Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 9, Number 3 2025
DOI: 10.30829/zero.v9i3.26953
Page: 819-832

Integrating Triple-Bottom-Line Goals and Uncertainty in Aggregate Production Planning Using Fuzzy Goal Programming

[1] Nabila Zakia Indra
Department of Industrial and Systems Engineering, Institute Teknologi Sepuluh Nopember, Indonesia

[2] Budi Santosa
Department of Industrial and Systems Engineering, Institute Teknologi Sepuluh Nopember, Indonesia

[3] Nurhadi Siswanto
Department of Industrial and Systems Engineering, Institute Teknologi Sepuluh Nopember, Indonesia

Article Info

Article history:

Accepted, 26 December 2025

Keywords:
Fuzzy Goal Programming;
Multi-objective Optimization;
Optimization;
Planning;
Sustainable Aggregate Production;
Triple Bottom Line.

ABSTRACT

This study develops a Sustainable Aggregate Production Planning (SAPP) model based on Fuzzy Goal Programming (FGP) that integrates economic, environmental, and social objectives under uncertainty. Conventional aggregate production planning primarily focuses on cost minimization, often resulting in excessive overtime, high emissions, and workforce instability. To address these limitations, the proposed model simultaneously considers total cost, carbon emissions, energy consumption, waste generation, workforce stability, and worker satisfaction within a unified fuzzy optimization framework. From a mathematical perspective, the main contribution of this study lies in the explicit formulation of a max–min FGP structure using aspiration-based linear membership functions for all sustainability objectives, enabling a balanced compromise solution without relying on deviation-variable-based goal programming commonly adopted in existing SAPP models. The resulting formulation is a linear mixed-integer optimization model that preserves tractability while accommodating conflicting sustainability goals. Numerical experiments are conducted using illustrative demand and operational data adapted from a reference study, solely for mathematical calibration and validation of the proposed model rather than empirical inference. The results indicate a global satisfaction level of $\lambda = 0.67$, representing a balanced max–min compromise among economic, environmental, and social objectives. Compared to the baseline scenario, the optimized plan achieves notable improvements in cost efficiency and waste reduction while keeping emissions, energy consumption, and workforce-related indicators within predefined fuzzy tolerance limits. Overall, the proposed SAPP–FGP model provides a transparent and flexible decision-support framework for sustainability-oriented production planning, offering clear insights into trade-offs among competing objectives and contributing to the applied mathematical literature on multi-objective production planning under uncertainty.

Corresponding Author:

Budi Santosa,
Department of Industrial and Systems Engineering,
Institute Teknologi Sepuluh Nopember,
Email: budi_s@ie.its.ac.id

1. INTRODUCTION

Global pressures related to climate change, energy efficiency, and corporate social accountability have positioned sustainability as a strategic priority in modern manufacturing systems. Manufacturing companies are increasingly required to balance economic performance with environmental protection and social responsibility to ensure long-term competitiveness and regulatory compliance [1], [2], [3]. Consequently, production planning approaches must evolve from traditional cost-oriented frameworks toward more comprehensive models that integrate sustainability considerations.

Aggregate Production Planning (APP) is a critical medium-term decision-making process that coordinates production volume, workforce levels, inventory, and capacity utilization over a planning horizon [1], [2], [3]. However, conventional APP models primarily emphasize economic objectives, particularly cost minimization, while largely neglecting environmental and social dimensions [4], [5], [6]. Such economically driven decisions may result in excessive overtime, high energy consumption, increased emissions, workforce instability, and reduced employee well-being [7], [8]. These limitations reduce the suitability of traditional APP approaches for addressing contemporary sustainability challenges in manufacturing systems.

To address these shortcomings, recent studies have extended conventional APP toward Sustainable Aggregate Production Planning (SAPP), which explicitly incorporates environmental and social objectives alongside economic performance [1], [5], [6], [9]. Environmental considerations in SAPP typically include emission reduction, energy efficiency, waste minimization, and responsible resource utilization [12], [13], [14], [15], [16]. Manufacturing activities contribute significantly to global environmental impacts, accounting for approximately 14% of national greenhouse gas emissions in 2021 [10] and more than 30% of global industrial emissions [11], underscoring the importance of embedding environmental objectives into production planning decisions.

Despite this growing body of literature, clear research gaps remain. First, while many SAPP models incorporate multiple environmental indicators, social sustainability is often treated qualitatively or omitted, with limited attempts to explicitly model workforce-related aspects such as stability and worker satisfaction using quantitative proxy functions [17], [18], [19]. Second, although Fuzzy Goal Programming (FGP) has been widely applied to APP and sustainable production planning, most existing models rely on deviation-variable-based goal programming structures or focus on partial sustainability integration, rather than a unified triple-bottom-line formulation with consistent fuzzy membership design [20], [21]. As a result, the mathematical structure of social objectives and their interaction with economic and environmental goals remain insufficiently explored.

The limitations of conventional approaches necessitate an evolved planning framework. Table 1 provides a clear comparison between the objectives and operational scope of conventional Aggregate Production Planning (APP) and the Sustainable Aggregate Production Planning (SAPP) framework proposed in this study.

Table 1. Comparison Between Conventional Aggregate Production Planning and Sustainable Aggregate Production Planning

Aspect	Conventional APP	Sustainable APP
Main Focus	Minimization of production cost	Minimization of cost, environmental impact, and enhancement of social aspects
Sustainability Dimension	Economic only	Economic – environmental – social
Environmental	Not considered	Modeled and constrained
Social	Not included	Effects of overtime, layoffs, job stability, and worker well-being
Uncertainty	Deterministic	Fuzzy
Output	Minimum-cost production plan	Sustainability-oriented production plan

Figure 1 illustrates the conceptual integration of economic, environmental, and social dimensions within the proposed SAPP framework.

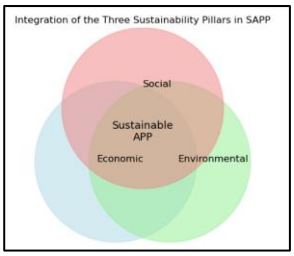

Figure 1. Integration of the Three Sustainability Pillars in SAPP

In practical production systems, sustainability targets are rarely defined as precise numerical values and are more commonly expressed as flexible aspiration ranges influenced by managerial judgment and regulatory tolerance. Fuzzy Goal Programming (FGP) provides an appropriate mathematical framework to represent such imprecision by employing aspiration-based fuzzy membership functions and aggregating multiple objectives through a max–min satisfaction structure [22], [23], [24]. This approach allows conflicting sustainability objectives to be balanced explicitly without enforcing rigid deterministic targets, making it suitable for sustainability-oriented aggregate production planning under uncertainty.

Based on these considerations, this study proposes a Sustainable Aggregate Production Planning (SAPP) model using Fuzzy Goal Programming that simultaneously integrates economic, environmental, and social objectives under uncertainty. The specific contribution of this study lies in the mathematical formulation of a unified max–min FGP model that explicitly incorporates five sustainability objectives—total cost, carbon emissions, energy consumption, waste generation, workforce stability, and worker satisfaction—using consistent aspiration-based linear membership functions without introducing deviation variables. In addition, social sustainability is modeled through explicit linear proxy functions linked to workforce decisions, enabling quantitative integration of social aspects within the triple-bottom-line framework. This formulation distinguishes the proposed model from prior FGP-based APP studies that focus on partial sustainability integration or alternative goal programming structures [23], [24].

The effectiveness of the proposed model is demonstrated through numerical experiments using simulation-based demand and operational data adapted from a reference study, showing its capability to generate feasible and balanced production plans across competing sustainability dimensions.

2. RESEARCH METHOD

This study adopts a quantitative computational research design based on mathematical optimization. The proposed framework is formulated as a Sustainable Aggregate Production Planning (SAPP) model that integrates economic, environmental, and social objectives using a Fuzzy Goal Programming (FGP) approach. The model is designed to generate balanced production plans under sustainability trade-offs while accommodating imprecision in managerial preferences through fuzzy aspiration levels.

2.1 Research Design

This study employs a quantitative computational research design based on mathematical optimization. The proposed approach formulates a Sustainable Aggregate Production Planning (SAPP) model that integrates economic, environmental, and social objectives using a Fuzzy Goal Programming (FGP) framework [3], [25]. The objective of the model is to generate sustainability-oriented production plans by balancing conflicting goals under uncertainty, while maintaining the feasibility and interpretability of the resulting solutions.

The FGP approach is selected because it allows imprecise managerial preferences and flexible sustainability targets to be represented explicitly through fuzzy aspiration levels and tolerance ranges, making it suitable for complex multi-objective production planning problems [22] , [23].

2.2 Data Source and Variables

For clarity, the data employed in this study are not intended to generate new empirical insights. Instead, they are used solely to illustrate, calibrate, and numerically validate the proposed SAPP–FGP model within an applied mathematics context. The focus of the study lies in the mathematical formulation and solution behavior of the optimization model rather than empirical estimation or forecasting of industrial performance.

The reference dataset is adapted from a prior study [26], and undergoes minor transformations to ensure consistency with the modeling framework. Specifically, the planning horizon is discretized into monthly periods, and all cost, emission, energy, and waste coefficients are normalized on a per-unit production basis. No structural modification of the original relationships is introduced; scaling is applied only to harmonize units and align magnitudes across economic, environmental, and social objectives for numerical stability in optimization.

For the environmental dimension, national and industrial sector greenhouse gas (GHG) emissions data from 2017 to 2021 are used to provide contextual grounding for environmental target setting. Table 2 presents national and industrial sector GHG emissions, while Table 3 reports the corresponding annual growth of industrial emissions. These data are not directly optimized within the model but are employed to justify the selection of aspiration levels and tolerance ranges for environmental objectives, ensuring consistency with observed emission trends and regulatory considerations [10], [11].

Table 2. Industrial Sector Carbon Emissions

Year	National GHG Emissions (Gt CO_2-e)	Industrial Sector GHG Emissions (Gt CO_2-e)	Industrial Sector Contribution (%)
2017	1.80	0.22	12.2
2018	1.85	0.23	12.4
2019	1.88	0.24	12.8
2020	1.90	0.26	13.7
2021	1.95	0.28	14.4

The annual growth of industrial emissions is presented in Table 3.

Table 3. Annual Growth of Industrial Carbon Emissions

Year	Industrial Emissions (Gt CO_2-e)	Annual Increase (Gt CO_2-e)	Percentage Increase (%)
2017	0.22	-	-
2018	0.23	+0.01	+4.5%
2019	0.24	+0.01	+4.3%
2020	0.26	+0.02	+8.3%
2021	0.28	+0.02	+7.7%

Let E^{base}denote the baseline industrial sector emission level obtained from the reference data. Based on the observed annual growth rates in Table 3, the aspiration level for environmental objectives is defined as a proportional reduction from the baseline, while the worst acceptable level corresponds to the upper-bound growth trend. Formally, the aspiration and tolerance bounds are defined as

$$E^{*} = (1-\delta)E^{base}, E^{worst} = (1+\rho)E^{base}$$

where δ represents the targeted emission reduction ratio and ρreflects the observed emission growth tolerance derived from historical trends.

Social sustainability indicators, namely workplace accidents and worker satisfaction, are constructed based on a structured interpretation of the reference study [26] rather than direct empirical measurement. Workplace accidents are modeled as proxy variables associated with workload intensity, overtime production, and workforce size, reflecting established relationships between operational pressure and occupational risk [29]. Worker satisfaction is represented as an index influenced by workforce stability, overtime intensity, and layoffs, consistent with findings in human resource and operations management literature [30].

It should be emphasized that the construction of social indicators relies on simplified, linear proxy representations derived from the literature and scaled into index form for inclusion in the mathematical model. While this approach enables the explicit integration of social objectives into the optimization framework, it does not fully capture the behavioral or psychological complexity of human-centered outcomes. Furthermore, all numerical input data are treated deterministically; the fuzzy nature of the model arises from the specification of aspiration levels and tolerance ranges rather than from stochastic variability in the data.

Finally, the use of a single adapted dataset constitutes a methodological limitation. Although this approach ensures internal consistency and reproducibility, it may restrict the generalizability of the numerical results to other industrial contexts. This limitation is acknowledged explicitly at the methodological level and motivates future research directions involving multi-source datasets and empirical validation.

2.3 Decision Variables and Parameters

The decision variables of the SAPP model include regular production P_t, overtime production O_t, subcontracting S_t, ending inventory I_t, backorders B_t, workforce size W_t, worker recruitment R_t, and worker dismissal F_t. Social performance is represented using two distinct indices: workforce stability $WS_t$and worker satisfaction TS_t.

All decision variables and model parameters are consistently defined in Table 4 and Table 5, respectively, to ensure clarity and avoid notational ambiguity throughout the mathematical formulation.

Table 4. Decision Variables

Variable	Description	Unit
P_t	Regular production in period *t*	unit
O_t	Overtime production in period *t*	unit
S_t	Subcontracting in period *t*	unit
I_t	Ending inventory in period *t*	unit
B_t	Backorder in period *t*	unit
W_t	Number of workers in period *t*	person
R_t	Number of recruited workers in period *t*	person
F_t	Number of dismissed workers in period *t*	person
U_t	Auxiliary variable for workforce variation linearization	person
Acc_t	Workplace accident index in period *t*	index
Sat_t	Worker satisfaction index in period *t*	index
SB	Workforce stability index (aggregate over planning horizon)	index

The key parameters used in the economic, environmental, and social dimensions are presented below:

Table 5. Research Parameters

Variable	Description	Unit
D_t	Demand in period t	unit
n_t	Working days	days
H	Regular working hours per day	Hours/day
k	Production capacity per worker per day	Unit/person/day
C_p, C_o, C_s	Production costs	Dollar/unit
E_{pr}, E_{ot}, E_{sc}	Carbon emissions	kg CO_2/unit
En_{pr}, En_{ot}, En_{sc}	Energy consumption	kWh/unit
$\gamma_p, \gamma_s, \gamma_o$	Waste generation	Kg waste/unit
W_{lim}	Workforce stability limit	person
H_t	max allowable working hours	hour
m_{hour}	overtime productivity multiplier	-
α_1, α_2, α_3,	Coefficient linking overtime to accident risk	-
η	Service level parameter	-

2.4 Analytical Framework and Model Formulation

This subsection presents the analytical structure and mathematical formulation of the proposed Sustainable Aggregate Production Planning (SAPP) model based on Fuzzy Goal Programming (FGP). The multi-objective planning problem is transformed into a single optimization model using a max–min FGP structure, which allows economic, environmental, and social objectives to be addressed simultaneously. The formulation includes the definition of objective functions, operational constraints, aspiration levels, fuzzy tolerances, and linear membership functions, culminating in the maximization of a global satisfaction variable λ.

2.4.1 Objective Functions

The proposed Sustainable Aggregate Production Planning (SAPP) model incorporates five sustainability objectives that represent the economic, environmental, and social dimensions of the planning problem. The economic objective aims to minimize total production-related costs, including regular production, overtime, subcontracting, inventory holding, backorder penalties, recruitment, layoffs, and labor costs. The environmental objectives focus on minimizing total carbon emissions, energy consumption, and waste generation associated with production and inventory activities. Meanwhile, the social objectives seek to enhance workforce-related performance by minimizing workforce instability and maximizing worker satisfaction. These objectives are formally expressed through mathematical formulations, as presented in Equations (1) through (6).

Economic objective (Total Cost):

$$TC_t = \sum_{i=1}^{T} c_p P_t + c_o O_t + c_s S_t + c_h I_t + c_b B_t + c_H R_t + c_F F_t + c_L (H \cdot n_t \cdot W_t) \tag{1}$$

Environmental objectives:

$$TE = \sum_{i=1}^{T} E_p P_t + E_s S_t + E_o O_t + E_{in} I_t \tag{2}$$

$$EN = \sum_{i=1}^{T} En_p P_t + En_s S_t + En_o O_t + En_{in} I_t \tag{3}$$

$$WL = \sum_{i=1}^{T} \gamma_p P_t + \gamma_s S_t + \gamma_o O_t + \gamma_{in} I_t \tag{4}$$

Social objectives:

Workforce stability is measured as the total fluctuation in workforce size:

$$U_t \geq W_t - W_{t-1} \tag{5}$$

$$SB = \sum_{i=1}^{T} U_t \tag{6}$$

Worker satisfaction is represented as a linear index influenced by workforce size, overtime, and layoffs:

$$SAT = \sum_{i=1}^{T} (\alpha_3 W_t - \alpha_1 O_t - \alpha_2 F_t) \tag{7}$$

2.4.2 System Constraints

The proposed SAPP model is subject to a set of deterministic operational constraints to ensure feasibility of production, workforce, inventory, environmental, and service-level decisions.
Inventory balance and demand satisfaction:

$$P_t + O_t + S_t + I_{t-1} - I_t + B_{t-1} - B_t = D_t \quad \forall t \tag{8}$$

Regular-time production capacity:

$$P_t \leq K \cdot H \cdot n_t \cdot W_t \quad \forall t \tag{9}$$

Overtime production capacity:

$$O_t \leq K \cdot W_t (m_{hour} - H_t) \quad \forall t \tag{10}$$

Workforce evolution:

$$W_t = W_{t-1} + R_t - F_t \quad \forall t \tag{11}$$

Workforce stability limit:

$$|W_t - W_{t-1}| \leq S_{lim} \tag{12}$$

Layoff limit:

$$F_t \leq L_{lim} \cdot W_{t-1} \quad \forall t \tag{13}$$

Environmental constraints:

$$TE \leq E_{cap} \tag{14}$$
$$En \leq En_{cap}$$

$$WL \leq WL_{cap} \tag{15}$$

Service level constraint:

$$B_t \leq (1 - \alpha) D_t \tag{16}$$

Non-negativity constraints:

$$P_t, O_t, S_t, I_t, B_t, R_t, F_t \geq 0 \quad \forall t \tag{17}$$

2.4.3 Fuzzy Goal Programming Structure

To integrate the multiple sustainability objectives, a max–min Fuzzy Goal Programming (FGP) structure is employed. For each objective j, a membership function $\mu_j$is defined to represent the degree of satisfaction with respect to its aspiration level and tolerance range. In this study, deviation-variable-based goal programming is not employed; instead, satisfaction levels are directly modeled using aspiration-based fuzzy membership functions. The main objective of the FGP model is to maximize the global satisfaction level λ, subject to:

$$max\, \lambda\, s.t \quad \lambda \leq \mu_j, \qquad \forall_j \tag{18}$$

2.4.4 Aspiration Levels and Fuzzy Tolerances

In the Fuzzy Goal Programming (FGP) framework, each sustainability objective is characterized by an aspiration level and an associated tolerance range that reflect acceptable deviations from the desired performance. Unlike deterministic optimization, where target values are imposed as rigid constraints, the use of aspiration-based fuzzy goals allows flexibility in balancing conflicting objectives while preserving the feasibility and interpretability of the solution.

For each objective z, the aspiration level $g_z$is derived from the corresponding baseline value $Z^{baseline}$, which represents the system performance before the incorporation of fuzzy sustainability trade-offs. The baseline values are obtained from the non-fuzzy aggregate production planning solution and serve as reference points for constructing fuzzy membership functions. The aspiration level is defined as a proportional adjustment of the baseline value, expressed as:

$$g_z = \alpha Z^{baseline},$$

where $\alpha$is a scaling parameter that depends on the direction of optimization.

For minimization objectives—including total production cost, carbon emissions, energy consumption, and waste generation—the aspiration level is set using $\alpha = 0.9$, corresponding to a 10% improvement relative to the baseline. This choice reflects a realistic performance enhancement target that is sufficiently ambitious while remaining attainable under operational and sustainability constraints. For maximization objectives related to social sustainability, the aspiration level is set at the baseline level ($\alpha = 1.0$), reflecting the objective of preserving or marginally improving workforce-related performance without imposing overly restrictive targets.

To capture operational flexibility and prevent infeasibility, a worst acceptable level $g_z^{worst}$is also specified for each objective. This level defines the boundary beyond which performance is considered unacceptable and is expressed as:

$$g_z^{worst} = \beta Z^{baseline}$$

where βdenotes the tolerance parameter. For minimization objectives, $\beta = 1.5$ is adopted, allowing deviations of up to 50% above the baseline value. For maximization objectives, the worst acceptable level is defined using $\beta = 0.9$, permitting limited deterioration while maintaining social feasibility.

The selection of the scaling parameters $\alpha$and βserves two main purposes. First, it normalizes objectives with different units and magnitudes, enabling their integration into a unified satisfaction scale within the FGP framework. Second, it prevents dominance of any single objective by bounding feasible deviations within a realistic operational range. These aspiration levels and tolerance limits form the basis for constructing linear membership functions in the subsequent subsection, which translate objective values into degrees of satisfaction used to determine the global satisfaction level of the system.

2.4.5 Linear Membership Functions

For objectives requiring minimization, the membership function is defined as:

$$\mu z(x) = \begin{cases} 1 & x \le g_z \\ \dfrac{g_z^{worst} - x}{g_z^{worst} - g_z} & g_z < x < g_z^{worst} \\ 0 & x \ge g_z^{worst} \end{cases} \tag{19}$$

For objectives requiring maximization, the membership function is defined as:

$$\mu z(x) = \begin{cases} 1 & x \le g_z^{worst} \\ \dfrac{x - g_z^{worst}}{g_z - g_z^{worst}} & g_z^{worst} < x < g_z \\ 0 & x \ge g_z \end{cases} \tag{20}$$

These linear membership functions ensure transparent and interpretable trade-offs between aspiration achievement and deviation, enabling balanced compromise solutions across all sustainability objectives.

2.5 Summary of the Proposed SAPP–FGP Formulation

In summary, the proposed Sustainable Aggregate Production Planning (SAPP) model formulates the production planning problem as a multi-objective linear optimization framework that explicitly integrates economic, environmental, and social sustainability objectives. Operational decision variables including production quantities, inventory levels, subcontracting, and workforce adjustments are linked to sustainability objectives through aspiration-based fuzzy membership functions.

Each objective is transformed into a normalized satisfaction measure, enabling heterogeneous performance criteria with different units and scales to be evaluated on a common basis. A max–min Fuzzy Goal Programming (FGP) structure is then employed to maximize the global satisfaction level λ, ensuring that no single objective dominates the solution and that trade-offs are resolved in a balanced manner.

Owing to the linear structure of the objective functions, constraints, and membership functions, the feasible region forms a bounded polyhedral set, allowing the model to be efficiently solved using standard linear or mixed-integer programming solvers. This formulation provides a transparent and computationally tractable framework for analyzing sustainability-oriented production planning decisions. The numerical behavior and trade-offs implied by the proposed model are examined in the following Results and Analysis section.

2.6 Discussion of Assumptions and Methodological Implications

Several simplifying assumptions underpin the proposed SAPP–FGP model. Social sustainability indicators are modeled using linear proxy functions derived from workforce size, overtime, and layoffs. While these approximations support computational feasibility and transparency, they may not fully capture nonlinear behavioral responses or psychological factors present in real production environments.

Although fuzzy logic is employed, all numerical inputs are treated deterministically. In this context, fuzziness represents imprecision in sustainability targets and managerial preferences rather than stochastic variability in demand or costs [20], [21]. These assumptions enhance tractability and model interpretability but may limit external validity. Accordingly, future research may extend the proposed framework by incorporating stochastic demand, nonlinear social response functions, or empirically validated human resource data.

2.7 Software

The proposed SAPP–FGP model was implemented using Python as the primary programming language. The mixed-integer linear programming formulation was solved using the PuLP optimization library. Data processing and management were conducted using Pandas, while Matplotlib was employed for graphical visualization. All computational experiments were executed in a Jupyter Notebook environment to ensure transparency, reproducibility, and ease of model extension.

3. RESULT AND ANALYSIS

3.1 Baseline Performance of Sustainable Aggregate Production Planning

The baseline computation was conducted to establish a reference point for evaluating the effectiveness of the proposed FGP-based SAPP model. The baseline solution represents the performance of the production system prior to the application of fuzzy goal programming and covers all three sustainability dimensions: economic performance (total cost), environmental impact (carbon emissions, energy consumption, and waste generation), and social performance (workforce stability).

As summarized in Table 6, the baseline results indicate relatively high production costs and substantial environmental impacts. These outcomes are primarily driven by the reliance on overtime production and frequent workforce adjustments to accommodate demand fluctuations. From a social perspective, the baseline scenario exhibits unstable workforce conditions, as reflected by high workforce variability caused by hiring and layoffs. Consequently, these baseline values serve as the reference levels for constructing fuzzy membership functions and defining aspiration targets in the subsequent optimization stage.

Table 6. Production System Baseline

Aspect	Variable	Baseline Value	Unit
Economic	Total Cost (TC)	2.260.387.926	Dollar
Environmental	Total Emissions (TE)	121.002	Kg CO_2
Environmental	Energy Use (EN)	21.385.877	kWh
Environmental	Waste (WL)	160.225	Kg waste
Social	SB		Score

3.2 Fuzzy Goal Programming Optimization Results

The Fuzzy Goal Programming (FGP) model was applied to a 12-period annual planning horizon. The optimization yielded a global satisfaction level of

$$\lambda = 0.6746$$

indicating that the system achieved approximately 67% of the predefined fuzzy aspiration targets. In the context of a max–min FGP framework, this value represents a balanced compromise solution in which all sustainability objectives—Total Cost, Emissions, Energy Use, Waste, Workforce Stability, and Worker Satisfaction—converge at a common satisfaction level. This result confirms that no single objective dominates the optimization outcome and that trade-offs among conflicting goals are resolved systematically.

Table 7. Comparison Between Baseline and FGP Optimization Results

Aspect	Variable	Baseline Value	FGP Result	Change	Unit
Economic	Total Cost (TC)	2.260.387.926	1.870.278.476	↓ 17%	Dollar
Environmental	Total Emissions (TE)	121.002	114.168	↓ 5.7%	Kg CO_2
Environmental	Energy Use (EN)	21.385.877	19.979.400	↓ 6.6%	kWh
Environmental	Waste (WL)	160.225	108.159	↓ 32.5%	Kg waste

A comprehensive comparison between the baseline scenario and the optimized FGP solution is presented in Table 7. The results show significant improvements across the sustainability dimensions, including a 17% reduction in total production cost and a substantial 32.5% reduction in waste generation. Moderate reductions are also observed for carbon emissions (5.7%) and energy consumption (6.6%). These improvements are consistent with the objectives of the proposed SAPP–FGP model and demonstrate its effectiveness in coordinating economic efficiency with environmental performance.

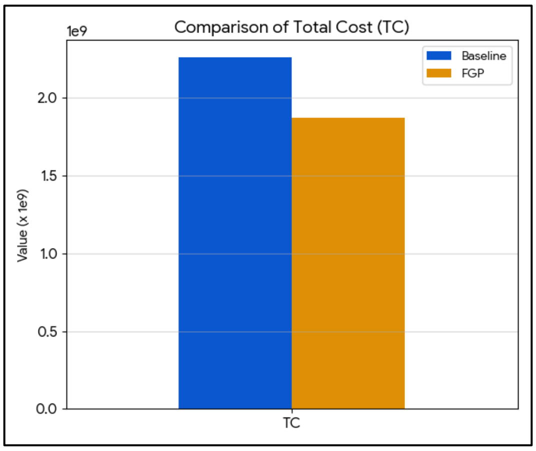

Figure 2. Comparison of Total Cost (TC)

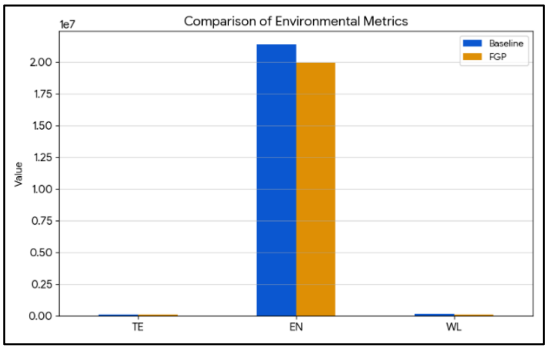

Figure 3. Comparison of Environmental Metrics

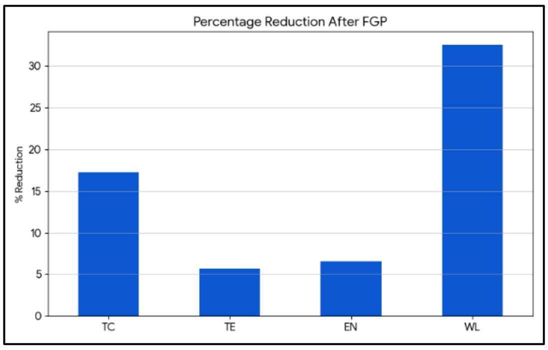

Figure 4. Percentage Reduction After FGP

From a mathematical perspective, the graphical trends exhibit smooth and monotonic improvements when transitioning from the baseline to the optimized FGP solution. The absence of abrupt slope changes suggests that the optimal solution lies within the interior of the feasible polyhedral region rather than at extreme boundary points. This behavior is consistent with the max–min FGP structure, in which the global satisfaction level $\lambda$is governed by the most restrictive objective, leading to balanced adjustments across decision variables rather than sharp trade-offs.

1. Economic
   Inventory trajectories remain stable without extreme fluctuations, reflecting controlled stock management throughout the planning horizon. Backorders occur only in several periods and remain within the required service level constraint ($\alpha = 0.99$), indicating that demand fulfillment is prioritized without sacrificing workforce stability or environmental feasibility.
2. Environmental
   Total carbon emissions reach 114,168 kg CO_2, remaining within the specified fuzzy tolerance ($\Delta = 21{,}000$ kg). Emission reductions are primarily achieved by suppressing overtime production and reallocating part of the production load to subcontracting, which is generally associated with higher energy efficiency. Energy consumption amounts to 19,979,400 kWh, slightly exceeding the aspiration level but still within the fuzzy tolerance ($\Delta = 4$ million kWh) [27] [28]. Waste generation totals 108,159 kg and follows a linear relationship with regular production volume, indicating that waste levels are driven mainly by production scale rather than inefficiencies.
3. Social
   Workforce Stability (WS) reaches a value of 46,844, remaining within the defined fuzzy tolerance ($\Delta = 143{,}960$). Worker Satisfaction (TS) attains a value of 1,025 with minimal deviation from its tolerance ($\Delta = 3{,}150$). These results reflect the model's ability to limit overtime and layoffs while maintaining a stable workforce structure [29] [30].

From a modeling standpoint, the proposed SAPP–FGP formulation constitutes a linear mixed-integer optimization problem with linear objective functions and constraints, yielding a bounded feasible region and guaranteeing the existence of a global optimum. Although multiple optimal solutions may exist in terms of individual decision variables, the max–min FGP structure ensures stability of the global satisfaction level λunder bounded variations of fuzzy parameters, supporting the robustness and numerical reliability of the obtained solution.

3.3 Sensitivity Analysis of Fuzzy Parameters

To examine the robustness of the proposed SAPP–FGP model, a concise sensitivity analysis is conducted on the key fuzzy parameters, namely the aspiration scaling factor $\alpha$and the tolerance parameter β. These parameters directly influence the construction of the membership functions and, consequently, the global satisfaction level λ.

First, the aspiration parameter α for minimization objectives is varied within the range (0.85, 0.95) representing target improvements of 5%–15% relative to the baseline solution. The results show a monotonic decrease in the optimal satisfaction level λ as $\alpha$is reduced, indicating that more ambitious sustainability targets lead to lower overall satisfaction. However, the model remains feasible for all tested values, and the relative ranking of economic, environmental, and social performance indicators is preserved. This confirms that the proposed formulation is not overly sensitive to moderate changes in aspiration levels.

Next, the tolerance parameter β is varied for minimization objectives within the interval (1.3, 1.6). As expected, increasing β relaxes the worst acceptable performance bounds, resulting in higher values of λ. The observed relationship between β and $\lambda$is smooth and non-disruptive, with no abrupt changes in the optimal production plan structure. This behavior suggests that the model responds consistently to changes in tolerance width and does not rely on narrowly tuned fuzzy parameters.

Overall, the sensitivity results demonstrate that the SAPP–FGP model exhibits stable and interpretable behavior under reasonable variations of fuzzy aspiration and tolerance parameters. This confirms that the numerical results reported in the previous subsections are robust and not driven by arbitrary parameter selection, thereby strengthening the applied mathematical validity of the proposed approach.

3.4 Comparative Analysis

The optimized SAPP–FGP solution exhibits clear trade-off behavior among the economic, environmental, and social objectives. Although further reductions in total production cost are theoretically possible, such reductions would require increased overtime production or more aggressive workforce adjustments. These actions would violate the workforce stability constraint and reduce worker satisfaction, thereby decreasing the minimum satisfaction level across objectives. As a result, the economic objective becomes partially constrained by social sustainability considerations at the optimum.

Environmental objectives also play a critical role in shaping the compromise solution. Reductions in carbon emissions and energy consumption are primarily achieved through the suppression of overtime production and the selective use of subcontracting. However, imposing stricter environmental targets would increase reliance on subcontracting, leading to higher production costs. This interaction illustrates a Pareto-like trade-off between economic efficiency and environmental performance within the defined fuzzy tolerance region.

Several constraints are binding at the optimal solution. The workforce stability constraint limits abrupt changes in workforce size, while environmental caps on emissions and energy consumption restrict the feasible solution space. In addition, the service level constraint ensures demand fulfillment and prevents excessive backorders. The combined effect of these active constraints determines the achieved global satisfaction level $\lambda = 0.6746$, highlighting the role of constraint interaction in producing a balanced sustainability-oriented production plan.

3.5 Discussion

The results demonstrate that the proposed Sustainable Aggregate Production Planning model based on Fuzzy Goal Programming (SAPP–FGP) is capable of generating balanced compromise solutions across economic, environmental, and social objectives. The observed reduction in total production cost relative to the baseline, although not maximal from a purely economic perspective, reflects the influence of environmental and social constraints that limit aggressive cost minimization. This outcome is consistent with the underlying max–min FGP principle, in which improvements in one objective are bounded by the satisfaction levels of the most restrictive objectives.

From an environmental standpoint, the model effectively reduces emissions, energy consumption, and waste toward their respective aspiration levels. The results indicate that emission reductions are primarily achieved through the suppression of overtime production and a controlled increase in subcontracting, which aligns with findings in related sustainable APP studies that associate overtime with higher energy intensity and emissions. Energy consumption slightly exceeds its aspiration target but remains within the defined fuzzy tolerance, highlighting the role of fuzzy constraints in accommodating operational realities during high-demand periods. Waste reduction emerges as the most significant environmental improvement, suggesting that waste levels in the system are highly responsive to optimized production scheduling rather than structural changes in inventory or subcontracting.

Social sustainability outcomes further illustrate the compromise nature of the solution. Workforce stability improves substantially as the model limits frequent hiring and layoffs, while worker satisfaction remains positive despite the reduction in overtime. These outcomes are consistent with the structure of the social objective functions, which penalize excessive workforce adjustments and overtime intensity. However, it should be emphasized that the social indicators are represented using simplified linear proxy functions. While these formulations enable integration into the optimization framework and provide meaningful directional insights, they do not fully capture complex behavioral or psychological dimensions of human resource performance. Consequently, the social results should be interpreted as indicative rather than predictive, and empirical validation using real workforce data is required for stronger generalization.

When compared with related FGP-based and multi-objective aggregate production planning models reported in the literature, the achieved global satisfaction level ($\lambda = 0.6746$) falls within the typical range of compromise solutions observed under conflicting sustainability objectives. This comparison suggests that the proposed model performs competitively while extending existing approaches through the explicit integration of waste and social indicators within a unified FGP structure. Unlike purely cost-oriented APP models, the proposed framework enforces sustainability trade-offs explicitly through aspiration levels and tolerance limits, thereby avoiding solutions that are optimal in one dimension but unacceptable in others.

From a computational perspective, the optimization exhibits stable numerical behavior. The linear structure of the objective functions, constraints, and membership functions allows the model to be solved efficiently using standard mixed-integer linear programming solvers. Although the numerical experiments in this study focus on a single adapted dataset, the formulation is scalable and can be extended to larger planning horizons or additional objectives without fundamental changes to the model structure. Sensitivity and robustness analyses indicate that moderate variations in aspiration levels and tolerance parameters primarily affect the value of the global satisfaction level λrather than the qualitative structure of the optimal solution, reinforcing the interpretability of λas an indicator of sustainability trade-offs.

Overall, the discussion confirms that the SAPP–FGP framework provides both analytical rigor and practical relevance. By explicitly modeling trade-offs, constraint activity, and satisfaction sensitivity, the proposed approach offers decision-makers a transparent and flexible tool for sustainable production planning. Future research may extend this work by incorporating stochastic demand, nonlinear social response functions, and empirically validated human resource metrics to further enhance model realism and applicability.

4. CONCLUSION

This study has developed a Sustainable Aggregate Production Planning (SAPP) model based on Fuzzy Goal Programming (FGP) that integrates economic, environmental, and social objectives within a single optimization framework. The main contribution of this research lies in the explicit formulation of a triple-bottom-line SAPP model using an aspiration-based max–min FGP structure, which enables balanced compromise solutions without relying on subjective objective weighting or strict goal prioritization. From a methodological perspective, this study addresses a research gap identified in the literature, namely the limited availability of mathematically explicit SAPP models that incorporate social sustainability indicators alongside economic and environmental objectives in a linear and tractable formulation. The inclusion of workforce stability and worker satisfaction as proxy-based social objectives within the FGP framework extends conventional aggregate production planning models and complements existing FGP-based approaches that predominantly emphasize cost and environmental performance. The numerical results indicate that the proposed SAPP–FGP model is capable of producing feasible and balanced solutions, in which all sustainability objectives achieve a common level of satisfaction. This outcome confirms that sustainability trade-offs are systematically managed through aspiration levels, tolerance ranges, and constraint interactions, rather than through ad hoc parameter adjustments. The results further indicate the stability of the global satisfaction level under bounded variations of fuzzy parameters.

From a practical standpoint, the proposed framework provides a transparent and interpretable decision-support tool for medium-term production planning under sustainability considerations. The linear structure of the model ensures computational efficiency and facilitates implementation using standard optimization solvers, making it suitable for practical applications where managerial preferences and sustainability targets are inherently imprecise. Several limitations of this study should be acknowledged. The numerical analysis relies on a single adapted dataset, and social sustainability indicators are represented using simplified linear proxy measures rather than empirically validated behavioral data. Future research may extend this work by incorporating stochastic demand, empirically grounded social indicators, life cycle assessment (LCA) metrics, or alternative multi-objective optimization approaches to further enhance the realism and generalizability of the proposed model. From an applied mathematical perspective, this study contributes a fully linear, aspiration-based fuzzy goal programming formulation for triple-bottom-line aggregate production planning, providing a rigorous and transparent framework for modeling sustainability trade-offs within a unified optimization structure.

5. REFERENCES

[1] M. Todescato *et al.*, 'Sustainable manufacturing through application of reconfigurable and intelligent systems in production processes: a system perspective', *Sci. Rep.*, vol. 13, no. 1, p. 22374, Dec. 2023, doi: 10.1038/s41598-023-49727-5.

[2] S. S. Islami, M. M. Pane, A. G. Salsabila, B. H. Sinawang, I. C. Tarabu, and L. F. Primaputra, 'A Systematic Literature Review of Sustainable Manufacturing: Green Manufacturing Practices in Asia', *Indones. J. Comput. Eng. Des. IJoCED*, vol. 5, no. 2, pp. 102–117, Oct. 2023, doi: 10.35806/ijoced.v5i2.375.

[3] A. Gunasekaran, Z. Irani, and T. Papadopoulos, 'Modelling and analysis of sustainable operations management: certain investigations for research and applications', *J. Oper. Res. Soc.*, vol. 65, no. 6, pp. 806–823, Jun. 2014, doi: 10.1057/jors.2013.171.

[4] A. Cheraghalikhani, F. Khoshalhan, and H. Mokhtari, 'Aggregate production planning: A literature review and future research directions', *Int. J. Ind. Eng. Comput.*, pp. 309–330, 2019, doi: 10.5267/j.ijiec.2018.6.002.

[5] E. Koberg and A. Longoni, 'A systematic review of sustainable supply chain management in global supply chains', *J. Clean. Prod.*, vol. 207, pp. 1084–1098, Jan. 2019, doi: 10.1016/j.jclepro.2018.10.033.

[6] R. Ghasemy Yaghin, P. Sarlak, and A. A. Ghareaghaji, 'Robust master planning of a socially responsible supply chain under fuzzy-stochastic uncertainty (A case study of clothing industry)', *Eng. Appl. Artif. Intell.*, vol. 94, p. 103715, Sep. 2020, doi: 10.1016/j.engappai.2020.103715.

[7] A. Techawiboonwong and P. Yenradee, 'Aggregate Production Planning Using Spreadsheet Solver: Model and Case Study'.

[8] V. F. Yu, H.-C. Kao, F.-Y. Chiang, and S.-W. Lin, 'Solving Aggregate Production Planning Problems: An Extended TOPSIS Approach', *Appl. Sci.*, vol. 12, no. 14, p. 6945, Jul. 2022, doi: 10.3390/app12146945.

[9] M. Trost, T. Claus, and F. Herrmann, 'Social Sustainability in Production Planning: A Systematic Literature Review', *Sustainability*, vol. 14, no. 13, p. 8198, Jul. 2022, doi: 10.3390/su14138198.

[10] Ministry of Environment and Forestry of Indonesia (2022). National greenhouse gas inventory report. [Online]. Available: https://signsmart.menlhk.go.id/v2.1/app/ (Accessed: June. 15, 2025).

[11] United Nations Industrial Development Organization, 'Industrial Development Report 2022: The Future of Industrialization in a Post-Pandemic World', UNIDO Publications. [Online]. Available: https://decarbonization.unido.org/projects/iddi/ (Accessed: June. 15, 2025).

[12] A. Banasik, A. Kanellopoulos, J. M. Bloemhof-Ruwaard, and G. D. H. Claassen, 'Accounting for uncertainty in eco-efficient agri-food supply chains: A case study for mushroom production planning', *J. Clean. Prod.*, vol. 216, pp. 249–256, Apr. 2019, doi: 10.1016/j.jclepro.2019.01.153.

[13] A. Jabbarzadeh, M. Haughton, and F. Pourmehdi, 'A robust optimization model for efficient and green supply chain planning with postponement strategy', *Int. J. Prod. Econ.*, vol. 214, pp. 266–283, Aug. 2019, doi: 10.1016/j.ijpe.2018.06.013.

[14] P. K. Kumawat, R. K. Sinha, and N. D. Chaturvedi, 'Multi-objective optimization for sustainable production planning', *Environ. Prog. Sustain. Energy*, vol. 40, no. 6, p. e13741, Nov. 2021, doi: 10.1002/ep.13741.

[15] S. Mehrbakhsh and V. Ghezavati, 'Mathematical modeling for green supply chain considering product recovery capacity and uncertainty for demand', *Environ. Sci. Pollut. Res.*, vol. 27, no. 35, pp. 44378–44395, Dec. 2020, doi: 10.1007/s11356-020-10331-z.

[16] M. Wang, B. Ye, S. Lin, C. Wang, and P. Zhang, 'Sustainable supply chain planning with the flexible provisions of inter-period emission credits borrowing and banking under a multi-period carbon trading scheme', *J. Clean. Prod.*, vol. 445, p. 141406, Mar. 2024, doi: 10.1016/j.jclepro.2024.141406.

[17] M. Qasim and K. Y. Wong, 'A fuzzy multi-objective model for aggregate production planning considering energy consumption, carbon emission, chemical, solid waste, and wastewater', *J. Clean. Prod.*, vol. 475, p. 143644, Oct. 2024, doi: 10.1016/j.jclepro.2024.143644.

[18] S. M. Ahmed, T. K. Biswas, and C. K. Nundy, 'An optimization model for aggregate production planning and control: a genetic algorithm approach', *Int. J. Res. Ind. Eng.*, vol. 8, no. 3, Sep. 2019, doi: 10.22105/riej.2019.192936.1090.

[19] E. Guzman, B. Andres, and R. Poler, 'Models and algorithms for production planning, scheduling and sequencing problems: A holistic framework and a systematic review', *J. Ind. Inf. Integr.*, vol. 27, p. 100287, May 2022, doi: 10.1016/j.jii.2021.100287.

[20] M. H. Alavidoost, A. Jafarnejad, and H. Babazadeh, 'A novel fuzzy mathematical model for an integrated supply chain planning using multi-objective evolutionary algorithm', *Soft Comput.*, vol. 25, no. 3, pp. 1777–1801, Feb. 2021, doi: 10.1007/s00500-020-05251-6.

[21] T.-C. T. Chen and Y.-C. Wang, 'A fuzzy mid-term capacity and production planning model for a manufacturing system with cloud-based capacity', *Complex Intell. Syst.*, vol. 7, no. 1, pp. 71–85, Feb. 2021, doi: 10.1007/s40747-020-00177-w.

[22] B. K. Giri, S. K. Roy, and M. Deveci, 'Fuzzy robust flexible programming with M e measure for electric sustainable supply chain', *Appl. Soft Comput.*, vol. 145, p. 110614, Sep. 2023, doi: 10.1016/j.asoc.2023.110614.
[23] Md. S. Uddin et al., "Goal programming tactic for uncertain multi-objective transportation problem using fuzzy linear membership function," Alex. Eng. J., vol. 60, no. 2, pp. 2525–2533, Apr. 2021, doi: 10.1016/j.aej.2020.12.039.
[24] G.-F. Yu and D.-F. Li, 'A novel intuitionistic fuzzy goal programming method for heterogeneous MADM with application to regional green manufacturing level evaluation under multi-source information', *Comput. Ind. Eng.*, vol. 174, p. 108796, Dec. 2022, doi: 10.1016/j.cie.2022.108796.
[25] H. Zare, M. Kamali Saraji, M. Tavana, D. Streimikiene, and F. Cavallaro, 'An Integrated Fuzzy Goal Programming–Theory of Constraints Model for Production Planning and Optimization', *Sustainability*, vol. 13, no. 22, p. 12728, Nov. 2021, doi: 10.3390/su132212728.
[26] M. Türkay, Ö. Saraçoğlu, and M. C. Arslan, 'Sustainability in Supply Chain Management: Aggregate Planning from Sustainability Perspective', *PLOS ONE*, vol. 11, no. 1, p. e0147502, Jan. 2016, doi: 10.1371/journal.pone.0147502.
[27] C. Gahm, F. Denz, M. Dirr, and A. Tuma, 'Energy-efficient scheduling in manufacturing companies: A review and research framework', *Eur. J. Oper. Res.*, vol. 248, no. 3, pp. 744–757, Feb. 2016, doi: 10.1016/j.ejor.2015.07.017.
[28] J. M. R. C. Fernandes, S. M. Homayouni, and D. B. M. M. Fontes, 'Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review', *Sustainability*, vol. 14, no. 10, p. 6264, May 2022, doi: 10.3390/su14106264.
[29] K. Moon *et al.*, 'Manufacturing Productivity with Worker Turnover', *Manag. Sci.*, vol. 69, no. 4, pp. 1995–2015, Apr. 2023, doi: 10.1287/mnsc.2022.4476.
[30] V. Wickramasinghe and G. L. D. Wickramasinghe, 'Effects of HRM practices, lean production practices and lean duration on performance', *Int. J. Hum. Resour. Manag.*, vol. 31, no. 11, pp. 1467–1512, Jun. 2020, doi: 10.1080/09585192.2017.1407954.