Ignatius Ajuru University of Education
Journal of Computing Sciences
ISSN: 3156-3570
Print ISSN: 3156-3570 https://iauejournals.com Volume 1; Issue 1; April 2026; Page No. 32-43.

Energy-Aware Production Planning Using Fuzzy Goal Programming Techniques: A Review

[1]Pelemo, J., [2]Molokwu,M.I., [3]Ayinuola, A.P., [4]Oyefolahan, A.O., [4]Oke,O.O, [4*] Adedeji, W.O., & [5]Adekoya, A.O.

[1]Department of Welding and Fabrication, Yaba college of Technology, Lagos, Nigeria
[2]Department of Welding and Fabrication, Nigerian Navy Institute of Technology, Sapele, Nigeria
[3]Department of Marine Engineering, Nigerian Navy Institute of Technology, Sapele, Nigeria
Department of Mechatronics Engineering, Osun State University, Osogbo, Nigeria
[5]Department of Mechatronics Engineering, Yaba College of Technology, Lagos, Nigeria

***Corresponding author email:** wasiu.adedeji@uniosun.edu.ng

Abstract
With industries grappling with escalating energy expenses, environmental control requirements, and global efforts for sustainability, energy-aware production planning is a critical priority in modern manufacturing.Energy-aware production planning has become a cornerstone in today's manufacturing landscape, driven by the industries' need to balance the rising costs of energy, environmental regulations, and global sustainability initiatives. The review aims to gather the latest developments of fuzzy goals programming (FGP) coupled with production planning models for energy efficiency. Although traditional deterministic and classical goal programming are well-established techniques, and are used as powerful tools for decision-making, they may fail to address situations with uncertainty and imprecision encountered in actual manufacturing systems with harmful renewables such as energy costs, random machine performance or fluctuations in renewable energy. Based on fuzzy set theory, flexible goals for energy consumption, cost, time, and quality are represented by the fuzzy goal programming, thus it helps the decision makers to handle the complex trade-off between various goals. The review showcases a wide array of applications covering different manufacturing and process industries and even smart factory settings, reflecting the versatility of FGP-based models. Adding genetic algorithms, simulation models, machine learning and multi-criteria decision-making techniques to the FGP approach, extends the scalability and robustness of the solution. However, there are still some obstacles in its way, such as the requirement of more real-time optimization frameworks, standardized assessment measures, easier integration of renewables, etc. Finally, the obtained findings highlight the crucial role of fuzzy techniques and Industry 4.0 tools based on AI in the future development of energy-aware production planning. Such future developments will lead to more intelligent, resilient, and sustainable manufacturing systems that will be able to adapt dynamically to changing demands for energy and process operations

Keywords: Energy-Aware Production Planning, Fuzzy Goal Programming, Sustainability, Hybrid Optimization, Uncertainty Modelling.

Introduction

Modern manufacturing systems have become highly complex and interdependent, in which all resources, materials and machine capacities must be planned synchronously. The goal of production planning is typically cost minimisation, throughput and delivery performance, but more complex energy markets, environmental concerns and increasing uncertainty affect the operations of today's systems (Park & Ham, 2022; Trevino-Martinez et al., 2022). Industries have entered a new era: smart manufacturing and intelligent operation. In modern times, production planning has therefore become a multidimensional process that encompasses operational and energy-related aspects as well (Leenders et al., 2023).

There has been a shift in priorities towards scheduling and planning activities, driven by the growing importance of energy efficiency and environmental sustainability. Fisco-Compte et al. (2025) and Germscheid et al. (2023) examined the increased pressure from carbon policies on manufacturing, the volatility of energy markets, and the expectations to meet demand-side flexibility in the market. Wang et al. (2024) and Ghorbanzadeh & Ranjbar (2023) demonstrated that integrating demand response, renewable energy, and carbon footprint minimisation directly into scheduling models can significantly reduce environmental impacts and operational costs. Energy-aware production planning has become a major research field in sustainable engineering as well as in operations management.

While much work has been invested, traditional optimization approaches struggle in the presence of imprecision, ambiguity and conflicting objectives often inherent in decisions around energy. It is difficult to represent uncertainty in energy demand and renewable generation availability and dynamic pricing schemes in the deterministic models (Ma et al., 2022; Jagana et al., 2025). Furthermore, classical goal programming (CGP) can be applied to the cases with multiple goals, but these goals are subject to precise aspiration levels which are not easily encountered in industrial cases (Samouilidou et al., 2024).

The FGP model allows for the representation of flexible goals, uncertain constraints, and imprecise preference information using fuzzy sets and membership functions, thereby relaxing the model's rigid nature. This has made FGP particularly suitable for dealing with intricate production-energy trade-offs (Tian et al., 2024; Zhang et al., 2023). This review summarises the latest advances in energy-aware production planning approaches based on FGP techniques. Methodological trends, application areas, challenges, and prospects for future research and practice are discussed to build a "meshed" overview of the field for researchers and practitioners.

Production Planning

Manufacturing systems: Production planning is simple, helping to coordinate the moves and allocate resources effectively, and achieve production goals. The critical parts include capacity planning, scheduling and resource allocation, and they all play an important role in matching the required demand when the condition becomes stable in the work process (Samouilidou et al., 2024; Chen et al., 2022). The purpose of capacity planning is to determine the production capacity required of the system to satisfy anticipated loads, while scheduling refers to the process of assigning jobs to machines and specifying the order of their processing to maximize production benefit based on e.g. makespan, cost, or tardiness (Park & Ham, 2022). Resource allocation involves deciding how to allocate labor, material and equipment resources optimally, typically to a set of operational constraints (Leenders et al., 2023).

Energy aspects are gaining importance for production planning in modern production environments. In addition to the machine's power ratings, energy use in the production system will be affected by the processes of starting and stopping the machines, as well as load variations and the timing of production compared to electricity rates (Wang et al., 2024; Ghorbanzadeh & Ranjbar, 2023). Energy for energy- using production processes such as energy intensive processes of metals, chemicals and polysilicon industry is very varying across various production steps and hence becomes a significant parameter to optimize by energy aware scheduling. When planning with variables like production throughput and varying energy costs—which needs to be done by a manager—dynamic electricity tariffs like time-of-use and real-time pricing die added to this mix. When planning with variables such as production throughput and costs of energy that fluctuate over time, as would be the case for a manager balancing production throughput versus variable costs of energy, the whirl of dynamic electricity tariffs, like time-of-use and real-time pricing, is added to this mix. (An et al., 2023)

This variance is compounded by renewable sources such as solar or wind energy, as the energy output needs to be flexible and activities planned in line with it. In its general aspects, production planning is now more a strategic instrument in the industries journey to low carbon and sustainable operations to reduce the carbon footprint, ensure the energy demand is stable and to improve the efficiency of resources in general. The increasing complexity necessitates the advanced models of decision-making that have the ability to address uncertainties for operation and energy.

Energy-Aware Manufacturing

Thus, energy-aware manufacturing has become one of the most important paradigms in modern industrial systems, driven by rising energy costs, stringent environmental laws, and the global effort towards sustainable production.

Frequent and unpredictable energy costs push manufacturers to use energy efficiently in order to remain competitive, particularly in energy-intensive industries such as metals, chemicals, and semiconductor manufacturing. Regulatory pressures, such as carbon policies, limits on greenhouse gas emissions, and green manufacturing standards, also push businesses to reduce their greenhouse gas emissions through increased energy planning and greater flexibility on the demand side. In addition, societal expectations and companies' sustainability goals have placed greater emphasis on sustainable production methods.

Energy consumption, carbon footprint, and energy peak demand are among the metrics that are important to benchmark for evaluating Energy Awareness in manufacturing. Although total energy consumption is a first-order operational metric, it requires additional effort because it directly affects production costs and system-level efficiencies (Zhao et al., 2024; Ghorbanzadeh & Ranjbar, 2023). Carbon footprint quantification typically relates to characteristics of energy sources or emissions processes, which are important for complying with environmental legislation and embarking on low carbon energy sourcing or emission processes. Peak demand management refers to actions that reduce energy use during peak demand times, typically through demand response and load-shifting measures, and is often implemented when electricity prices are high or when the grid is under demand stress. Indeed, effective peak load control can help in the same ways to not only lower energy bills, but also aid with the smoothing of industrial load profiles to aid in grid stability.

With a growing number of renewable energy sources, automation and advanced analytics are increasingly being brought to manufacturing products and on-site; the energy-aware decision process will become increasingly complex. It is thus important to employ effective optimization and scheduling techniques to address these issues of co-optimizing in terms of operational performance, environmental impact and energy variability.

Fuzzy Goal Programming (FGP)

In contrast, Fuzzy Goal Programming (FGP) is an extension of the traditional Goal Programming theory that introduces the poor language of the fuzzy set theory to represent uncertainty, vagueness and imprecision in the decision making process. Thanks to the inherent flexibility of fuzzy set theory, a variable, constraints, and/or objectives can be partially in sets, which allows to embed the ambiguity found in real life situations. In the manufacturing scenario, not all manufacturing parameters are enumerable or have clear numerical values, like energy consumption, processing time, electricity price, etc., which are well suitable for the above-mentioned features (Ma et al., 2022; Jagana et al., 2025).

The goals in the FGP are the acceptable ranges of various criteria such as minimum energy consumption, minimum cost and/or carbon footprint and the membership functions indicate the degree to which these goals are satisfied. Values indicated by the aspiration levels represent the desired values under the uncertainty condition for each goal, and achieving the precise value for each goal may not be achievable (Tian et al., 2024). Contrary to the perception of goals as being set indiscriminately, FGP offers decision-makers the flexibility to satisfy the goals somewhat.The flexibility offered by FGP does not preset goal levels, but enables decision-makers that they can achieve, to balance competing objectives to a greater degree.

FGP can take a number of different forms such as linear, nonlinear and multi-objective formulations. In problems where linear relationships govern production and energy uses, linear FGP models can be used, while more complicated production-energy relationships are possible with more sophisticated manufacturing systems can be addressed using nonlinear FGP approaches (Ghorbanzadeh & Ranjbar, 2023). However, energy-aware scheduling is significantly affected by multi-objective FGP because of the trade-offs that can be observed between the objectives of energy, cost, carbon footprint, and production throughput (Trevino-Martinez et al., 2022).

The primary advantage FGP offers in manufacturing is its ability to deal with uncertainty along with the ability to incorporate multiple goals that may be contradictory. In contrast to the deterministic models that assume system parameters to be exactly and consistently known, the FGP accounts for the uncertainty in energy price, renewable energy and production parameters (Ertem, 2024). This will support the manufacturing industries to make strong, flexible and energy effective planning decision. FGP offers a powerful tool for production optimization in uncertain environments where industries are increasingly expected to embrace a low carbon approach and dynamic energy management.

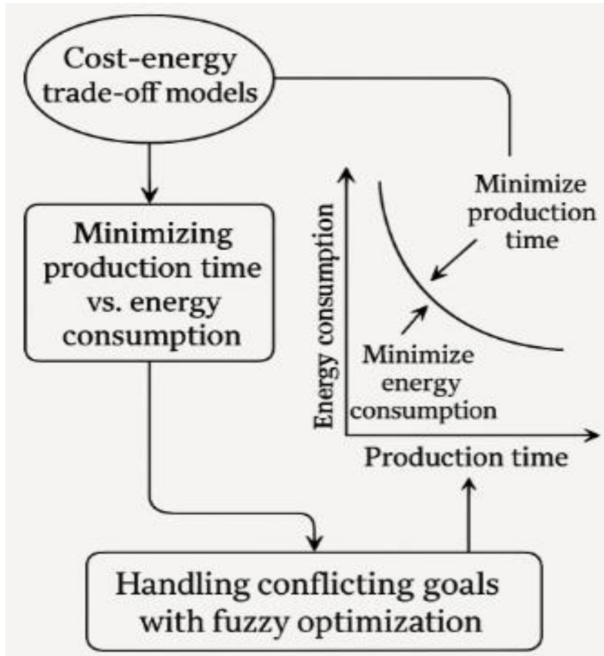

Figure 1: Fuzzy Goal Programming

Energy-Aware Production Planning

Assumptions for early research of production planning and scheduling relied significantly on the deterministic optimization models, as well as classical type of goal programming formulations, which all considered system parameters such as processing times, energy consumption rates, machine availabilities and electricity prices as given values beforehand and assumed to be constant throughout the planning horizon (Park & Ham, 2022; Chen et al., 2022). From this perspective, classical GP could provide a strategically structured method for dealing multi-objective trade-offs by keeping the various objectives such as cost, makespan and resource utilization within specific limits, or aspirations (Samouilidou et al., 2024). These formulations were especially helpful for manufacturing applications that operated in defined manufacturing environments with known demand trends.

The initial attempt of energy-aware scheduling utilized deterministic approaches that incorporated energy consumption averages or assumed fixed energy use in scheduling operations, alongside the operational costs (Trevino-Martinez et al., 2022; An et al., 2023). These methods are computationally tractable and have good visibility but they cannot depict the operational volatility of energy systems in the present days. The deterministic assumption is no longer reflected in fluctuating electricity prices, variable time-dependent demand response signals and varying production load of industries with high energy intensity (e.g., metal production or polysilicon processing), which is not beneficial (Germscheid et al., 2023; Wang et al., 2024).

Deterministic classical GP models have several limitations, foremost of which is their inability to cope with uncertainty, vagueness and imprecision of real-world data. However, deterministic models are limited in their ability to capture the complexity of renewable energy source, which presents a challenge due to its variability, short-term price instability and impreciseness of production parameters (Ma et al., 2022; Jagana et al., 2025). In addition, classical GP for energy-aware manufacturing comes with strictly defined aspiration, which is however impractical in the real application where the trade-offs between the cost, the energy consumption and carbon emission involved are inherently fuzzy (Tian et al., 2024).
Such constraints encouraged more general and open methods such as fuzzy goal programming that enable uncertainties to be represented and enable more flexible decision making in more complex and energy-sensitive manufacturing systems.

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.

Fuzzy Approaches

The use of fuzzy approaches in production planning brought a dramatic shift from "black and white" deterministic approaches to more flexible and realistic decision-making. The concept of fuzzy Goal Programming and the development of fuzzy optimisation techniques were first developed to capture the uncertainty and imprecision in the objectives, constraints and system parameters. These approaches permit the decision-maker to define goals in terms of fuzzy aspiration goals and membership functions, thus making a more refined representation of production environments where the uncertainty of variables like energy demand, process times, and electricity price is natural. Ma et al. (2022) and Tian et al. (2024) have shown that fuzzy objectives have enabled manufacturers to model ambiguous trade-offs, such as reducing energy consumption or carbon footprint targets while reducing costs.By incorporating fuzzy objectives into production planning, manufacturers have been able to model fuzzy trade-offs, like reducing energy consumption or carbon footprint targets while reducing costs, according to Ma et al. (2022) and Tian et al. (2024).

The use of fuzzy approaches has been proven effective in decision making in various industrial domains in the form of case studies. Fuzzy scheduling models, for instance, are more suitable for optimizing the scheduling of energy-intensive industries that experience variable loads and energy prices, as well as fluctuating energy price patterns (Germscheid et al., 2023; An et al., 2023). Fuzzy optimisation has been used to optimise production activities in a manufacturing system to match the availability of renewable and intermittent energy sources, thereby maximising energy efficiency and minimising peak demand, which is an important benefit in the context of these systems (Ertem, 2024; Germscheid et al., 2024).

Apart from that, in the formulation of fuzzy multi-objective models, one can achieve much more balanced solutions among competing objectives such as throughput, energy cost and environmental effects (Trevino-Martinez et al., 2022). The distinctions of the fuzzy approaches in the more real production context, in which uncertainty cannot be eliminated, but must be managed, can be outlined in these successes. As a consequence, fuzzy techniques have been used as a key pillar of the evolution of current energy-focused and sustainability-oriented production planning models.

Multi-Objective Energy-Based Models

Energy has become one of the objectives in manufacturing systems and therefore a number of researchers began to construct models with multiple objectives involving explicit energy vs. operational performance trade-offs. In the past, the multi-objective energy-based models focused on minimizing energy consumption and at the same time reducing production costs, with energy usually being one of the most important contributors to manufacturing costs (Zhao et al., 2024; Ghorbanzadeh & Ranjbar, 2023). Cost–energy trade-off models enable the decision maker to ask questions about situations where the lower cost of production might require a higher energy consumption, or the other way around, to gain energy savings for a given situation, either alter the production schedule or change the load profile (Tang et al., 2024).

The other dimension that is explored as part of multi-objective modeling relates to the compromise between production time and energy usage. In many industries, there is a conflict between fast throughput and efficient energy consumption, particularly under TOU pricing or trying to limit the energy demand during peak hours (Park & Ham, 2022; Wang et al., 2024). Scheduling decisions such as job sequencing, batch formation and machine assignment can have a substantial impact on both makespan and energy consumption. In Trevino-Martinez et al. (2022) it was also demonstrated that the inclusion of carbon footprint or energy metrics in addition to production time gives a more realistic picture of today's operations, which are geared towards sustainability.

In multi-objective energy-based models, fuzzy optimization methods have proven to be of great assistance in addressing conflicting objectives. As mentioned by Tian et al. (2024), the goals of cost minimization, energy consumption and carbon emission are usually conflicting, and FGP is one mechanism that is useful to represent flexible aspirations level and to capture the decision maker's uncertainty preferences. Ertem (2024) and Germscheid et al. (2024) note that the FGP is flexible enough to allow partial fulfillment of goals and provide solutions that are more flexible in the face of variable energy costs, variable renewable energy availability, and uncertain processing conditions.

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.

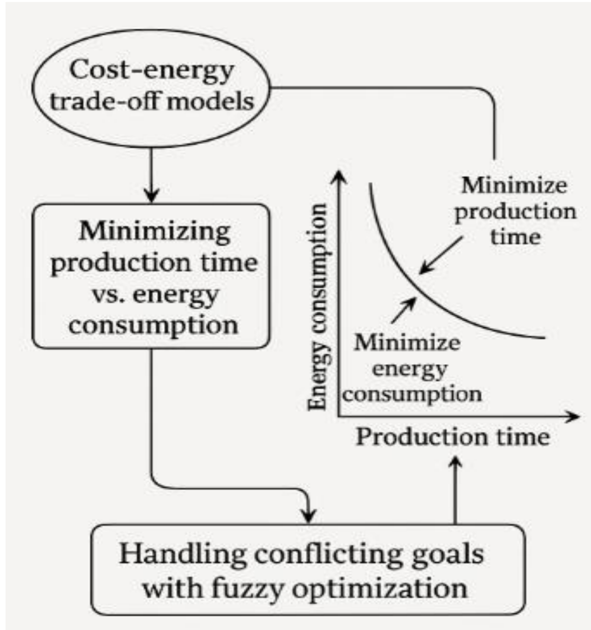

Figure 2: Multi-Objective Energy-Based Models

Hybrid approaches

Hybrid approaches are gaining momentum as a promising complement to fuzzy goal programming (FGP) to provide more powerful and scalable solutions in energy-awareness production plans. The researchers have developed models that tackle the complex and uncertain nature of today's manufacturing systems by using a combination of FGP and heuristic, simulation-based, and data-driven techniques. An important class of such approaches is combining FGP and genetic algorithms (GAs) to improve the search for good solutions when solving large-scale scheduling problems. GA-based hybrid formulations have proven advantageous in addressing the non-linear interaction of energy consumption, machine allocation and carbon emission (Geetha et al., 2024; Sagar et al., 2024).

A further hybrid approach involves the use of simulation models to model realistic production conditions and take into account variations in energy supply, machine behaviour and processing times. When industries are subjected to volatile energy markets or depend on intermittent renewable resources, simulation can help with a much greater understanding of system performance, making simulation-enhanced fuzzy models more appropriate. Moreover, the adoption of machine learning techniques has also been included in FGP to enhance predictive decision making in uncertainty scenarios. In reinforcement learning and graph-based learning models, fuzzy objectives have been integrated to address the intricate production-energy dynamics in flexible job-shop systems and demand response environments (Wang et al., 2022). Such hybrid intelligent systems can facilitate predictive scheduling that can be adjusted in real time to meet fluctuations in resource loads and electricity pricing.

On the other hand, multi-criteria decision making techniques provide a complementary layer, enabling possible structured assessment for conflicting objectives (e.g. cost, energy consumption, carbon footprint and production efficiency). It can be concluded that MCDM-FGP frameworks can be used to prioritise objectives, which will allow for the consideration of Bok et al. (2024) and Fisco-Compte et al. (2025) stakeholder preferences and regulatory constraints. Through comparative performance analysis, it has been established that the hybrid FGP always outperforms the traditional deterministic and standalone fuzzy model with respect to solution quality and adaptability. This approach provides greater resistance to uncertainty, better energy optimisation, and more operational flexibility for a variety of industrial applications. Trevino-Martinez et al., 2022; Ghorbanzadeh & Ranjbar, 2023).

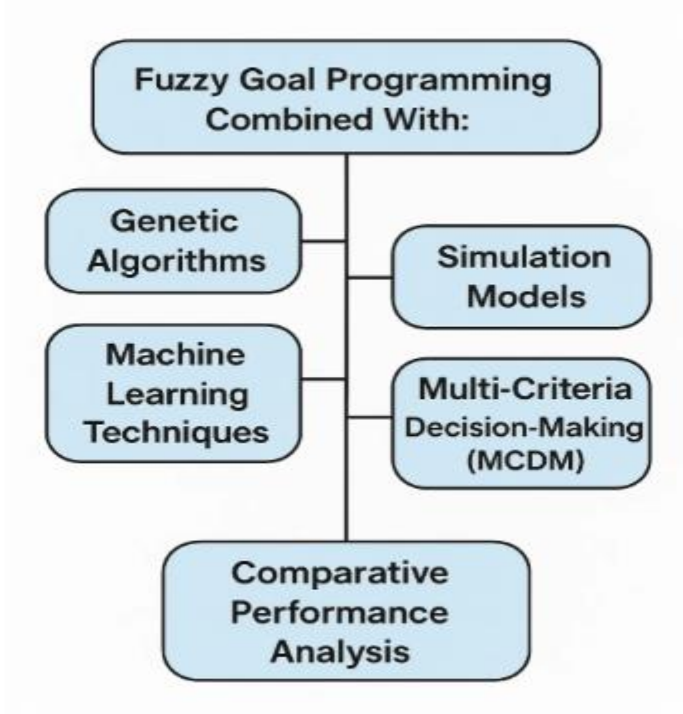

Figure 3: Hybrid Approaches

Sectoral Applications

The energy-aware production planning method developed by fuzzy goal programming (FGP) has been used in various fields of the industry, showing the method is useful in coping with the uncertainty and optimizing multi-objective systems. The discrete manufacturing industries like the automotive, electronics and textile industries can be greatly supported by fuzzy-based scheduling approaches in their energy consuming manufacturing processes like machining and assembly processes. In jobs with changing demands and workload, machine efficiencies that can vary by job phase and complicated task sequencing, FGP can be an appropriate approach for managing energy use, production time, and cost (Park & Ham, 2022; Bok et al., 2024). In flexible job-shop applications as found in electronics manufacturing and in automotive manufacturing, models with FGP have been applied to cut peak energy use and yet, maintain product throughput under time-of-use pricing (Wang et al., 2022).

With the continuous and batch processing nature of process industries like chemical, food and pharmaceutical industries, fuzzy optimisation has also begun to be used. Typically, these industries have strict regulatory requirements, are highly energy intensive and have very sensitive operating conditions. However, fuzzy-based models were highlighted for improving the robustness of scheduling in processes with more uncertainty and variability in energy prices, like the chemical and metallurgical processes, as noted by Germscheid et al. (2023) and Wang et al. (2024). Furthermore, FGP can perform temperature-dependent operations, perishability and strict quality requirements, which benefit from flexible and uncertainty-tolerant decision-making procedures (Samouilidou et al., 2024). With the advent of smart factories and Industry 4.0, energy-driven production planning has broadened to include monitoring through IoT, digital twins, and AI-driven analysis. Such advanced environments produce large amounts of real-time data, and with the energy price, equipment state and availability of renewable energy sources dynamically changing, fuzzy optimisation models can dynamically adjust the schedules. These are shown in the works of Ertem (2024). Further, cyber-physical production systems will enhance the ability of FGP models to serve the demand response, carbon reduction strategy and integrated energy production coordination as indicated by Fisco-Compte et al. (2025). The diversity of the applications of fuzzy goal programming in various domains, however, indicates how flexible fuzzy goal programming is in modelling complex energy-aware production problems in modern industries.

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.

Methodological Frameworks
In this step, we establish a goal for energy-aware models. In this step, we set up a goal for energy-aware models. Goal formulation is one of the basic components of the energy-aware fuzzy goal programming (FGP) modelling process, which helps to represent, prioritize and solve the multiple performance objectives under uncertainty. The definite goals are generally set for important criteria like energy usage, manufacturing cost, quality of the products and completion time in manufacturing systems. These targets are operation and sustainability goals, which can help planners to achieve a balance between economic performance and energy efficiency and environmental issues (Tian et al., 2024; Ghorbanzadeh & Ranjbar, 2023). For instance, an energy objective could be to reduce energy consumption during high energy cost times and a cost objective could be to reduce total operational cost. Likewise, quality and time objectives guarantee that the system's performance and deadlines are kept despite the uncertainties in the production conditions (Park & Ham, 2022).

It will be important to come up with the right membership functions to translate these fuzzy goals into computational models to calculate how well a solution meets each of these goals. As such, there is some flexibility in interpretation of the performance levels, as if there were threshold constraints, there would be no.Thus, there is not a strict definition of performance levels in terms of thresholds, but rather some flexibility to interpretation, because without thresholds, there would be no. Triangular, trapezoidal and nonlinear membership functions can be used for tolerance ranges of energy consumption, cost variations at acceptable limits or desired cycle times (Trevino-Martinez et al., 2022). These functions are usually specified based upon the information of experts, past experiences or regulations, so that the fuzzy goals set are consistent with the industrial experiences.

Other attributes of FGP that are important are the following: the treatment of vagueness in forecasting energy needs. Machine load variability, process disturbances, integration of renewable energies and dynamic tariffs are just a few elements that affect energy consumption in the manufacturing processes and thus make the planning process more uncertain (Germscheid et al., 2023; Ertem, 2024). Therefore, the fuzzy models are able to incorporate uncertain predictions of energy demand in terms of energy demand ranges or linguistic variables like the terms low, medium and high, thus improving the robustness of the decisions made. Thus, FGP provides a flexible and realistic basis for the energy aware optimization in modern manufacturing systems.

Model Structures
The structures of models of energy-aware production planning are very diverse depending on the time horizon, the type of uncertainty and the mathematical complexity of the production system under consideration. A basic difference between the models is the type of planning for one period vs multi-period. Single period models consider the situation in which energy decisions and production decisions are optimized at a single point in time, usually a single shift, day or batch cycle, and they are appropriate either for short term scheduling or for a system with stable energy conditions (Park & Ham, 2022; Trevino-Martinez et al., 2022). Multi-period models, on the other hand, include multiple subsequent time periods in order to account for changes in energy demand, electricity prices, machine states and availability of renewable energy. This structure is particularly useful in industries that are sensitive to electricity costs, such as those with time-based pricing or demand response initiatives, as it can greatly impact their operations (Germscheid et al., 2023; Wang et al., 2024).

Another characteristic feature is the type of fuzzy environment which the model works in deterministic or stochastic. Deterministic fuzzy models consider the fuzziness of goals and constraints, but a priori set the values of the parameters involved. While they can work for a system with only small variations, they may not accurately capture all the uncertainties in the real world, including variations in renewable energy generation and in energy markets (Ma et al., 2022). To overcome this shortcoming, the stochastic fuzzy models are developed by incorporating probability distributions or uncertainty owing to the operational variability for the various operational scenarios, which presents a more realistic picture of the operational variability (Jagana et al., 2025; Ertem, 2024). Hybrid uncertainty structures are especially important in Industry 4.0 settings where prediction is paramount and data streams are real-time.

Depending on the mathematical relations between the decision variables, the establishment of fuzzy goal programming can be non-linear or linear. Linear formulations are simpler to solve — and can be used to model systems with linear interactions of energy use and energy generation processes. But in many manufacturing systems, there are nonlinear relations like machine power curves, temperature dependent process etc., and in such situations, nonlinear fuzzy model

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.

is needed to describe the behaviour of the system accurately. All of this enables flexible modeling according to the complexity and uncertainty of modern energy-aware manufacturing systems when combined.

Solution Methods

Energy-aware fuzzy goal programming (FGP) models have several solution methods including classical optimization approaches, systematic approaches for sensitivity analysis and parameter tuning, and meta-heuristic improvement methods. Classical FGP algorithms rely on the concept of fuzzy aspiration levels and satisfaction for the goals and the minimization of deviations from the aspiration level in terms of the linear or nonlinear programming formulation. Classical FGP algorithms are based on the concept of fuzzy aspiration levels and satisfaction for the goals, and minimization of deviations from fuzzy aspiration levels is done through the linear / nonlinear programming formulations, and the degree of satisfaction is determined through the membership functions. The technical simplicity and efficiency of these methods make them applicable in cases where the relationships of production and the energy variables are fairly linear (Samouilidou et al., 2024; Tian et al., 2024). The most common algorithms used in classical algorithms are the ones where conflicting objectives are balanced by either a weighted preference function or a lexicographical one, both with a focus on either energy consumption, cost or throughput.

To resolve the complexity and non-linear nature of actual manufacturing environments, the researchers favour adding meta-heuristic improvements to FGP models with increasing frequency. Some of these techniques include genetic algorithms, memetic algorithms, hybrid heuristic–fuzzy frameworks, and reinforcement learning, each contributing to further enhanced search efficiency and the robustness of the solutions, especially when dealing with large-scale or highly nonlinear scheduling situations (Geetha et al., 2024; Chen et al., 2022). In particular, hybrid systems with genetic algorithms (GA) have been shown to be effective in the multi-objective case of energy-carbon trade-offs, and deep reinforcement learning (DRL) systems with fuzzy objectives can enable adaptive scheduling when incorporating demand response (DR) programs (Wang et al., 2022). However, these hybrid approaches provide greater flexibility to FGP models by enabling them to explore wider ranges of solution space and cope with dynamic energy conditions better than the classical deterministics.

To guarantee the reliability of the FGP solutions, sensitivity analysis and parameter tuning are important. Membership function parameters, aspiration levels and weights have significant impact on the optimization results so they need to be tuned systematically to obtain realistic and interpretable results. Sensitivity analyses are used to assess the robustness of the solutions with respect to fluctuations in energy pricing, availability of renewable energy resources, uncertainty in production, etc. (Germscheid et al., 2023; Ghorbanzadeh & Ranjbar, 2023). The results of these evaluations inform decision makers on adjusting the other model parameters and testing model performance on various operational changes.

These solution methods contribute significantly to the applicability and effectiveness of FGP, even in more complex scenarios characterized by energy considerations for production planning.

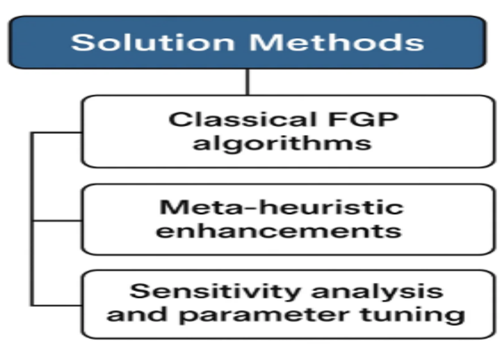

Figure 4: Solution Methods

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.

Analysis

There is significant variation in the modeling and solution techniques and results of the studies on energy-aware production planning. The studies on energy-aware production planning have shown significant differences in modeling approaches, solution techniques, and results. In the literature, the various types of models are from classical formulation of fuzzy goal programming (FGP) to the hybrid models involving meta-heuristic methods, machine learning techniques, and multi-criteria decision making. For example, in relatively stable manufacturing environments, classical FGP models have been extensively used to optimize energy use, cost, and scheduling efficiencies (Samouilidou et al., 2024; Tian et al., 2024). Hybrid techniques like genetic algorithms combined with FP, and reinforcement learning with fuzzy frameworks show greater scalability and adaptability, especially in dynamic scenarios where electricity prices fluctuate or renewable energy sources are intermittent (Geetha et al., 2024). Applications also span the industry, ranging from polysilicon processing (Wang et al., 2024) to metallurgical applications (Germscheid et al., 2023), and sustainable manufacturing systems (Fisco-Comte et al., 2025).

Frequently used criteria for the evaluation of the studies are computational efficiency, model flexibility, and solution quality. Classical FGP models tend to have faster computation time because they are linear or mildly nonlinear, but may not be flexible if they have an energy–production interaction that is highly uncertain or non-convex (Park & Ham, 2022). While the resulting solution quality is typically better (including better energy savings, carbon emissions reductions or better production throughput), hybrid and meta-heuristic enhanced models generally require longer computation times (Chen et al., 2022; Ghorbanzadeh & Ranjbar, 2023). Modelling systems that include fuzzy membership functions and/or scenario or stochastic components are the most flexible and will perform best when there is variability in the real world, for example from changing tariffs and changes to renewable energy supply (Ertem, 2024; Jagana et al., 2025).

There are a number of important trends that can be gleaned from this comparative analysis. First, there is a clear trend of combining AI-based approaches, such as the use of reinforcement learning and predictive analytics, with fuzzy optimization. Second, energy-aware models are now more and more multi-objective, which correspond to the industry focus on carbon reduction and sustainability. Last but not least, the applications are growing in the Industry 4.0 field, where real-time data and smart manufacturing technologies increase the responsiveness and intelligence of FGP-based decision systems.

Challenges and Research Gaps

Although a wide range of studies on the energy efficient production planning have been carried out by adopting fuzzy goal programming (FGP), there are still some problems and research gaps to be addressed. One of the key problems is the ability to deal with real-time production environments and fluctuating energy prices. Electricity costs often change quite rapidly from one time to the next for many industrial sectors, sometimes as a result of demand response programs, and sometimes due to market volatility. Most of the current models based on FGPs, however, support decision-making under static or near-static conditions, which are not applicable to real-time decision-making scenarios that involve continuous data streams and rapid changes (Tang et al., 2024; Germscheid et al., 2023). Real-time data analytics and adaptive fuzzy decision making are still open areas of research.

Another gap is related to the integration of renewable energy sources in production planning. Renewable supply (e.g., solar, wind) is very variable and adds further uncertainty. While a few works focus on renewable energy-based processes, most works are still based on energy supply assumptions of stability or predictability (Ertem, 2024; Germscheid et al., 2024). There is a need for a more powerful fuzzy–stochastic hybrid model to better schedule in applications where the availability of renewable sources is not constant. Large-scale industrial systems also pose a major problem with regard to scalability. High-dimensional optimization problems often exist in complex systems like multi-stage chemical plants, large manufacturing networks or flexible job shops. The classical FGP models become intractable in computation with larger problems and meta-heuristic or AI-integrated models may need a lot of tuning (Geetha et al., 2024).

One consistent impediment is the absence of uniform evaluation metrics. Although some studies combine energy efficiency and carbon reduction, computational efficiency and operational feasibility, and others measure all of them separately, it is difficult to compare studies directly (Fisco-Compte et al., 2025; Ghorbanzadeh & Ranjbar, 2023). Consistency and comparability could be improved if there were some standardised benchmarks.

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.

Lastly, the demand for sophisticated hybrid AI techniques that integrate machine learning, predictive analysis, and reinforcement learning with FGP has increased, aiming to enhance adaptability and decision-making in uncertain scenarios (Wang et al., 2022; Jagana et al., 2025). These sophisticated approaches have acquired tremendous potential but have not been exploited in industry.

Conclusion

The literature shows substantial progress in energy-aware production planning in modern manufacturing systems that combine sustainability, energy efficiency, and operational performance. In the last decade, research has evolved from a cost and time-based production planning process into an energy-, emission- and environmental-related process. Different modelling frameworks, ranging from classical deterministic models to sophisticated fuzzy and hybrid optimisation models, have highlighted the increasing complexity of manufacturing environments and the need for flexibility and uncertainty tolerance in methods. From discrete manufacturing to process industries and emerging Industry 4.0 production environments, research indicates that energy-aware models consistently outperform traditional scheduling models, especially in the case of dynamic pricing, variable workloads, and/or renewable energy integration.

Fuzzy Goal Programming (FGP) is a significant method for sustainable and energy-efficient production planning. Its ability to allow for imprecision, linguistic variables and flexible aspiration levels make it suitable for environments where demand variability, fluctuating price of energy, and uncertainty in production are inevitable. FGP allows multi-objective decision-making, where goals include minimising costs, reducing emissions, improving energy efficiency, and maintaining production performance, and it lets the decision maker set the relative importance of these goals. The flexibility makes FGP a key approach for companies looking to achieve sustainability goals and maintain competitiveness.

In the future, the following trends are expected to drive the development of energy-aware production planning. Incorporating AI, machine learning, and real-time analytics can improve the adaptability of FGP models, enabling them to adjust dynamically to changing production and energy scenarios. The Industry 4.0 technologies, including digital twins, monitoring using IoT and smart grids, will further unlock the potential of making decisions on the fly, based on data. Furthermore, hybrid systems will be expected to be more scalable and effective for large, complex manufacturing systems, particularly those using FGP in conjunction with other more sophisticated meta-heuristic or predictive algorithms. These advancements signal a future where energy-conscious, sustainable planning becomes an integral and intelligent part of modern industrial operations.

References

An, X., Si, G., Xia, T., Wang, D., Pan, E., & Xi, L. (2023). An energy-efficient collaborative strategy of maintenance planning and production scheduling for serial-parallel systems under time-of-use tariffs. *Applied Energy, 336*, 120794.

Bok, Y., Lee, N. K., Jo, S., Lee, S., Kweon, S. J., & Na, H. S. (2024). The production scheduling problem employs non-identical parallel machines with due dates, considering carbon emissions, and multiple types of energy sources. *Expert Systems with Applications, 238*, 121990.

Chen, J., Ning, T., Xu, G., & Liu, Y. (2022). A memetic algorithm for energy-efficient scheduling of integrated production and shipping. *International Journal of Computer Integrated Manufacturing, 35*, 1246–1268.

Ertem, M. (2024). Renewable energy-aware machine scheduling under intermittent energy supply. *IEEE Access, 12*, 23613–23625.

Fisco-Compte, P., Juanpera, M., Domenech, B., Pastor, R., Ranaboldo, M., & Bullich-Massagué, E. (2025). Sustainable optimal production scheduling methodology under implicit demand response and carbon policy: A manufacturing industry case study. *Applied Energy, 384*, 125403.

Geetha, M., Chandra Guru Sekar, R., Marichelvam, M. K., & Tosun, Ö. (2024). A sequential hybrid optimization algorithm (SHOA) to solve hybrid flow shop scheduling problems to minimize carbon footprint. *Processes, 12*, 143.

Germscheid, S. H. M., Nilges, B., von der Assen, N., Mitsos, A., & Dahmen, M. (2024). Optimal design of a local renewable electricity supply system for power-intensive production processes with demand response. *Computers & Chemical Engineering, 185*, 108656.

Germscheid, S. H. M., Röben, F. T. C., Sun, H., Bardow, A., Mitsos, A., & Dahmen, M. (2023). Demand response scheduling of copper production under short-term electricity price uncertainty. *Computers & Chemical Engineering, 178*, 108394.

Ghorbanzadeh, M., & Ranjbar, M. (2023). Energy-aware production scheduling in the flow shop environment under sequence-dependent setup times, group scheduling, and renewable energy constraints. *European Journal of Operational Research, 307*, 519–537.

Jagana, J. S., Amaran, S., & Zhang, Q. (2025). Multistage robust mixed-integer optimization for industrial demand response with interruptible load. *Computers & Chemical Engineering, 194*, 108974.

Leenders, L., Hagedorn, D. F., Djelassi, H., Bardow, A., & Mitsos, A. (2023). Bilevel optimization for joint scheduling of production and energy systems. *Optimization and Engineering, 24*, 499–537.

Ma, K., Qiao, D., Zhao, W., Guo, S., & Yang, J. (2022). Collaborative optimization of multi-energy operation and industrial production scheduling. In *Proceedings of the IEEE International Conference on Control and Automation (ICCA)* (pp. 784–789). IEEE.

Park, M. J., & Ham, A. (2022). Energy-aware flexible job shop scheduling under time-of-use pricing. *International Journal of Production Economics, 248*, 108507.

Sagar, K. V., Jerald, J., & Khan, M. A. (2024). An energy-aware optimisation model to minimise energy consumption and carbon footprint in a flexible manufacturing system. *International Journal of Interactive Design and Manufacturing, 18*, 2869–2880.

Samouilidou, M. E., Georgiadis, G. P., & Georgiadis, M. C. (2024). A multi-bucket time representation framework for optimal scheduling in beverage production facilities. *Computers & Chemical Engineering, 183*, 108611.

Tang, X., O'Neill, R., Hale, E., Baldick, R., & Baldea, M. (2024). Demand bidding vs. demand response for industrial electrical loads. *Computers & Chemical Engineering, 189*, 108768.

Tian, G., Wang, W., Zhang, H., Zhou, X., Zhang, C., & Li, Z. (2024). Multi-objective optimization of the energy-efficient remanufacturing system scheduling problem with lot-streaming production mode. *Expert Systems with Applications, 237*, 121309.

Trevino-Martinez, S., Sawhney, R., & Shylo, O. (2022). Energy-carbon footprint optimization in sequence-dependent production scheduling. *Applied Energy, 315*, 118949.

Wang, S., Li, J., Tang, H., & Wang, J. (2022). CEA-FJSP: Carbon emission-aware flexible job-shop scheduling based on deep reinforcement learning. *Frontiers in Environmental Science, 10*, 1059451.Rui, Z., Zhang, X., Liu, M., Ling, L., Wang, X., Liu, C., & Sun, M. (2024). Graph reinforcement learning for flexible job shop scheduling under industrial demand response: A production and energy nexus perspective. *Computers & Industrial Engineering, 193*, 110325.

Wang, X., Chen, B., Xiao, Y., Liao, S., Ye, X., & Bai, J. (2024). Optimized scheduling model considering the demand response and sequential requirements of polysilicon production. *Energies, 17*, 6048.

Zhang, Z., He, X., Man, Y., & He, Z. (2023). Multi-objective scheduling in a dynamic household paper workshop considering energy consumption in the production process. *Journal of Smart Environments and Green Computing, 3*, 87–105.

Zhao, Z., Jiang, Q., Liu, S., Zhou, M. C., Yang, X., & Guo, X. (2024). Energy, cost, and job-tardiness-minimized scheduling of energy-intensive and high-cost industrial production systems. *Engineering Applications of Artificial Intelligence, 133*, 108477.

Cite this article as:
Gbadebo, A. D., Aiyegbusi, A. E., Abimbola, O. G., & Opeisa, O. Z. (2026). Energy-aware production planning using fuzzy goal programming techniques: A review. *IAUE Journal of Computing Sciences*, *1*(1), 32-43.