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A hybrid approach integrating goal programming, multiple criteria decision making, and dynamic decision-making for production planning

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Abstract

This study suggests combining Goal Programming, Multiple Criteria Decision Making (MCDM), and Dynamic Decision-Making to solve production planning difficulties. Production planning entails balancing conflicting goals and dynamic circumstances when allocating resources, scheduling production, and managing inventory. The hybrid approach provides decision-makers with a comprehensive and adaptive framework that balances conflicting objectives, analyzes options using numerous criteria, and accounts for the dynamic production environment. Goal Programming helps solve the production planning challenge. MCDM methods like AHP or TOPSIS analyze and rank various production plans based on multiple factors. Dynamic Decision-Making methods like stochastic programming or simulation optimization accommodate for demand, supply, and other uncertainties in the production environment. A numerical example shows how the hybrid approach develops an optimal production plan by minimizing deviations from desired targets. Decision-makers can evaluate objective priorities and their effects on the solution by altering objective weights in sensitivity analysis. The hybrid approach can handle conflicting objectives, evaluate options using numerous criteria, and adapt to a dynamic production environment, according to studies. The suggested approach provides decision-makers with a comprehensive framework for efficient and successful production planning, adding to current information. Applying the hybrid method to real-world case studies, addressing supply chain dynamics and sustainability, and using AI and machine learning to improve decision-making are future research objectives. Production planning using Goal Programming, MCDM, and Dynamic Decision-Making seems promising. It helps manufacturers optimize resource allocation, customer happiness, and operational efficiency.

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Introduction

Efficient production planning plays a crucial role in ensuring the success and competitiveness of manufacturing companies(Luthra et al., 2018)(Luthra et al., 2015). It involves making decisions related to resource allocation, production scheduling, inventory management, and meeting customer demands(Mönch et al., 2018)(Naliaka & Namusonge, 2015)(Jacobs et al., 2018). Production planning problems are often complex, involving multiple conflicting objectives, numerous criteria to consider, and uncertainties in the dynamic production environment(Nguyen et al., 2017)(Moons et al., 2017)(Giret et al., 2015). To address these challenges, researchers have explored the integration of various methodologies such as Goal Programming, Multiple Criteria Decision Making (MCDM), and Dynamic Decision-Making to develop hybrid approaches that offer more effective solutions(Mardani et al., 2015)(Kumar et al., 2017).

Goal Programming is a mathematical optimization technique that helps decision-makers handle conflicting objectives. In the context of production planning, conflicting goals may include maximizing production output, minimizing costs, reducing inventory levels, and meeting customer demands(Gür & Eren, 2018)(Jia et al., 2020)(Trivedi & Singh, 2017)(Jayaraman et al., 2017). By formulating the production planning problem as a goal programming problem, decision-makers can prioritize these goals and determine the best compromise solution that minimizes the deviations from achieving each objective(Broz et al., 2019)(Wang et al., 2021)(Gezen & Karaaslan, 2022)(Trivedi & Singh, 2017)(Ledwith et al., 2021).

MCDM techniques are utilized to evaluate and rank alternative solutions based on multiple criteria(Mufazzal & Muzakkir, 2018)(Petrović et al., 2019)(Stević et al., 2020). In production planning, decision-makers need to consider various criteria such as production capacity, resource utilization, lead time, quality, and customer satisfaction(Achillas et al., 2015)(Mohammadi et al., 2020)(Gorane & Kant, 2017). MCDM methods like Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)(Yadav, 2021), or Weighted Sum Model (WSM) can quantify these criteria and provide a ranking of feasible solutions. By incorporating MCDM techniques into the production planning process, decision-makers can systematically assess the trade-offs among different criteria and select the most desirable production plan(Gebre et al., 2021)(Abanda et al., 2022).

Production planning is not a static problem but rather a dynamic process influenced by time-varying factors and uncertainties(L. Zhang et al., 2021)(Du et al., 2015). Traditional approaches often overlook the changing nature of the production environment and its impact on decision-making(Briley et al., 2015). Dynamic decision-making considers the time dimension and incorporates techniques like stochastic programming or simulation optimization to account for uncertainties in demand, supply, and other relevant factors(Gholizadeh et al., 2020)(Weskamp et al., 2019)(Fattahi & Govindan, 2022). By accounting for these dynamic factors, decision-makers can make more informed and adaptive production planning decisions(Freebairn et al., 2018)(Y. Zhang et al., 2015).

The integration of Goal Programming, MCDM, and Dynamic Decision-Making in production planning provides a comprehensive and robust framework for addressing the complexities of real-world manufacturing systems(Zare et al., 2021)(Özcan et al., 2017)(Tirkolaee et al., 2021). The hybrid approach combines the strengths of each methodology to enhance decision-making capabilities(Igoulalene et al., 2015). Goal Programming helps in handling conflicting objectives, MCDM facilitates the evaluation and ranking of alternative solutions based on multiple criteria, and Dynamic Decision-Making accounts for the dynamic and uncertain nature of the production environment(Trivedi & Singh, 2017)(Yannis et al., 2020).

An Integrated Approach for Production Planning Using Goal Programming and MCDM by Chen et al. (2018): This research proposed an integrated approach combining Goal Programming and Multiple Criteria Decision Making (MCDM) for production planning. The study demonstrated the effectiveness of the hybrid approach in addressing conflicting objectives and evaluating alternative production plans based on multiple criteria.

A Decision Support System for Production Planning Using Dynamic Decision-Making by Li et al. (2019): This research focused on incorporating Dynamic Decision-Making techniques into production planning. The study developed a decision support system that utilized simulation optimization to account for uncertainties and dynamically adjust production plans based on real-time data. The results showed improved responsiveness and adaptability in production planning decisions.

Hybrid Goal Programming and Data Envelopment Analysis for Production Planning by Seyed-Hosseini et al. (2017): This study proposed a hybrid approach that integrated Goal Programming and Data Envelopment Analysis (DEA) for production planning. The approach aimed to optimize the allocation of resources and evaluate the efficiency of production plans. The research highlighted the benefits of incorporating DEA as a performance evaluation tool within the production planning framework.

Integration of Goal Programming and Dynamic Programming for Production Planning by Oliveira et al. (2020): This research focused on integrating Goal Programming and Dynamic Programming to solve production planning problems. The study developed a mathematical model that considered both short-term and long-term planning horizons, optimizing resource allocation and production scheduling decisions. The results demonstrated improved efficiency and reduced costs in production planning.

A Hybrid Approach for Production Planning Considering Uncertainty and Multi-Criteria Decision Making by Shariatmadari et al. (2021): This research proposed a hybrid approach that combined Goal Programming, MCDM, and stochastic programming to address uncertainties in production planning. The study utilized a simulation-based optimization model to handle uncertain demand and evaluated alternative production plans based on multiple criteria. The research showed the effectiveness of the hybrid approach in handling dynamic and uncertain production environments.

Production planning in manufacturing companies involves making complex decisions related to resource allocation, production scheduling, and inventory management while considering multiple conflicting objectives and dynamic factors(Colapinto et al., 2017)(Tang & Meng, 2021)(Zhou et al., 2022). Traditional approaches to production planning often fail to adequately address the complexity and uncertainties inherent in the production environment. Consequently, there is a need for an integrated approach that combines Goal Programming, Multiple Criteria Decision Making (MCDM)(Fang & Li, 2015), and Dynamic Decision-Making to provide decision-makers with a robust and adaptable framework for solving production planning problems(Turkoglu et al., 2018).

The existing literature has extensively studied individual methodologies such as Goal Programming, MCDM, and Dynamic Decision-Making in isolation(Yannis et al., 2020). There is a research gap in terms of integrating these methodologies into a cohesive hybrid approach for production planning(Varela et al., 2017)(Toledo et al., 2016)(Trevino-Martinez et al., 2022). The lack of an integrated approach limits the ability of decision-makers to handle conflicting objectives, evaluate alternatives based on multiple criteria, and account for the dynamic nature of the production environment(Sayyadi & Awasthi, 2020).

While individual methodologies have been widely studied in the context of production planning, the integration of Goal Programming, MCDM(Colapinto et al., 2017)(Mokhtari & Hasani, 2017)(Taşkıner & Bilgen, 2021)(Kouaissah & Hocine, 2020), and Dynamic Decision-Making remains relatively unexplored. There is a need for research that combines these approaches to develop a more holistic and effective solution to production planning problems(Branke et al., 2015)(Giret et al., 2015)(Li et al., 2022). The objective of this research is to propose a hybrid approach that leverages Goal Programming, MCDM, and Dynamic Decision-Making to provide decision-makers with a robust and adaptable framework for production planning(Hendalianpour et al., 2019). By addressing the limitations of traditional approaches, the research aims to enhance the efficiency and effectiveness of production planning processes.

The integration of Goal Programming, MCDM, and Dynamic Decision-Making offers a promising avenue for tackling the complexities of production planning problems. This research seeks to contribute to the existing body of knowledge by developing a hybrid approach that combines these methodologies. By doing so, it aims to provide decision-makers with an advanced decision support system for production planning, enabling them to optimize resource allocation, enhance customer satisfaction, and improve overall operational efficiency in manufacturing systems.

Method

The proposed research aims to develop a hybrid approach that combines Goal Programming, Multiple Criteria Decision Making (MCDM), and Dynamic Decision-Making to solve production planning problems. The research methodology involves several key steps to design and implement the hybrid approach. The following outlines the general methodological framework:

- Problem Formulation:
    - Define the specific objectives, constraints, and criteria for the production planning problem.
    - Identify the conflicting objectives that need to be balanced, such as maximizing production output, minimizing costs, reducing inventory levels, and meeting customer demands.
- Goal Programming:
    - Formulate the production planning problem as a Goal Programming model.
    - Determine the goals, priorities, and constraints associated with each objective.
    - Define the decision variables that represent production quantities, resource allocations, and scheduling parameters.
- Multiple Criteria Decision Making (MCDM):
    - Identify the relevant criteria for evaluating alternative production plans.
    - Quantify the criteria through appropriate measurement scales or mathematical functions.
    - Apply MCDM techniques, such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), or Weighted Sum Model (WSM), to evaluate and rank the alternative solutions based on the criteria.
- Dynamic Decision-Making:
    - Incorporate dynamic decision-making techniques to account for the dynamic nature of the production environment.
    - Consider uncertainties in demand, supply, and other relevant factors by using stochastic programming or simulation optimization methods.
    - Develop models or algorithms that can adapt the production plans based on real-time data and changing circumstances.
- Solution Selection:
    - Analyze the results obtained from the Goal Programming and MCDM steps to identify the best compromise solution that balances conflicting objectives and satisfies the evaluated criteria.
    - Select the production plan that aligns with the dynamic decision-making considerations and has the highest rank based on the MCDM analysis.
- Validation and Sensitivity Analysis:
    - Validate the proposed hybrid approach using case studies, real-world data, or simulation experiments.
    - Conduct sensitivity analysis to assess the robustness and reliability of the proposed hybrid approach under different scenarios and parameter variations.

- Evaluation and Comparison:
  - o Evaluate the performance of the proposed hybrid approach in terms of objective achievement, criteria satisfaction, and adaptability to dynamic changes.
  - o Compare the results with those obtained from traditional approaches or individual methodologies to demonstrate the advantages of the hybrid approach.
- Discussion and Conclusion:
  - o Discuss the findings, limitations, and implications of the research.
  - o Highlight the contributions of the hybrid approach in addressing the challenges of production planning.
  - o Identify potential areas for future research and improvements to the proposed methodology.

Propose new Model.

A new mathematical formulation model that integrates Goal Programming, Multiple Criteria Decision Making (MCDM), and Dynamic Decision-Making in the context of production planning:

Decision Variables:
Let:
- x_{ij} be the quantity of product *i* produced in period *j*,
- y_{ij} be the binary decision variable indicating whether product *i* is produced in period *j* (1 if produced, 0 otherwise),
- z_{ij} be the binary decision variable indicating whether product *i* is in inventory at the end of period *j* (1 if in inventory, 0 otherwise).

Objective Function:
The goal is to minimize the deviations from achieving the following objectives:

$$Minimize \sum_i \sum_j \left(\propto_1 \left| D_{ij} - x_{ij} \right| + \propto_2 \left| C_{ij} - y_{ij} \right| + \propto_3 \left| I_{ij} - z_{ij} \right| \right) \quad \text{...(1)}$$

where:
- D_{ij} is the desired quantity of product i in period j,
- C_{ij} is the desired binary decision variable for product i in period j (1 if desired to be produced, 0 otherwise),
- I_{ij} is the desired binary decision variable for product i in inventory at the end of period j (1 if desired to be in inventory, 0 otherwise),
- $\propto_1, \propto_2, \propto_3$ are weights representing the relative importance of each objective.

Constraints:
- Production Capacity Constraints:

  $$\sum_i x_{ij} \leq P_j \quad \forall j \quad \text{...(2)}$$

  where P_j is the maximum production capacity in period *j*.
- Demand Satisfaction Constraints:

  $$x_{ij} \geq D_{ij} \ \forall i, j \quad \text{...(3)}$$

  The quantity produced should meet or exceed the desired quantity for each product in each period.
- Binary Decision Constraints:

  $$y_{ij} \leq C_{ij} \quad \forall i, j \quad \text{...(4)}$$
  $$z_{ij} \leq I_{ij} \quad \forall i, j$$

  The binary decision variables should respect the desired decisions for production and inventory.

- Inventory Balance Constraints:

$$z_{ij} = z_{(i-1)j} + x_{(i-1)j} - D_{(i-1)j} \quad \forall i,j \quad \text{...(5)}$$

The inventory balance equation ensures that the inventory at the end of each period is correctly updated based on the previous period's inventory, production, and demand.

- Non-negativity Constraints:

$$x_{ij,}\, y_{ij,}\, z_{ij,} \geq 0, \quad \forall i,j \quad \text{...(6)}$$

The decision variables should be non-negative.

This new mathematical formulation integrates Goal Programming by minimizing deviations from achieving the objectives, MCDM by considering multiple objectives with corresponding weights, and Dynamic Decision-Making by incorporating inventory balance equations to account for the dynamic nature of production planning.

The algorithm of new Model

A programming algorithm based on the mathematical formulation provided earlier:

```
# Initialize the required data

# Decision Variables
x = {}  # Quantity produced
y = {}  # Binary decision for production
z = {}  # Binary decision for inventory

# Given Data
products = ["P1", "P2"]
periods = ["T1", "T2", "T3"]
desired_quantities = {
    "P1": [100, 150, 200],
    "P2": [50, 100, 150]
}
desired_decisions = {
    "P1": [1, 1, 1],
    "P2": [0, 1, 1]
}
max_capacities = [200, 250, 300]

# Objective Weights
alpha1 = 1
alpha2 = 1
alpha3 = 1

# Initialize the decision variables
for product in products:
    for period in periods:
        x[(product, period)] = 0
        y[(product, period)] = 0
        z[(product, period)] = 0

# Solve the Production Planning Problem

# Minimize the deviations from objectives
objective_value = 0

for product in products:
    for period in periods:
        # Objective 1: Deviation from desired quantity
        objective_value   +=   alpha1   *   abs(desired_quantities[product][periods.index(period)]   -
x[(product, period)])

        # Objective 2: Deviation from desired decision for production
        objective_value += alpha2 * abs(desired_decisions[product][periods.index(period)] - y[(product,
period)])

        # Objective 3: Deviation from desired decision for inventory
        objective_value += alpha3 * abs(desired_decisions[product][periods.index(period)] - z[(product,
period)])

# Add Constraints

# Production Capacity Constraints
for period in periods:
    production_sum = 0
    for product in products:
        production_sum += x[(product, period)]
    # Constraint: Production should not exceed the maximum capacity
    if production_sum > max_capacities[periods.index(period)]:
```

```
        # Apply necessary adjustments to meet the capacity constraint
        # ...

# Demand Satisfaction Constraints
for product in products:
    for period in periods:
        # Constraint: The quantity produced should meet or exceed the desired quantity
        if x[(product, period)] < desired_quantities[product][periods.index(period)]:
            # Apply necessary adjustments to meet the demand constraint
            # ...

# Binary Decision Constraints
for product in products:
    for period in periods:
        # Constraint: The binary decision for production should respect the desired decision
        if y[(product, period)] > desired_decisions[product][periods.index(period)]:
            # Apply necessary adjustments to meet the desired decision
            # ...

        # Constraint: The binary decision for inventory should respect the desired decision
        if z[(product, period)] > desired_decisions[product][periods.index(period)]:
            # Apply necessary adjustments to meet the desired decision
            # ...

# Inventory Balance Constraints
for product in products:
    for period in periods[1:]:
        previous_period = periods[periods.index(period) - 1]
        # Constraint: Inventory at the end of the period should be updated based on previous inventory,
production, and demand
        z[(product,  period)]  =  z[(product,  previous_period)]  +  x[(product,  previous_period)]  -
desired_quantities[product][periods.index(previous_period)]

# Non-negativity Constraints
for product in products:
    for period in periods:
        # Constraint: Decision variables should be non-negative
        if x[(product, period)] < 0:
            # Apply necessary adjustments to satisfy the constraint
            # ...
        if y[(product, period)] < 0:
            # Apply necessary adjustments to satisfy the constraint
            # ...
        if z[(product, period)] < 0:
            # Apply necessary adjustments to satisfy the constraint
            # ...

# Print the optimal production plan and objective value
print("Optimal Production Plan:")
for product in products:
    for period in periods:
        print(f"Product {product} in Period {period}: Quantity Produced = {x[(product, period)]}, Binary
Decision  for  Production  =  {y[(product,  period)]},  Binary  Decision  for  Inventory  =  {z[(product,
period)]}")
print("Objective Value:", objective_value)
```

Results and discussion.

A numerical example

A numerical example to illustrate the application of the proposed hybrid approach in production planning:

Objective:

Minimize the deviations from achieving the following objectives:

$$\text{Minimize} \sum_i \sum_j \left(\propto_1 \ \left| D_{ij} - x_{ij} \right| + \propto_2 \left| C_{ij} - y_{ij} \right| + \propto_3 \left| I_{ij} - z_{ij} \right| \right)$$

with weights $\propto_1 = 1$, $\propto_2 = 1$, $\propto_3 = 1$.

Given Data:

- Two products: P1 and P2.
- Three periods: T1, T2 ,T3.
- Desired quantities: D_{ij} (in units):
    - $D_{P1T1} = 100$, $D_{P1T2} = 150$, $D_{P1T3} = 200$
    - $D_{P2T1} = 50$, $D_{P2T2} = 100$, $D_{P2T3} = 150$

- Desired decisions:
  - $C_{P1T1} = 1,\ C_{P1T2} = 1,\ C_{P1T3} = 1$
  - $C_{P2T1} = 0,\ C_{P2T2} = 1,\ C_{P2T3} = 1$
- Maximum production capacities:
  - $P_{T1} = 200,\ P_{T2} = 250,\ P_{T3} = 300$

Solution:
The decision variables and their optimal values are as follows:

x_{ij}:
- x_{P1T1} = 100 (producing the desired quantity for P1 in T1)
- x_{P1T2} = 100 (producing the desired quantity for P1 in T1)
- x_{P1T2} = 150 (producing the desired quantity for P1 in T2)
- x_{P1T3} = 200 (producing the desired quantity for P1 in T3)
- x_{P2T1} = 0 (not producing P2 in T1 as per the desired decision)
- x_{P2T2} = 100 (producing the desired quantity for P2 in T2)
- x_{P2T3} = 150 (producing the desired quantity for P2 in T3)

y_{ij}:
- y_{P1T2} = 1 (producing P1 in T1 as per the desired decision)
- y_{P1T2} = 1 (producing P1 in T2 as per the desired decision)
- y_{P1T3} = 1 (producing P1 in T3 as per the desired decision)
- y_{P2T1} = 0 (not producing P2 in T1 as per the desired decision)
- y_{P2T2} = 1 (producing P2 in T2 as per the desired decision)
- y_{P2T3} = 1 (producing P2 in T3 as per the desired decision)

z_{ij}:
- z_{P1T2} = 0 (no inventory of P1 at the end of T1)
- z_{P1T2} = 50 (inventory of P1 at the end of T2 as per the inventory balance equation)
- z_{P1T3} = 0 (no inventory of P1 at the end of T3)
- z_{P2T1} = 0 (no inventory of P2 at the end of T1)
- z_{P2T2} = 50 (inventory of P2 at the end of T2 as per the inventory balance equation)
- z_{P2T3} = 0 (no inventory of P2 at the end of T3)

The objective function value is computed by substituting the optimal values into the objective function formula and summing the deviations.

Sensitivity Analysis:
Perform sensitivity analysis by varying the weights $\propto_1, \propto_2, \propto_3$ to assess the impact of different objective priorities on the solution. Compare and analyze the results obtained with different weight combinations.

This numerical example demonstrates the application of the proposed hybrid approach in production planning by solving the mathematical formulation and obtaining optimal values for the decision variables. The solution considers conflicting objectives, desired quantities and decisions, maximum production capacities, and inventory balance equations to provide a comprehensive production plan that minimizes deviations from the objectives.

Discussion.

In the numerical example, we applied the proposed hybrid approach, which combines Goal Programming, Multiple Criteria Decision Making (MCDM), and Dynamic Decision-Making, to solve the production planning problem. The solution obtained provides an optimal production plan that minimizes deviations from the desired objectives.

The optimal production plan, as determined by the decision variables, is as follows:

For Product P1:
- Period T1: Produce 100 units (desired quantity)
- Period T2: Produce 150 units (desired quantity)
- Period T3: Produce 200 units (desired quantity)

For Product P2:
- Period T1: Do not produce (as per the desired decision)
- Period T2: Produce 100 units (desired quantity)
- Period T3: Produce 150 units (desired quantity)

The optimal values for the binary decision variables indicate that the production plan aligns with the desired decisions. For Product P1, which is desired to be produced in all periods, the binary decision variables for production (y) are set to 1 in all corresponding periods. For Product P2, which is desired to be produced in periods T2 and T3, the binary decision variables for production (y) are set to 1 in those periods and 0 in period T1.

The inventory levels, determined by the binary decision variables for inventory (z), indicate that there is no inventory of either Product P1 or Product P2 at the end of any period, except for a 50-unit inventory of Product P1 at the end of period T2. This is in accordance with the inventory balance equations, which ensure that the inventory is correctly updated based on the previous period's production and demand.

The objective function value is calculated based on the deviations from the desired objectives. The objective function value will vary depending on the specific values of the desired quantities, desired decisions, and weights assigned to the objectives. By minimizing the deviations, the production plan aims to achieve a balance among the objectives, considering the priorities assigned to each objective.

Sensitivity analysis can be performed by adjusting the weights $\propto_1, \propto_2, \propto_3$ in the objective function. This analysis allows for the assessment of different objective priorities and their impact on the solution. By comparing the results obtained with different weight combinations, decision-makers can gain insights into the trade-offs among the objectives and determine the most suitable production plan based on their preferences and priorities.

Conclusion.

We proposed a hybrid approach that integrates Goal Programming, Multiple Criteria Decision Making (MCDM), and Dynamic Decision-Making to address the complexities of production planning problems. The objective was to develop a robust and adaptable framework that enables decision-makers to balance conflicting objectives, evaluate alternatives based on multiple criteria, and account for the dynamic nature of the production environment. Through the application of the hybrid approach to a numerical example, we demonstrated its effectiveness in providing an optimal production plan that minimizes deviations from the desired objectives. The solution aligned with the desired decisions, considered production capacity constraints, and maintained inventory balance throughout the planning periods. The sensitivity analysis allowed for the examination of different objective priorities, facilitating a deeper understanding of the trade-offs among the objectives. By combining Goal Programming, MCDM, and Dynamic Decision-Making, the hybrid approach offers several advantages. It allows decision-makers to consider multiple conflicting objectives simultaneously, evaluate alternative production plans based on various criteria, and dynamically adapt the plans to changing circumstances. This comprehensive approach enhances decision-making capabilities and improves the efficiency and effectiveness of production planning processes. The research contributes to the existing body of knowledge by providing a methodology that integrates different methodologies into a cohesive framework for production planning. By addressing the limitations of traditional approaches and considering the dynamic nature of the production environment, the hybrid approach offers a more holistic solution that better meets the needs of manufacturing companies. The proposed hybrid approach can be further extended and customized to fit specific industrial contexts and decision-making requirements. Future research can explore the application of the hybrid approach in real-world case studies, considering additional factors such as supply chain dynamics, pricing, and sustainability. Moreover, the integration of advanced technologies such as artificial intelligence and machine learning can enhance the hybrid approach by enabling predictive analytics and automated decision-making. The hybrid approach combining Goal Programming, MCDM, and Dynamic Decision-Making provides a powerful tool for production planning. Its integration of multiple methodologies enables decision-makers to make informed and optimized decisions, leading to improved resource allocation, customer satisfaction, and operational efficiency in manufacturing systems.

Reference

Abanda, F. H., Chia, E. L., Enongene, K. E., Manjia, M. B., Fobissie, K., Pettang, U., & Pettang, C. (2022). A systematic review of the application of multi-criteria decision-making in evaluating Nationally Determined Contribution projects. *Decision Analytics Journal*, 100140.

Achillas, C., Aidonis, D., Iakovou, E., Thymianidis, M., & Tzetzis, D. (2015). A methodological framework for the inclusion of modern additive manufacturing into the production portfolio of a focused factory. *Journal of Manufacturing Systems*, *37*, 328–339.

Branke, J., Nguyen, S., Pickardt, C. W., & Zhang, M. (2015). Automated design of production scheduling heuristics: A review. *IEEE Transactions on Evolutionary Computation*, *20*(1), 110–124.

Briley, L., Brown, D., & Kalafatis, S. E. (2015). Overcoming barriers during the co-production of climate information for decision-making. *Climate Risk Management*, *9*, 41–49.

Broz, D., Vanzetti, N., Corsano, G., & Montagna, J. M. (2019). Goal programming application for the decision support in the daily production planning of sawmills. *Forest Policy and Economics*, *102*, 29–40.

Colapinto, C., Jayaraman, R., & Marsiglio, S. (2017). Multi-criteria decision analysis with goal programming in engineering, management and social sciences: a state-of-the art review. *Annals of Operations Research*, *251*, 7–40.

Du, J., Park, J., Harjunkoski, I., & Baldea, M. (2015). A time scale-bridging approach for integrating production scheduling and process control. *Computers & Chemical Engineering*, *79*, 59–69.

Fang, L., & Li, H. (2015). Multi-criteria decision analysis for efficient location-allocation problem combining DEA and goal programming. *RAIRO-Operations Research-Recherche Opérationnelle*, *49*(4), 753–772.

Fattahi, M., & Govindan, K. (2022). Data-driven rolling horizon approach for dynamic design of supply chain distribution networks under disruption and demand uncertainty. *Decision Sciences*, *53*(1), 150–180.

Freebairn, L., Atkinson, J.-A., Kelly, P. M., McDonnell, G., & Rychetnik, L. (2018). Decision makers' experience of participatory dynamic simulation modelling: methods for public health policy. *BMC Medical Informatics and Decision Making*, *18*, 1–14.

Gebre, S. L., Cattrysse, D., Alemayehu, E., & Van Orshoven, J. (2021). Multi-criteria decision making methods to address rural land allocation problems: A systematic review. *International Soil and Water Conservation Research*, *9*(4), 490–501.

Gezen, M., & Karaaslan, A. (2022). Energy planning based on Vision-2023 of Turkey with a goal programming under fuzzy multi-objectives. *Energy*, *261*, 124956.

Gholizadeh, H., Fazlollahtabar, H., & Khalilzadeh, M. (2020). A robust fuzzy stochastic programming for sustainable procurement and logistics under hybrid uncertainty using big data. *Journal of Cleaner Production*, *258*, 120640.

Giret, A., Trentesaux, D., & Prabhu, V. (2015). Sustainability in manufacturing operations scheduling: A state of the art review. *Journal of Manufacturing Systems*, *37*, 126–140.

Gorane, S., & Kant, R. (2017). Supply chain practices and organizational performance: An empirical investigation

of Indian manufacturing organizations. *The International Journal of Logistics Management*, *28*(1), 75–101.
Gür, Ş., & Eren, T. (2018). Scheduling and planning in service systems with goal programming: Literature review. *Mathematics*, *6*(11), 265.
Hendalianpour, A., Fakhrabadi, M., Zhang, X., Feylizadeh, M. R., Gheisari, M., Liu, P., & Ashktorab, N. (2019). Hybrid model of IVFRN-BWM and robust goal programming in agile and flexible supply chain, a case study: automobile industry. *IEEE Access*, *7*, 71481–71492.
Igoulalene, I., Benyoucef, L., & Tiwari, M. K. (2015). Novel fuzzy hybrid multi-criteria group decision making approaches for the strategic supplier selection problem. *Expert Systems with Applications*, *42*(7), 3342–3356.
Jacobs, R. F., Berry, W. L., Whybark, D. C., & Vollmann, T. E. (2018). *Manufacturing planning and control for supply chain management: The CPIM Reference*. McGraw-Hill Education.
Jayaraman, R., Liuzzi, D., Colapinto, C., & Malik, T. (2017). A fuzzy goal programming model to analyze energy, environmental and sustainability goals of the United Arab Emirates. *Annals of Operations Research*, *251*, 255–270.
Jia, R., Liu, Y., & Bai, X. (2020). Sustainable supplier selection and order allocation: Distributionally robust goal programming model and tractable approximation. *Computers & Industrial Engineering*, *140*, 106267.
Kouaissah, N., & Hocine, A. (2020). Optimizing sustainable and renewable energy portfolios using a fuzzy interval goal programming approach. *Computers & Industrial Engineering*, *144*, 106448.
Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., & Bansal, R. C. (2017). A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews*, *69*, 596–609.
Ledwith, M. C., Hufstetler, B. J., & Gallagher, M. A. (2021). Stochastic preemptive goal programming to balance goal achievements under uncertainty. *Journal of Multi-Criteria Decision Analysis*, *28*(1–2), 85–98.
Li, Y., Li, K., Yang, Z., Yu, Y., Xu, R., & Yang, M. (2022). Stochastic optimal scheduling of demand response-enabled microgrids with renewable generations: An analytical-heuristic approach. *Journal of Cleaner Production*, *330*, 129840.
Luthra, S., Garg, D., & Haleem, A. (2015). Critical success factors of green supply chain management for achieving sustainability in Indian automobile industry. *Production Planning & Control*, *26*(5), 339–362.
Luthra, S., Mangla, S. K., Shankar, R., Prakash Garg, C., & Jakhar, S. (2018). Modelling critical success factors for sustainability initiatives in supply chains in Indian context using Grey-DEMATEL. *Production Planning & Control*, *29*(9), 705–728.
Mardani, A., Jusoh, A., & Zavadskas, E. K. (2015). Fuzzy multiple criteria decision-making techniques and applications–Two decades review from 1994 to 2014. *Expert Systems with Applications*, *42*(8), 4126–4148.
Mohammadi, S., Al-e-Hashem, S. M. J. M., & Rekik, Y. (2020). An integrated production scheduling and delivery route planning with multi-purpose machines: A case study from a furniture manufacturing company. *International Journal of Production Economics*, *219*, 347–359.
Mokhtari, H., & Hasani, A. (2017). A multi-objective model for cleaner production-transportation planning in manufacturing plants via fuzzy goal programming. *Journal of Manufacturing Systems*, *44*, 230–242.
Mönch, L., Uzsoy, R., & Fowler, J. W. (2018). A survey of semiconductor supply chain models part III: master planning, production planning, and demand fulfilment. *International Journal of Production Research*, *56*(13), 4565–4584.
Moons, S., Ramaekers, K., Caris, A., & Arda, Y. (2017). Integrating production scheduling and vehicle routing decisions at the operational decision level: a review and discussion. *Computers & Industrial Engineering*, *104*, 224–245.
Mufazzal, S., & Muzakkir, S. M. (2018). A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals. *Computers & Industrial Engineering*, *119*, 427–438.
Naliaka, V. W., & Namusonge, G. S. (2015). Role of inventory management on competitive advantage among manufacturing firms in Kenya: A case study of Unga Group Limited. *International Journal of Academic Research in Business and Social Sciences*, *5*(5), 87–104.
Nguyen, S., Mei, Y., & Zhang, M. (2017). Genetic programming for production scheduling: a survey with a unified framework. *Complex & Intelligent Systems*, *3*, 41–66.
Özcan, E. C., Ünlüsoy, S., & Eren, T. (2017). A combined goal programming–AHP approach supported with TOPSIS for maintenance strategy selection in hydroelectric power plants. *Renewable and Sustainable Energy Reviews*, *78*, 1410–1423.
Petrović, G., Mihajlović, J., Ćojbašić, Ž., Madić, M., & Marinković, D. (2019). Comparison of three fuzzy MCDM methods for solving the supplier selection problem. *Facta Universitatis, Series: Mechanical Engineering*, *17*(3), 455–469.
Sayyadi, R., & Awasthi, A. (2020). An integrated approach based on system dynamics and ANP for evaluating sustainable transportation policies. *International Journal of Systems Science: Operations & Logistics*, *7*(2),

182–191.
Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). *Computers & Industrial Engineering*, *140*, 106231.
Tang, L., & Meng, Y. (2021). Data analytics and optimization for smart industry. *Frontiers of Engineering Management*, *8*(2), 157–171.
Taşkıner, T., & Bilgen, B. (2021). Optimization models for harvest and production planning in agri-food supply chain: A systematic review. *Logistics*, 5(3), 52.
Tirkolaee, E. B., Dashtian, Z., Weber, G.-W., Tomaskova, H., Soltani, M., & Mousavi, N. S. (2021). An integrated decision-making approach for green supplier selection in an agri-food supply chain: Threshold of robustness worthiness. *Mathematics*, *9*(11), 1304.
Toledo, C. F. M., da Silva Arantes, M., Hossomi, M. Y. B., & Almada-Lobo, B. (2016). Mathematical programming-based approaches for multi-facility glass container production planning. *Computers & Operations Research*, *74*, 92–107.
Trevino-Martinez, S., Sawhney, R., & Shylo, O. (2022). Energy-carbon footprint optimization in sequence-dependent production scheduling. *Applied Energy*, *315*, 118949.
Trivedi, A., & Singh, A. (2017). A hybrid multi-objective decision model for emergency shelter location-relocation projects using fuzzy analytic hierarchy process and goal programming approach. *International Journal of Project Management*, *35*(5), 827–840.
Turkoglu, D. C., Cedolin, M., & Genevois, M. E. (2018). An Integrated Approach for ATM Location Strategy Using Analytic Network Process and Weighted Goal Programming. *WSEAS Transactıons on Business and Economics 15*, 236–248.
Varela, M. L. R., Trojanowska, J., Carmo-Silva, S., Costa, N. M. L., & Machado, J. (2017). *Comparative simulation study of production scheduling in the hybrid and the parallel flow*.
Wang, C.-N., Nhieu, N.-L., & Tran, T. T. T. (2021). Stochastic chebyshev goal programming mixed integer linear model for sustainable global production planning. *Mathematics*, *9*(5), 483.
Weskamp, C., Koberstein, A., Schwartz, F., Suhl, L., & Voß, S. (2019). A two-stage stochastic programming approach for identifying optimal postponement strategies in supply chains with uncertain demand. *Omega*, *83*, 123–138.
Yadav, R. (2021). Analytic hierarchy process-technique for order preference by similarity to ideal solution: a multi criteria decision-making technique to select the best dental restorative composite materials. *Polymer Composites*, *42*(12), 6867–6877.
Yannis, G., Kopsacheili, A., Dragomanovits, A., & Petraki, V. (2020). State-of-the-art review on multi-criteria decision-making in the transport sector. *Journal of Traffic and Transportation Engineering (English Edition)*, *7*(4), 413–431.
Zare, H., Kamali Saraji, M., Tavana, M., Streimikiene, D., & Cavallaro, F. (2021). An Integrated Fuzzy Goal Programming—Theory of Constraints Model for Production Planning and Optimization. *Sustainability*, *13*(22), 12728.
Zhang, L., Lu, J., & Yang, Z. (2021). Optimal scheduling of emergency resources for major maritime oil spills considering time-varying demand and transportation networks. *European Journal of Operational Research*, *293*(2), 529–546.
Zhang, Y., Zhang, G., Wang, J., Sun, S., Si, S., & Yang, T. (2015). Real-time information capturing and integration framework of the internet of manufacturing things. *International Journal of Computer Integrated Manufacturing*, *28*(8), 811–822.
Zhou, L., Jiang, Z., Geng, N., Niu, Y., Cui, F., Liu, K., & Qi, N. (2022). Production and operations management for intelligent manufacturing: A systematic literature review. *International Journal of Production Research*, *60*(2), 808–846.