Simulation-based Risk Assessment for Productivity and Safety in Facility Layouts

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Abstract

Efficient facility layout and risk-aware planning are critical to both productivity and safety in manufacturing environments. This study examines the impact of workspace dimensions and performance on risk and production rates in a dry transformer production line. A nonlinear model is developed to estimate operators' failure rates due to stress caused by workspace dimensions and workload, which are dependent on facility layout. The model is evaluated using discrete-event simulation (DES) with Arena software and a case study. Scenario analyses examined variations in workspace dimensions, and the results indicated that increasing maneuvering area and optimizing spatial allocation can reduce operator failure rates while improving production output. Average weekly production increased from 142 units (baseline) to 154 units (an 8.4% increase), while operator uptime (F) rose from 16.92 to 28.21 hours, from 13.54 to 23.69 hours, and from 16.92 to 28.21 hours across the three main work areas on the production floor. These findings show that strategic layout adjustments enhance safety and productivity, enabling manufacturers to design risk-informed workspaces that reduce failures and improve efficiency.

Keywords

Discrete-event simulation, Risk modelling, Manufacturing modelling, Facility layout, Efficiency, Safety

1. Introduction

Manufacturing enterprises often encounter limitations in both short-term and long-term planning, which negatively impact their competitiveness and long-term sustainability [1]. Addressing these challenges requires the adoption of practices that enhance efficiency, promote innovation, and facilitate adaptation to dynamic environments. A key objective in manufacturing is cost reduction, achieved by improving productivity and system performance through resource optimization, demand-driven planning, and efficiency gains. Production, therefore, focuses on maximizing profit through effective scheduling, capacity evaluation, and bottleneck identification [2].

In this context, discrete-event simulation (DES) is a strategic tool for analyzing scenarios and supporting operational decisions [3]. By modeling production in a virtual environment, DES helps identify bottlenecks and evaluate both qualitative (workflow logic) and quantitative (throughput, downtime) factors. Simulating events such as arrivals, operations, and maintenance enables rapid testing of alternatives without physical trials, cutting time and costs while improving decision speed [4, 5]. Studies highlight its impact across various sectors - from resource management in the footwear industry [6] and planning under uncertainty [7] to reduced waiting times in retail [8, 9] and optimized layouts in manufacturing [10, 11, 12, 13, 14, 15, 16, 17]. Overall, DES proves to be a versatile strategy for enhancing efficiency, safety, and competitiveness.

Beyond efficiency gains, safety can also be enhanced through predictive risk assessment, as DES enables the simulation of failures, workflow interruptions, and hazardous scenarios to address vulnerabilities proactively [5, 18, 19, 20]. Common DES platforms, such as Arena, PROMODEL, FlexSim, Sand, and SIMIO, support these applications while reducing logistics costs [21, 22, 23, 24]. Building on this foundation, this study examines production efficiency as a function of risk assessment linked to facility layout, emphasizing how spatial configuration affects both safety and performance. A nonlinear risk

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model based on workspace dimensions, workload, and utilization is developed and validated through a dry transformer case study using DES. The results confirm that DES can support decision-making by integrating safety and efficiency, addressing a critical gap in safe manufacturing.

The remainder of this manuscript is structured as follows: Section 2 introduces the proposed risk model; Section 3 presents the case study and data collection; Section 4 describes the DES model developed in Arena®; Section 5 reports validation and results with the risk model; and Section 6 provides conclusions and directions for future research.

2. Risk Model for Assessment of Workplace Safety

All operations within manufacturing processes are fundamental to ensuring effectiveness; identifying risk factors allows companies to maintain infrastructure, equipment, and other production elements in optimal condition [25]. Ensuring safety further requires the proper selection, installation, and maintenance of equipment, complemented by critical practices such as machine guarding, the use of safety devices, preventive maintenance, the appropriate use of personal protective equipment (PPE), and comprehensive operator training [26, 27].

Proper facility layout is consistently identified as a key factor in reducing accident risk [28]. Effective layouts minimize unnecessary movement, reduce congestion, and ensure clear pathways for both workers and materials. The segregation of hazardous areas and the logical sequencing of operations further prevent cross-contamination and limit exposure to risks [29]. Moreover, flexible layouts enable adaptation to process changes and improve responsiveness during emergencies [30].

The present work advances this field by modelling risk as a function of the available space for human maneuvers and integrating this risk model with DES to estimate its impact on production and resource performance dynamically. This approach enables a more comprehensive evaluation of how spatial constraints and layout decisions influence both safety and operational efficiency on the manufacturing floor.

Accidents and failures in industrial systems result from the combined influence of multiple operational drivers, each contributing to overall risk through distinct mechanisms. The number of workers during interval t (W_t) increases the frequency of potential interactions; as the workforce size grows, the probability of interference, hand-offs, and uncoordinated actions rises accordingly. The processing pace during interval t (P_t) determines exposure intensity, since higher throughput per worker elevates cognitive load and fatigue, thereby increasing the likelihood of unsafe actions. Spatial constraints, represented by the crowding factor during interval t ($D_t = 1/A_t$), limit maneuverability and elevate the chance of collisions or restricted movements. Finally, resource utilization during interval t (ρ_t) captures the extent to which the system operates near its adequate capacity. As utilization approaches unity, operational buffers diminish, queues lengthen, and time pressure intensifies, producing a nonlinear escalation in accident probability. Note that these mechanisms act multiplicatively rather than additively: small, simultaneous increases in workforce size, pace, crowding, and utilization may combine to generate a disproportionately large rise in risk. To capture this behavior, the model adopts a log–linear specification that transforms into a multiplicative power-law form after exponentiation [31].

By defining λ_0 as the baseline accident rate under reference operating conditions (W_0, P_0, D_0) the log-linear mean accident rate during interval t (λ_t) is represented as:

$$ln(\lambda_t) = ln(\lambda_0) + \theta_1 ln(\frac{W_t}{W_0}) + \theta_2 ln(\frac{P_t}{P_0}) + \theta_3(\frac{D_t}{D_0}) - \gamma ln(1 - \rho_t) \tag{1}$$

This logarithmic formulation offers statistical tractability, ensuring dimensional consistency and interpretability. The coefficients $\theta_1, \theta_2, \theta_3$, and γ represent the proportional change in accident risk resulting from a proportional change in the associated factor (W_t, P_t, D_t, and ρ_t, respectively). Table 1 provides additional details on the dimensions and characteristics of these variables and terms.

Exponentiation of both sides of (1) leads to the multiplicative power-law form:

Table 1
Overview of variables and dimensions of the proposed risk model.

Variable	Description
W	Number of workers (count, dimensionless).
P	Work pace (items processed per worker per hour, items/worker/hour).
A	Space available per worker (m^2/worker).
$D = 1/A$	Crowding factor (m^{-2}).
W_0	Median(W) from the last 30-60 days.
P_0	Median(P) from the last 30-60 days.
A_0	Median(A) from last 30-60 days (then, $D_0 = 1/A_0$).
$\rho = \frac{\varrho}{C_{eff}}$	The resource utilization ratio, defined as demand throughput relative to effective system capacity, is a dimensionless quantity bounded in the interval [0, 1).
C_{eff}	Items/hour that the space can truly deliver at steady state.
λ_0	Baseline accidents/hour at (W_0, P_0, D_0).
λ	Expected accidents/hour.
$\theta_1, \theta_2, \theta_3$	Elasticity coefficients measuring the proportional sensitivity of accident risk to changes in W_0, P_0, and D_0,, respectively.
$\gamma > 0$	Captures the utilization stress effect, with risk diverging as $\rho \to 1$

$$\lambda_t = \lambda_0(\frac{W_t}{W_0})^{\theta_1}(\frac{P_t}{P_0})^{\theta_2}(\frac{D_t}{D_0})^{\theta_3}(1-\rho_t)^{-\gamma} \tag{2}$$

Because λ_t represents the expected accidents per unit of time t (e.g., an hour), $F = 1/\lambda_t$ represents the time between accidents or failures (i.e., failure uptime). This model involves precise quantification of physical workspace dimensions and worker occupancy density within shared areas, irrespective of task-specific workflows.

Previous research on safety and efficiency in manufacturing exhibits several important gaps. Most studies address these dimensions separately, without integrating safety and operational performance within a single framework. Existing models do not simultaneously quantify the impact of facility layout decisions on both outcomes, and metrics such as effective workspace and worker density—factors directly influencing accidents and efficiency—are seldom incorporated. Furthermore, DES has rarely been extended to include space-dependent risk variables, and validation efforts using current empirical data remain limited. In this context, the model presented in (1) and (2) represents a significant contribution by bridging these gaps and providing a unified approach to assessing safety and efficiency.

3. Case Study

The company in the case study specializes in the manufacture of dry transformers. The analysis focuses on the materials warehouse area, where the company is proposing the development of a production line for the final assembly of transformer units (coils). Key operations in this line include unpacking, subassembly, part joining, quality inspections, product identification, electrical testing, insulation application, and final packaging. The process flow is illustrated in Figure 1.

For each operation, ten samples were collected to support the statistical modelling process. To account for variability in activity times, a 15% fatigue factor was incorporated. Table 2 presents the fitted probability distributions associated with the time required to complete all activities.

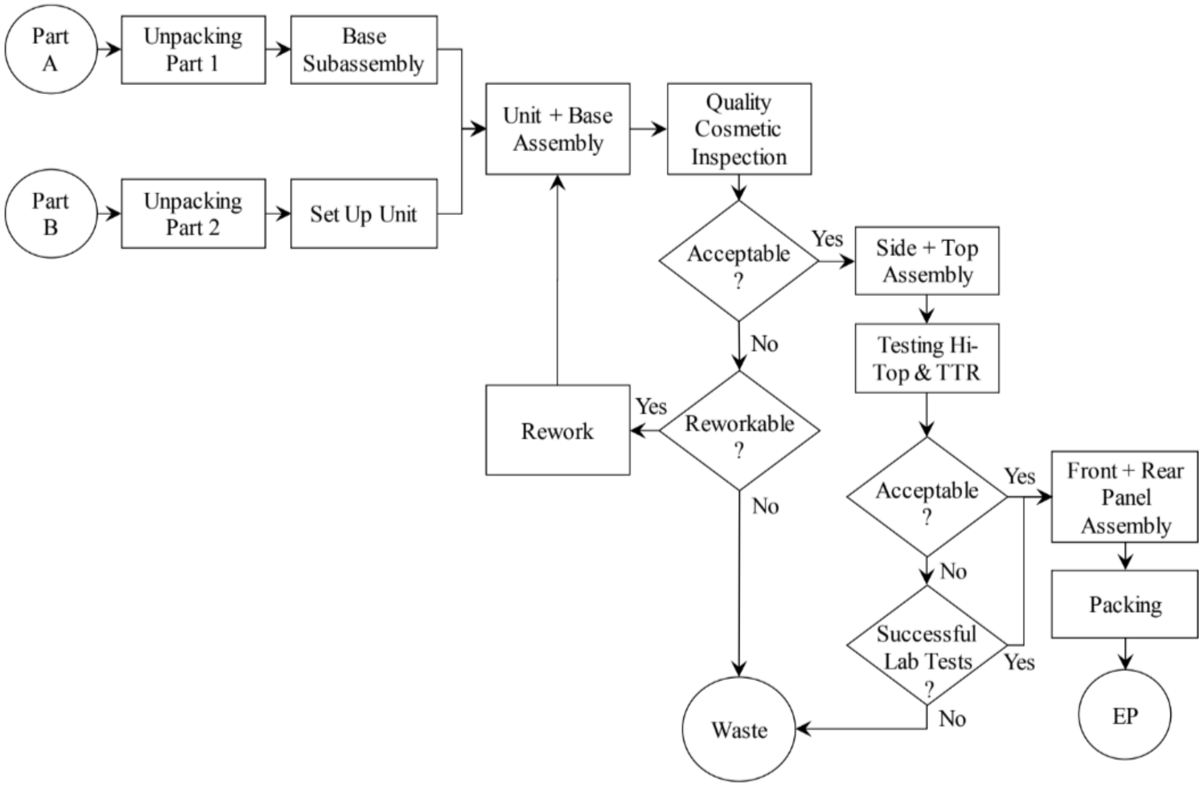

Figure 1: Flow diagram of the production line considered in the case study. (Own Work).

Table 2
Distribution models for activity times (in seconds) of the case study processes.

Process activities	Operator	Description
Unpacking Part A	2	1.15*[362.50 + 232 * BETA(0.553, 0.946)+ 13 * BETA(0.834, 0.887)]
Unpacking Part B	1	1.15*[85.5 + 60 * BETA(0.784, 0.602)+UNIF(71, 184)]
Base Subassembly	2	1.15*[307.5 + 89 * BETA(0.489, 0.863)+NORM(5.5, 1.28)+ 12 * BETA(1.07, 1.15)+ 69 * BETA(0.656, 0.479)+POIS(57.7)+ 7 * BETA(1.03, 1.38)+ 8 * BETA(0.711, 0.914)+ 53 * BETA(0.457, 0.512)+ 177 * BETA(0.357, 0.376)]
Set-Up Unit	1	1.15*[120 + 44 * BETA(0.73, 0.842)+ ERLA(2.65, 2)+ 51 * BETA(0.53, 0.868)+ 7 * BETA(0.518, 0.778)]
Unit+Base Assembly	1	1.15*[104.5 + WEIB(3.41, 1.43)+ 100 * BETA(0.729, 0.785)+ 48 * BETA(0.826, 0.541)]
Quality Cosmetic Inspection	1	1.15*[149 + 39 * BETA(0.612, 0.826)]
Side+Top Assembly	1	1.15*[107 + EXPO(52.8)]
Testing Hi-Top & TTR	1	1.15*POIS(85.6)
Front and Rear Panel Assembly	1	1.15*[103 + 49 * BETA(0.564, 0.675)]
Packing	2	1.15*[39.5 + 18 * BETA(0.781, 1.19)+NORM(11.9, 2.02)+POIS(63.1)+TRIA(231, 261, 332)]
Rework	1	471.73

As production rate reference, four units of Part A and Part B are received each hour for processing within an eight-hours shift. This leads to a weekly input of 4 units $*$ 8 hours $*$ 5 days = 160 units approximately. However, the actual production rate is estimated to be 28 units per day, which translates to approximately 140 units per week.

4. Simulation Model

Rockwell's Arena® software was used for modelling and analyzing the case study. The software includes modules for different processes and operations, animation, execution, and results visualization. The general simulation model is presented in Figure 2. In accordance with Figure 1, the process begins with the arrival of Part A and Part B components. Both components arrive at a rate of four parts per hour during the 07:00 to 15:00 shift. Figure 3 shows the configurations of the "Create" modules. Meanwhile, Figure 4 illustrates the configurations of the "Process" models, considering the operators and processing times outlined in Table 2.

As presented in Figure 2, "Decide" modules "Acceptable 1" and "Reworkable" are added to verify whether the product passes the "Quality Inspection" process. Statistics report that 90% of the units pass the "Quality Inspection" process while 10% are sent to "Rework". Of the reworked units, 10% are discarded. The "Decide" modules "Acceptable 2" and "Successful Lab Tests" are added to verify if the product complies with the "Hi Top TTR" test. If it complies (90% of cases), it advances to the following process. If it fails, it is sent to subsequent laboratory tests. If it passes the retest (in approximately 90% of cases), it proceeds to the following process; if not, it is discarded.

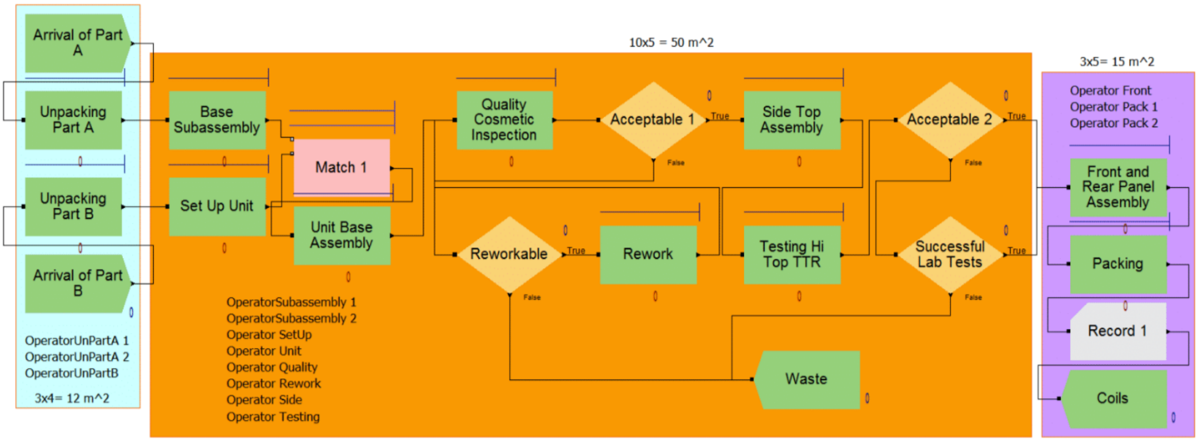

Figure 2: Simulation model of the production line with Arena modules. (Own Work).

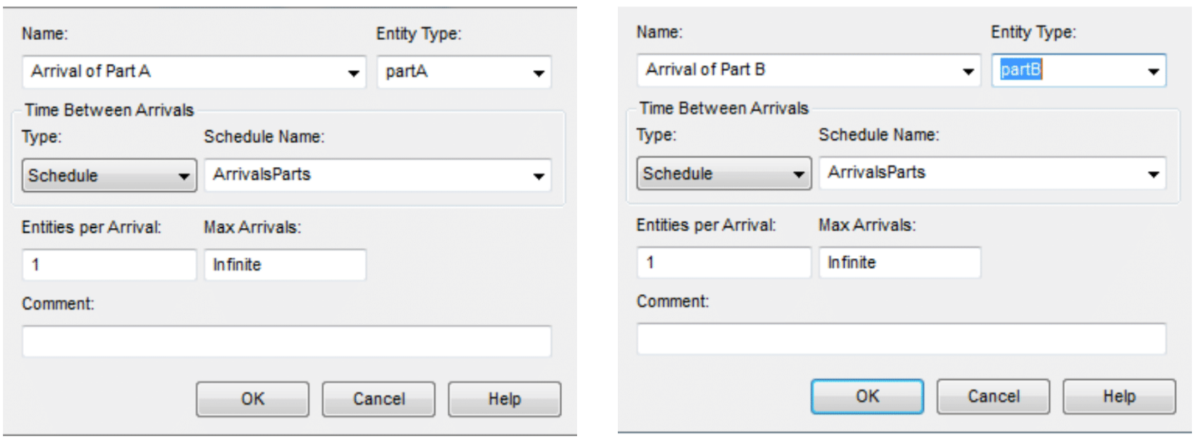

Figure 3: "Create" modules for Part A's and Part B's components arrivals. (Own Work).

5. Results

5.1. Validation without Risk Model

To support the analysis of the current system and guide improvement initiatives, the virtual model underwent statistical validation. A total of 30 weeks of output data were collected from the real system (X_1), and 30 corresponding replications of weekly production were generated using the simulation model (X_2). Validation was performed using Welch's t-test [32], where the null hypothesis $H_0 : \mu_1 = \mu_2$ states that the means of the real and simulated systems are equal. The test rejects H_0 if $|t_0| \geq t_{\alpha/2,v}$, with t_0 being the computed test statistic and $t_{\alpha/2,v}$ the critical value from the t-distribution with v degrees of freedom.

Table 3 presents the results of the validation with $v = 47$ degrees of freedom and a significance level $\alpha = 0.01$, yielding a critical value of $t_{\alpha/2,v} = 2.687$. Since $|t_0| \leq t_{\alpha/2,v}$ the null hypothesis cannot be rejected, indicating that both systems exhibit statistically similar behavior.

Table 3
Statistical validation of the virtual system without the risk model.

X_1	**Real System**								
134	142	148	134	137	147	138	137	147	139
138	141	144	150	137	147	137	147	140	137
147	150	151	137	142	137	147	136	150	145
$\overline{X_1} = 142$ $S_1^2 = 29.5$									
X_2	**Virtual Model**								
142	154	152	140	140	125	162	148	146	163
153	144	136	147	152	148	138	138	155	141
153	161	125	151	148	140	142	164	147	146
$\overline{X_2} = 147$ $S_1^2 = 93.5$									
$v = \frac{(\frac{S_1^2}{n_1}+\frac{S_2^2}{n_2})^2}{\frac{(\frac{S_1^2}{n_1})^2}{n_1+1}+\frac{(\frac{S_2^2}{n_2})^2}{n_2+1}} - 2$			$t_0 = \frac{\overline{X_1}-\overline{X_2}}{\sqrt{\frac{S_1^2}{n_1}+\frac{S_2^2}{n_2}}}$				$v = 47$ $t_0 = -2.271$ $\alpha = 0.01$ $t_{\frac{\alpha}{2},v} = 2.687$		

5.2. Assessment with Risk Model

Table 4 presents baseline data for statistical validation, considering 20% of the physical space available for human maneuvers. A reference λ_0 = one accident per 1000 $hours$ = 0.001 $hours^{-1}$, and downtime duration between 30 minutes and 3.0 hours is considered for this scenario.

For Zone 1, $W = W_0 = 3$ workers and $A = A_0 = 2.4m$, as there are no changes in the number of workers and available workspace dimensions. Because the standard production rate is 4 units per hour over an 8-hour shift (32 units per day), compared to the actual output of 28 units per day, the effective production rate is 3.5 units per hour. Hence, $P_0 =$ (4 units per hour / W_0) = 1.33 units/hour/worker, $P =$(3.5 units per hour / $W = 1.17$) units/hour/worker, and $C_{eff} = 4$ units per hour. This leads to a utilization ratio of $\rho = 0.875$ and $\lambda = 0.06$ accidents per hour, which implies 16.92 hours between accidents for workers in this zone.

For Zone 2, $W = W_0 = 8$ workers, $A_0 = 10m^2, A = 8m^2$ due to additional materials in the workspace, $P_0 = 0.50$ units/hour/worker, and $P = 0.4375$ units/hour/worker. This leads to a utilization ratio of $\rho = 0.875$ and $\lambda = 0.074$ accidents per hour, which implies 13.54 hours between accidents for workers in this zone. For Zone 3, $W = W_0 = 3$ workers, $A_0 = 3m^2, A = 2m^2$ due to transportation machinery in the workspace, $P_0 = 1.33$ units/hour/worker, and $P = 1.17$ units/hour/worker. This leads to a utilization ratio of $\rho = 0.875$ and $\lambda = 0.06$ accidents per hour, which implies 16.92 hours between accidents for workers in this zone.

The virtual model, configured with the risk models for all resources as specified in Table 4, yields an average output of 145 units across 30 replications, which closely approximates the real system's

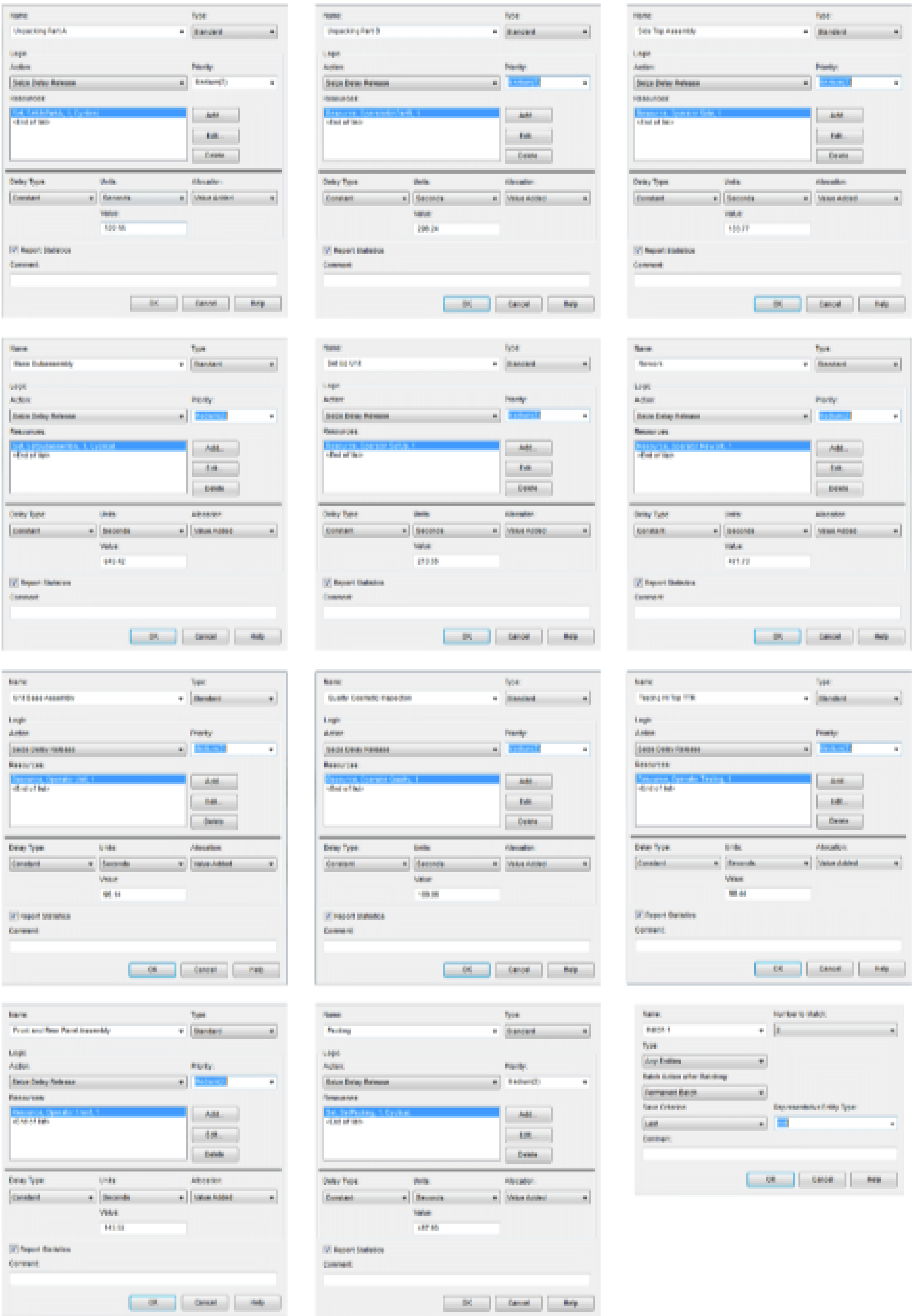

Figure 4: “Create” modules for Part A’s and Part B’s components arrivals. (Own Work).

Table 4
Estimation of F (uptime) for the virtual system with the risk model ($\theta_1 = 0.8, \theta_2 = 0.6, \theta_3 = 1.0, \gamma = 2$)

Resource	W_0	A_0	λ	F
OperatorUnPartA 1 OperatorUnPartA 2 OperatorUnPartB	3	Zone 1: 12 m^2 × 0.20 = 2.4 m^2	0.06	16.92
OperatorSubassembly 1 OperatorSubassembly 2 Operator SetUp Operator Unit Operator Quality Operator Rework Operator Side Operator Testing	8	Zone 2: 50 m^2 × 0.20 = 10 m^2	0.074	13.54
Operator Front Operator Pack 1 Operator Pack 2	3	Zone 3: 15 m^2 × 0.20 = 3 m^2	0.06	16.92

average output ($\overline{X_1} = 142$).

5.3. Improvements

Improvement is aimed at reducing the failure rate in the production shop. As described by (2), this can be accomplished by increasing A. Table 5 presents the system's output with the following increases in A: Zone 1 from 12 m^2 to 20 m^2, Zone 2 from 50 m^2 to 70 m^2, and Zone 3 from 15 m^2 to 25 m^2. As presented, an increase in F can be achieved by expanding the area available for human maneuvers.

With the updated risk models (Table 5), the virtual model yields 154 units on average, an 8.4% increase over the real system, suggesting that investment in parameter A could reduce failure rates and enhance productivity.

Table 5
Estimation of F (uptime) for the virtual system with the risk model and increased ($\theta_1 = 0.8, \theta_2 = 0.6, \theta_3 = 1.0$, $\gamma = 2$)

Resource	W_0	A_0	A	λ	F
OperatorUnPartA 1 OperatorUnPartA 2 OperatorUnPartB	3	Zone 1: 12 m^2 × 0.20 = 2.4 m^2	Zone 1: 20 m^2 × 0.20 = 4.0 m^2	0.035	28.21
OperatorSubassembly 1 OperatorSubassembly 2 Operator SetUp Operator Unit Operator Quality Operator Rework Operator Side Operator Testing	8	Zone 2: 50 m^2 × 0.20 = 10 m^2	Zone 2: 70 m^2 × 0.20 = 14 m^2	0.042	23.69
Operator Front Operator Pack 1 Operator Pack 2	3	Zone 3: 15 m^2 × 0.20 = 3 m^2	Zone 3: 25 m^2 × 0.20 = 5 m^2	0.035	28.21

6. Discussion and Future Work

The results of the simulation model validation indicate that the virtual model is more representative of the real system, as it does not exhibit statistically significant differences compared to the case study data. The inclusion of probabilistic distributions for processing times is confirmed, and the consideration of failures allows for capturing the variability and interruptions of the production system more accurately. The data show that the failure rate (λ) decreases considerably when the area available for human maneuvers (A) increases, translating into improvements in the average production rate (e.g., increased average weekly production from 142 to 154 units). These results demonstrate the importance of considering physical limitations in simulating production processes.

Also, this work demonstrates that DES is a practical approach for analyzing and optimizing manufacturing systems, providing a virtual environment to evaluate different operational scenarios and their impact on both productivity and safety. By modeling facility layout and incorporating spatial risk assessment, the research establishes that the area available for human maneuvers is a critical factor in reducing operational failures and improving overall system reliability.

Beyond the dry-transformer case study, the λ-model and DES workflow are scalable. Because the model variables—workforce size, work pace, available space, and utilization—are general descriptors of human–space interaction, they can be recalibrated for multi-line facilities or adapted to non-assembly domains. Likewise, the modular design of DES software, such as Arena, allows the framework to be extended to larger systems.

Future work will advance in three directions: (a) sensitivity analysis of the power-law formulation, (b) integration of real-time data from industrial sensors and IoT devices to enable dynamic risk assessment and adaptive process optimization, and (c) exploration of parallel or cloud-based simulation to further enhance scalability for enterprise-level applications. These extensions will strengthen the model's applicability and support continuous monitoring, predictive maintenance, and rapid response to operational disruptions.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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