times (mPT and sPT). The task times listed in Table 4 are computed using the notation provided in Table 1, along with the standard time data from Table 2. For instance, the mean task processing time for a worker with a skill level of 7 (classified as an excellent performer) is calculated as μ-3σ. Taking Task 1 as an example from Table 2, with a standard mean processing time (μ) of 10 and a standard deviation (σ) of 1.5, the excellent performer's mean processing time is determined as μ-3σ=10-3*1.5=5.5, with a standard deviation of 0.3333σ = 0.3333*1.5=0.49995.

TABLE 4
SAMPLE SKILL LEVEL MATRIX OF A NEWBIE TEAM

Skill Matrix	Worker 1 (Excellent Performer)	Worker 2 (Worst Performer)	Worker 3 (Worst Performer)	Worker 4 (Worst Performer)
Task 1	7	1	1	1
Task 2	7	1	1	1
Task 3	7	1	1	1
Task 4	7	1	1	1
Task 5	7	1	1	1
Task 6	7	1	1	1

TABLE 5
THE MEAN AND STANDARD DEVIATION OF TASK PROCESSING TIME (IN MINUTES) OF A NEWBIE TEAM

	Worker 1(Skill Level 7): Excellent Performer		Worker 2 (Skill Level 1): Worst Performer		Worker 3 (Skill Level 1): Worst Performer		Worker 4 (Skill Level 1): Worst Performer	
Task	**mPT**	**sPT**	**mPT**	**sPT**	**mPT**	**sPT**	**mPT**	**sPT**
1	5.50	0.49995	14.5	4.50	14.5	4.50	14.5	4.50
2	4.40	0.39996	11.6	3.60	11.6	3.60	11.6	3.60
3	2.75	0.249975	7.25	2.25	7.25	2.25	7.25	2.25
4	3.85	0.349965	10.15	3.15	10.15	3.15	10.15	3.15
5	1.65	0.149985	4.35	1.35	4.35	1.35	4.35	1.35
6	4.95	0.449955	13.05	4.05	13.05	4.05	13.05	4.05

*mPT: Mean Task Processing Time, sdPT: Standard Deviation of Task Processing Time

Experimentation Data-1

A total of 10 datasets were directly adopted from (Abdullah, 2018) for fair comparison and continuity of the scientific literature, since the proposed stochastic optimization (SMILP) approach in this paper is compared with the existing deterministic optimization approach used in (Abdullah, 2018). Table 5 depicts the skill levels of four-worker teams in each dataset, along with mean and standard deviation of skill levels. The skill levels of workers were randomly generated in 7 datasets and remaining 2 datasets consists of entirely average workers in Dataset 10 and excellent workers in Dataset 9 (See the standard deviation of skill levels in datasets 9 and 10 are 0 since all skill levels are the same).For instance, in Dataset 1, worker 1's skill levels range between poor performer (PP) and average performer (AP), since each worker could perform differently on different tasks. Similarly, worker 2's skill levels range between poor performer (PP) and average performer. Furthermore, worker 3's skill level is an average performer across all the tasks, and worker 4's skill levels range between average performer (AP) and good performer (GP). Each dataset's corresponding mean and standard deviation of skill levels are also provided in Table 5. See Appendix file for more information.

TABLE 6
DATASET CHARACTERISTICS OF (ABDULLAH, 2018)

Data	Worker Skill Levels				Team Skill Levels	
	Worker 1	Worker 2	Worker 3	Worker 4	Mean	St. Dev.
Dataset 1	PP - AP	PP-AP	AP	AP-GP	3.8	1.5
Dataset 2	AP	PP-AP	PP-AP	AP-GP	4	1.6
Dataset 3	AP	PP-AP	AP	AP-GP	4	0.7
Dataset 4	AP-GP	AP-GP	AP	AP	4.1	1.4
Dataset 5	AP	AP-GP	AP-GP	AP	4.3	2.2
Dataset 6	PP-AP	AP-GP	AP-GP	AP-GP	4.5	2.1
Dataset 7	PP-AP	AP-GP	AP-GP	AP-GP	4.5	2.1
Dataset 8	VGP-EP	AP	WP-VPP	PP-AP	3.8	2.1
Dataset 9	EP	EP	EP	EP	7	0
Dataset 10	AP	AP	AP	AP	4	0

Experimentation Data-2

Although we initially employed previously used datasets (Experimentation Data-1) developed by Abdullah (2018) to maintain continuity in the literature and ensure a fair comparison with our proposed approach; we found that employing 7 skill levels could be very exhaustive in terms of experimentation and could pose challenges for interpretation and practical application by production managers. Furthermore, since the skill levels were randomly generated in Abdullah (2018), which is advantageous from a randomized experimentation perspective; it made it difficult to draw definitive conclusions regarding the superiority of either the SERU system or the assembly line, when worker team identity is not considered.

To address the aforementioned disadvantages, we propose using a set of 5 skill levels instead of 7, as illustrated in Table 6. We took the average performer (AP) worker proposed by Abdullah (2018) as a starting point, and calculated the mPT and sPT values based on the notation shown in Table 6.

TABLE 7
PROPOSED NEW SKILL LEVELS, MPT AND SPT FORMULAS

Skill Level	mPT	sPT	Worker Type
1	$\mu+2\sigma$	2σ	Inexperienced
2	$\mu+1\sigma$	1.5σ	Beginner
3	μ	1σ	Intermediate
4	$\mu-1\sigma$	0.666667σ	Good
5	$\mu-2\sigma$	0.5σ	Great

When generating the experimentation data-2, we focused on the team identity as a starting point. Team identity could have a significant impact on manufacturing performance, particularly in labor-intensive production systems where worker performance, in other words skill level, strongly influences production throughput. Because, teams are not assembled randomly in real world but based on experience of workers.

Given that labor-intensive manufacturing processes are often the primary application area for SERU systems in the literature, we chose to generate datasets based on five types of team identity: “Newbie”, “Beginner”, “Intermediate”, “Good”, and “Great”. In real-world manufacturing shops, there is typically at least one lead worker who possesses deep experience and knowledge of the entire system and its tasks. This lead worker often trains others, particularly new workers in the shop. Therefore, we assumed that each team consists of at least 1 “Great” worker. Moreover, the team’s identity was characterized by the skill levels of the remaining workers (see Table 7). By designing teams with these specific identities, we aimed to investigate the performance of different team types between assembly line and SERU structures. We designed these five teams with the team identities in the hopes of making the application of the proposed research framework and the interpretation convenient and effective. See Appendix file for more information.

TABLE 8
PROPOSED NEW TEAM TYPES

Team Identity	Worker 1	Workers 2, 3, and 4
Inexperienced Team	Great	Newbie
Beginner Team	Great	Beginner
Intermediate Team	Great	Intermediate
Good Team	Great	Good
Great Team	Great	Great

RESULTS

The results are explained in two sections. In the first section, the first set of experimentation data was obtained from Abdallah, 2018 and the proposed stochastic optimization approach was compared in terms of SERU vs. traditional assembly line for continuity of the literature. Then, the second section presents the results of experimentation with the proposed stochastic optimization approach based on the newly generated dataset with respect to set of five skill levels.

Results of Experimentation Data-1

The results of first experimentation with 10 datasets obtained from Abdullah (2018) was presented in Figure 3 and Table 8 and Table 9. See Appendix file for more information. Figure 3 presents results of proposed stochastic optimization approach in comparison of SERU vs. assembly line in terms of throughput (the total production amount/day). Tables 8 and 9 provides results of simulation experiments based on the stochastically optimized worker-task allocation. Twenty simulation models were developed for the 10 datasets experimentation on SERU and traditional assembly line.

According to the optimization results (Fig. 3), SERU shop outperformed the traditional assembly line for Datasets 3, 4, 6, 8, 9, and 10 while the traditional assembly line was found to be superior for Datasets 1, 2, 5, and 7.Here, it is important to note that such optimization approaches while we propose a novel stochastic optimization approach, won’t be able to provide a holistic understanding about the manufacturing system’s performance due to the limits of objective function (e.g. being limited to throughput or cycle time observed in many studies in the literature). Thus, it becomes an important task to simulate the stochastically optimized solution and measure the performance from the perspective of 5 KPIs (throughput, cycle time, WIP, waiting time, and capacity utilization).

FIGURE 3
RESULTS OF STOCHASTIC OPTIMIZATION APPROACH WITH EXPERIMENTATION

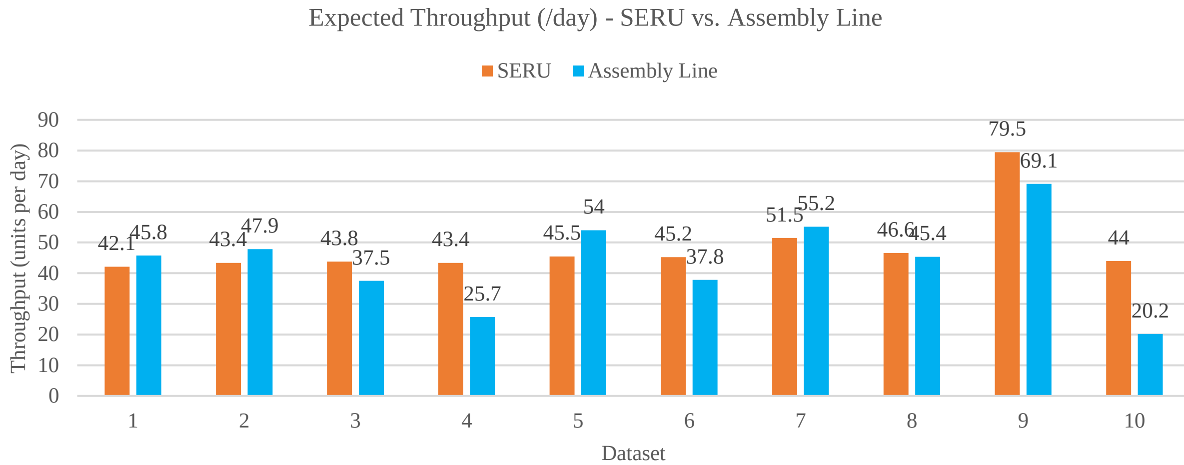


Table 8 shows the results of simulation experiments based on the throughput and cycle time in terms of mean and half-width. In terms of throughput, cycle time, and WIP, same results were obtained with the stochastic optimization approach and SERU found superior in datasets 3,4,6,8,9, and 10. Moreover, in terms of waiting time and capacity utilization KPIs, SERU was superior in all of the datasets. From just-in-time manufacturing and total quality management perspective, close to zero waiting times and close to 100% capacity utilization are ideal for a highly competitive and good performing manufacturing system.

TABLE 9
RESULTS OF SIMULATION EXPERIMENTS BASED ON THE PROPOSED SMILP APPROACH

Datasets	**Throughput (Units per 8-hour workday)**				**Cycle Time (minutes)**		**Superior System**
	Assembly Line		SERU		Assembly Line	SERU	
	Average	Half-width	Average	Half-width	Average	Average	
Dataset 1	**45.8**	0.1133	42.1	0.0172	**10.5**	11.4	Assembly Line
Dataset 2	**47.9**	0.1408	43.4	0.0288	**10**	11	Assembly Line
Dataset 3	37.5	0.1412	**43.8**	0.0205	12.8	**11**	SERU
Dataset 4	25.7	0.1305	**43.4**	0.0194	18.7	**11.1**	SERU
Dataset 5	**54**	0.1027	45.5	0.0388	**8.9**	10.6	Assembly Line
Dataset 6	37.8	0.1657	**45.2**	0.0306	12.7	**10.6**	SERU
Dataset 7	**55.2**	0.1132	51.5	0.0402	**8.7**	9.3	Assembly Line
Dataset 8	45.4	0.1083	**46.6**	0.0244	10.6	**10.3**	SERU
Dataset 9	69.1	0.1267	**79.5**	0.1361	6.9	**6**	SERU
Dataset 10	20.2	0.1083	**44**	0.0032	23.8	**10.9**	SERU

TABLE 10
RESULTS OF SIMULATION EXPERIMENTS BASED ON THE PROPOSED SMILP APPROACH CONT'D

Datasets	WIP		Waiting Time (Hours)		Utilization (%)	
	Assembly Line	**SERU**	**Assembly Line**	**SERU**	**Assembly Line**	**SERU**
Dataset 1	**74.8**	75.9	4.5	**3.8**	91.6	**100.0**
Dataset 2	**73.9**	75.2	4.3	**3.8**	90.5	**100.0**
Dataset 3	79.2	**75.2**	4.6	**3.8**	89.5	**100.0**
Dataset 4	85.1	**75.3**	4.0	**3.8**	74.3	**100.0**
Dataset 5	**71.4**	74.3	4.0	**3.8**	68.3	**100.0**
Dataset 6	79.2	**74.3**	4.1	**3.8**	85.1	**100.0**
Dataset 7	**70.5**	71.3	4.0	**3.9**	84.0	**100.0**
Dataset 8	75.2	**73.7**	4.5	**3.8**	91.8	**99.9**
Dataset 9	63.3	**56.6**	4.7	**3.8**	93.3	**98.3**
Dataset 10	87.8	**75.1**	4.0	**3.9**	72.5	**100.0**
Mean	76.04	**72.69**	4.27	**3.82**	84.09	**99.82**
Std. Dev.	7.16	**5.80**	0.28	**0.04**	9.14	**0.53**

Results of Experimentation Data-2

Results of experimentation data-2 was focused on the impact of team type. Five types of teams were characterized and experimented with the deterministic optimization model proposed by the closest work in the literature (Abdullah, 2018) and then compared with the results of the proposed stochastic optimization approach. See Appendix file for more information. Table 10 shows the results obtained based on the Abdullah (2018)'s deterministic optimization model, while the proposed stochastic optimization approach's results are provided in Table 11. It was important to find out that SERU outperformed the traditional assembly line in all team types.

TABLE 11
SUMMARY OUTPUT FOR SERU AND ASSEMBLY LINE (DETERMINISTIC MODEL BY ABDULLAH (2018))

Deterministic Model	**Output in (Units per day)**		**Superior system**	**% Difference (SERU vs. Assy. Line)**
Dataset Name:	SERU	Assembly		
Data set 1-Newbie Team	39.51	35.56	SERU	10%
Data set 2-Beginner Team	43.84	37.65	SERU	14%
Data set 3-Intermediate Team	49.23	40.00	SERU	19%
Data set 4-Good Team	56.14	47.06	SERU	16%
Data set 5- Great Team	65.31	57.14	SERU	13%

TABLE 12
SUMMARY OUTPUT FOR SERU AND ASSEMBLY LINE (THE PROPOSED SMILP MODEL)

Stochastic Model	Output in (Units per day)		Superior system	% Difference
Dataset Name:	SERU	Assembly		**(SERU vs. Assy. Line)**
Data set 1-Newbie Team	35.23	30.15	SERU	14%
Data set 2-Beginner Team	39.78	33.15	SERU	17%
Data set 3-Intermediate Team	45.64	35.96	SERU	21%
Data set 4-Good Team	52.80	42.07	SERU	20%
Data set 5- Great Team	61.65	51.55	SERU	16%

DISCUSSION

The literature on production system design (e.g., assembly line balancing, cellular layout, process layout, product layout, etc.) is typically overwhelmed with sophisticated optimization approaches from mixed integer linear programming to nonlinear optimization and metaheuristics (Egilmez et al., 2019; Mosadegh et al., 2020). While improving optimization procedures of production system design as well as control (e.g., scheduling) is critical, it is equally or arguable more important to study these solution procedures from a comprehensive perspective. Because, while production managers make a strategic or tactical decision on production system layout (design) and control (MPS, scheduling, sequencing, etc.), they typically need to look at several key performance indicators (KPIs) (Egilmez et al., 2019; Egilmez & Süer, 2014). Among the limitations of optimization approaches, they exclusively focus on one or two key metrics as the focal point of optimization, while other KPIs are neglected. This study proposes an integrated stochastic optimization and simulation approach which could enable practitioners to replicate while contributing to the state of art in the following ways: stochastic optimization to address uncertainty in task processing times as a result of different skill levels; multi-KPI evaluation: throughput, cycle time, WIP, waiting time and capacity utilization, team types and impact of team diversity in production system performance. Furthermore, it is crucial to evaluate optimization results as shown in this study, optimization results not only yield only average performance (e.g., throughput) while neglecting the impact of uncertainty (half-width, but also limits the analytical approaches focus on optimization parameters. When coupled with simulation, half-width results provide statistically reliable results as well as multiple KPIs could be investigated.

In terms of the benefits of employing stochastic optimization, the results indicate that stochastic optimization approaches not only enable defining select production system parameters such as processing times, as a random variable but also provide the results within much more close proximity to the simulation experiments' results. In this context, simulation can play a crucial role in providing a much-expanded performance overview over a period of time (mimicking steady state long run) with statistically significant results. The state of art and production practitioners could benefit with these integrated approaches with multi-faceted KPIs to make more informed decisions about the production system design and control phases (Alhawari et al., 2021; Egilmez et al., 2012).

CONCLUSION

This study contributes to the understanding and optimization of SERU production systems by addressing important gaps in the existing literature. By proposing a stochastic optimization approach, the study models the relationship between worker skill levels and task processing time, considering uncertainty, which is a significant contribution in the field. Additionally, the research provides a comprehensive investigation by comparing SERU systems with traditional assembly lines, highlighting the impact of worker skill levels and uncertain task processing times. By integrating stochastic optimization models with discrete event simulation, the study evaluates production system performance using multiple key performance indicators, offering a comprehensive evaluation of the system's performance. Moreover, the research proposes an integrated stochastic optimization and discrete event simulation framework, providing valuable guidance to production managers for designing and optimizing their production systems using a SERU layout. These contributions enhance our understanding of SERU systems and support informed decision-making in production system design and optimization. Considering that labor-intensive manufacturing processes are commonly associated with SERU systems in the literature, we decided to create datasets based on different team styles. As a result, we developed five types of teams: "Newbie," "Beginner," "Intermediate," "Good," and "Great" teams. Each team consists of one expert worker and the remaining workers possess the same skill level. The findings of this study demonstrate that the SERU system surpasses traditional assembly lines in terms of throughput when considering the uncertainty in task processing times. Additionally, the integrated optimization and simulation approach proposed in this research offers more statistically reliable system performance indicators compared to the deterministic optimization-only approaches typically used in the literature. The study further highlights the benefits of the SERU system in terms of production output by considering worker skill levels within team identities. As a future research direction, it will be important to study the impact of learning effect on production performance. In addition, investigation of other team identity characteristics would be important and left as a future work.

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