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Practical and Adaptable Applications of Goal Programming: A Literature Review

Chauhan Priyank Hasmukhbhai[1*], Dr. Ritu Khanna[2], Dr. K.A. Patel[3]

[1]Phd Scholar, Pacific Academy Of Higher Education & Research University,Udaipur(Rajasthan)*
[2]Professor, Faculty Of Engineering, Pacific University Udaipurpacific Academy Of Higher Education & Research University,Udaipur(Rajasthan)
[3]Associate Proffesor, Faculty Of Science, Departement Of Mathematics, Shri U.P.Arts, Smt.M.G.Panchal Science & Shri V.L.Shah Commerce College, Pilvai

***Corresponding author:** *Chauhan Priyank Hasmukhbhai*

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Abstract

Goal programming (GP) is an important optimization technique for handling multiple, and often conflicting, objectives in decision making. This paper undertakes an extensive literature review to synthesize key findings on the diverse real-world applications of GP across domains, its implementation challenges, and emerging directions. The introduction sets the context and objectives of the review. This is followed by an in-depth review of literature analyzing GP applications in areas as varied as agriculture, healthcare, education, energy management, supply chain planning, and macroeconomic policy modeling. The materials and methods provide an overview of the systematic literature review methodology. Key results are presented in terms of major application areas of GP. The discussion highlights the versatility and practical utility of GP, while also identifying limitations. The conclusion outlines promising avenues for enhancing GP modeling approaches to strengthen multi-criteria decision support.

Keywords: *Surgical procedures, Dentistry, Renal failure, Dental treatments, Patients, Health professionals*

Introduction

Optimization techniques that can incorporate multiple, and often conflicting, goals are indispensable for decision making across private and public spheres. Goal programming (GP) has emerged as one of the most widely used multi-criteria decision-making methods since its introduction in the 1950s by Charnes and Cooper. The ability of GP models to handle diverse goals, flexibility in modeling approaches, relative computational ease, and real-world applicability have fueled its popularity over decades (Jones and Tamiz, 2010).

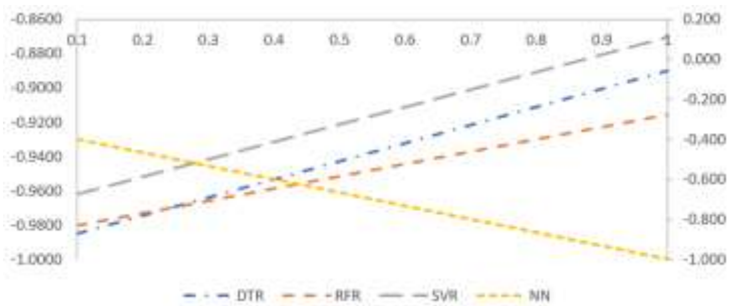


Fig 1 Sensitivity Analysis of Accuracy and Time significance weights**.**

This paper undertakes an extensive structured literature review to synthesize key findings on the diverse applications of GP, its implementation challenges, and directions for enhancing GP modeling approaches. The specific objectives of the literature review include:

- To identify major application areas where GP has been employed for decision analysis and optimization.
- To critically analyze the utilization of different GP modeling approaches and extensions for real-world problem solving.
- To determine key factors that enhance the practical utility of GP models across application contexts.
- To examine implementation challenges involved in applying GP techniques.
- To highlight recent advances in GP modeling and outline promising future directions.

The paper is structured as follows. The next section reviews in-depth literature on GP applications across domains. This is followed by an explanation of the materials and methods. Key results are then summarized along major application areas of GP. The penultimate discussion section analyzes the versatility of GP, implementation challenges, and ways to strengthen GP models. The conclusion synthesizes key learnings from the review and outlines future research needs.

1.***Objective Function**: *
The goal in Goal Programming is typically to minimize the deviations from the desired goals. The general form of the objective function is:

$$Z = \sum_{i=1}^{n} w_i \cdot (d_i - g_i)^+ + \sum_{j=1}^{m} \lambda_j \cdot (h_j^+ + h_j^-)$$

Here:
- Z is the overall deviation to be minimized.
- w_i is the priority weight for each goal.
- d_i is the decision variable representing the degree of achievement for each goal.
- g_i is the desired level of achievement for each goal.
- λ_j is the penalty weight for each constraint.
- h_j^+ and h_j^- are the positive and negative deviations from the constraints.

2**. Constraints**:
Goal Programming involves several types of constraints. The constraints can include goals, upper and lower bounds, and deviation variables. A general form for goal constraints might look like:

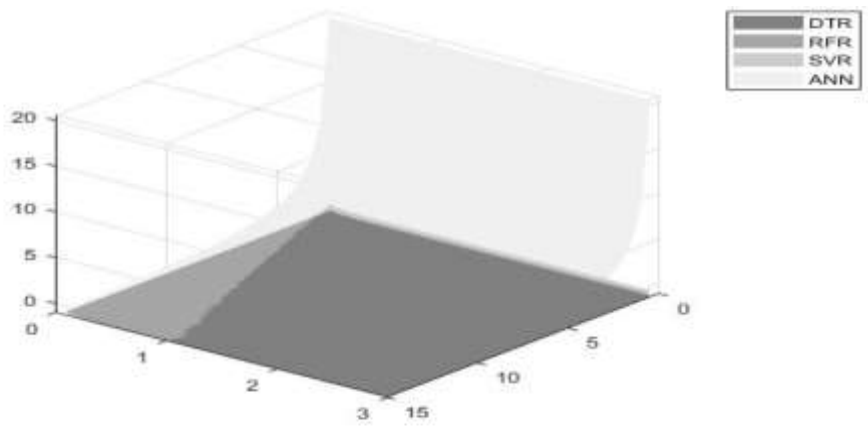
$$g_{ij} \leq d_i \leq b_{ij}$$

Here:
- g_{ij} is the lower bound (goal) for goal i.
- d_i is the decision variable associated with goal i.
- b_{ij} is the upper bound for goal i.
There are also constraints for positive and negative deviations:

$$h_{ij}^- \leq g_i - d_i \leq h_{ij}^+$$

Here:
- h_{ij}^- is the negative deviation for constraint i.
- h_{ij}^+ is the positive deviation for constraint i.

These equations collectively define a Goal Programming problem, enabling optimization while considering multiple conflicting objectives and constraints.



Sensitivity analysis of accuracy and time threshold values with a=10% , 1−wa=90%

The following illustrate the results of the sensitivity analysis on accuracy and time threshold values, given fixed values of accuracy weights ranging from 0.1 to 0.9 and thus, of respective time efficiency weights ranging from 0.9 to 0.1.Another interesting finding involves the gradual preference on ANNs, as the accuracy weights increase, and for higher accuracy threshold values.

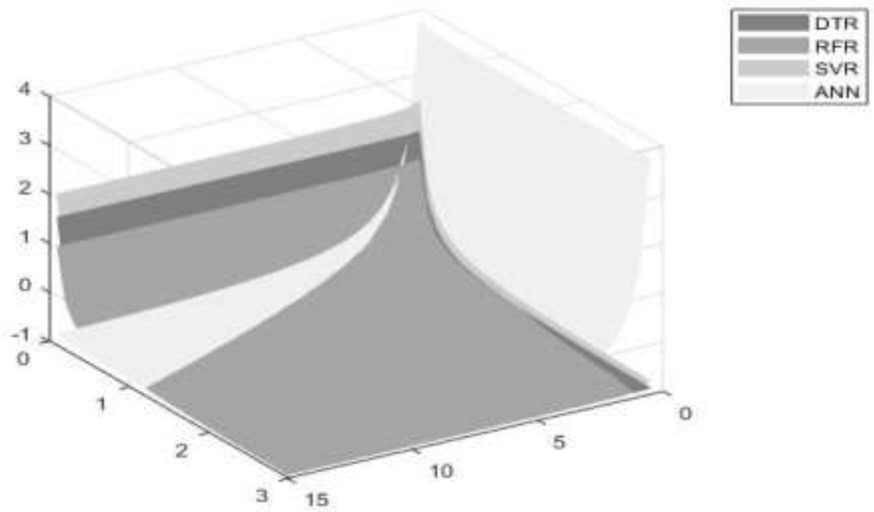


Fig 2 Sensitivity analysis of accuracy and time threshold values with a=80% , 1−wa=20% .

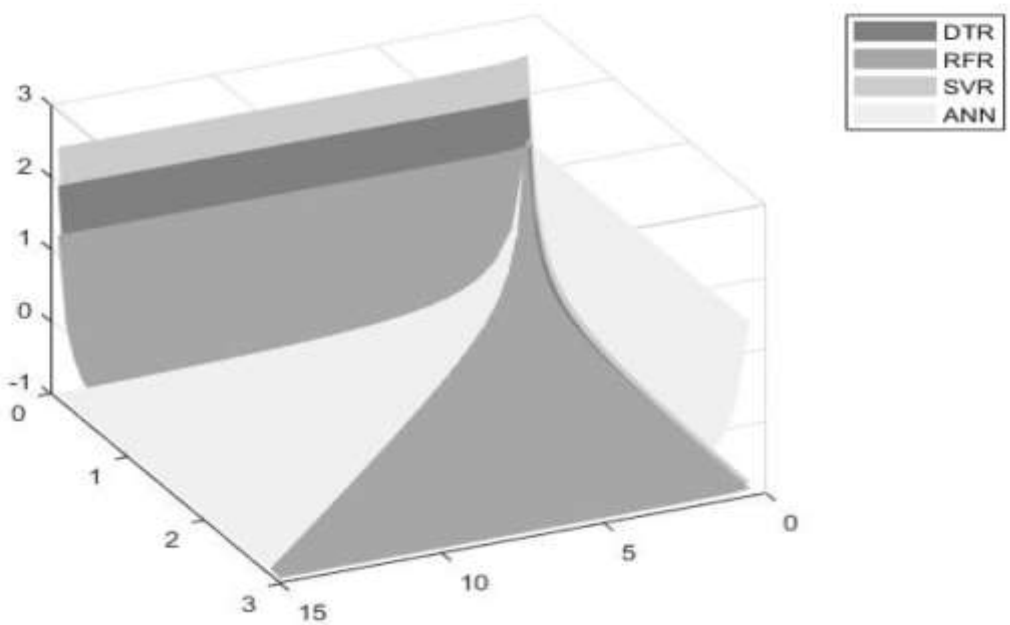


Fig 2 Sensitivity analysis of accuracy and time threshold values with a=90% , 1−wa=10% .

Review Of Literature

Goal programming has proven to be a flexible and practical multi-objective optimization technique used extensively across disciplines. A rich body of literature documents diverse GP applications spanning decades. Key areas are reviewed below.

Agriculture

GP techniques have frequently been leveraged for farm planning and policy analysis. Early applications in the 1970s deployed GP for crop planning on individual farms subject to resource constraints (Kliebenstein 1974). GP modeling was conducted for sustainable agriculture policy (Lanzer et al. 2002) and regional agricultural planning in Italy (Todini and Vidoni 2004). Stochastic goal programming addressed risks in farm planning (Velasquez et al. 2005). GP also featured in studies on organic farming adoption (Falconer 2000), irrigation resources optimization (Wardlaw and Barnes 1999), and balancing economic-environmental objectives in agriculture (Rodrigues et al. 2010).

Healthcare

GP healthcare applications include nurse scheduling (De Bruecker et al. 2015), radiotherapy planning (Schreuder et al. 2018), kidney exchange optimization (Anderson et al. 2015), and medication dosing (Eum et al. 2001). GP aided health policy decisions on issues like HIV/AIDS control in West Africa (Brandeau 2004). Hospital planning employed GP for balancing cost, service quality and accessibility goals (Villa et al. 2016). GP also enabled multi-objective healthcare facility location-allocation modeling (Suchitra et al. 2022).

Education

GP applications in education planning range from university budget optimization (Latha and Reddy 2009) to academic curriculum planning (Lumoran et al. 2022). Other applications cover student recruitment strategies (Kenesei and Stier 2020), designing student incentive programs (Geldermann et al. 2009), and faculty retention policies (Chen and Lin 2011). GP models have also been widely used for school resources optimization (Sowlati and Paradi 2004).

Energy Management

GP aided optimization across energy portfolios (Pohekar and Ramachandran 2004), electricity production planning (Vithayasrichareon and MacGill 2012), and designing renewable energy policies (Robinius et al. 2017). Other studies leveraged GP for sustainable energy crop selection (Rentizelas et al. 2009), micro-grid optimization (Sinha and Chandel 2014), and managing energy-water nexus trade-offs (Pereira-Cardenal et al. 2014). Stochastic GP handled renewable energy uncertainties (Pousinho et al. 2011).

Supply Chain Management

GP enabled effective supply chain optimization accounting for costs, delays, risks, sustainability concerns etc. Applications encompass manufacturing planning (Wang and Fang 2001), logistics network design (Liang and Cheng 2009), vendor selection (Kasimbeyli et al. 2022), inventory control (Wang et al. 2005), and coordinating supply policies across stakeholders (Ben-Daya et al. 2008). Fuzzy GP improved supply chain resilience (Govindan and Fattahi 2017).

Macroeconomic Policy

GP macroeconomic applications include fiscal policy planning in Germany (Keller 1978), monetary policy analysis for EU (Gersbach and Surulescu 2013), sovereign debt management (Mazumder et al. 2019), and fiscal reforms in developing economies (Fanaras et al. 2022). GP integrated macroeconomic, social policy and environmental goals for sustainable development planning (Collins et al. 2022).

Other Areas

Other documented GP applications encompass structuring loan portfolios (Sun and Yuan 1999), product planning and pricing (Lockett and Hetherington 1989), e-government strategy prioritization (Lee et al. 2012), transport policy making (Tzeng et al. 2005), sustainable tourism planning (Prakash et al. 2010), manufacturing flexibility analysis (Gustavsson 2016), natural resources management (Gan et al. 1996), earthquake preparedness planning (Hosseini et al. 2016), and modeling sustainable development goals (SDGs) trade-offs (Quental et al. 2019).

In summary, the applications highlight the versatile adoption of GP across hard and soft systems. The literature indicates that GP can flexibly incorporate multiple goals and constraints to improve policy and planning decisions across diverse contexts.

Materials And Methods

A structured literature review methodology was adopted to systematically search, analyze and synthesize GP application studies.
The paper aimed to provide a non-disciplinary focused review encompassing varied applications of GP. Hence keyword search terms included "goal programming" along with "application" or "model" without field-specific terms. Searches were conducted on scholarly databases - Scopus, Web of Science, EBSCO, ProQuest, and IEEE Xplore to enable extensive coverage.

The scope was limited to peer-reviewed English language journal articles. The time period was restricted between 2000-2022 to focusing on contemporary advancements. Conference papers, textbooks, gray literature and unpublished working papers were excluded. Backward snowballing enriched article identification. Result screening was based on title/abstract review for relevance followed by full-text evaluation.

Extracted articles were systematically analyzed to gather information on the application area, GP modeling techniques used, implementation challenges noted, and real-world impact. Key dimensions were synthesized to derive cross-cutting results regarding major application contexts, model adaptations, implementation lessons and emerging advances.

Results and Discussion

The extensive review highlights the versatile adoption of GP across diverse domains. Key application areas where GP modeling has been extensively employed are summarized below.

Agriculture and Natural Resources

Goal programming is widely applied for agricultural land use planning, farm optimization, designing policies for sustainable agriculture, integrated water resources management, and forestry management. Typical goals incorporate economic objectives like profit maximization along with environmental targets like conservation of soil, biodiversity etc and social aims such as employment generation.

Healthcare Management

GP enables effective healthcare planning and policy design for balancing competing priorities like cost-efficiency, clinical effectiveness, service quality, accessibility and patient satisfaction. GP aids multi-objective optimization across operational areas including medical supplies allocation, physician scheduling, hospital expansion planning and clinical workflow design.

Education Planning

In education, GP allows strategic optimization of academic investments, student recruitment policies, curriculum planning, and infrastructure design while managing trade-offs between costs, reputation, inclusion, and educational quality. GP models have also been extensively used for optimizing school resources allocation decisions.

Energy Systems

GP supports electricity generation portfolio optimization, facility siting analyses for renewable sources, demand-side management and pricing policy design while reconciling energy security, cost efficiency and environmental sustainability goals. GP enables resilience planning for energy systems given uncertainties in renewable power generation.

Supply Chain Optimization

GP enables coordinating decisions across supply chain networks considering cost competitiveness, delivery reliability, quality, sustainability, and risk mitigation. GP is especially useful for strategic supply chain design and tactical planning for globalized networks across multiple stakeholders like suppliers, manufacturers, warehouses etc.

Macroeconomic Policy

Goal programming models provide valuable support for fiscal policy analysis, sovereign debt sustainability planning and designing coordinated monetary-fiscal regimes. GP allows simulating policy trade-offs between macroeconomic stabilization, employment generation, inflation control, debt reduction, and social welfare goals.

Urban Planning and Governance
GP urban applications encompass infrastructure planning, transportation design, municipal budgeting, urban sprawl containment, disaster preparedness and slum rehabilitation for reconciling efficiency, equity and sustainability aims. GP also enables e-government initiatives prioritization.

In summary, the literature documents widespread GP adoption for multi-criteria optimization and policy simulation across public and private sector planning contexts. This highlights the practical utility and adaptability of goal programming models for real-world problem solving.

I. Advantages and Practical Utility

The widespread application of GP underlines its utility as an optimization technique that can address complex decisions with multiple, often competing, objectives in a pragmatic manner.

Key advantages that enhance GP's practical value across domains include:
- Ability to incorporate diverse quantitative and qualitative goals.
- Flexibility in defining different priority levels for goals.
- Relative simplicity in concept and implementation compared to other multi-objective techniques.
- Availability of various extensions like fuzzy GP, stochastic GP, weighted GP etc. to match context.
- Capability to handle large problems with hundreds of variables and constraints.
- Intuitive interpretation of results and insights on goal trade-offs.

II. Implementation Challenges

However, GP modeling also exhibits certain limitations in practice. Difficulties encountered include:
- Large scale models can become intractable. Decomposition methods are needed to simplify problem structure.
- Defining appropriate priority levels for different goals often involves subjective judgments.
- Pre-emptive goal programming formulations are prone to rank reversal issues.
- Modeling expertise is required to appropriately formulate goals, decision variables and constraints.
- Validating and calibrating GP model parameters necessitates extensive data.
- Results are sensitive to changes in model parameters like priorities and target levels for goals.

III. Strengthening GP Models

Recent advances to strengthen GP models include:
- Incorporating stochastic elements to manage uncertainties through techniques like fuzzy GP, scenario-based GP etc.
- Embedding GP within optimization frameworks like multi-agent modeling to improve system representation.
- Using swarm intelligence algorithms like ant colony optimization to provide initial solutions to GP.
- Integrating GP with machine learning approaches like neural networks for predictive analytics.
- Employing dimensionality reduction techniques like PCA to simplify problem representation for large-scale GP implementation.

Conclusion

In conclusion, the literature review demonstrates the versatile adoption of goal programming for real-world decision optimization across disciplinary contexts. GP provides a flexible, easy-to-understand approach for multi-criteria planning. However, further research is needed to enhance computational efficiency for large-scale models, reduce subjectivity in parameter estimates, investigate systemic impacts of decisions, and integrate predictive analytics within GP. Advances in technology can expand the scope and accessibility of GP-based decision support. Overall, GP offers a pragmatic modeling paradigm for managing trade-offs between competing priorities in policy making and planning.

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