A DISCUSSION ON SUPPLIER SELECTION MODELING APPROACHES

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ABSTRACT

Supplier selection is a subfield of supply chain management that involves multiple steps in order for decision-makers to find suitable suppliers. Supplier selection is important as it could influence the whole company positively or negatively. It has, recently, become a topic of interest because of the recent pandemic and its effect on the global supply chain, which causes supply shortages. As such, the focus of this paper is on characteristics of decision-making modeling approaches, specifically agent-based modeling and multi-agent systems, in supplier selection, as its modeling has always been a challenge for companies due to its complex nature.

Keywords: supplier selection, strategic decision-making, agent-based modeling, multi-agent systems.

1 INTRODUCTION

Supplier selection considers a multi-criteria decision-making (Tirkolaee, Sadeghi et al. 2021) that involves processes such as identification, evaluation, and assessment of suppliers (Chai and Ngai 2020). There are three key concepts in supplier selection: (i) evaluation criteria, (ii) environment, (iii) and decision-making models (De Boer, Labro et al. 2001). Evaluation criteria are about selecting criteria for calculating supplier performance, environment refers to the diversity of purchasing situation with regards to its complexity (i.e., first time buy, modified rebuys, straight rebuys of routine or strategic) and the decision-making models enhance the effectiveness and efficiency of purchasing decisions while dealing with complexity (De Boer, Labro et al. 2001). In this paper, only the decision-making models will be discussed with a focus on agent-based modeling and multi-agent systems.

Supplier selection is defined by the processes which decision-makers choose to go through to end up in the final list of suppliers. The core structure of the supplier selection model has problem definition, formulation of criteria, qualification, and choice (De Boer, Labro et al. 2001, Van Weele 2001, Cousins, Lamming et al. 2008). The problem definition refers to the intuition behind selecting the supplier, formulation of criteria refers to the processes in which the best criteria and their related importance weights should be selected to calculate supplier performance, qualification refers to the list of qualified suppliers based on their performance, and the choice refers to the final list of selected suppliers. An extension to the core structure model is the case where supplier performance is evaluated and monitored after being selected (Zhu and Geng 2001, Morton 2002), and feedback send to the suppliers of the information used in the qualification and formulation of criteria steps (Igarashi, de Boer et al. 2013). The core structure of supplier selection along with the extension is depicted in Figure 1.

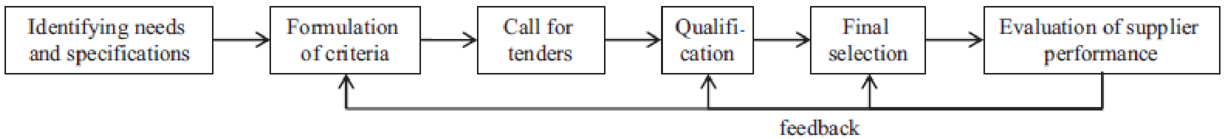

Figure 1: An extended model of supplier selection is taken from Igarashi, de Boer et al. (2013).

As it can be inferred from Figure 1, each of the steps in supplier selection is tied to decision-making. As such, multiple modeling approaches emerged in order to address and ease decision-making. A selected modeling technique intuition in supplier selection is to elevate the effectiveness and efficiency of purchasing decisions; by effectiveness it is mean: solving the right problem, selecting the best evaluation criteria, and modeling the decision situation more accurately. Efficiency refers to facilitating the decision-making process, increasing information availability, and improving communication between supply chain members (De Boer, Labro et al. 2001).

Formal models that support decision-making in supplier selection can be categorized as (i) mathematical-based programming models (MP), (ii) multi-criteria decision-making models (MCDM), (iii) AI-based and data mining models (AIDM), and (iv) others.

MP models focus on finding the best possible solution to a problem (optimization). MCDM models aim for ranking between available alternatives to give knowledgeable recommendations from multiple viewpoints (Chai, Liu et al. 2013). AI-based and data mining models methods mainly focus on classification, clustering, and optimization of alternatives, along with forecasting. Others refer to modeling approaches that are not classified in the other three classifications like agent-based modeling. We should note that multi-agent systems are under the AI-based models.

The focus of this paper is on characteristics of decision-making modeling approaches, specifically agent-based modeling and multi-agent systems in supplier selection, comparison of different modeling approaches, and the current increasing trend in utilizing modeling approaches. In addition, validation is an important concept in modeling and simulation. As such, a discussion on how researchers validate their supplier selection models will be covered in this paper.

2 BACKGROUND

Considering all the above modeling approaches in three major categories as (i) mathematical-based programming models, (ii) multi-criteria decision-making models, and (iii) AI-based and data mining models, ABM and MAS focus is not either of their focuses, as we mentioned earlier. In the following strengths and weaknesses of each category with a focus on ABM and MAS and future trends will be discussed respectively in the field of supplier selection.

2.1 Mathematical Based Programming Models

As the Focus of MP models is to find the best possible solution, this characteristic makes them face major limitations in supplier selection choice. The advantage that MP models have compared to other approaches is that they are easy to build, but in complex situations, they are hard to solve (Collins, Vegesana et al. 2013). Besides their inability to be solved in a complex situation, they have other limitations like; everything in the model needs to be precise, which may not always be the case as there is always some information that is not available to decision-makers and eventually makes the model be far from reality (Chai and Ngai 2020). Also, they only work with quantitative criteria and require to have objective function provided by decision-makers (De Boer, Labro et al. 2001). These limitations may prevent MP models from working best in the supplier selection process with qualitative criteria and also the high level of uncertainty and imprecision.

2.2 Multi-criteria Decision-making Models

MCDM is able to support the decision-making process by evaluating multiple alternatives (Guo, Yuan et al. 2009). The advantage that MCDM models have is their ability to be combined with other modeling approaches; this is why it is the prevalent approach in building hybrid models in the literature of supplier selection (Zimmer, Fröhling et al. 2016). Along with this advantage, it also has limitations like it cannot be used in a situation with a large number of evaluation criteria and suppliers, more suitable for static environments (Tirkolaee, Sadeghi et al. 2021). A major limitation of this modeling approach is subjectivity which comes from being heavily dependent on human decisions incorporated to its framework (Chai and Ngai 2020). These limitations may cause less effectiveness of this modeling approach in solving supplier selection problems.

2.3 AI-based and Data Mining Models

Tavana, Fallahpour et al. (2016) proposed that supplier behavior can be replicated by the capability in AI models. AI like other modeling has limitations; such as it cannot incorporate human judgments (Chai and Ngai 2020), and it is usually hard to be explained to others in the case of external justification (De Boer et al. 2001). Also, in general, they work better with a large amount of data. Multi-agent systems, one focus of this paper, are classified under this category and will be discussed in the following.

2.4 Multi-agent Systems and Agent-based Modeling

Multi-agent systems and agent-based models are suitable for modeling, designing, and implementing a complex system like a supply chain (Toorajipour, Sohrabpour et al. 2021). They have applications in supply chain management, as it is shown in Figure 2. Their applications in supply chain management are extracted from (Min 2010, Toorajipour, Sohrabpour et al. 2021), which covers the years between 1998 and 2018.

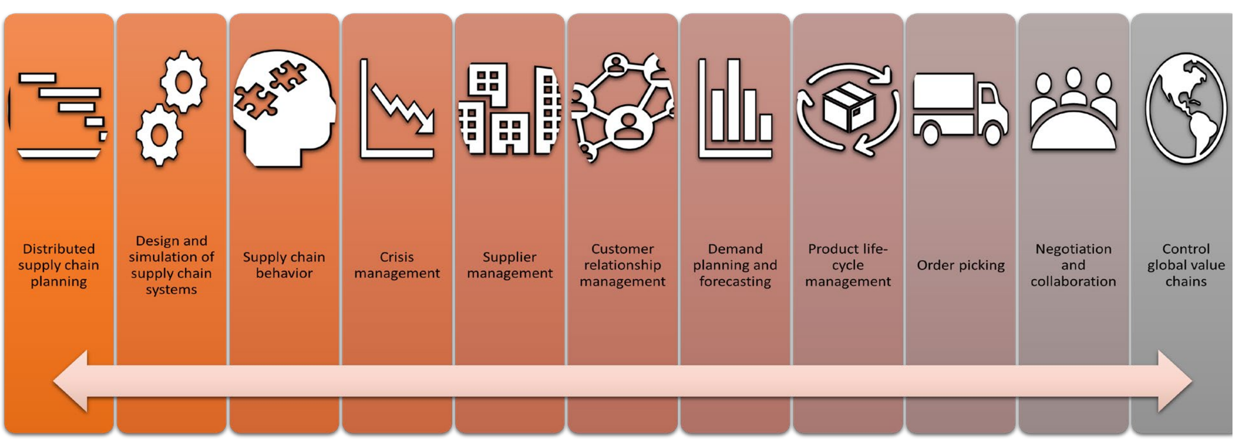

Figure 2: ABM and MAS applications in supply chain management.

The broad applications of these modeling approaches in supply chain management show their capabilities in handling supply chain problems.

Even though ABM and MAS are used interchangeably in the literature, but they are fundamentally different (Collins, Petty et al. 2015). As we mentioned earlier MAS is classified under AI, but ABM is not part of AI. ABM has agents managed by simple rules that interact with each other to give an explanatory insight of the system of study while MAS is an information system that has multiple intelligent agents that interact with each other whose ultimate goal is to solve a problem that is not possible to be solved using one agent. To show the difference between these two concepts, we did research by applying ABM to a paper that used

MAS to handle a supplier selection problem (Etemadidavan and Collins 2022). As the focus of this paper is on the comparison of ABM and MAS in supplier selection to other modeling methods, in the following each will be discussed.

2.4.1 MAS

MAS is an information system with multiple intelligent agents that facilitate the decision-making process. MAS forms when there exist multiple agents that interact, communicate, and coordinate to solve a problem (Wooldridge and Jennings 1995) based on a set of rules and standards (Pérez-Pons, Alonso et al. 2021). It is recommended to use MAS when all the processes and objectives cannot be handled by one agent (Wooldridge and Jennings 1995). It would be used to automate supplier selection as well (De Boer, Labro et al. 2001). MAS is used in supplier selection (Ghadimi, Toosi et al. 2018, Drakaki, Gören et al. 2019, Pérez-Pons, Alonso et al. 2021) to lessen subjectivity in decision making and provide more transparent information to members of the supply chain. This way, it provides more reliable and valid results in the process of supplier evaluation and selection with less human intervention.

2.4.2 ABM

ABM is about the emergent macro-level outcome caused by micro-level activities in a computerized environment (Hughes, Clegg et al. 2012). The idea of ABM is about enabling a complex system to be modeled and studied multiple times by creating a system of agents, their environment, agent-agent, and agent-environment interactions (Wilensky and Rand 2015). ABM addresses the bottom-up issue of how collective behavior emerges from individual action, and it is useful for making sense of systems that have multiple interacting entities and therefore have unpredictable results also when the aggregate results are dependent on the interactions of agents and interactions of agents with the environment (Wilensky and Rand 2015). ABM in supplier selection (Bora and Krejci 2015, Pourabdollahi, Karimi et al. 2017) does not solve problems but rather just gives further information about the consequences of what will happen if certain things happen in a system of study, simply observing what is happening.

3 COMPARISON OF MODELS IN SUPPLIER SELECTION

Unlike MP, MCDM, or AI and data mining, neither ABM nor MAS (without hybridization with other techniques) will optimize, rank, predict, cluster, or classify alternatives. MAS is an information system that helps the decision-making process by automation, transparency in information, and facilitating communication between decision-makers by making its agents intelligent to achieve a specified goal, and ABM only gives an explanatory insight into a system, not a solution. Table 1. gives a brief overview of the comparison among different modeling approaches.

Table 1: Comparison among different modeling approaches.

MP	**MCDM**	**AI-based and data mining**	**MAS**	**ABM**
Best possible solution among alternatives (Optimization)	Ranking alternatives	Classifying, clustering, and optimizing alternatives, along with forecasting	Information system (facilitate and automate decision-making process)	Explanatory insight of a system

In the following, the popular trends in modeling supplier selection will be discussed.

4 TRENDS

Multiple trends have been discovered through systematic literature reviews conducted by the experts in the field of supply chain management, specifically supplier selection, from 1997 until 2018 (De Boer, Labro et al. 2001, Chai, Liu et al. 2013, Zimmer, Fröhling et al. 2016, Chai and Ngai 2020, Rashidi, Noorizadeh et al. 2020, Schramm, Cabral et al. 2020, Tirkolaee, Sadeghi et al. 2021, Toorajipour, Sohrabpour et al. 2021).

We have discovered two major trends that are commonly noticed in the literature reviews.

(i) increasing trend in using AI and data mining techniques, (ii) increasing trend in using hybrid models in solving problems, (iii) other trends.

4.1 The Increasing Trend in Using AI and Data Mining (AIDM) Techniques

Nowadays, predictive models, AI, are in demand in supply chain management rather than descriptive models like MP and MCDM (Tirkolaee, Sadeghi et al. 2021).

Chai and Ngai (2020) claimed that the core trend is the incorporation of AI and data mining techniques into supplier selection such as classification and clustering because there exists a potential in AI techniques for future studies to directly group or classify suppliers. They rise by the rise of gigantic databases which contain information that would be precious for decision-makers to be aware of (Toorajipour, Sohrabpour et al. 2021). So, all of these issues cause AI and data mining to rise.

Chai and Ngai (2020) also found MAS, an emerging technique since 2013 in supplier selection literature which started with a paper by Yu and Wong (2015). No paper used MAS in their previous supplier selection literature review conducted between 2008 and 2013 (Chai, Liu et al. 2013). Pourghahreman and Qhatari (2015) recognized the potential of MAS in the decentralized, emergent, and concurrent environment like supply chain.

Among all the AI techniques used in supply chain management, neural networks, fuzzy logic, and MAS techniques are the prevalent techniques that make them have the highest impression on the discipline (Toorajipour, Sohrabpour et al. 2021). AI approaches like neural networks, genetic algorithms, and case-based reasoning can be used in supplier selection to enhance objectivity in decision-making (Zimmer, Fröhling et al. 2016).

4.2 The Increasing Trend in Using Hybrid Models

Hybridization is another trend in supplier selection (Chai, Liu et al. 2013, Zimmer, Fröhling et al. 2016, Chai and Ngai 2020) because supplier selection has multiple stages that need to be completed, each stage can be done by using an appropriate approach (Zimmer, Fröhling et al. 2016). Over 62.2% of papers used hybrid models between 1997 to 2014 in supplier selection (Zimmer, Fröhling et al. 2016).

Current AI approaches are developed by combining various AI techniques, rather than by employing a singular AI technique (Toorajipour, Sohrabpour et al. 2021). Analytic hierarchy process (AHP) and Analytic network process (ANP), from MCDM, have recently been used more as a hybrid rather than a single individual approach (Zimmer, Fröhling et al. 2016). Also, AI and MCDM hybrid modeling methods are a new trend in supplier selection (Zimmer, Fröhling et al. 2016). MP combined methods and QUALIFLEX, an MCDM method, became popular to be used as a hybridized approach (Chai and Ngai 2020).

Recently, hybrid models have been introduced to solve supplier selection problems more efficiently which shows inadequacies of single approaches to solve supplier selection problems (Rashidi, Noorizadeh et al. 2020). The complexity of single models is less, and they cannot handle most situations in supplier selection while combined models can handle different situations and compensate for each other weaknesses (Zimmer, Fröhling et al. 2016). The major intuition in using all these methods is to enhance effectiveness and efficiency in supplier selection decision-making (De Boer, Labro et al. 2001). We have provided a full list of different methods under the MP, MCDM, and AI models in Appendix A along with their weaknesses and strengths of them.

5 VALIDATION

Validation, in Modeling and Simulation (M&S), is a process of determining if a model adequately represents the system under study for the model's intended purpose (Sargent and Balci 2017); this can including determining if the model has adequate fidelity. Fidelity is used to show the degree to which the proposed model accurately represents the real-world in the context of the study (Sanders 1996).

In the supplier selection context, researchers used case studies, either real-world or artificial examples, to validate the applicability of their proposed models. Also, they have validated the feasibility of their proposed model with sensitivity analysis by running the model with different values or comparing their proposed model to the previously validated models. There are multiple examples for each of these validation cases; from the applicability point of view, Amindoust and Saghafinia (2017) used a real-world case study in the textile industry to validate a modular fuzzy inference system model of supplier selection. Ghadimi, Toosi et al. (2018) used a real-world case study in the electronics sector in the medical device industry to validate a multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain. Amindoust, Ahmed et al. (2012) used an illustrative example to show the applicability of a ranking model of sustainable supplier selection based on a fuzzy inference system.

Validation from the feasibility point of view; Kumar, Jain et al. (2014) used sensitivity analysis to examine the environmentally friendly model of supplier selection with different values to check if they get a similar result. Amindoust and Saghafinia (2017) compare their modular fuzzy inference system model to the existing Fuzzy Adaptive Resonance Theory (ART) algorithm in literature for supplier selection, and they get similar results in clustering suppliers with different groups, which showed the validity of their proposed approach.

All in all, Zimmer, Fröhling et al. (2016) argued that there is a lack of studies that used sensitivity analysis in the supplier selection literature while it is helpful to validate the robustness of weighting evaluation criteria. Additionally, there is a need for validating a proposed model by comparing it to different existing models with the same supplier data (Zimmer, Fröhling et al. 2016, Rashidi, Noorizadeh et al. 2020). More real-world case studies are needed to test the proposed approaches in supply chain management (Toorajipour, Sohrabpour et al. 2021).

6 CONCLUSION

As supplier selection is tied to extensive decision-making that finally affects companies economically, it is important to understand the characteristics of each modeling approach in order to enhance the effectiveness and efficiency of the process. This paper discusses the different modeling approaches to modeling decision-making in supplier selection. It also introduces ABM and MAS as possible methods for supplier selection. As such, in order to lessen subjectivity in decision-making and provide more transparent information to members of the supply chain with less human intervention, MAS is proposed. On the other hand, ABM is proposed in order to give further information about the consequences of what will happen if certain things happen in a system of study, simply observing what is happening. Additionally, a combination of different modeling techniques would be a great path for future studies as one can compensate for the other weaknesses in order to enhance the reliability of the proposed model.

A APPENDIX

The methods in each modeling approach along with their strengths and weaknesses are demonstrated in Table 1. All the information provided in Table 1. is being extracted from Jain, Wadhwa et al. (2009), Chai, Liu et al. (2013), Genovese, Lenny Koh et al. (2013), Pal, Gupta et al. (2013), Govindan, Rajendran et al.

(2015), Sabaei, Erkoyuncu et al. (2015), Zimmer, Fröhling et al. (2016), Si, You et al. (2018), Chai and Ngai (2020), Schramm, Cabral et al. (2020), Toorajipour, Sohrabpour et al. (2021). We should also note that methods that were only found once or superseded in the literature were removed from our discussion.

Table 1: An overview of the methods used to model supplier selection modeling.

Methods	Strengths	Weaknesses
Mathematical based programming models		
Data envelopment analysis (DEA)	▪ Works well with both quantitative and qualitative data. ▪ A good complement to other models.	▪ limitations of data accuracy and decision-making units among constraints. ▪ Users cannot set up their own criteria weight preferences.
Linear Programming (LP)	▪ Simple to create.	▪ Needs objective function ▪ Needs numbers of requirements represented as a linear relationship. ▪ Works only with quantitative data. ▪ One objective function allowed.
Nonlinear programming (NLP)	▪ Allow nonlinear objective function and constraint.	▪ Works only with quantitative data. ▪ One objective function allowed.
Multi-objective programming (MOP)	▪ Objective evaluation. ▪ Can guarantee an optimum solution.	▪ An optimal value for all objectives at the same time cannot be achieved.
Goal programming (GP)	▪ Deal with multiple and conflicting objective measures. ▪ Enough flexibility compared to other MP.	▪ Works only with quantitative data.
Stochastic programming (SP)	▪ Suitable mathematical tool for dealing with several real-world SS problems.	▪ Mathematically extensive. ▪ Complex.
Multi criteria decision-making models		
Analytic hierarchy process (AHP)	▪ Intuitional nature and capacity to reflect people's daily thinking. ▪ Suitable for hybridization. ▪ Works well with both quantitative and qualitative data. ▪ Provides an easily understandable and defensible approach to practitioners. ▪ Simple and convenient to use. ▪ Easy to use, and flexible without hard mathematics. ▪ Ability to consider subjective opinions and to be combinable with other methods that usually handle objective data. ▪ Works well with unstructured problems.	▪ Generate arbitrary outcomes. ▪ Lack of support of a normative foundation. ▪ Ability to consider subjective opinions and to be combinable with other methods that usually handle objective data. ▪ High labor input. ▪ Needs a large amount of initial data. ▪ Limited nature of assessment scale.

Analytical network process (ANP)	▪ Intuitional nature and capacity to reflect people's daily thinking. ▪ Suitable for hybridization. ▪ Works well with both quantitative and qualitative data. ▪ Ability to consider subjective opinions and to be combinable with other methods that usually handle objective data.	▪ Generate arbitrary outcomes. ▪ Lack of support of a normative foundation. ▪ Ability to consider subjective opinions and to be combinable with other methods that usually handle objective data.
Elimination and choice expressing reality (ELECTRE)	▪ Can handle both quantitative and qualitative data for outranking alternatives. ▪ Handle high uncertainty in data very well. ▪ Less sensitive to any changes in data. ▪ Stable and reliable result.	▪ Complex and less transparent to decision-makers. ▪ Needs an additional threshold for ranking alternatives.
Preference ranking organization method for enrichment evaluation (PROMETHEE)	▪ No demand for normalization of scores.	▪ Complex and less transparent to decision-makers. ▪ Only works for a finite number of alternatives. ▪ Only works with quantitative data.
Technique for order performance by similarity to ideal solution (TOPSIS)	▪ It is easy to construct. ▪ Universality.	▪ High subjectivity.
Multicriteria optimization and compromise solution (VIKOR)	▪ Easy to use.	▪ Searching for the compromise ranking order, i.e., a compromise between pessimistic and expected solution. ▪ No robust results. ▪ Needs complex linear normalization in the formula for calculating.
Decision making trial and evaluation laboratory (DEMATEL)	▪ Solve complicated and intertwined problems. ▪ Effectively analyzes the mutual influences among different factors. ▪ Able to find out critical evaluation criteria and measure the weights of them.	▪ Determines the ranking of alternatives based on interdependent relationships among them, but other criteria are not incorporated in the decision-making problem. ▪ Cannot consider the aspiration level of alternatives.
Simple multi-attribute rating technique (SMART)	▪ Deal with both quantitative and qualitative criteria. ▪ Easy to use. ▪ A good trade-off method between modeling error and elicitation error.	▪ Cannot effectively handle uncertain decision information.
Qualitative flexible multiple	▪ Suitable for handling cardinal and ordinal mixed information while	▪

criteria (QUALIFLEX)	the number of alternatives is less than the number of criteria. ▪ Good for hybridization. ▪ It has independence and compensatory feature. ▪ No need to convert qualitative attributes to quantitative.	
AI-based and data mining models		
Genetic algorithm (GA)	▪ Suitable for solving multi-objective problems.	▪ Cannot guarantee a truly optimal solution. ▪ Suffer from premature convergence.
Artificial Neural networks (ANN)	▪ High level of versatility. ▪ Solving data-intensive problems in which the rules or algorithms for solving the problem are unknown or difficult to express. ▪ High accuracy in results. ▪ Able to find complex patterns that humans cannot find. ▪ Do not need formalization function. ▪ ANN model saves money and time.	▪ Cannot incorporate human subjective judgment. ▪ Depend on a large number of experimental data to work precisely. ▪ Hard to be explained to others. ▪ Demands specialized software and require qualified personnel who are expert.
Rough set theory (RST)	▪ Identify structural relationships within imprecise or noisy data. ▪ Useful for developing decision rules.	▪ Not compatible with continuous-valued attributes.
Bayesian networks (BN)	▪ Suitable to be used in dealing with uncertainty.	▪ Cannot incorporate human subjective judgment.
Decision tree (DT)	▪ Works well with multi-class problems.	▪ Cannot incorporate human subjective judgment. ▪ Works with a small dataset and small available features.
K-means	▪ Suitable for resolving semi-structural and nonstructural problems. ▪ Flexible for analyzing subjects.	▪ Sensitivity to outliers due to the object's departure from the majority of data. ▪ Easily incorporate people's subjective judgment.
K-Nearest Neighbor (KNN)	▪ Easy to implement. ▪ Solve both classification and regression problems.	▪ Sensitive to noisy data, missing values, and outliers. ▪ Computationally expensive and requires an efficient storage technique. ▪ Does not work well with large datasets of data.
Case-based reasoning (CBR)	▪ Easy to create.	▪ Computationally expensive and requires an efficient storage technique. ▪ Bias toward past solutions.
Particular swarm optimization (PSO)	▪ Efficient at solving complicated problems.	▪ Robust results.

Support vector machine (SVM)	▪ Capable of deciphering subtle patterns in noisy and complex data sets. ▪ Predict with higher accuracy compared to existing methods. ▪ Works with both linear and nonlinear data.	▪ Cannot incorporate human subjective judgment.
Multi-agent systems (MAS)	▪ Able to give real-time information. ▪ Create a fully automated system without human intervention. ▪ Advanced complexity management capabilities for solving problems.	▪ Computational complexity. ▪ Appropriate for modeling the decentralized, emergent, and concurrent environment.
Fuzzy logic (FL)	▪ Suitable for hybridization. ▪ Addresses qualitative information perfectly in that it resembles the manner in which humans make inferences and decisions. ▪ Can deal with linguistic judgments of experts and can transfer them adequately into crisp numbers. ▪ Can handle ambiguity, imprecision, and uncertainty of objects. ▪ Useful for developing a set of rules.	▪ Information loss occurred in fuzzy calculations.
Other modeling		
Agent-based modeling (ABM)	▪ Easy to create. ▪ Give emergent phenomenon.	▪ Suffers from inconsistency in the data because ABM mostly builds on randomness.

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