An Evaluation of Production Plans Under Uncertainty in the Automotive Industry Using EDAS and Monte Carlo Simulation

Ulises Mercado Valenzuela
Department of Industrial Engineering, Faculty of Higher Studies Aragon, National Autonomous University of Mexico, Mexico
ulisesmv@comunidad.unam.mx (corresponding author)

Received: 30 January 2026 | Revised: 21 February 2026 | Accepted: 8 March 2026

ABSTRACT

This paper proposes a methodological framework that integrates Multi-Criteria Decision-Making (MCDM) methods and stochastic simulation to evaluate production planning alternatives under uncertainty. The Evaluation based on Distance from Average Solution (EDAS) method is integrated with a Monte Carlo simulation model to assess the feasibility and dynamic behavior of four alternative production plans in an automotive company. The analysis considers fifteen criteria covering economic, operational, logistical, risk, and environmental aspects to provide a comprehensive view of the problem. The results indicate that the combined plan with buffers and flexible capacity (A_3) achieves the best score in the EDAS method and is also more robust under variable demand scenarios. Furthermore, a sensitivity analysis is performed on the weights of the criteria and demand volatility, verifying that the integrated model offers better recommendations than those obtained by deterministic models or isolated MCDM methods. This work supports the development of advanced methodologies for decision-making in manufacturing, demonstrating that the integration of these approaches is of great value in the analysis of this type of problem.

Keywords-automotive manufacturing; Evaluation based on Distance from Average Solution (EDAS); Multi-Criteria Decision-Making (MCDM); production planning; Monte Carlo simulation; uncertainty

I. INTRODUCTION

Production planning is one of the most important functions in operations management [1]. In today's world, manufacturing companies face a highly competitive environment with variable demand, shorter product life cycles, sustainability pressures, fluctuating raw material and energy prices, and more complex supply chains [2]. Companies need comprehensive approaches encompassing a strategic, tactical, and operational vision [3]. In this context, making sound production planning choices influences not only internal efficiency but also the ability to compete in demanding markets where meeting delivery deadlines and controlling costs are critical factors.

The automotive industry, a key sector in this study, competes based on very demanding performance standards. In these industries, production delays, changes in quality, or inventory discrepancies can have significant effects.

The decision regarding resource allocation in production generally involves the simultaneous consideration of multiple and conflicting criteria [4]. For example, minimizing costs may mean reducing inventory, but this can compromise service levels; minimizing cycle times can require overtime, increasing labor costs, and staff burnout; maximizing equipment utilization reduces downtime but increases operational risk and decreases flexibility. These problems cannot be solved with a single approach. This is why Multi-Criteria Decision-Making (MCDM) methods have become so important in research and practice [5, 6].

However, MCDM methods have a structural limitation: they do not represent the production process adequately, especially under conditions of uncertainty [7]. A production plan that appears good in a static sense (for example, in terms of cost or efficiency) can lead to very different results when variability in demand or capacity is introduced. For example, a minimum-cost plan may fail to maintain adequate service levels during peak periods, or a very energy-efficient plan may be susceptible to operational variability. This justifies the inclusion of simulation [8], a tool capable of modeling the dynamic and stochastic behavior of the system [9].

The main contribution of this work is to propose a hybrid methodological framework that combines the Evaluation based on Distance from Average Solution (EDAS) method for multi-criteria evaluation, Monte Carlo simulation to validate behavior under uncertainty, and sensitivity analysis to measure robustness [10]. This integration allows for comparing alternatives from both tactical and operational perspectives, incorporating realistic uncertainty, analyzing risks, and obtaining robust and justifiable recommendations. The integration of multi-criteria evaluation, simulation, and sensitivity analysis can address the real complexity of current production systems [6].

A. Contributions to Research and Originality

Despite the increasing research integrating MCDM methodologies with simulation techniques, significant gaps remain in the evaluation of production planning decisions under conditions of uncertainty. Contemporary research has primarily focused on deterministic ranking or performance assessment, neglecting the significance of decision robustness and ranking stability under stochastic uncertainty.

This study contributes to the field by presenting a comprehensive decision-support system that integrates EDAS with Monte Carlo simulation and sensitivity analysis to evaluate production plans under uncertainty. The primary contributions of this research can be summarized as follows:

- A robust decision-making framework for production planning in uncertain situations. The proposed framework incorporates stochastic variations in demand, machine availability, and defect rates, distinguishing it from conventional MCDM implementations that rely on deterministic inputs. This enables decision-makers to evaluate solutions not only based on their efficacy but also in terms of their adaptability and robustness.
- Integration of EDAS with stochastic simulation to evaluate ranking stability. EDAS is frequently employed for multi-criteria evaluation; nonetheless, its efficacy in uncertain scenarios remains largely unexplored. This study integrates EDAS with Monte Carlo simulation to assess the stability of alternative rankings across various stochastic scenarios, providing a decision framework centered on robustness [11].
- Assessment of robustness based on performance variability. The study introduces a methodology for robustness assessment that incorporates cost variability, service level performance, and the coefficient of variation as metrics to evaluate the stability of production plans. This helps decision-makers, especially in uncertain environments, to recognize viable alternatives rather than those based on known information. A sensitivity analysis is also conducted to assess the resilience of the decisions.
- A comprehensive sensitivity analysis is conducted to evaluate the impact of changes in the weight structure and demand variability on the EDAS rankings. This enhances the understanding of decision resilience and provides greater confidence in selecting production strategies under changing operational conditions.
- Evaluation of the robustness of EDAS compared with other MCDM approaches. EDAS evaluates options according to the average solution, which makes it less likely to be affected by outliers and thus more stable in uncertain circumstances. This differs from approaches that measure distance to an ideal solution, like TOPSIS, or compromise-based methods, like VIKOR. This quality makes EDAS particularly helpful for production planning under changing conditions and increased operational risk.

These advancements collectively expand the applicability of EDAS beyond deterministic assessment, positioning the proposed framework as a robust decision-support tool for resilient production planning in uncertain industrial environments. Table I summarizes how this study compares with prior frameworks.

TABLE I. POSITIONING OF THIS STUDY RELATIVE TO RELATED MCDM AND MCDM–SIMULATION FRAMEWORKS

Representative studies	Domain	MCDM	Simulation	Uncertainty modeled	Robustness/ranking stability	Sensitivity analysis
[1]	Production planning in Industry 4.0	No	No	Not modeled	Not addressed	No
[2]	Manufacturing system complexity	No	No	Conceptual	Not addressed	No
[3]	Aggregate production planning	Fuzzy LP	No	Fuzzy uncertainty	Limited	No
[4]	Capacity planning & scheduling	Optimization	Limited	Operational variability	Not addressed	No
[5, 6]	MCDM systematic reviews	Multiple methods	No	Not modeled	Not addressed	Limited
[7]	Limitations of MCDM	Multiple methods	No	Not modeled	Not addressed	No
[8]	Simulation in production planning	No	Yes	Operational variability	Implicit	No
[9]	Monte Carlo robustness evaluation	No	Yes	Demand variability	Variability analysis	No
[10]	Hybrid MCDM integration	PSI–FUCA–RAM–PIV	No	Not modeled	Not addressed	Limited
[12-14]	Sensitivity analysis in MCDM	Multiple methods	No	Not modeled	Stability analysis	Yes
[15]	Industry 4.0 simulation & automation	No	Yes	Cyber-physical variability	Not addressed	No
[16]	Automotive manufacturing materials	GRA–EDAS	No	Deterministic	Not addressed	Limited
This study	Automotive production planning	EDAS	Monte Carlo	Demand, availability, defects	Explicit robustness & ranking stability	Weights + demand variability

Prior research has investigated production planning, MCDM procedures, and simulation tools either independently or in limited combinations. Research on production planning in Industry 4.0 underscores challenges pertaining to complexity and integration, although it lacks decision frameworks that emphasize robustness [1, 2]. Optimization and fuzzy techniques address uncertainty but lack comprehensive multi-criteria robustness evaluation [3, 4]. Reviews of MCDM methods highlight methodological diversity and limitations but neglect to consider stochastic uncertainty in decision ranking [5-7]. Research on simulation-based planning considers operational uncertainty but rarely integrates structured decision frameworks [8, 9]. Recent hybrid MCDM approaches and sensitivity studies underscore the necessity for methodological integration and stability evaluation; yet, the challenge of uncertainty-driven robustness in production planning remains insufficiently addressed [10, 12-14]. Consequently, there is a clear necessity for decision-support frameworks that incorporate multi-criteria evaluation, stochastic simulation, and robustness assessment. This study addresses this gap by integrating EDAS with Monte Carlo simulation and sensitivity analysis to enhance robust production planning decisions under uncertainty.

II. PROBLEM STATEMENT

The study is conducted in an automotive company in Mexico City, Mexico, which produces high-precision metal bolts. This sector requires tight tolerances, dimensional stability, controlled cycle times, and high levels of reliability.

Four strategic production alternatives are considered in this study:

- Level production (A_1): This involves minimizing internal variability, simplifying scheduling, generating moderate inventories, and maintaining a certain level of stability but with limited flexibility.
- Strict demand tracking (A_2): Production is adjusted month by month, inventories are minimized, the risk of overloads increases, and the plan is closely linked to forecast accuracy.
- Mixed plan with buffers (A_3): Safety stock is used, flexible capacity is maintained, workloads are stabilized, and the risk of backlogs is reduced.
- Energy-efficient production (A_4): Energy consumption is optimized, energy costs are reduced, the use of maximum capacity is minimized, and the plan is vulnerable to high demand fluctuations.

To evaluate these alternatives, 15 criteria are considered, corresponding to five essential dimensions as shown in Table II, where each criterion is classified based on two elements: a benefit criterion (better performance occurs when the value is higher), and a cost criterion (better performance occurs when the value is lower).

For the multi-criteria analysis, data on the manufacturing processes of automotive bolts are collected for the four alternatives and the 15 criteria. The base case assumes equal weights for all criteria and provides measurement units, justification of values, normalization assumptions, and consistency assumptions.

TABLE II. DIMENSIONS AND CRITERIA

Dimension	Criteria
Economics	Unit cost; overtime cost; inventory carrying cost
Operational	Cycle time; lead time; machine utilization; available capacity
Quality	Waste index; labor efficiency; defective product
Risk and flexibility	Operational risk; level of flexibility; supplier reliability
Sustainability	Energy consumption; associated emissions

III. METHODOLOGY

The application of the EDAS method involves seven steps [5], as described below.

Step 1. Let A_i $(i = 1,2,\dots,m)$ denote the set of alternatives and C_j $(j = 1,2,\dots,n)$ denote the set of evaluation criteria. The decision matrix $X = [x_{ij}]$ is defined as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2. The average value for each criterion is computed as:

$$AV_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \quad (2)$$

where:

- $m = 4$ alternatives
- $j = 1,\dots,15$ criteria

Step 3. The positive distances (PDA) are calculated, considering benefit and cost criteria.

For benefit criteria:

$$PDA_{ij} = \max\left(0, \frac{x_{ij} - AV_j}{AV_j}\right) \quad (3)$$

For cost criteria:

$$PDA_{ij} = \max\left(0, \frac{AV_j - x_{ij}}{AV_j}\right) \quad (4)$$

Both represent how much better the alternative is compared to the average.

Step 4. Next, the negative distances (NDA) are calculated, again considering the benefit and cost criteria.

For benefit criteria:

$$NDA_{ij} = \max\left(0, \frac{AV_j - x_{ij}}{AV_j}\right) \quad (5)$$

For cost criteria:

$$NDA_{ij} = \max\left(0, \frac{x_{ij} - AV_j}{AV_j}\right) \quad (6)$$

These represent how much worse the alternative is compared to the average.

Step 5. Weighted aggregation is performed for SP (sum of positive distances) and SN (sum of negative distances). Let w_j be the weight associated with criterion j:

For benefit criteria:

$$SP_i = \sum_{j=1}^{n} w_j \cdot PDA_{ij} \tag{7}$$

For cost criteria:

$$SN_i = \sum_{j=1}^{n} w_j \cdot NDA_{ij} \tag{8}$$

where $\Sigma\, w_j = 1$.

Step 6. Standardization of SP and SN is performed as follows:

$$NSP_i = \frac{SP_i}{\max(SP)} \tag{9}$$

$$NSN_i = 1 - \frac{SN_i}{\max(SN)} \tag{10}$$

Step 7. The final score is calculated to obtain the EDAS ranking (AS_i):

$$AS_i = \frac{NSP_i + NSN_i}{2} \tag{11}$$

On the other hand, Monte Carlo simulation focuses on several stochastic aspects, including:

1. Demand
2. Defect rate
3. Energy consumption
4. Machinery and equipment utilization

For example, demand is modeled as:

$$D_t \sim N(\mu, \sigma) \tag{12}$$

where:

- μ is the average monthly demand
- σ depends on the volatility (low and high cases)

The defect rate can be simulated as:

$$Q_t = p_{defect} * Production_t \tag{13}$$

where p_{defect} follows an approximate binomial distribution.

Energy consumption is modeled as:

$$C_{energy,t} = k_e * E_t \tag{14}$$

where k_e is the random variable sampled per unit of time, and E_t is the energy consumed in the month.

Machinery and equipment utilization is given by:

$$M_t = M_{max}(1 - F_t) \tag{15}$$

where F_t is the simulated failure proportion following a Beta distribution.

Each iteration simulates one month of operation, considering factors such as random demand arrivals, capacity allocation, activation of overtime, if necessary, inventory calculation, backlog determination, cost calculation, and measurement of key indicators. 10,000 iterations per alternative (40,000 total iterations) are performed to ensure statistical stability.

A sensitivity analysis is conducted focusing on two aspects [12-14]. The first is sensitivity to criteria weights, generating three scenarios:

- Balanced weights
- Weights focused on cost-service
- Weights focused on sustainability-risk

The second is sensitivity to demand variability, analyzing:

- Low variability case ($\sigma = 5\%$)
- High variability case ($\sigma = 20\%$)

Finally, a robustness index is defined as:

$$Robustness_i = 1 - \frac{Var(Sim_i)}{E(Sim_i)} \tag{16}$$

where alternatives are compared based on the variability and expected value of the simulation outcomes.

A. Stochastic Assumptions and Model Justifications

Variability in production systems is caused by variations in demand, equipment and material availability, and the performance of quality control systems. Simulation models use random input numbers based on well-known behavioral patterns from manufacturing research to capture the dynamics of real-world operations.

Customer demand was modeled using a normal distribution. This assumption is commonly utilized in production planning research because aggregate demand typically arises from various independent variables, resulting in almost symmetric fluctuation around the mean. Previous studies have shown that normally distributed demand provides good estimates for short-term planning and tactical decisions.

Machinery availability was simulated using a Beta distribution. This distribution is particularly useful for bounded variables represented as percentages (0–1), such as equipment uptime. Literature on maintenance reliability frequently uses the Beta distribution to represent operational variability resulting from maintenance cycles, failure rates, and deterioration in machinery performance [17].

The defect rate was modeled using the binomial distribution, representing the discrete probability of defective products arriving at the production area. This approach aligns with quality control theory, which indicates that the defect rates arise from probabilistic variability in operational processes [18].

The EDAS model utilized equal weighting as the baseline configuration to prevent the introduction of subjective bias when clear stakeholder preferences are unavailable. This approach is commonly employed in MCDM to evaluate structural performance disparities among alternatives.

The simulation horizon is set to one month, corresponding to the typical tactical production planning period in manufacturing. This duration allows the assessment of operational performance while accounting for fluctuations in demand and system dynamics. To obtain accurate results and apply the Monte Carlo method for tactical planning, each simulation period was treated independently. This strategy focuses on evaluating how well decisions perform under uncertainty, rather than on the system's evolution over time. Nevertheless, relationships between periods are important; researchers can extend the model by including multiple periods and adjusting the initial data to analyze future system behavior.

Robustness in production planning refers to a strategy's ability to remain effective and stable under changes or unforeseen events, such as demand fluctuations or delays. In this study, robustness is tested through simulations in which key variables are intentionally altered. If the results remain consistent despite these changes, the plan is considered reliable and resilient under real-world uncertainty.

The coefficient of variation (CV) is used as a scale-independent metric for assessing performance stability. Defined as the ratio of the standard deviation to the mean, CV allows for the comparison of different alternatives with varying magnitudes of costs and service levels. This metric is widely used in engineering decision analysis and risk management to evaluate the consistency under uncertainty.

The suggested approach allows decision-makers to create production plans that provide both efficiency and stability by integrating expected performance metrics with variability measures.

IV. CASE STUDY

Using the initial data, the EDAS matrix was constructed as shown in Table III. This includes the five dimensions, the 15 evaluation criteria applied to the four alternatives, the criterion type, and the corresponding unit.

TABLE III. EDAS DECISION MATRIX

Dimension	**Criterion**	**Type**	A_1	A_2	A_3	A_4	**Unit**
Economics	C1: Unit cost	Cost	2.41	2.68	2.34	2.51	USD/unit
	C2: Overtime cost	Cost	29,500	42,800	19,700	25,900	USD/month
	C3: Inventory carrying cost	Cost	18,200	9,400	14,500	13,600	USD/month
Operational	C4: Cycle time	Time	2.73	3.95	2.51	2.88	min/unit
	C5: Lead time	Time	5.2	7.8	4.4	6.1	d
	C6: Machine utilization	Benefit	81	89	77	72	%
	C7: Available capacity	Benefit	117,000	102,000	132,000	95,000	Units/month
Quality	C8: Waste index	Cost	3.2	4.5	2.8	2.9	%
	C9: Labor efficiency	Benefit	88	82	93	85	%
	C10: Defective product	Cost	1.9	3.4	1.6	2.1	%
Risk and flexibility	C11: Operational risk	Cost	0.21	0.39	0.15	0.28	Index (0–1)
	C12: Level of flexibility	Benefit	0.58	0.43	0.79	0.64	Index (0–1)
	C13: Supplier reliability	Benefit	0.88	0.75	0.92	0.85	Index (0–1)
Sustainability	C14: Energy consumption	Cost	108,700	121,300	104,500	88,000	kWh
	C15: Associated emissions	Cost	7.2	8.0	6.8	5.9	t CO_2

Applying the seven steps of the EDAS method, the final scores (AS_i) for each alternative are presented in Table IV. Alternative A_3 achieves the highest score, identifying it as the preferred option.

TABLE IV. EDAS FINAL SCORES FOR ALTERNATIVES

Alternative	NSP_i	NSN_i	AS_i **(final score)**
A_3	1.000	0.928	0.964
A_4	0.842	0.881	0.861
A_1	0.702	0.765	0.733
A_2	0.512	0.000	0.235

The Monte Carlo simulation was carried out using a dynamic evaluation of total monthly cost, service level, average inventory, overtime, and energy consumption [9]. Each alternative was simulated under 10,000 scenarios, assuming: an average variability of 12%; a horizon of one month (treated as independent); a normal distribution for demand; machinery availability following a Beta distribution ($\alpha = 4$, $\beta = 2$); defect rates following a binomial distribution p = 0.002–0.035 depending on the alternative; and backlog penalties.

The key results for total cost are shown in Table V, indicating that A_3 is consistently the lowest cost alternative, even under extreme conditions (P99). A_4 outperforms A_1, highlighting the importance of energy savings, whereas A_2 incurs the highest costs due to overtime and backlog penalties.

TABLE V. SIMULATED TOTAL MONTHLY COST (MONTE CARLO RESULTS)

Alternative	**Total cost (mean)**	**Total cost (P90)**	**Total cost (P99)**
A_3	\$182,400	\$195,300	\$225,100
A_4	\$194,100	\$205,900	\$247,400
A_1	\$202,700	\$214,800	\$267,100
A_2	\$238,200	\$294,300	\$388,900

Table VI indicates that A_3 consistently maintains the highest service level, even under low variability. A_1 outperforms A_4, emphasizing the importance of higher service levels, whereas A_2 exhibits the lowest service level due to high variability.

TABLE VI. SIMULATED SERVICE LEVEL (MONTE CARLO RESULTS)

Alternative	**Service level (%)**	**Variability**
A_3	96.2	Low
A_1	93.4	Medium
A_4	91.7	Low
A_2	84.9	High

Table VII indicates that A_3 balances inventory and backlog, whereas A_2 has low inventory but a high backlog risk.

TABLE VII. SIMULATED AVERAGE INVENTORY (MONTE CARLO RESULTS)

Alternative	**Average inventory**	**Inventory (P90)**
A_3	940	1300
A_1	1450	1970
A_4	1020	1600
A_2	510	1860

Table VIII demonstrates that A_3 maintains acceptable overtime with low standard deviation. In contrast, A_2 exhibits the highest average overtime and variability.

TABLE VIII. SIMULATED OVERTIME (MONTE CARLO RESULTS)

Alternative	**Average overtime**	**Standard deviation**
A_3	42	Low
A_4	55	Low
A_1	73	Medium
A_2	128	High

Table IX highlights that A_4 achieves the most significant energy savings, whereas A_2 consumes the most energy.

TABLE IX. SIMULATED ENERGY CONSUMPTION AND SAVINGS (MONTE CARLO RESULTS)

Alternative	**Energy consumption (kWh)**	**Savings**
A_4	–15%	Significant savings
A_3	–3%	Low
A_1	0%	Baseline
A_2	+12%	Higher consumption

With the information obtained, it is possible to construct a robust ranking that integrates EDAS and Monte Carlo simulation, resulting in a combined index, IR_i, calculated as:

$$IR_i = 0.5 * AS_i + 0.5 * (1 - CV_i) \qquad (17)$$

where CV_i is the coefficient of variation of total cost. Table X presents the resulting values. It can be observed that alternative A_3 retains the highest AS_i value and the lowest CV_i, together yield the highest IR_i. In contrast, alternative A_2 exhibits both a low AS_i and high CV_i, resulting in the lowest combined score.

The sensitivity analysis evaluates the impact of both criteria weights and demand variability. For the weights, three scenarios were considered:

- Scenario A: Weights focused only on costs, where A_3 remains the best alternative, A_4 and A_1 retain robustness, and A_2 remains last.
- Scenario B: Weights focused on sustainability, where A_3 remains first, A_4 is second with a small margin, and A_1 and A_2 show minimal change.
- Scenario C: Weights focused on risk and flexibility, where A_3 dominates by a wide margin, A_4 remains second, and A_2 performs worse.

Regarding sensitivity to demand variability, two cases were analyzed:

- Low variability (σ = 5%): A_3 and A_4 perform similarly, A_1 becomes more stable, and A_2 improves slightly but remains last.
- High variability (σ = 20%): A_3 dominates by a wide margin, A_4 loses robustness at times, A_1 becomes inconsistent, and A_2 collapses due to extreme backlog.

TABLE X. COMBINED EDAS AND MONTE CARLO ROBUSTNESS INDEX (IR_i)

Alternative	$\boldsymbol{AS_i}$	$\boldsymbol{CV_i}$	$\boldsymbol{IR_i}$
A_3	0.964	0.11	0.927
A_4	0.861	0.18	0.811
A_1	0.733	0.21	0.662
A_2	0.256	0.38	0.438

Figures 1 and 2 illustrate the multi-scenario sensitivity analysis of the EDAS score and total cost response to demand variations.

To improve statistical rigor and enable precise comparisons among alternatives, simulation results were assessed using percentile ranges, confidence intervals, and variability indicators. Percentile ranges were calculated from the Monte Carlo simulation outputs for each Key Performance Indicator (KPI), including total cost and service level. The P10–P90 interval was used to illustrate the core variability band, providing a clear perspective on performance dispersion while reducing sensitivity to extreme outliers. This approach allows decision-makers to assess both expected performance and the spectrum of potential system outcomes under uncertainty.

When analyzing average costs, 95% confidence intervals were applied to create a statistical safety margin that accounts for the inherent variability of the simulation. This ensures that observed differences among alternatives reflect true performance rather than random fluctuations. The results indicate that alternative A_3 is consistently superior to A_2, maintaining lower costs and higher service levels. In contrast, A_1 and A_4 exhibit statistically equivalent performance under moderate conditions, as their confidence intervals overlap, resulting in a technical tie.

To support objective interpretation, qualitative variability labels were replaced with quantitative indicators:

- Standard deviation (σ) as a metric for assessing dispersion.
- Coefficient of Variation (CV) for assessing stability.

- Percentile range (P90–P10) to denote variability span.

The coefficient of variation was particularly useful for comparing alternatives with different mean costs, enabling the formulation of production strategies that optimize both efficiency and stability.

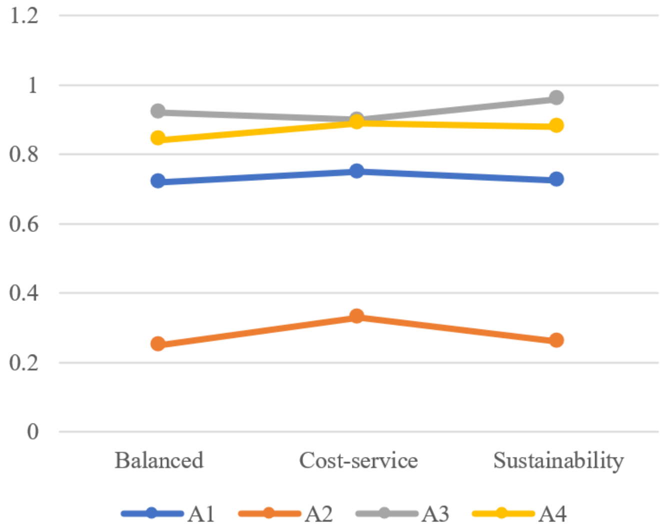

Fig. 1. Multi-scenario sensitivity analysis of the EDAS score for all alternatives.

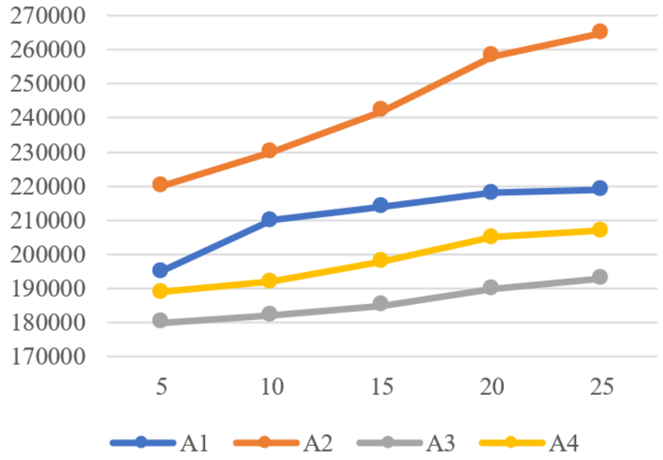

Fig. 2. Sensitivity of total cost to demand variations for all alternatives.

Beyond raw numerical comparisons, the operational impact of variability was considered. Alternative A_3 is the most reliable choice, combining low costs with minimal variation, ensuring stable performance even under fluctuating demand. In contrast, A_2 exhibits high variability, making it a riskier option in dynamic environments. This illustrates that averages alone may be misleading: two alternatives with similar mean costs can differ significantly in terms of risk. It is vital to include variability metrics (such as risk or volatility) in decision-making, as they capture operational reliability and mitigate exposure to unexpected costs or failures.

Table XI confirms that A_3 is the best option because it is the most robust and, above all, the most predictable: its results don't change much, making it very reliable. Conversely, A_2 is the riskiest, since its results are very unstable and vary too much, meaning that the final performance could be very different from what is expected, increasing the risk of failures or operational losses.

TABLE XI. STATISTICAL PERFORMANCE INDICATORS FROM MONTE CARLO SIMULATION

Alternative	**Mean cost**	**95% CI**	**St. dev.**	***CV***	**P10**	**P90**
A_4	202,700	±3,200	18,000	0.089	196,900	214,800
A_3	238,200	±7,400	42,000	0.176	210,500	294,300
A_1	182,400	±2,800	15,000	0.082	170,900	195,300
A_2	194,100	±4,100	22,000	0.113	178,400	205,900

A. *Discussion*

Production planning must evolve from an approach based solely on efficiency and minimizing costs to one that emphasizes robustness and operational resilience. Through the evaluation of different strategies using the EDAS method and stochastic simulations, it has been demonstrated that options that include capacity buffers and flexibility (such as alternative A_3) are superior, as they maintain service stability and mitigate risks under uncertainty. It is recommended that managers move beyond prioritizing average performance in deterministic scenarios and adopt tools that integrate variability, enabling more reliable decision-making in dynamic environments.

B. *Limitations and Future Directions*

It is recognized that, although the framework is rigorous, its external validity is limited by the use of a hypothetical case study and a short-term tactical time horizon that does not account for seasonal dynamics or complex interdependencies between periods. Furthermore, the simplification of probabilistic assumptions and the use of equal weightings for the criteria may not capture the empirical complexity of a real plant. Therefore, it is proposed as future research directions to integrate digital twins, multi-period planning models, and additional sustainability variables. In essence, the text defines the current scope of the model as a solid basis for decision-making under uncertainty, while emphasizing the need to progress toward real-data environments and dynamic systems to maximize its industrial applicability.

V. CONCLUSIONS

This work demonstrated that integrating the Evaluation based on Distance from Average Solution (EDAS) multi-criteria decision-making (MCDM) method with stochastic Monte Carlo simulation techniques constitutes a solid, flexible, and robust approach for evaluating and selecting production planning strategies under conditions of uncertainty [9, 12]. The results show that, through EDAS analysis and the 10,000 simulated scenarios, alternative A_3 consistently proved superior in terms of total cost, service level, operational stability, variability management, overtime reduction, resilience to disruptions, and performance under extreme scenarios. By using the average as a benchmark, EDAS is particularly appropriate in industrial contexts where extreme values can distort evaluation, no feasible or known "ideal" exists, and realistic alternatives must be compared. The stability of the EDAS ranking under moderate changes in criteria weights confirms that the method provides reliable and consistent results.

The use of Monte Carlo simulation revealed patterns that a static method could not capture, such as feedback loops between demand, capacity, and defects; propagation of variability throughout the system; nonlinear effects on cycle times; operational breakdowns under volatile demand; and cumulative backlog penalties. This finding reinforces the idea that MCDM methods alone are insufficient in uncertain environments and must be complemented with simulation [15].

The study demonstrates that MCDM identifies preliminary superior alternatives, simulation validates their performance under uncertainty, and sensitivity analysis measures robustness, resulting in a more realistic and rigorous evaluation. This integrated approach is especially useful in manufacturing environments, where uncertainty is structural. The study's results have important implications for industry professionals, production engineers, and plant managers.

ACKNOWLEDGMENT

This work was made possible thanks to the support of the National Autonomous University of Mexico.

REFERENCES

[1] J.-P. Herrmann, S. Tackenberg, E. Padoano, and T. Gamber, "Approaches of production planning and control under industry 4.0: A literature review," *Journal of Industrial Engineering and Management*, vol. 15, no. 1, pp. 4–30, Feb. 2022, https://doi.org/10.3926/jiem.3582.

[2] G. Herrera Vidal and J. R. Coronado Hernández, "Complexity in manufacturing systems: a literature review," *Production Engineering*, vol. 15, no. 3, pp. 321–333, June 2021, https://doi.org/10.1007/s11740-020-01013-3.

[3] D. H. Tuan and N. Chiadamrong, "Solving an aggregate production planning problem by using interactive fuzzy linear programming," *Asia-Pacific Journal of Science and Technology*, vol. 26, no. 1, Jan. 2021, Art. no. APST-26-01-05, https://doi.org/10.14456/apst.2021.5.

[4] X. Yao, N. Almatooq, R. G. Askin, and G. Gruber, "Capacity planning and production scheduling integration: improving operational efficiency via detailed modelling," *International Journal of Production Research*, vol. 60, no. 24, pp. 7239–7261, Dec. 2022, https://doi.org/10.1080/00207543.2022.2028031.

[5] S. L. Gebre, D. Cattrysse, and J. V. Orshoven, "Multi-Criteria Decision-Making Methods to Address Water Allocation Problems: A Systematic Review," *Water*, vol. 13, no. 2, Jan. 2021, Art. no. 125, https://doi.org/10.3390/w13020125.

[6] S. K. Sahoo and S. S. Goswami, "A Comprehensive Review of Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions," *Decision Making Advances*, vol. 1, no. 1, pp. 25–48, June 2023, https://doi.org/10.31181/dma1120237.

[7] R. K. Dhurkari, "MCDM methods: Practical difficulties and future directions for improvement," *RAIRO - Operations Research*, vol. 56, no. 4, pp. 2221–2233, July 2022, https://doi.org/10.1051/ro/2022060.

[8] M. A. Abdelmegid, V. A. González, M. O'Sullivan, C. G. Walker, M. Poshdar, and L. F. Alarcón, "Exploring the links between simulation modelling and construction production planning and control: a case study on the last planner system," *Production Planning & Control*, vol. 34, no. 5, pp. 459–476, Apr. 2023, https://doi.org/10.1080/09537287.2021.1934588.

[9] S. Franke, F. Franke, and R. Riedel, "Robustness evaluation of production plans using Monte Carlo simulation," *Procedia Manufacturing*, vol. 54, pp. 130–135, Jan. 2021, https://doi.org/10.1016/j.promfg.2021.07.021.

[10] N. T. Mai, "Hybrid Multi-Criteria Decision Making Methods: Combination of Preference Selection Index Method with Faire Un Choix Adèquat, Root Assessment Method, and Proximity Indexed Value," *Engineering, Technology & Applied Science Research*, vol. 15, no. 1, pp. 19086–19090, Feb. 2025, https://doi.org/10.48084/etasr.9235.

[11] J. Xu and J. Lv, "Exploration of Crop Planting Strategies Based on Monte Carlo Simulation and D-MOPSO," in *2025 IEEE International Conference on Electronics, Energy Systems and Power Engineering*, Shenyang, China, 2025, pp. 1–6, https://doi.org/10.1109/EESPE63401.2025.10987113.

[12] G. Demir, P. Chatterjee, and D. Pamucar, "Sensitivity analysis in multi-criteria decision making: A state-of-the-art research perspective using bibliometric analysis," *Expert Systems with Applications*, vol. 237, Mar. 2024, Art. no. 121660, https://doi.org/10.1016/j.eswa.2023.121660.

[13] S. P. Singh, A. Mehta, and H. Vasudev, "Application of Sensitivity Analysis for Multiple Attribute Decision Making in Lean Production System," *Engineering Management Journal*, vol. 37, no. 4, pp. 390–413, Aug. 2025, https://doi.org/10.1080/10429247.2024.2383855.

[14] S. R. Nabavi, Z. Wang, and G. P. Rangaiah, "Sensitivity Analysis of Multi-Criteria Decision-Making Methods for Engineering Applications," *Industrial & Engineering Chemistry Research*, vol. 62, no. 17, pp. 6707–6722, May 2023, https://doi.org/10.1021/acs.iecr.2c04270.

[15] M. Nagy, G. Lăzăroiu, and K. Valaskova, "Machine Intelligence and Autonomous Robotic Technologies in the Corporate Context of SMEs: Deep Learning and Virtual Simulation Algorithms, Cyber-Physical Production Networks, and Industry 4.0-Based Manufacturing Systems," *Applied Sciences*, vol. 13, no. 3, Jan. 2023, Art. no. 1681, https://doi.org/10.3390/app13031681.

[16] T. Monmongkol, N. Sriputtha, N. Kanchanaruangrong, and P. Nasawat, "Hybrid GRA-EDAS-Based Evaluation of Electrode Materials for Automotive Spot Welding Applications," *Engineering, Technology & Applied Science Research*, vol. 15, no. 4, pp. 25088–25094, Aug. 2025, https://doi.org/10.48084/etasr.11871.

[17] L. Benkhelifa, "The Beta Reduced Modified Weibull Distribution with Applications to Reliability Data," *Journal of Reliability and Statistical Studies*, vol. 14, no. 1, pp. 311–322, June 2021, https://doi.org/10.13052/jrss0974-8024.14116.

[18] Y. Guan, "Research On Multi-Stage Production Inspection and Decision Optimization Based on Dynamic Programming," *Highlights in Science, Engineering and Technology*, vol. 159, pp. 285–292, Dec. 2025, https://doi.org/10.54097/mm53b623.