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Modeling Lean Manufacturing Strategies in the Supply Chain of Natural Stone Industry: A Hybrid Simulation and Multi-Criteria Decision-Making Approach

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ABSTRACT

Objective: Reducing waste and improving productivity are crucial challenges in today's competitive manufacturing landscape. Lean production tackles these issues by eliminating activities that do not add value, cutting costs, and enhancing quality. However, the success of lean implementation relies on selecting strategies that align with an organization's operational context. This study evaluates four fundamental lean strategies under various production conditions: Work-in-Progress (WIP) Inventory Reduction, Batch Size Reduction, Setup Time Reduction, and Multi-skilled Workforces.

Methods: A hybrid methodology was utilized, integrating discrete-event simulation (DES) with multi-criteria decision-making (MCDM). Six scenarios were modeled, varying production capacity (low, medium, and high) and work shift schedules (one or two shifts). The Best-Worst Method (BWM) was employed to determine the weights of the evaluation criteria: total cost, available inventory, waiting time, and lead time. The VIKOR method was then used to rank the strategies for each scenario.

Results: The results indicate that total cost (weight = 0.54) is the most critical evaluation criterion, followed by available inventory (0.27), waiting time (0.11), and lead time (0.08). Both simulation and VIKOR analyses demonstrated a contextual pattern: reducing setup time was more effective than other strategies in low-capacity environments. In contrast, reducing batch size consistently ranked highest in medium and high-capacity environments, regardless of the shift schedule.

Conclusion: The findings highlight that lean strategies' effectiveness depends on the context. Reducing setup time is most beneficial for resource-limited systems, while reducing batch size offers greater advantages in high-output environments. The hybrid simulation-MCDM framework created in this study is a structured and objective tool for managers, allowing them to choose lean strategies aligned with their specific operational conditions. This, in turn, enhances supply chain performance and fosters long-term competitiveness.

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Introduction

Waste in manufacturing processes is defined as any action or resource that adds no value to the finished goods and can include unnecessary time, materials, energy, or costs. These wastes can manifest as excess inventory, waiting times, machine setup times, overproduction, unnecessary processes, inefficient transportation, unnecessary movements, and the production of defective products. Reducing or eliminating these wastes can improve productivity, reduce costs, and increase product quality (Kumar et al., 2022).

The Iranian natural stone industry faces critical challenges concerning waste generation. According to studies, approximately 51% of the extracted materials from natural stone mines become waste during the extraction stage. In comparison, nearly 41% of the materials transported to processing plants become waste during processing. Consequently, only about 29% of the extracted materials are converted into marketable final products, indicating a considerable loss of resources and the generation of substantial waste (Jalalian et al., 2021).

Lean manufacturing is a managerial philosophy aimed at improving productivity and quality by eliminating waste and focusing on value-adding activities. This approach seeks to optimize production processes through tools and techniques such as Just-in-Time (JIT), Kaizen (continuous improvement), value stream mapping, and workplace organization. Various strategies exist for implementing lean manufacturing in factories. Successfully applying these strategies can reduce costs and waste, improve quality, shorten production lead times, and enhance customer satisfaction (Bizuneh & Omer, 2024; Ferrazzi et al., 2025).

According to a report by the United States Environmental Protection Agency (EPA), implementing lean strategies has generated annual cost savings of nearly USD 1.5 million. Moreover, reduced resource consumption, improved product quality, and enhanced customer satisfaction have strengthened firms' competitive position in the market.

Given the high levels of waste in Iran's natural stone industry, implementing lean manufacturing strategies can significantly reduce waste and improve productivity. Therefore, the main objective of the present study is to evaluate lean manufacturing strategies in the natural stone industry by employing DES and hybrid MCDM methods.

In the following parts of this study, the related literature is presented in the second section; the third section presents problem description and case study; the fourth section describes the proposed methodology. The results and analysis are presented in the fifth section. Finally, in the sixth section, conclusions and future research are provided.

Literature Background

Lean Manufacturing and Decision-Making Systems

Lean manufacturing has been introduced as a comprehensive managerial philosophy to eliminate waste, continuously improve, and enhance customer value through optimizing production processes (Womack & Jones, 1997). Emerging from the Toyota production system, this approach has attracted widespread attention in various industries over recent decades. Recent studies indicate that lean strategies improve productivity, reduce lead times, and increase customer satisfaction. Moreover, adopting lean manufacturing requires technical tools, organizational readiness, leadership commitment, and an appropriate organizational culture (Shah & Ward, 2007). Also, due to its dynamic and multidimensional nature, a precise evaluation of lean manufacturing strategies requires advanced analytical tools.

Lean manufacturing should be considered an integrated socio-technical system encompassing technical tools and requiring effective coordination among supply chain partners, cross-functional collaboration, and adopting digital technologies to enhance operational visibility and responsiveness. Furthermore, the successful implementation of this approach necessitates aligning lean strategies with digital capabilities, alongside a strong emphasis on continuous learning and employee empowerment (Ejsmont et al., 2020; Nazari-Shirkouhi & Zarei Babaarabi, 2025).

Nevertheless, the practical implementation of lean manufacturing faces challenges such as employee resistance to change, resource constraints, and difficulties in measuring long-term benefits. In other words, the success of lean manufacturing is highly contingent upon the contextual conditions of each organization; factors such as company size, product complexity, process maturity, and even national culture can significantly influence its effectiveness (Izadyar et al., 2020; Xu et al., 2024). From this perspective, lean manufacturing cannot be considered a one-size-fits-all solution; instead, it must be designed and adapted per environmental conditions, organizational structures, and strategic objectives. Therefore, assessing and evaluating lean strategies should account for these contextual differences to create sustainable value for the organization and its stakeholders.

Discrete-event simulation, as a tool for analyzing the dynamic behavior of systems over time, enables the prediction of the impacts of implementing lean manufacturing strategies (Uriarte et al., 2018). Tanasic et al. (2022) evaluated the impact of implementing lean techniques, including the 5S system, total productive maintenance, and setup time reduction through simulation in a European manufacturing company. Their findings revealed that these lean practices increased labor productivity by up to 22% and reduced overall production time. Uriarte et al. (2018) investigated the impact of combining lean tools such as value stream mapping, pull production, and Kaizen by modeling production processes in a European automotive company using discrete-event simulation. They identified scenarios with the lowest waiting times and highest resource utilization.

Harrison and Chowdary (2023) developed two Arena-based simulation models, one reflecting the existing system and the other integrating lean interventions with Industry 4.0 technologies. The results demonstrated that the proposed actions reduced cycle time by 46%, waiting time by 57%, and work-in-process inventory by 61%. Likewise, Félix-Jácquez et al. (2025) designed a diesel engine remanufacturing line by integrating simulation with supply chain management tools. Applying value stream mapping and workflow adjustments reduced the total project lead time to less than 215 hours.

Azzolini Júnior et al. (2025) designed and implemented a tool to support the execution of lean manufacturing practices by integrating simulation with a hierarchical approach based on the Moore–Hodgson algorithm and a genetic algorithm. They further evaluated the performance of lean strategies in a textile production system, focusing on material handling and machine setup times. They employed DES to test scenarios, optimize decisions, and assess the improvements.

MCDM techniques compare alternatives and select optimal solutions for conflicting criteria (Jeong et al., 2018). Wan et al. (2014) applied the analytic hierarchy process to identify key lean tools in the manufacturing sector. Their findings indicated that implementing total productive maintenance and the 5S methodology significantly reduced the gap between actual and desired performance. Prasad et al. (2016) proposed a comprehensive approach for ranking lean strategies in the Indian foundry industry. By integrating SWOT, ANP, and TOPSIS methods, they evaluated existing strategies and demonstrated that TPM, Kanban, and Kaizen held higher priority than other alternatives. Hussain and Malik (2016), in a study of public and private hospitals in the United Arab Emirates, identified and prioritized different types of waste, such as waiting time, inventory, and transportation, using AHP. The results revealed that waiting time and excessive employee movements were among the critical areas where lean practices could yield significant improvements.

Jeong et al. (2018) employed the fuzzy VIKOR method to evaluate lean production system design alternatives in the Chinese construction industry. By considering variables such as feasibility, risk tolerance, and return on investment, they developed a group decision-making model that demonstrated strong performance in selecting the optimal option. Aminjarahi et al. (2021) applied the SAW and VIKOR methods to rank lean tools in the emergency department of a hospital. Their findings revealed that the medical staff perceived Jidoka and the 5S methodology as the most critical factors in improving emergency department performance.

Narula et al. (2023) integrated MCDM with Industry 4.0 concepts to evaluate lean strategies. They demonstrated that combining big data, the internet of things (IoT), and decision-making models can significantly enhance the accuracy of lean performance assessments in complex environments. Odeyinka and Akinwale (2024) developed a hybrid decision-making model combining fuzzy BWM and TOPSIS for selecting Lean–Six Sigma projects. They considered cost, lead time, and strategic impact criteria, and implemented the model in consulting firms. The results indicated improved accuracy in selecting optimal projects.

A summary of studies on lean manufacturing using simulation and MCDM methods is presented in Table 1.

Table 1. A Review of the Research Conducted

Author (s). Year	Lean Manufacturing Strategies	Simulation	MCDM
Wan et al. (2014)	*		*
Prasad et al. (2016)	*		*
Hussain and Malik (2016)	*		*
Uriarte et al. (2018)	*	*	
Jeong et al. (2018)	*		*
Aminjarahi et al. (2021)	*		*
Tanasic et al. (2022)	*	*	
Harrison and Chowdary (2023)	*	*	
Narula et al. (2023)	*		*
Odeyinka and Akinwale (2024)	*		*
Félix-Jácquez et al. (2025)	*	*	
Our Paper	*	*	*

To our knowledge, no research in the literature integrates discrete event simulation and hybrid MCDM for evaluating lean manufacturing strategies, as shown in Table 1.

Materials and Methods

This study adopts an analytical, quantitative, and applied approach regarding its objectives, methodology, and outcomes. It combines DES and hybrid MCDM, utilizing real operational data and expert insights.

First, discrete-event simulation models were developed under multiple scenarios to assess lean manufacturing strategies in a natural stone production facility, using five lean evaluation criteria. Following this, a hybrid MCDM framework was applied, combining the BWM for determining criteria weights and the VIKOR method for ranking the lean strategies.

The inputs for the VIKOR method included the outputs from the simulation models and the criteria weights obtained via BWM. The lean evaluation criteria and strategies were identified through a comprehensive literature review and structured interviews with industry experts. These criteria and strategies are summarized in Tables 2 and 3, respectively.

Table 2. Lean Manufacturing Evaluation Criteria

Evaluation Criterion	Code	Explanation	Researcher/ Year
Lead Time	C_1	It is the time between the start of a process (e.g., placing an order) and its end (e.g., receiving a product or service).	Simchi-Levi et al. (2008)
Waiting Time	C_2	When a customer or a work unit waits in a queue for the completion of product or service processing.	Lashkevich et al. (2024)
Available Inventory	C_3	The inventory of finished goods that a factory currently holds to meet demand.	Aldrighetti et al. (2021)
Total Cost	C_4	The total of production, ordering, holding, and backorder costs.	Jeong et al. (2018)

Table 3. Lean Manufacturing Strategies

Lean Manufacturing Strategy	Code
WIP Inventory Reduction	S_1
Batch Size Reduction	S_2
Setup Time Reduction	S_3
Multi-skilled Workforces	S_4

Simulation Model

Simulation is one of the standard analytical approaches in engineering and management sciences, enabling the recreation and modeling of real system behavior in a computer-based environment. Computer simulation refers to a set of methods employed to study and analyze models of real systems by conducting numerical evaluations and reproducing system operations and characteristics over specified time intervals (Kogler & Rauch, 2018). The steps involved in conducting a simulation are illustrated in Figure 1 (Banks et al., 2015).

This study considered a two-tier supply chain of the natural stone industry. A base simulation model encompassing production and distribution processes was designed in the first step. Subsequently, simulation models for each lean manufacturing strategy were developed by applying modifications to the base model under different scenarios. All simulation models were created using Arena software.

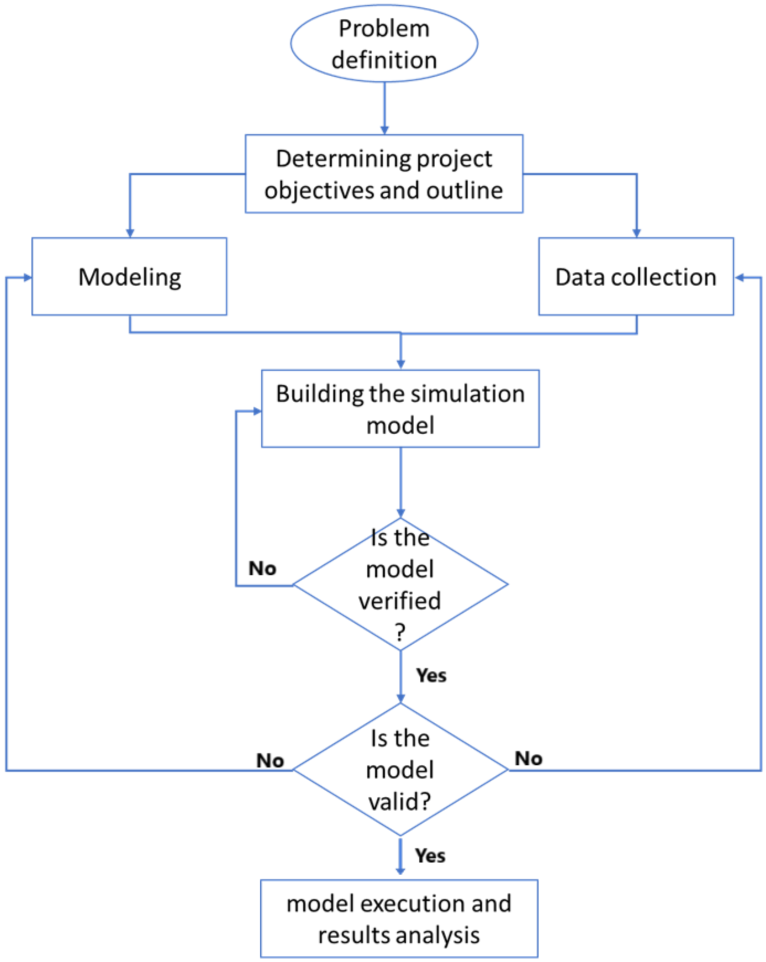

Figure 1. The Simulation Process

Case Study

Natural Stone Industry

Natural stone is a highly demanded product. Numerous Iranian factories produce various natural stones with different dimensions and applications, such as travertine, granite, marble, onyx, antique, and crystalline. The supply chain of the natural stone consists of suppliers (stone quarries), manufacturers (stone-cutting factories), distribution centers (wholesalers and retailers), and end customers. In this chain, large stone blocks of various dimensions are extracted from quarries and transported by trucks to cutting factories. After undergoing production processes in the factory, the stones are purchased in different dimensions by wholesalers and retailers (distribution centers) and subsequently delivered to end consumers. This study considers a two-tier supply chain comprising production and distribution processes in the natural stone industry.

Production Process of Natural Stone

The stone blocks extracted from quarries enter the factory as raw materials and are unloaded using fixed cranes. These blocks are then placed on movable wagons to be transferred to the gang saw machine. At this stage, the gang saws the blocks into large slabs with varying thicknesses. After this initial cutting, the stone slabs are directed to the longitudinal cutting machine, which slices them lengthwise according to the predetermined dimensions set by the operators. Subsequently, the slabs are transferred to the cross-cutting machine and divided into specified sizes.

Conveyor belts then move the cut stones to the drying machine to eliminate any remaining moisture. Afterward, they are transferred to the resin treatment section, where the cavities in the stones are filled with resin materials. After resin application, the stones are again passed through the drying machine to ensure proper curing. In the final stage, the resin-coated stones undergo polishing, during which their surfaces are ground and finished to achieve a smooth, shiny, and glossy appearance. Finally, the stones are sorted and categorized according to size, priced, and prepared for market distribution.

Base Simulation Model

The base simulation model, shown in Figure 2, is divided into two main sections: the production process of natural stone and the distribution and delivery. In the production stage, each working day begins with a stone block entering the gang saw machine, which is cut into slabs. These slabs are stored in the work-in-process (WIP) inventory and then sequentially processed. A batch is first sent to the longitudinal cutting machine, then to the cross-cutting machine, and the next batch enters the longitudinal cutter. This cycle continues until all slabs in the WIP inventory are processed. Each batch must pass through the longitudinal cutter, cross-cutter, dryer, resin treatment, and polishing machines. Once completed, the slabs are added to the finished product inventory and available for customer delivery.

As depicted in Figure 2, the second section of the model represents the customer demand fulfillment process. Here, two conditions are evaluated: (1) the availability of sufficient inventory, and (2) the absence of backorder demand in the system. Customer demand is fulfilled if both conditions are satisfied, and the corresponding amount is deducted from the inventory. Otherwise, the demand is added to the backorder queue until the inventory level becomes sufficient to satisfy it.

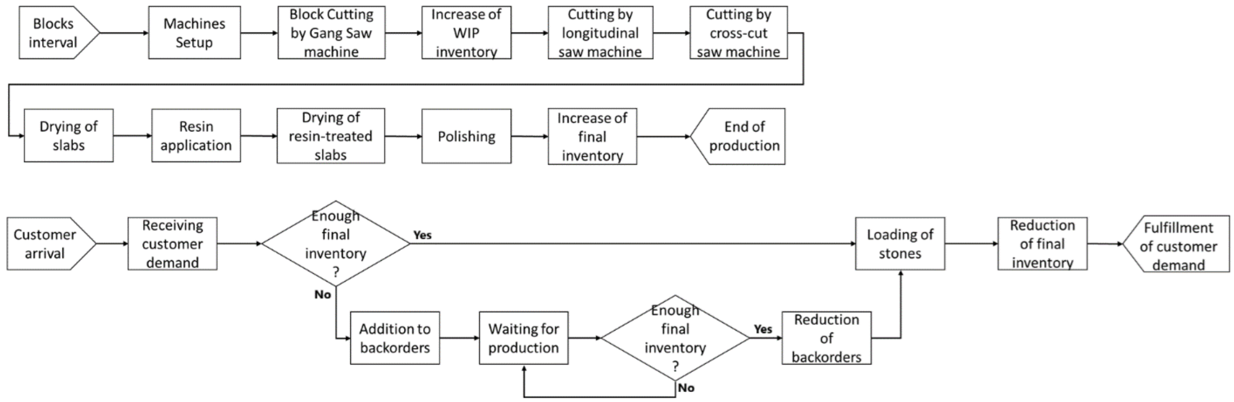

Figure 2. The Base Simulation Model

The Input Variables and Parameters

The input variables and parameters of the simulation models were derived from real-world data, as presented in Table 4. The Input Analyzer tool in Arena software was employed to identify the best-fit distribution functions. Specifically, all available data from recent periods, required for the simulation models, were entered into the Input Analyzer. The results indicated that the square error of each fitted distribution function was less than 0.004.

Table 4. Input Variables and Parameters of the Simulation Model

Variable / Parameter	Distribution Function / Value	Unit
Safety Stock	(min, average, max) = (240, 420, 600)	Tons
Production Capacity	600	m^2
Batch Size	30	m^2
Production Time	Constant (8)	Hours
Number of Daily Orders Received	DISC (0.4, 0, 0.75, 1, 0.9, 2, 1, 3)	
Order Size	100 + EXPO (220)	m^2
Machine Setup Time	Constant (20)	Minutes
Gang Saw Operation Time per Unit	Constant (2)	Minutes
Longitudinal Cutting Operation Time per Unit	Constant (5)	Minutes
Cross-Cutting Operation Time per Unit	Constant (3)	Minutes
Dryer Operation Time per Unit	Constant (4)	Minutes
Resin Treatment Operation Time per Unit	Constant (3)	Minutes
Polishing Operation Time per Unit	Constant (10)	Minutes

Scenario Analysis

Under each of the lean manufacturing strategies, six types of scenarios are defined. Their titles are presented separately for each strategy in Table 5.

Table 5. Simulation Scenarios

Scenario No.	Strategy	Scenario Definition
1	WIP Inventory Reduction	Low production capacity and one shift (Type 1 scenario)
2		Medium production capacity and one shift (Type 2 scenario)
3		High production capacity and one shift (Type 3 scenario)
4		Low production capacity and two shifts (Type 4 scenario)
5		Medium production capacity and two shifts (Type 5 scenario)
6		High production capacity and two shifts (Type 6 scenario)
7	Batch Size Reduction	Low production capacity and one shift (Type 1 scenario)
8		Medium production capacity and one shift (Type 2 scenario)
9		High production capacity and one shift (Type 3 scenario)
10		Low production capacity and two shifts (Type 4 scenario)
11		Medium production capacity and two shifts (Type 5 scenario)
12		High production capacity and two shifts (Type 6 scenario)
13	Setup Time Reduction	Low production capacity and one shift (Type 1 scenario)
14		Medium production capacity and one shift (Type 2 scenario)
15		High production capacity and one shift (Type 3 scenario)
16		Low production capacity and two shifts (Type 4 scenario)
17		Medium production capacity and two shifts (Type 5 scenario)
18		High production capacity and two shifts (Type 6 scenario)
19	Multi-skilled Workforces	Low production capacity and one shift (Type 1 scenario)
20		Medium production capacity and one shift (Type 2 scenario)
21		High production capacity and one shift (Type 3 scenario)
22		Low production capacity and two shifts (Type 4 scenario)
23		Medium production capacity and two shifts (Type 5 scenario)
24		High production capacity and two shifts (Type 6 scenario)

Best-Worst Method

In MCDM methods, a set of alternatives is evaluated against multiple criteria for selecting the most appropriate option. The BWM, introduced by Rezaei in 2015, is based on selecting the best and worst criteria by the decision-maker. The procedure involves pairwise evaluations in which the best criterion is compared against all others, while the others are contrasted with the worst criterion. Subsequently, a max–min optimization model is formulated and solved to find out the weights of the criteria. Finally, a consistency ratio is calculated to assess the accuracy of the comparisons (Rezaei, 2015; 2016).

One of the advantages of BWM over other MCDM methods is its significant reduction in pairwise comparisons, which simplifies the evaluation process and enhances efficiency. BWM has been applied in various domains, including supply chain and logistics performance evaluation, technology assessment, and selection of green innovation.

The main steps of BWM are as follows (Rezaei, 2015):

1. Identifying the set of decision criteria:

At this stage, the decision-maker defines the criteria required for decision-making as $\{C1, C2, \ldots, Cn\}$.

2. Selecting the best (most desirable, top-priority) and the worst (least desirable, lowest-priority) criteria:

Here, the best and worst criteria are identified in general terms, without comparing them.

3. Assigning a rating on a 1–9 scale to indicate the relative preference of the best criterion over all other criteria (elicited from experts):

The preference vector of the best criterion over all others is denoted as $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$. In this vector, a_{Bj} denotes how the best criterion (B) is favored over criterion j, $(a_{BB=1})$.

4. Establishing how strongly each criterion is favored compared to the worst criterion through a numerical rating from 1 to 9 (elicited from experts):

The Vector of relative preferences of the other criteria over the worst criterion is denoted as $A_W = (a_{1W}, a_{2W}, \ldots, a_{3W})^T$. In this vector, a_{jW} represents the preference of criterion j over the worst criterion (W), where it is clear that $a_{WW} = 1$.

5. Deriving the optimal weights $(V_1^*, V_2^*, \ldots, V_n^*)$:

To determine the optimal weights of the criteria, the following conditions are considered: $\frac{V_B}{V_j} = a_{Bj}$ and $\frac{V_j}{V_w} = a_{jw}$. In order to satisfy these conditions for all j, a solution is required that minimizes the maximum absolute differences $\left|\frac{V_B}{V_j} - a_{Bj}\right|$ and $\left|\frac{V_j}{V_w} - a_{jw}\right|$ for all j. Considering the non-negativity of weights and the constraint that their sum equals one, the following formulation represents the model:

$$\min \max_j \left\{ \left|\frac{V_B}{V_j} - a_{Bj}\right|, \left|\frac{V_j}{V_w} - a_{jw}\right| \right\} \tag{1}$$

$$s.t$$

$$\sum_j V_j = 1$$

$$V_j \geq 0\,, for\ all\ j$$

It is also possible to transform the above model into Model 2:

$$\min \xi \tag{2}$$

$$s.t.$$

$\left|\frac{V_B}{V_j} - a_{Bj}\right| \leq \xi \text{ , for all } j$

$\left|\frac{V_j}{V_w} - a_{jw}\right| \leq \xi \text{ , for all } j$

$\sum_j V_j = 1$

$V_j \geq 0 \text{ , for all } j$

The linear programming formulation of the above model is presented in detail below. The lean manufacturing evaluation criteria weights are derived using the linear BWM model in this study.

$$\min \boldsymbol{\xi} \tag{3}$$

$s.t$

$\left|V_B - a_{Bj} V_j\right| \leq \xi \text{ , for all } j$

$\left|V_j - a_{jw} V_w\right| \leq \xi \text{ , for all } j$

$\sum_j V_j = 1$

$V_j \geq 0 \text{ , for all } j$

By solving Equation 3, the optimal weights $(V_1^*, V_2^* , \ldots , V_n^*)$ and the optimal value ξ^* are obtained.

Calculating the Consistency Ratio

Comparisons between criteria are entirely consistent if the following relationship holds for each criterion (j). $a_{Bj} \times a_{jw} = a_{Bw}$

In BWM, the consistency ratio (CR) is calculated using Equation (4) and the consistency index table (Table 6). The CR takes a value between 0 and 1, where values closer to zero indicate higher consistency, while values closer to one reflect lower consistency.

$$CR = \frac{\xi^*}{CI} \tag{4}$$

Table 6. Consistency Indices

$\boldsymbol{a_{Bw}}$	1	2	3	4	5	6	7	8	9
(CI)	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

The VIKOR Method

The VIKOR method was first introduced by Opricovic in 1998 and later developed by Opricovic and Tzeng in 2004 to optimize MCDM in complex systems. VIKOR derives from a Serbian phrase meaning “compromise solution” in multi-criteria decision-making. This method focuses on ranking alternatives and selecting the best among options. Employing a compromise measure identifies a solution that balances conflicting criteria and assists decision-makers in reaching the final decision (Opricovic & Tzeng, 2004).

The steps of the VIKOR method are as follows:

1. Construct the decision matrix

$$D_k = \begin{bmatrix} d11 & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mn} \end{bmatrix}$$

where xij represents the performance of alternative i evaluated against criterion j, i=1, 2, …, m and j=1, 2, …, n

2. Compute the average decision matrix

$$D = \frac{1}{k}\sum_{k=1}^{k} D_k \tag{5}$$

where D denotes the aggregated decision matrix and K represents the number of experts.

3. Normalize the decision matrix

$$f_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \ \mathrm{i} = 1,2,\dots,\mathrm{m}, \mathrm{j} = 1,2,\dots,\mathrm{n} \tag{6}$$

4. Find out the positive and negative ideal solutions

$$A^+ = \{f_1^*, \dots, f_n^*\} = \begin{Bmatrix} c_j \rightarrow positive\ aspect \rightarrow A^* = \max_i\{f_{ij}\} \\ c_j \rightarrow negative\ aspect \rightarrow A^* = \min_i\{f_{ij}\} \end{Bmatrix} \tag{7}$$

$$A^- = \{f_1^-, \dots, f_n^-\} = \begin{Bmatrix} c_j \rightarrow positive\ aspect \rightarrow A^- = \min_i\{f_{ij}\} \\ c_j \rightarrow negative\ aspect \rightarrow A^- = \max_i\{f_{ij}\} \end{Bmatrix} \tag{8}$$

5. Compute the utility and regret measures for each alternative

$$S_i = \sum_{j=1}^{n}\left(V_j \times \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}\right), \mathrm{i} = 1,2,\dots,\mathrm{m}, \mathrm{j} = 1,2,\dots,\mathrm{n} \tag{9}$$

$$R_i = \max_j\left(V_j \times \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}\right), \mathrm{i} = 1,2,\dots,\mathrm{m}, \mathrm{j} = 1,2,\dots,\mathrm{n} \tag{10}$$

where S_i indicates the average regret of alternative i, R_i represents the maximum regret of alternative i, and V_j is the weight of criterion j.

$$S^* = min\{S_i\} \tag{11}$$

$$R^* = min\{R_i\} \tag{12}$$

$$S^- = max\{S_i\} \tag{13}$$

$$R^{-} = max\{R_i\} \tag{14}$$

6. Calculate the VIKOR index (Qi)

$$Q_i = v \times \frac{(S_i - S^*)}{(S^- S^*} + (1 - v) \times \frac{(R_i - R^*)}{(R^- R^*} \tag{15}$$

where v is the VIKOR weight (between 0 and 1). In most applications, v=0.5 is assumed. Values of v closer to 1 emphasize maximizing overall utility, while values closer to 0 minimize individual regret (Amiri et al., 2017).

7. Prioritize the alternatives

Finally, the alternatives are ranked according to their Qi values. The option with the lowest VIKOR index is considered the best compromise solution.

The conceptual framework of the present study is shown in Figure 3.

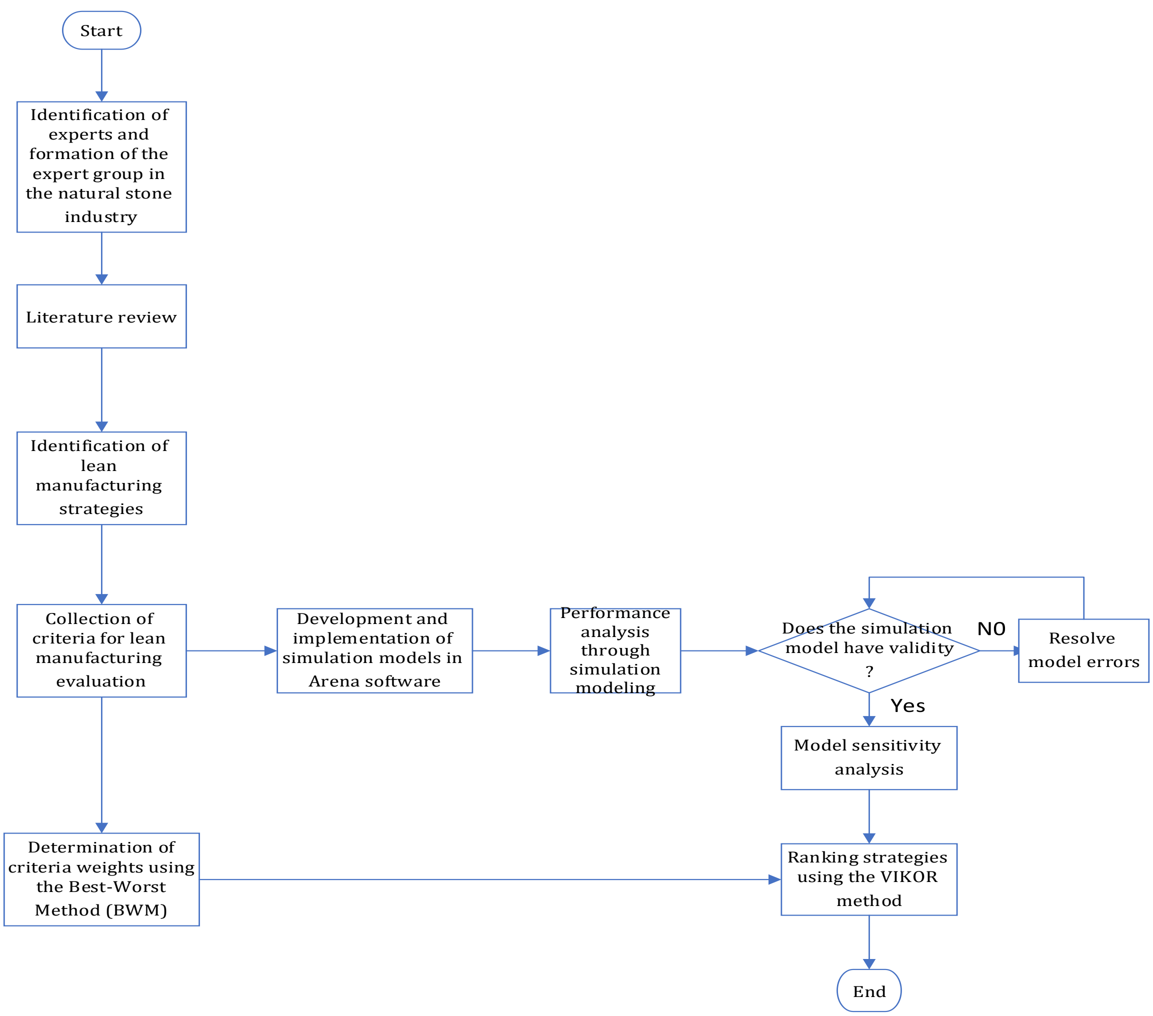

Figure 3. The Conceptual Framework

Results

Outputs of the Base Simulation Model

The base simulation model runs for one year (365 working days) with 100 replications. In this model, the warm-up period was set to zero, since the system and production process are restarted at the beginning of each day. In the natural stone industry, this period can be considered negligible. The average values of the performance indicators obtained from the simulation are as follows: 1. Lead time: 9 hours; 2. Waiting time: 10 hours; 3. Available inventory: 3,600 m²; 4. Total cost: 630,500,000,000 IRR

Verification and Validation of the Base Simulation Model

For the verification of the base simulation model, different parts of the model were reviewed and confirmed by experts during its development. The average results from 100 simulation replications were compared with the available data to validate the base simulation model in Arena. The Mean Absolute Error (MAE), as a standard prediction error metric, was used for evaluation. The results indicated that the MAE values for all performance measures were less than 0.05, confirming the base model's validity.

Outputs of the Simulation Models for Lean Manufacturing Strategies

The performance of each lean manufacturing strategy was evaluated under varying conditions, including different production capacities (low, medium, and high) and varying numbers of working shifts (1 or 2). Scenarios were generated through combinations of production capacity and the number of shifts. As previously discussed, six scenarios were designed for each lean manufacturing strategy. The results of running the simulation models, categorized by performance criteria, are presented in Tables 7 to 10.

Table 7. Outputs of simulation models of lean manufacturing strategies relative to lead time (hours)

Strategy	Number of Shifts	Low Capacity	Medium Capacity	High Capacity
Inventory Reduction in Work-in-Process	1	30	24	20
	2	22	14	11
Batch Size Reduction	1	20	16	12
	2	14	10	7
Setup Time Reduction	1	17	13	11
	2	12	8	7
Multi-skilled Workers	1	13	8	6
	2	6	5	3

Table 8. Outputs of simulation models of lean manufacturing strategies relative to waiting time (hours)

Strategy	Number of Shifts	Low Capacity	Medium Capacity	High Capacity
Inventory Reduction in Work-in-Process	1	27	23	19
	2	20	13	10
Batch Size Reduction	1	19	14	10
	2	12	9	6
Setup Time Reduction	1	15	11	9
	2	10	7	6
Multi-skilled Workers	1	11	6	4
	2	5	3	2

Table 9. Outputs of simulation models of lean manufacturing strategies relative to available inventory (m2)

Strategy	Number of Shifts	Low Capacity	Medium Capacity	High Capacity
Inventory Reduction in Work-in-Process	1	240	450	630
	2	170	210	420
Batch Size Reduction	1	980	1120	1540
	2	760	890	1120
Setup Time Reduction	1	1030	1520	2050
	2	1980	2700	3610
Multi-skilled Workers	1	1810	2200	3070
	2	2670	3400	4940

Table 10. Outputs of simulation models of lean manufacturing strategies relative to total cost

Strategy	Number of Shifts	Low Capacity	Medium Capacity	High Capacity
Inventory Reduction in Work-in-Process	1	39	44	51
	2	42	49	58
Batch Size Reduction	1	36	41	54
	2	40	46	60
Setup Time Reduction	1	41	49	57
	2	44	54	64
Multi-skilled Workers	1	46	51	59
	2	49	58	65

Weighting of Lean Manufacturing Evaluation Criteria Using the BWM

The opinions of experts in the natural stone industry were utilized to calculate the weights of lean manufacturing evaluation criteria. In the first step, each expert identified the best and worst criteria. Next, all experts expressed their judgments regarding how the best criterion is preferred over the others, and how the remaining criteria compare to the worst one. Subsequently, the linear programming model of the BWM was formulated based upon Equation (3) using LINGO version 17, and by solving the model, the weight of each criterion was determined. Since an individual optimal weight was obtained from each expert's judgment, the weights were aggregated using their geometric mean to derive a single integrated weight for each criterion. The weights of all criteria are presented in Table 11.

Table 11. Weight of lean manufacturing evaluation criteria

Criterion	C_1	C_2	C_3	C_4
Final Weight	0.08	0.11	0.27	0.54

As shown in Table 11, the total cost criterion carries the highest weight (0.54), while the lead time criterion has the lowest weight (0.08) for evaluating lean production strategies. The consistency ratio is a numerical value between 0 and 1, where values closer to zero indicate higher consistency, and conversely, values closer to one indicate lower consistency (Rezaei, 2015). In this study, the consistency ratio was calculated as 0.011, indicating that the obtained results are acceptable.

Ranking Lean Manufacturing Strategies Using the VIKOR Method

After obtaining the lean manufacturing evaluation criteria weights, the lean manufacturing strategies were ranked using the VIKOR method. The simulation and Best-Worst methods outputs were considered inputs to the VIKOR method. Lean manufacturing strategies were ranked for each scenario to determine the most suitable under each condition. Therefore, in this study, six different decision matrices were constructed, and the aggregated averages of these matrices are presented in Table 12. The VIKOR outputs for each scenario are provided in Tables 13 to 18.

Table 12. Decision Matrix

Scenario	Strategy	C_1	C_2	C_3	C_4
Type 1	S_1	30	27	240	39
	S_2	20	19	980	36
	S_3	17	15	1030	41
	S_4	13	11	1810	46
Type 2	S_1	24	23	450	44
	S_2	16	14	1120	41
	S_3	13	11	1520	49
	S_4	8	6	2200	51
Type 3	S_1	20	19	630	51
	S_2	12	10	1540	54
	S_3	11	9	2050	57
	S_4	6	4	3070	59
Type 4	S_1	22	20	170	42
	S_2	14	12	760	40
	S_3	12	10	1980	44
	S_4	6	5	2670	49
Type 5	S_1	14	13	210	49
	S_2	10	9	890	46
	S_3	8	7	2700	54
	S_4	5	3	3400	51
Type 6	S_1	11	10	420	58
	S_2	7	6	1120	60
	S_3	7	6	3610	64
	S_4	3	2	4940	65

Table 13. Ranking of lean manufacturing strategies based on scenario type 1

Lean Manufacturing Strategies	S	R	Q	Rank
S_1	0.159450761	0.053000345	1	4
S_2	0.071689616	0.026517665	0.164556826	2
S_3	0.06896827	0.024625008	0.119770677	1
S_4	0.040466657	0.040585335	0.281235903	3

Table 14. Ranking of lean manufacturing strategies based on scenario type 2

Lean Manufacturing Strategies	S	R	Q	Rank
S_1	0.160885066	0.053922661	1	4
S_2	0.077245779	0.028024059	0.089030745	1
S_3	0.084996753	0.026939095	0.108874775	2
S_4	0.063872258	0.052760935	0.478473456	3

Table 15. Ranking of lean manufacturing strategies based on scenario type 3

Lean Manufacturing Strategies	S	R	Q	Rank
S_1	0.094762081	0.045754134	0.48772415	3
S_2	0.061994644	0.028271428	0.024221833	1
S_3	0.086002171	0.026484421	0.165973655	2
S_4	0.13431795	0.063372765	1	4

As shown in Tables 13 to 15, the setup time reduction strategy ranks first when production capacity is low and the factory operates with a single shift. In contrast, the batch size reduction, multi-skilled workforces, and WIP inventory reduction strategies rank second, third, and fourth, respectively, for implementation. Conversely, when production capacity is medium and the factory operates with a single shift, the batch size reduction strategy ranks first, the setup time reduction strategy ranks second, and the multi-skilled workforces and WIP inventory reduction strategies rank third and fourth, respectively. Moreover, when the factory has high production capacity and operates with a single shift, the batch size reduction, setup time reduction, multi-skilled workforces, and WIP inventory reduction strategies achieve the first to fourth ranks, respectively, for implementation.

Table 16. Ranking of lean manufacturing strategies based on scenario type 4

Lean Manufacturing Strategies	S	R	Q	Rank
S_1	0.105701492	0.047745941	0.82038625	3
S_2	0.085355919	0.027371614	0.137772667	2
S_3	0.07344382	0.028454679	0.023777772	1
S_4	0.116674816	0.05014634	1	4

Table 17. Ranking of lean manufacturing strategies based on scenario type 5

Lean Manufacturing Strategies	S	R	Q	Rank
S_1	0.114907102	0.050443238	0.708713615	3
S_2	0.075304838	0.030813533	0.037017723	1
S_3	0.09242381	0.028423868	0.158910653	2
S_4	0.129168352	0.060701169	1	4

Table 18. Ranking of lean manufacturing strategies based on scenario type 6

Lean Manufacturing Strategies	S	R	Q	Rank
S_1	0.1099924	0.049687743	0.489425	3
S_2	0.067625014	0.031039523	0.001639	1
S_3	0.096877193	0.030898491	0.187199	2
S_4	0.145756152	0.073934892	1	4

Based on the results presented in Tables 16 to 18, when the factory has low production capacity and operates with two shifts, the setup time reduction strategy ranks first, the batch size reduction strategy ranks second, and the WIP inventory reduction and multi-skilled workforces strategies rank third and fourth, respectively. Furthermore, under conditions where the factory has low or medium production capacity and operates with two shifts (scenario types 5 and 6), the strategies rank from first to fourth: batch size reduction, setup time reduction, WIP inventory reduction, and multi-skilled workforces.

Conclusion

Based on lean manufacturing evaluation criteria, this study employed DES and integrated MCDM methods to evaluate four lean manufacturing strategies in the natural stone industry. To this end, the BWM was used to find out the weights of the evaluation criteria. DES was applied to evaluate the performance of the strategies relative to the evaluation criteria. Initially, a base simulation model was constructed in which none of the lean manufacturing strategies were implemented. Subsequently, for each lean strategy, a simulation model was developed by introducing specific changes to the base model, and under each strategy, six types of scenarios were designed and executed.

The weighting results indicated that the total cost criterion is the most significant factor in evaluating lean manufacturing strategies. The VIKOR method results are summarized as follows: the setup time reduction strategy ranks first under scenarios of low production capacity with one shift and low production capacity with two shifts, while the batch size reduction strategy ranks first under scenarios of medium production capacity with one shift, high production capacity with one shift, medium production capacity with two shifts, and high production capacity with two shifts. The results obtained from the present research are applicable and generalizable to the natural stone industry, similar sectors such as the tile and ceramics industry, and in contexts where the objective is to evaluate lean manufacturing strategies.

For future research, the following suggestions are provided:

- In this study, only those lean manufacturing strategies that could be modeled using simulation were evaluated. Therefore, researchers are advised to consider other lean strategies as well.

- This research applied DES and integrated MCDM methods to evaluate lean manufacturing strategies in the natural stone industry. Researchers can utilize these methods to assess lean strategies in other industries and compare their results with those obtained in this study.
- The BWM was used for weighting the lean manufacturing evaluation criteria, and the VIKOR method was used for ranking the strategies. Researchers can apply other MCDM methods and compare their results with the findings of this study.

Data Availability Statement

Data are available on request from the authors.

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Conflict of interest

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