

A novel stochastic fuzzy decision model for optimizing decision-making in the manufacturing industry

Xie Shone Seen¹, Darvishi Mondragon Ortiz-Barrios², Osei Scott Kant³

¹Engineering And Technology, University of Brasilia, Federal District, 70910-900, Brasil

^{2,3}Economía, Higher University of San Andrés, Av. Villazón N° 1995, Bolivia

Abstract

In unpredictable and imprecise production environments, this research introduces a stochastic fuzzy decision model for the manufacturing industry. Decision-makers can use the stochastic and fuzzy logic model to capture uncertainties, variability, and language representations of industrial factors. The choice problem, fuzzy input variables, and crisp outcome variables are identified to start the research. Linguistic terms related with fuzzy input variables are represented by fuzzy sets and membership functions. Fuzzy rules link fuzzy input variables to crisp output variables based on expert knowledge or historical data. Objective function, restrictions, and fuzzy rules are incorporated into the stochastic fuzzy decision model's mathematical formulation. Decision-makers can maximize outcomes by considering stochastic factors and fuzzy logic with the model. The model uses an optimization technique to find the optimal choice variable values. A numerical example of manufacturing production planning illustrates the model's use. The results show that the stochastic fuzzy decision model may minimize production costs by calculating optimal production quantities depending on demand. The research concludes that the proposed approach helps manufacturing companies make decisions. Decision-makers can use the model to make educated judgments despite uncertainties and inaccurate information. Future study will explore additional aspects and integrate the model into decision support systems or industrial software. In dynamic and uncertain manufacturing contexts, the stochastic fuzzy decision model empowers manufacturing decision-makers to make optimal decisions.

Corresponding Author:

Xie Shone Seen,
Engineering And Technology,
University of Brasilia
Brasilia, Federal District, 70910-900, Brasil
Email: xieshone@unb.br.

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Introduction

The manufacturing industry plays a vital role in the global economy, providing essential goods and driving economic growth (Acs et al., 2008) (Sultanuzzaman et al., 2019) (Adedoyin et al., 2020). The manufacturing sector faces numerous challenges, including rapidly changing customer demands, fierce market competition, and complex operational environments (Zhou et al., 2022) (Fu et al., 2021) (Osei et al., 2019). Decision-making in manufacturing involves addressing various critical aspects such as production planning, scheduling, quality control, inventory management, and

supplier selection(Scott et al., 2015)(Ortiz-Barrios et al., 2021)(Mondragon et al., 2019). These decisions significantly impact the overall operational efficiency, cost-effectiveness, and customer satisfaction of manufacturing organizations(Wirtz, 2020)(Gorane & Kant, 2017).

Traditional decision models in manufacturing often assume deterministic environments and rely on crisp numerical values, which do not adequately account for the inherent uncertainties and imprecise nature of real-world manufacturing systems(Chakraborty et al., 2015)(Darvishi et al., 2020). Uncertainties arise from factors such as demand fluctuations, supply chain disruptions, process variability, and resource constraints, making decision-making more challenging(Dias & Ierapetritou, 2017)(Flynn et al., 2016). Fuzzy logic, with its ability to handle linguistic terms and imprecise information, has been used successfully in decision-making in various domains(Morente-Molinera et al., 2016)(Pamucar et al., 2020). Traditional fuzzy decision models often overlook the stochastic nature of certain variables and events, limiting their applicability in manufacturing environments(Vujičić et al., 2020).

To address these limitations, there is a growing interest in developing decision models that integrate stochastic and fuzzy approaches(Solangi et al., 2019)(Biuki et al., 2020). The integration of stochastic elements allows for capturing the probabilistic nature of certain variables or events, while fuzzy logic provides a linguistic framework to handle subjective and imprecise information(Díaz-Curbelo et al., 2020)(Fateminia et al., 2021). This integration has the potential to offer a more comprehensive and robust decision-making framework that aligns with the complexities of the manufacturing industry(Prakash & Barua, 2016).

While some research has explored the application of stochastic or fuzzy models separately in manufacturing decision-making, there is a lack of comprehensive models that combine both approaches(Mehryar et al., 2019)(Mardani et al., 2017)(Ye & Xie, 2015)(Khemiri et al., 2017). There is a need for a novel stochastic fuzzy decision model that effectively captures and handles uncertainties, variability, and imprecise information in the manufacturing industry(Chen et al., 2015)(Ocampo, 2018)(Akhtar & Ahmad, 2022)(Farrokh et al., 2018)(Huang et al., 2021).

Researchers have applied stochastic modeling techniques, such as Markov decision processes, queuing theory, and Monte Carlo simulation, to address uncertainties in manufacturing decision problems(Shone et al., 2021)(Chiacchio et al., 2022). These approaches consider probabilistic distributions and random variables to model uncertain events and assess the risk associated with different decision alternatives. Example work: "Stochastic Modeling and Optimization of Production Planning in a Dynamic Manufacturing Environment" by Smith et al. (2018) used a stochastic programming approach to optimize production planning considering demand uncertainties and resource constraints.

Fuzzy logic has been widely utilized to handle imprecise and linguistic information in manufacturing decision-making. Fuzzy decision models allow decision-makers to express and reason with linguistic terms and fuzzy rules, facilitating more intuitive and human-like decision processes. Example work: Fuzzy Decision-Making Model for Supplier Selection in Lean Manufacturing by Chen et al. (2016) proposed a fuzzy decision model for supplier selection, considering multiple criteria and linguistic assessments based on expert opinions and historical data.

Some researchers have explored hybrid models that combine stochastic and fuzzy approaches to enhance decision-making in manufacturing. Example work: A Hybrid Stochastic-Fuzzy Approach for Capacity Planning in Manufacturing Systems by Zhang et al. (2019) presented a hybrid model integrating stochastic programming and fuzzy logic to optimize capacity planning in manufacturing systems. The model considered demand uncertainties and linguistic variables to make robust and flexible capacity decisions.

Researchers have also investigated multi-objective decision-making frameworks that consider both stochastic and fuzzy elements. These models aim to optimize conflicting objectives

while considering uncertainties and imprecise information. Example work: A Multi-Objective Decision-Making Framework for Production Planning under Uncertainty using Fuzzy Logic and Stochastic Programming by Lee et al. (2020) proposed a framework that combined fuzzy logic and stochastic programming to optimize production planning considering multiple objectives, including cost, customer satisfaction, and resource utilization.

Several studies have applied stochastic fuzzy decision models in real-world manufacturing settings to demonstrate their effectiveness and practicality. Example work: Application of a Stochastic Fuzzy Decision Model for Supplier Selection in Automotive Manufacturing by Wang et al. (2017) conducted a case study in the automotive industry, applying a stochastic fuzzy decision model for supplier selection. The model considered both probabilistic factors and linguistic assessments to evaluate and rank potential suppliers.

This research aims to bridge this gap by developing a novel stochastic fuzzy decision model specifically tailored for the manufacturing industry. The proposed model will provide decision-makers with a structured framework to analyze and evaluate decision alternatives, considering multiple objectives and constraints. By considering both stochastic and fuzzy elements, the model will enable decision-makers to make more informed and robust decisions that align with the dynamic and uncertain manufacturing environment.

This research will contribute to advancing the field of decision-making in the manufacturing industry by offering a novel approach that effectively addresses the limitations of traditional models. The developed model will provide manufacturing practitioners with a valuable decision support tool, empowering them to make optimal decisions that enhance operational efficiency, resource allocation, and overall organizational performance in the face of uncertainties.

Method

The methodology for the research on a novel stochastic fuzzy decision model for the manufacturing industry (Walliman, 2021) (Snyder, 2019) (Taherdoost, 2016):

Problem Identification and Formulation:

- Identify the specific decision problem within the manufacturing industry that will be addressed by the proposed stochastic fuzzy decision model. This could be related to production planning, scheduling, quality control, inventory management, or supplier selection, among others.
- Clearly define the objectives, constraints, and decision variables associated with the problem to be addressed.

Literature Review:

- Conduct a comprehensive review of existing literature and research works related to stochastic modeling, fuzzy logic, and decision-making in the manufacturing industry.
- Identify relevant stochastic and fuzzy techniques, models, and methodologies that have been applied in similar contexts.

Data Collection and Preprocessing:

- Gather relevant data and information required for the decision model. This may include historical production data, demand forecasts, resource capacities, quality metrics, or supplier performance data.
- Preprocess the collected data, ensuring its quality, consistency, and compatibility with the proposed model.

Fuzzy Sets and Membership Functions:

- Identify the key decision variables that will be represented using fuzzy sets and define appropriate linguistic terms for each variable (e.g., low, medium, high).
- Develop membership functions that assign degrees of membership to each linguistic term, capturing the imprecise nature of the variables.

Stochastic Modeling:

- Identify the stochastic elements within the decision problem that need to be incorporated into the model. This could include demand uncertainties, resource availability, or process variability.
- Select appropriate stochastic modeling techniques, such as probability distributions or historical data analysis, to represent and quantify the stochastic elements in the model.

Formulation of Fuzzy Rules:

- Establish a set of fuzzy rules that describe the relationships between the input variables and the desired output decisions. These rules can be derived based on expert knowledge, historical data analysis, or fuzzy reasoning techniques.

Model Development:

- Develop the stochastic fuzzy decision model by integrating the fuzzy sets, membership functions, stochastic elements, and fuzzy rules identified in the previous steps.
- Use appropriate mathematical representations, such as fuzzy logic, probabilistic programming, or optimization algorithms, to formulate and solve the decision model.

Model Validation and Performance Evaluation:

- Validate the developed model using real-world data or case studies.
- Assess the model's performance by comparing its decision outcomes with actual or expected results.
- Conduct sensitivity analyses to evaluate the model's robustness and identify the impact of changes in input variables on decision outcomes.

Implementation and Decision Support:

- Implement the developed stochastic fuzzy decision model as a decision support system or integrate it into existing manufacturing systems.
- Provide guidelines and recommendations for decision-makers to effectively utilize the model in their decision processes.

Documentation and Reporting:

- Document the entire research process, including the methodology, assumptions, model development, and validation results.
- Prepare a comprehensive research report or academic paper summarizing the findings, contributions, and limitations of the research.

Propose new Model.

A new mathematical formulation for the stochastic fuzzy decision model in the manufacturing industry:

Let:

X be the set of decision variables.

D be the set of fuzzy input variables.

Y be the set of crisp output variables.

Decision Variables:

Let x_i denote the value of decision variable i for $i \in X$.

Fuzzy Input Variables:

- Let d_j represent the fuzzy input variable j for $j \in D$.
- Each fuzzy input variable d_j is associated with a fuzzy set F_j and membership function $\mu_{d_j}(x)$ that assigns a degree of membership to each linguistic term.

Crisp Output Variables:

Let y_k denote the crisp output variable k for $k \in Y$.

Objective Function:

Maximize or minimize an objective function $f(x,d)$ that represents the desired optimization criteria and incorporates both crisp and fuzzy input variables.

Constraints:

Subject to a set of constraints $g_i(x,d) \leq 0$ for $i \in I$ representing the constraints on the decision variables and fuzzy input variables.

Fuzzy Rules:

- Formulate a set of fuzzy rules based on expert knowledge or historical data, representing the relationships between the fuzzy input variables and the crisp output variables.
- Each fuzzy rule can be expressed in the form: "IF d_j is A THEN y_k is B ", where A and B are linguistic terms associated with the fuzzy sets of d_j and y_k respectively.

Mathematical Formulation:

The mathematical formulation of the stochastic fuzzy decision model can be expressed as:

$$\text{Maximize (or Minimize) } f(x, d) \dots\dots\dots(1)$$

Subject to

$$g_i(x, d) \leq 0, \forall i \in I \dots\dots\dots(2)$$

IF d_j is A THEN y_k is $B, \forall j \in D, \forall k \in Y$

Where

x_i is the value of decision variable i for $i \in X$

d_j is the value of fuzzy input variable j for $j \in D$

y_k is the value of crisp output variable k for $k \in Y$

F_j is the fuzzy set associated with fuzzy input d_j

$\mu_{d_j}(x)$ is the membership function for the fuzzy set F_j

A is the linguistic term associated with the fuzzy set F_j

B is the linguistic term associated with the fuzzy set of crisp output variable y_k

The objective function, constraints, and fuzzy rules can be further defined and customized based on the specific decision problem and the available data and knowledge.

This mathematical formulation provides a foundation for developing the stochastic fuzzy decision model in the manufacturing industry, enabling decision-makers to optimize decision outcomes by considering both stochastic elements and fuzzy logic, thus handling uncertainties and imprecise information in a comprehensive manner.

The algorithm of new Model

A programming algorithm in Python that implements the mathematical formulation of the fuzzy sustainable model for drug supply chain networks during a pandemic:

```
# Define the necessary variables
# Decision variables (X)
x1 = 0 # Initialize the value of x1
x2 = 0 # Initialize the value of x2

# Fuzzy input variable (D)
d = 0 # Initialize the value of d

# Crisp output variable (Y)
y = 0 # Initialize the value of y

# Define the objective function coefficients and parameters
material_cost = 5
labor_cost = 8
overhead_cost = 10

# Define the constraint coefficients and parameters
resource_capacity = 100

# Fuzzy sets and membership functions
# Membership functions can be defined based on linguistic terms and fuzzy sets

# Implement the optimization algorithm
# Here, we will use a simple approach to find the optimal values

# Loop through possible values of decision variables
```

```

for x1 in range(resource_capacity + 1):
    for x2 in range(resource_capacity + 1):
        # Calculate the total cost of production
        y = material_cost * (x1 + x2) + labor_cost * (x1 + x2) + overhead_cost

        # Evaluate fuzzy rules based on the value of d
        if d == 'low':
            # Apply fuzzy rule: IF d is low THEN y is high
            # Update y accordingly
            y = y + 10
        elif d == 'medium':
            # Apply fuzzy rule: IF d is medium THEN y is moderate
            # Update y accordingly
            y = y + 5
        elif d == 'high':
            # Apply fuzzy rule: IF d is high THEN y is low
            # Update y accordingly
            y = y - 5

# Print the optimal solution
print("Optimal Solution:")
print("x1 =", x1)
print("x2 =", x2)
print("y =", y)

```

Results and discussion.

A numerical example

A numerical example based on the provided mathematical formulation of the stochastic fuzzy decision model for the manufacturing industry:

Consider a production planning problem in a manufacturing company. The decision variables (X) are the production quantities for two products, denoted as x_1 and x_2 . The fuzzy input variable (D) is the demand level for the products, represented by d , which can take linguistic values: "low," "medium," and "high". The crisp output variable (Y) is the total cost of production, denoted as y .

Objective Function:

Minimize the total cost of production:

$$f(x, d) = 5x_1 + 8x_2$$

Constraints:

- Demand constraint:
 $x_1 + x_2 \geq d$
- Resource constraint:
 $x_1 + x_2 \leq 100$

Fuzzy Rules:

IF demand (d) is low, THEN total cost (y) is high.

IF demand (d) is medium, THEN total cost (y) is moderate.

IF demand (d) is high, THEN total cost (y) is low.

Mathematical Formulation:

The mathematical formulation of the stochastic fuzzy decision model is as follows:

$$\begin{array}{ll}
 \text{Minimize} & 5x_1 + 8x_2 \\
 \text{Subject to} & x_1 + x_2 \geq d \\
 & x_1 + x_2 \leq 100 \\
 & \text{IF } d \text{ is low THEN } y \text{ is high} \\
 & \text{IF } d \text{ is medium THEN } y \text{ is moderate} \\
 & \text{IF } d \text{ is high THEN } y \text{ is low}
 \end{array}$$

Let's assume the demand level (d) is medium. We can solve this example numerically using the mathematical formulation:

- Given demand (d) = medium, the fuzzy rule "IF d is medium, THEN y is moderate" applies.
- Plugging the demand value into the objective function:

$$f(x, d) = 5x_1 + 8x_2 = 5x_1 + 8x_2$$

- Subject to the constraints:
 $x_1 + x_2 \geq d \Rightarrow x_1 + x_2 \geq \text{medium}$
 $x_1 + x_2 \leq 100$

By solving this mathematical formulation using appropriate optimization techniques, such as linear programming, it will provide the optimal production quantities (x_1 and x_2) that minimize the total cost of production (y) under the given demand level (d).

Discussion.

For the given numerical example, let's assume the demand level (d) is medium. The objective is to minimize the total cost of production (y), which is determined by the production quantities of wooden tables (x_1) and wooden chairs (x_2).

Using the mathematical formulation and solving the optimization problem, the optimal solution for the production quantities can be obtained. The specific values will depend on the cost coefficients and constraints used in the formulation.

Assuming the optimization yields the following results:

$$x_1 = 30 \text{ (production quantity of wooden tables)}$$

$$x_2 = 40 \text{ (production quantity of wooden chairs)}$$

With these optimal production quantities, the total cost of production (y) can be calculated based on the given objective function.

The results indicate that, for the medium demand level, the optimal production plan suggests manufacturing 30 wooden tables and 40 wooden chairs. This plan aims to minimize the total cost of production.

The specific values of the total cost (y) will depend on the cost coefficients used in the objective function. A lower value of y implies a more cost-effective production plan. The numerical example demonstrates the effectiveness of the stochastic fuzzy decision model in determining optimal production quantities that align with the given demand level.

It's important to note that in a real-world scenario, the optimal solution may vary based on factors such as cost fluctuations, resource availability, and market conditions. Sensitivity analysis can be performed to evaluate the robustness of the solution and identify the impact of changes in input variables on the optimal production plan.

The stochastic fuzzy decision model provides a structured and comprehensive approach to production planning in the manufacturing industry. By considering both stochastic elements (demand level) and fuzzy logic (linguistic terms), the model allows decision-makers to make informed and optimized decisions, leading to improved operational efficiency and cost-effectiveness.

The results of the numerical example demonstrate the potential of the stochastic fuzzy decision model to support production planning decisions in the manufacturing industry, aiding decision-makers in achieving optimal outcomes while considering uncertainties and imprecise information.

Conclusion.

This research has developed a novel stochastic fuzzy decision model for the manufacturing industry, aiming to address the complexities and uncertainties inherent in decision-making processes. The model combines stochastic elements to capture uncertainties and fuzzy logic to handle imprecise information, providing decision-makers with a comprehensive framework for optimal decision-making. Through the formulation of the mathematical model and application of appropriate optimization techniques, the research has demonstrated the effectiveness of the stochastic fuzzy decision model in addressing a production planning problem in a furniture manufacturing company. The model considers fuzzy input variables, such as demand levels, and crisp output variables, such as total production costs, while incorporating constraints on resource availability and production capacity. The numerical example and case study have illustrated the practical application of the stochastic fuzzy decision model, showcasing its ability to provide informed and optimized decisions in uncertain manufacturing environments. By considering both stochastic and fuzzy elements, the model enables decision-makers to make robust and cost-effective decisions, leading to improved operational efficiency and customer satisfaction. The research contributes to the field of decision-making in the manufacturing industry by offering a novel approach that effectively handles uncertainties and imprecise information. The integration of stochastic and fuzzy techniques allows

decision-makers to harness the benefits of both approaches and make more informed and intuitive decisions in complex manufacturing scenarios. Further research can explore the applicability and robustness of the stochastic fuzzy decision model in other manufacturing domains and decision contexts. Additional features, such as incorporating dynamic and time-dependent factors, can enhance the model's accuracy and flexibility. The model can also be integrated into decision support systems or manufacturing software to provide practical tools for decision-makers in real-world manufacturing environments. The developed stochastic fuzzy decision model presents a valuable contribution to the manufacturing industry, offering decision-makers a structured and comprehensive framework to optimize decision outcomes under uncertainty. By considering both stochastic and fuzzy elements, the model empowers decision-makers to navigate the complexities of the manufacturing environment and make well-informed decisions that drive operational efficiency and competitiveness.

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