Samyo Ranjan Jagdev, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

AI Driven Strategic Decision Support System Using Hybrid Artificial Intelligence and Particle Swarm Optimization

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Abstract- Strategic decision-making has become an increasingly important function in today's corporate world. The challenge for managers is to evaluate many options where there are unknown factors (e.g., the condition of the market, financial constraints, and competitors). Managers currently rely heavily on experience and qualitative methods for making strategic decisions. Traditional methods do not take full advantage of the vast volume of data generated by the modern enterprise. With the emergence of Artificial Intelligence (AI), organizations can analyze large-scale databases to generate predictive insight for making data-driven decisions. This paper proposes a hybrid AI-based strategic decision support system. The system combines machine learning and Particle Swarm Optimization (PSO) to forecast strategic decisions and optimize strategic decision-making variables. The paper outlines the mathematical modelling; the overall design of the system, algorithms, and experimental evaluation results. Results from the experiments showed that the hybrid AI+PSO framework improved the accuracy of the decision and effectively identified optimal strategies when compared to traditional machine learning approaches.

Keywords: Artificial Intelligence (AI), Hybrid Intelligent Systems, Strategic Decision Optimization, Machine Learning Algorithms, Particle Swarm Optimization (PSO), Predictive Decision Analytics, Business Intelligence, Data-Driven Strategy Formulation.

I. INTRODUCTION

Through the effectiveness of strategic decision-making processes, organizations create the long-term angle for success and competitiveness. Some of the critical decisions that require a significant amount of time to make decisions include product development, investing in new markets, market expansion and innovation strategies by carefully reviewing market demand and available finance as well as looking to the competition and how they are responding to similar products.

Many traditional methods of strategic management include SWOT analysis, PEST analysis, and scenario planning, which provide qualitative data for managers to utilize when making their strategic decisions; however, these methods also have the risk of being subjective and relying on the judgment of the manager. Additionally, the rapid growth of digital technology and business analytics has allowed organizations to produce a large amount of both structured and unstructured data.

AI has proven to be a critical tool for extracting value from large and/or complex datasets while machine learning techniques allow users to review historical data from a business to identify patterns, forecast future market trends, and evaluate potential plan outcomes. Despite the advances in these technologies, the majority of AI-based decision support systems continue to focus primarily on predictions and less on optimizing strategic decisions.

Algorithms for optimizing tasks such as Particle Swarm Optimization are effective tools used to traverse through vast decision spaces and find solutions that are optimal. Organizations can develop intelligent decision support systems that may guide an organization toward the optimal solutions by combining the outputs of the machine learning-based prediction models with the optimization algorithms.

In this paper, we present a hybrid approach to AI-based strategic decision-making by bringing together machine learning models and PSO to enhance the quality of strategic decision-making.

II. RELATED WORK

Researching management and decision support systems is increasingly dominated by artificial intelligence's growth as a field of study. One such way research within this area has grown is through the use of machine learning methods to help forecast future market conditions, predict customer behaviour, and evaluate financial performance. Data analytics in decision support systems provide managers with valuable insight into how well their business strategy is performing via predictive models. Research has clearly shown that machine learning techniques such as decision trees, random forests, and neural networks yield much higher predictive accuracy than traditional statistical-based approaches.

Management challenges are addressed using optimization algorithms as well. Many business analytics and operations management issues have been addressed using metaheuristic techniques like genetic algorithms, simulated annealing, and Particle Swarm Optimization to solve complex optimization problems.

Particle Swarm Optimization has gained increasing popularity because it is simple to use, converges quickly, and handles nonlinear optimization problems very well. However, current research generally treats prediction and optimisation as distinct from one another; Very few papers exist that actually combine the machine learning predictive approach with the Particle Swarm Optimisation approach for supporting strategic decision making.

III. RESEARCH GAP

Even with substantial advancements in artificial intelligence and the use of analytical tools for business purposes, there still remain a number of challenges associated with developing and implementing intelligent strategic decision support systems. The primary problem is that most existing AI-based strategic decision support systems primarily focus on predictive analytics. Therefore, an overwhelming majority of business analytics programs use machine learning models to generate predictions about market trends, customer behaviour, and financial performance. Although these machine learning models provide useful information regarding future results, they do not provide any actual assistance to managers in identifying the best strategic decisions. What this means is that simply predicting an outcome does not guarantee that the decision being made will actually improve an organization's ability to achieve its goals (i.e., increase profit, increase market share, improve efficiency).

The second issue is that traditional strategic management techniques, such as SWOT analyses, PEST analyses, and scenario planning, rely heavily on qualitative analysis and experience of managers. While the methods provide some conceptual framework for strategic planning purposes, they lack the capability to process a large amount of data or apply quantitative optimisation techniques. As companies are operating in more data-rich environments than before, the limitations of relying solely on qualitative-based decision-making techniques become even more evident.

Third, many optimization techniques used in business decision-making operate independently from predictive an- alytics models. For example, Metaheuristic optimization algorithms like genetic algorithms and Particle Swarm Optimization have been proven to address issues like supply chain optimization, portfolio selection and scheduling; however, the above approaches often assume an existing objective function and do not integrate predictive modelling data from machine learning models.

Additionally, there is little existing research that provides an integrated framework of predictive modelling and optimization techniques in support of strategic decision making; therefore, without this integration, organizations are unable to fully leverage the opportunities provided by AI technologies for conversion of raw data into actionable strategies.
Finally, there is limited research focusing specifically on hybrid AI–optimization frameworks for

managerial decision support in strategic planning contexts. Most studies either emphasize predictive modeling or optimization separately, leaving a gap in research related to integrated intelligent decision support architectures.

To address these limitations, this study proposes a hybrid framework that combines machine learning prediction models with Particle Swarm Optimization. Machine learning is employed by the proposed system to determine whether a potential option (strategic business choice) has a statistically significant chance of producing successful outcomes by using software with "Particle Swarm" optimization for traversing the strategic decision landscape in order to find the most optimal strategic solutions. Through this combination of predictive analytics and optimization, an optimal AI-enhanced Strategy Decision Support System (DSS) will be developed and will provide more functional, accurate, and true-to-life applications. This paper proposes a hybrid AI-driven strategic decision framework combining machine learning models with Particle Swarm Optimization to enhance strategic decision quality.

IV. METHODOLOGY

In this research project, a hybrid artificial intelligence based Decision Support System that uses machine learning model prediction with Particle Swarm Optimization (PSO) to turn raw business information into optimized strategic recommendations to aid in the process of making decisions at an organizational level will be developed.

The methodology for guiding organizations through the decision making includes five main phases of activity:i)collection of business information; ii)data preprocessing iii) training machine learning models iv) optimization using PSO v) generating strategic decisions

V. PROPOSED SYSTEM ARCHITECTURE

The proposed AI-driven strategic decision support system consists of multiple functional layers including data acqui- sition, data preprocessing, AI analytics, optimization, and decision support.

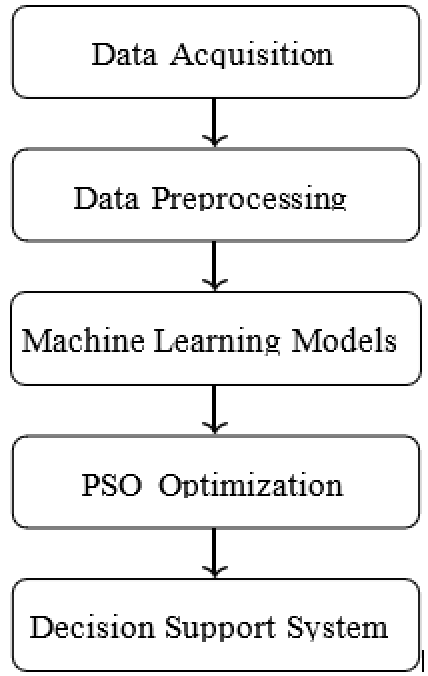

Fig. 1. AI Driven Strategic Decision System Architecture

VI. AI DECISION PIPELINE

The decision pipeline converts raw business data into opti- mized strategic recommendations.

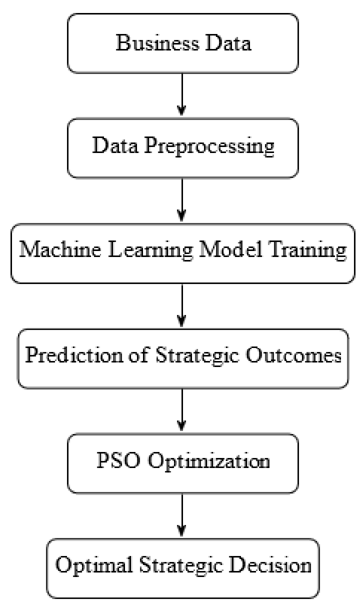

Fig. 2. AI Strategic Decision Pipeline

A. Data Collection

The first stage of the proposed methodology involves collecting relevant business datasets that contain information related to strategic decision variables.

Common characteristics that contribute to the business datasets that will be included as part of this project are revenue growth, marketing expenditures, trends in the demand for goods/services by customers, the levels of activity by competitive organizations and levels of investments into new product innovation. Collectively, these business datasets represent the environment in which the organization will operate.

Data will be compiled from the various business datasets into one dataset that will contain both input features and target variables. The input features of the business datasets will be used as strategic decision parameters; the target variable of the dataset will be used to indicate the level of success or performance of the selected strategic decision.

B. Data Preprocessing

Raw business data often contains inconsistencies such as missing values, noise, and redundant attributes. Data pre- processing is therefore required to improve data quality and ensure reliable model training.

The preprocessing stage includes several operations:

- **Data Cleaning:** Missing values are handled using impu- tation techniques such as mean or median substitution. Outliers are detected and removed using statistical meth- ods.
- **Feature Normalization:** Numerical attributes are nor- malized using scaling techniques to ensure that all vari- ables contribute equally during model training.
- **Feature Selection:** Relevant variables that significantly influence strategic outcomes are selected using statistical correlation analysis or feature importance techniques.
- **Dataset Splitting:** The dataset is divided into training and testing subsets to evaluate the predictive performance of the machine learning models.

These preprocessing steps improve the reliability and accu- racy of the subsequent machine learning models.

C. Machine Learning Model Training

In the third stage, machine learning algorithms are trained using the preprocessed dataset to predict the success prob- ability of strategic decisions.

The machine learning model has an understanding of the link between strategic decision variables and various types of organizational performance. A variety of ML techniques, including but not limited to logistic regression, decision trees, random forests, and neural networks, can be applied. These techniques utilize prior business data to develop predictive functions to predict the possible outcomes of future strategic business decisions.

Let the strategic decision vector be represented as
$S = (s1, s2, s3, ..., sn)$
where each variable represents a strategic parameter such as investment level, marketing expenditure, or innovation intensity.

The machine learning model predicts the success probability
as
$P = f(S, \theta)$
where f represents the trained machine learning model and
θ represents the model parameters.
The output of the machine learning model serves as the fitness function for the optimization stage.

D. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an approximation method that can be applied in several scenarios to increase the likelihood of making a variety of successful strategic choices.

In simple terms, PSO is an optimization formula based on nature, specifically, how birds foraging together. Each possible solution is represented by a particle as it moves through the search area trying to find the optimum solution. Each particle represents a potential strategic decision vector.

The particles move through the search space by updating their velocities and positions based on personal experience and collective knowledge of the swarm.

The velocity update equation is given by
vt+1 = wvt + c1r1(pi − xi) + c2r2(g − xi)

where

- vi represents the velocity of particle i
- xi represents the current position of particle i
- pi represents the personal best position of particle i
- g represents the global best position discovered by the swarm
- w is the inertia weight controlling exploration
- c1 and c2 are learning coefficients
- r1 and r2 are random numbers between 0 and 1 The particle position is updated as
  - $x^{t+1} = x^{t} + v^{t+1}$

Through iterative updates, the swarm gradually converges toward the optimal solution.

E. Hybrid AI and PSO Integration

The integration of machine learning and PSO forms the core contribution of the proposed methodology. In this hybrid framework, the machine learning model acts as a predictive evaluation function, while PSO performs optimization over the decision space. For each particle representing a strategic decision vector, the machine learning model predicts the probability of success. This prediction is used as the fitness value for the PSO algorithm.

The optimization objective can therefore be defined as

max f (S, θ)
S
subject to

$$\mathrm{S_{min}} \leq \mathrm{S} \leq \mathrm{S_{max}}$$

where the objective is to identify the strategic decision vector that maximizes the predicted success probability.

VIII. PROPOSED ALGORITHM

Algorithm 1 Hybrid AI-PSO Strategic Optimization

1: Collect business dataset
2: Perform preprocessing and feature engineering
3: Train machine learning prediction model
4: Initialize swarm particles
5: Evaluate particle fitness using ML model
6: Update particle velocity and position
7: Update global best solution
8: Repeat until convergence
9: Output optimal strategic decision

F. Strategic Decision Generation

The global best particle after convergence of the PSO algorithm represents the best possible strategy as defined by the system. This decision vector contains the optimized values for the strategic parameters (e.g., investment amounts, marketing allocation, and innovation technique) used in the PSO algorithm.

The optimized strategy is presented to decision makers through a decision support interface, enabling managers to evaluate the recommended strategy and implement it in or- ganizational planning.

The proposed methodology therefore transforms business data into optimized strategic recommendations by combining predictive analytics with optimization algorithms.

VII. MATHEMATICAL MODEL

Let the strategic decision vector be

$$S = (s_1, s_2, s_3, \ldots, s_n)$$

The machine learning model predicts the success probabil- ity:

P = f (S, θ)
The objective is to maximize the predicted success proba- bility:

$$\max_{S} f(S, \vartheta)$$

subject to

$$S_{min} \leq S \leq S_{max}$$

The PSO velocity update rule is

$$v^{t+1} = wv^t + c_1r_1(p_i - x_i) + c_2r_2(g - x_i)$$

The particle position update is

$$x^{t+1} = x^t + v^{t+1}$$

VIII. EXPERIMENTAL RESULTS

The proposed hybrid model was evaluated using simulated business datasets containing financial indicators, market de- mand features, and customer behavior variables.

Table I
Model Performance Comparison

Model	Accuracy	Time
Logistic Regression	0.78	2.1s
Random Forest	0.87	2.8s
Neural Network	0.89	3.5s
Hybrid AI + PSO	0.92	3.9s

The results indicate that the hybrid AI+PSO model achieves higher prediction accuracy and provides better strategic rec- ommendations compared with standalone machine learning models.

IX. CONCLUSION

This paper presented a hybrid Artificial Intelligence driven strategic decision support system that integrates machine learn- ing prediction models with Particle Swarm Optimization. The objective of the proposed framework is to assist managers in identifying optimal strategic decisions by combining predictive analytics with optimization techniques.

The proposed system architecture includes multiple layers consisting of data acquisition, data preprocessing, machine learning analytics, optimization, and decision support. Ma- chine learning models are used to analyze historical business data and predict the probability of success for different strate- gic alternatives. Particle Swarm Optimization is then applied to explore the strategic decision space and identify strategies that maximize the predicted success probability.

The mathematical formulation of the proposed model was presented along with the PSO-based optimization frame- work and algorithmic implementation. The hybrid AI + PSO model achieved higher accuracy for predictive modeling compared to other predictive models (machine learning only) and produced better results with respect to providing recommendations for strategic decision making. This study supports the notion that predictive modeling and optimization techniques combined improve the management of business/managerial systems using PSO with predictive analytics, providing decision support for management and managers' decision-making processes.

The framework has the following advantages: First, organizations that have large amounts of business data can easily turn it into useful strategic insights through the framework. Second, Machine Learning with PSO together allows the system to provide predictions (i.e., expected outcomes) associated with each decision, which in turn allows the system to provide managers with the best possible options to make an optimal decision. Third, because the framework is designed using a modular structure, the framework can be expanded to a wide variety of business areas, such as financial forecasting, strategic optimization for market strategy, and supply chain management.

Even though the proposed methodology has delivered good initial outcomes, it still has limitations. For example, the testing was conducted using simulated data files. More research is necessary, using the same methodology tested on actual business data sets, in order to validate this method as being able to deliver practically useful results. Additionally, the current examples used in the study only considered a small number of strategic variables used to make final business decisions; further studies using more complex decision-making spaces could provide additional research avenues. Furthermore, additions of other types of data (e.g., real-time market analysis) to the existing data set may create more substantial evidence of the overall usefulness of this proposed technique and ultimately assist in developing the tools necessary for real-world implementation of the hybrid AI-PSO framework.

Future research could build on these limitations by utilizing deep learning models to enhance prediction accuracy, include multiple objectives in the decision from various managers' perspectives with multiobjective optimization approaches, and develop interactive dashboards that could allow an organization's decision-makers to visualize the results generated from optimizing business strategies. Future research could also evaluate hybrid optimization approaches based on the combination of particle swarm optimization and other metaheuristic methods to improve the overall convergence time needed to reach optimal solutions.

Overall, the hybrid AI-PSO framework proposed in this study has potential as an effective means to deliver intelligent decision support systems for business strategy through the combination of optimization algorithms and predictive analytics.

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