A Review of Nature-Based Algorithms Applications in Green Supply Chain Problems

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Abstract— **In the recent years, there is a significant attention among researchers and practitioners to environmental issues and green supply chain (GrSC) because of legislations and profit oriented motivations.Because of considering environmental issues GrSC besides the economic variables, the models are very difficult to find optimal. Hence, complicated green problems call for development of modern optimization methods and algorithms to solve optimization models by efficient techniques. In recent decades, meta-heuristic algorithms have been developed to overcome the problem that most of them are inspired from nature. Some of the algorithms have been inspired from natural generation, some of them inspired from swarm behavior, and others simulate natural processes. In this research we summarize the recent advance evolutionary optimization algorithms and swarm intelligence algorithms which are applied to GrSC and green logistics. Literature reviewed in this paper shows the current state of the art and discusses the potential future research trends.**

Index Terms—**Evolutionary algorithms, green supply chain, meta-heuristic, swarm intelligence algorithms.**

I. Introduction

These days government and people are more cautions and careful with the environment and concerned about climate change such that businesses are taking an increasing active on in society [1]. Literature surveys show that after the quality revolution of the 1980s and the supply chain revolution of the 1990s, Green Supply Chain (GrSC) has been averted by researchers and scientists [2]. Thus, The supply chain concept has been changed by environmental concerns so that, not only is an efficient supply chain based on economic conditions, but also interest is growing in integrating environmental issues into the entire supply chain such that they are more "green" and produce zero waste. Wide range of activities has to be implemented while supply chains are being green. Green manufacturing, reverse logistics networks, emission reduction in logistics network, closed-loop supply chain, disassembling, remanufacturing, and waste management, and reducing raw material are some of initiatives belongs of green supply chain (GrSC) concept.

The implementation of greening supply chain and logistics networks involves a wide range of design, planning, and control optimization problems. Various mathematical modeling approaches such as Mixed Integer Linear Programming (MILP) [3]-[5], Mixed Integer Non-Linear Programming (MINLP) [6], Continuous Approximation (CA) [7], System Dynamic Modeling (SDM) [8]-[10] and Fuzzy Goal Programming (FGP) [11] have been used by researchers to design mathematical modeling GrSC problems. Recently, with regards to literatures in most of cases considering environmental constraints, parameters and variables along with economic issues to supply chain leads to complex models. In this situation the coordination between all aspects across the supply chain is more difficult in comparison with the traditional supply chains. This is because most of such problems are nonlinear, non-convex or maybe has multiple local optima. In addition to wide range activity that should be considered in GrSC the consideration of supply chain design with multi-objective optimization (generally incompatible objectives) is a new trend worthy of study and it causes more complicity in the models to be solved.

Since most of these models belong to the class of NP-hard problems [12] they cannot be successfully analyzed by analytical models. More ever, exact and traditional techniques such as Branch-and-Bound (B&B) and ε-constrain either cannot solve the models or computational requirements increase tremendously as models become more realistic [13]. In the few decades, researchers have tried to develop various approximate algorithms and modern heuristic algorithm to escape the problem. Heuristics and meta-heuristics as approximate algorithms seek to obtain acceptable near-optimal solutions and require low computation requirements and time. They work based on stochastic search methods are inspired from nature processes or animal swarm behavior. These techniques can help researchers to overcome the complexity issues in GrSC[14] and have gained popularity in the optimization of grass problems because usually they use a collection of agents (like ants or honey bees) and perform a parallel search with multiple starting points in solution space. It is noticeable that meta-heuristic algorithm may solve some problems better and some problems worse than other methods [15], [16] so that researchers should select proper algorithms regarding to the problem characteristics, available time to implementation of the model, computational requirement, and required solution quality.

Naturally inspired meta-heuristic optimization techniques are divided into two main categories (although there are minor other sub-branches): (i) evolutionary algorithms and (ii) algorithms based on swarm intelligence .In this research, we introduce briefly evolutionary and swarm intelligence algorithms and review particularly the latest researches in their applications in field of GrSC, reverse logistics, closed-loop supply chain, green logistics and logistics network design.

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II. Swarm Based Algorithms

Swarming has been defined "distributed problem solving devices inspired by the collective behavior of social insect colonies and other animal societies." Swarm intelligence (SI) is a relatively novel field of nature-inspired algorithms for multi-agent search and optimization. It refers to the study of the plural behaviors of systems that are made of many components. They usually use decentralized controls to coordinate and self-organization. The behaviors of a single animal such as ant, bee, termite, fish, or wasp often are too simple, but their swarm and social behavior is superior matter like smart population. A group of three fish behaves as if none of the fish are leading, but rather each fish has an influence on the whole and the global pattern is often advantageous to the organisms; let it be avoided predators, maximizing food collection or aiding the mating process and reproduction [17]. Few examples of nature swarming are tabulated regarding to Table I. Historically, Beni and Wang excogitated the phrase Swarm Intelligence in the late 1980s in the context of cellular robotics. SI systems are typically made up of a population of simple agents that everyone interact locally with another and with their environment [18]. In SI there is no centralized control unit to dictate how individual agents should behave; but local interactions between such agents often lead to the emergence of global behavior and match their position or speed with regards to the new situations.

TABLE I: Some Examples of Swarming in Nature.

Swarming Behavior	Entities
Flocking	Birds
Prev Surrounding	Wolves
Schooling	Fish
Web construction	Spiders
Synchronization	Fireflies
Feeding aggregation	Bark beetles
Hive Construction	Bees, Wasps, Hornets, Termites
Task allocation	Wasps
Thermo regulation	Bees
Food source selection	Ants, Bees
Cooperative transport	Ants
Nest sorting	Ants
Pattern generation	Bacteria, Slime Mold
Path formatting	Ants
Law of gravity	Mass interactions
Echolocation	Bat
Brooding	Cuckoo
Mammalian adaptive	Immune systems
Herding behavior	Krill individuals
Path optimizing	Natural rivers

SI algorithms are inspired by collective behaviors observed in natural systems included animal behavior or other natural processes such as the law of gravity or immune system. The foraging behavior of ants as in ant colony optimization (ACO) [13], [19], [20], the choreography of bird flocks as in the partial swarm optimization (PSO) [21], the intelligent behavior of honey bee swarms as in an artificial bee colony (ABC) [22], [23] are examples that inspired from animal collective life. In addition, the gravitational search algorithm (GSA) [15], [24] is based on the mass interactions and the law of gravity, Krill herd algorithm (KHA) [25] is inspired from herding behavior of krill individuals, and Intelligent water drops (IWD) [26] are simulated natural rivers and how they find almost optimal paths to their destination. Onthe rest of paper the first-fourth algorithms as most popular will be explained and reviewed their application in GrSC.

A. Particle Swarm Optimization

Particle swarm optimization (PSO) is one of the swarm-based global optimization algorithms that can move particles (as solutions) through feasible problem space to find the new optimum solutions. Initially, PSO inspired from flocks of birds, schools of fish, and even human social behavior. The nature-based meta-heuristic algorithm was proposed by Kennedy and Eberhart[21], [27]. They simulated a group of birds that are looking for food within some area and they don't know food location. Kennedy and Eberhart[21] treated each single solution of the optimization problem as a ''bird" that flies through the search space. They call each single solution at ''particle". Each particle is characterized by the fitness value, current position in the space and the current velocity [28], [29]. When flying through the solution space all particles try to follow the current optimal particles. A position vector and a velocity are nominated to each particle and they are adjusted in any iteration with regards to local and global best found in the whole swarm. In optimization science, PSO is computational algorithm that tries to improve a candidate feasible solution with attention to a given amount of quality. Then, move these particles around the search space regarding the candidate's solution's position and velocity.

Zhu *et al.* [30] developed the PSO search strategy for the vehicle routing traveling time problem that it can use to air pollution reduction in forwards and reverse logistics. In the research PSO has been tested on a few numerical examples and they compared the obtained results with genetic algorithm. They concluded the developed PSO algorithm got the optimal solutions much faster than the genetic algorithm (GA) algorithm due to it is a swarm-based algorithm. Similarly Moghaddam *et al.* [31] used PSO to solve the model to overcome uncertainly in vehicle routing planning. Nan *et al.* [32] used PSO to solve reverse logistics location of remanufacturing factory, and the distribution of goods is solved by the PSO algorithm to minimize cost. The optimal solution of the model is obtained by developed PSO and traditional PSO, which reduces the calculation complexity, selects the reverse logistics remanufacturing factory efficiently. In the field of reverse logistics network optimization another study has been done by Yanchao *et al.* [33]. Their study was established a reverse logistics network multi-objective optimization model that considered environment effect and the waste recycling factors, such as locations of facilities and frequency transportations. Then they improved PSO by adopting the grouping and the cataclysm theory and solved the complex model. In another case, Kannan *et al.* [34] used PSO to minimize cost and environment effect in closed-loop logistics network and compared the result with GA. These Empirical studies have shown that PSO has a high efficiency in convergence to desirable optima and performs on many GrSC complex problems. Since most green problems are belonging of multi-objective optimization, PSO can be employed in particular problems.

Although in multinomial function particle populations will quickly lose diversity and PSO will cause premature convergence and trap to local front rather than global ones [35]-[37], some researchers proposed some operators (like crossover) or hybridize by other algorithm to overcome partly the problem [35], [38]-[40]. Liu *et al.* [38] and Masrom *et al.* [39] hybridized PSO and GA to solve vehicle routing problem as a nonlinear transportation problem which the final algorithms can be used for logistics network optimization in GrSC problems.

B. Ant Colony Optimization

Ant colony optimization that is a probabilistic technique to solve complex problems is initially proposed by Dorigo in 1992 [19], [41]. ACO that can reduce finding best and shortest paths through the graphs is based on ant behavior for seeking a path to achieve the source of food. This is achieved by a substance called pheromone that shows the trace of an ant [42] that permit them to communicate to each other. To find the best way to food, ant employs heuristic information. They leave the nest and move randomly to find food but when they find a pheromone trail that made by other ants, they decide whether or not to follow it. If they decide to follow it they make own pheromones over the trail. Quality of pheromone in a path makes more chance to the path to be selected by ant over the other paths and gradually the amount of pheromone on the path would be highlighted among the others. ACO is a simulation of the colony of ant to find the shortest path as in the Fig. 1 is shown.

In the ACO algorithm, the nest is represented by initial condition and terminal condition play as the food. The ant moves in a network that the pheromones are deposited over vertices or edges. The ants choose a node on the network for the next steps based on a probabilistic decision that quantity of pheromone deposited over the node or edge can affect on the function for decision. The problem is represented by a set of constraints that every time an ant selects a vertex or edge, it has to evaluate the set of constraint [43].

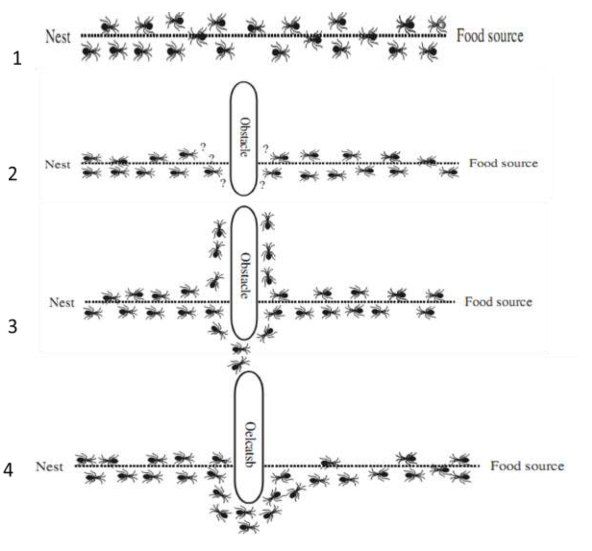

Fig. 1. Ants' behavior to find food: (1) ants walk along the shortest path, (2) ants have to choose one of the two available paths that have been made by obstacle, (3) ants find available paths and (4) the ants discover the new shortest path characterized.

One of the first applications of ACO in GrSC refers to McGovern et alhave studied in 2006 [44]. They implemented ACO to minimize the number of remanufacturing work stations, minimize idle time, and balances product disassembly line in recycling and remanufacturing systems. They emphasized ACO is used to provide a feasible solution very fast, near-optimal solution to the multiple objective for that particular problem. In the same light, Ding *et al.* [45] used ACO to solve multi objective optimization for minimizing the use of precious resources and maximizing the level of process capability in the disassembly process. Some researcher, the ACO has been employed to minimize vehicle rout in case of time and number of travels that it can minimize fossil fuel consumption and air pollution [46], [47]. And also, wastes collection facility location model has been developed by Bautista *et al.* [48] to minimize collection cost using ACO as solution method. Regarding to the capability of ACO to solve complex problems it seems the use of ACO techniques in GrSC design is yet in a fetal stage [49].

C. Artificial Bee Colony

Artificial bee colony (ABC) is a swarm-based meta-heuristic algorithm that introduced in 2005 by Karaboga [50] and open a new direction in the field of optimization algorithms in complex problems. Similar to PSO and ACO which are inspired from bird's life and ant colony social life, ABC is an algorithm inspired from bee colonies behavior in the nature. The ABC's function according to the bee's life in the nature can be explained as follows. Initially each bee explores the food individually and when a bee finds the food start dancing to inform other bees in the colonies. Other bees collect food and bring to the hive and then they can do one of the follow actions [51]:

1) Abandon the previous food source and become again uncommitted follower.
2) Continue to forage at the food source without recruiting the nest mates.
3) Dance and thus recruit the nest mates before the return to the food source.

With a certain probability that is dependent on the obtained feed quality, its distance from the hive and the number of the bees which are now engaged with this feed resource, a bee selects one of the stated actions and follows its work in a similar repetitive form [51]. This behavior can be applied to many complicated engineering problems including computational, control, optimization, transportation, etc.

Recently, regarding to ABC capabilities to solve complex problems scholars the algorithm has been interested inimplementing it in green problems. For instance, Vishwa *et al.* [52] used ABC to solve complex closed-loop logistics problem with return rates uncertainly. They concluded ABC algorithm has been implemented successfully and solution quality and convergence rate are significantly outperformed rather than PSO in their case study. In the same light, in 2012 Xing *et al.* [53] implemented ABC algorithm to optimize e-remanufacturing. They argued the simulation results showed that the proposed algorithm performance is satisfactory. In 2008, Banerjee et al. developed ABC and proposed the Pareto artificial bee colony (PABC) to solve multi-objective optimization [54]. With regards to in the most gross problems should be considered economic and environmental objectives then the PABC can be used as an efficient algorithm in these kinds of problems.

D. Gravitational Search Algorithm

One of the novel meta-heuristic stochastic optimization algorithm inspired by the law of gravity and mass interactions is Gravitational Search Algorithm [15]. GSA, the individuals, called agents, is the collection of masses which interact with each other based on the Newtonian gravity and the laws of motion. The agents share information using the gravitational force to guide the search toward the best location in the search space. At GSA, search agents are the collection of masses. All these objects attract one another by gravitational force, and this force causes a global movement of all objects toward the objects with heavier masses as Fig. 2 is shown. Hence, masses cooperate using a direct form of communication, through gravitational force. The heavy masses that correspond to good solutions move more slowly than lighter masses, which guarantee the exploitation step of the algorithm. Each agent has position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined using a fitness function. By changing the velocities over time, the agents are likely to move toward the global optima.

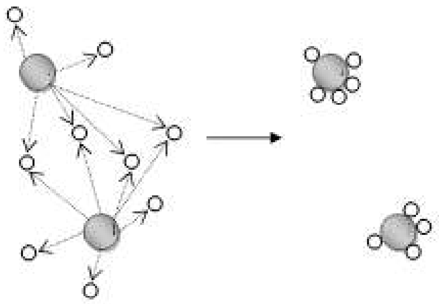

Fig. 2. Each mass accelerates toward the result force that acts it from the other masses.

Results of experiments undertaken previously show the high performance and the global search ability of GSA in solving various nonlinear functions comparing PSO [15], [55]. The superior solution and convergence rate cause GSA have been interested by researchers to be supply chain problems. In 2012, Sadrnia *et al.* [56] used GSA as a new solving technique to find optimal solutions in recycling automotive alternators close-loop logistics in end-of-life. They assumed all material and product flows between facilities in closed-loop supply chain such as suppliers, manufacturer, distributors, retailers, collection centers, and recycling centers as object with some respective masses. They compared the result with GA and expressed GSA tends to find the global optimum faster than GA; hence, it has a higher convergence rate. GSA also has been implemented recently to find out the optimum strategy in demand managing [57]. In the research, the authors argued GSA advantages to solve supply chain problems.

III. Evolutionary Algorithms

Another category of nature-based meta-heuristic algorithms are Evolutionary algorithms (EA). EAs are population search methods that are inspired by biological evolution, which leads to producing better and better approximations to a solution. In other words, the basic idea of evolutionary algorithms is to "select best, discard the rest." This means that better solutions have a better chance of surviving. The main evolutionary process in all EAs is same and benchmark from the nature evolution: given an individual's population the environmental pressure causes natural selection by survival of the best so that it can cause a better situation for populations (best fitness value of the populations). Initially a population of the candidate of solutions is randomly created. Then they are evaluated by fitness function (that is equal or fit to objective function in optimization problem). Based on this fitness values some of the best candidates are selected and keep for make next generation by applying some operators such as recombination and mutation to them. Recombination operator is responsible to select and combine two or more candidates that are called parents in the step and generate new candidates (the children). Mutation operator causes an old candidate change to new one by changing a bit internally. By implementing these operators lead to set of new candidate solutions (so-called offspring) that cause better fitness rather than old ones. This process has to iterate until sufficient quality of fitness function is reached by new candidate solutions. Fig. 3 is a pseudo-code that shows general schemes of any EA.

```
BEGIN
  INITIALISE population with random candidate solutions;
  EVALUATE each candidate;
  REPEAT UNTIL ( TERMINATION CONDITION is satisfied ) DO
    1 SELECT parents;
    2 RECOMBINE pairs of parents;
    3 MUTATE the resulting offspring;
    4 EVALUATE new candidates;
    5 SELECT individuals for the next generation;
  OD
END
```

Fig. 3. General schemes of evolutionary algorithms

The usage of Darwinian principles for automated problem solving in early 1950s resulted in the advent of evolutionary computing techniques [58]. Genetic algorithm (GA) that is the most popular EA is inspired from Darwinian principles and mimics the process of natural evolution is proposed by Holland [59]. Other algorithm in the sub-branch of meta-heuristic algorithms are evolutionary programming (EP) [60] and Differential Evolution Algorithm (DEA) [61]. In continue, evolutionary algorithm brief introduction and applications will be discussed. In the next we will explain just genetic algorithm as the most popular evolutionary algorithm and its application in GrSC activities. Recently Mondal *et al.* [62] used GSA to minimize the emission of nitrogen oxides and fuel consumption. Although this paper is in the field of load dispatch, but the same idea can be used to minimize fuel consumption and carbon emission in logistics network in GrSC.

A. Genetic Algorithm

Genetic Algorithm (GA) that is proposed by Holland in

1975 [59]is an evolutionary and adaptive search method. GA mimics the mechanics of natural selection and evaluation. In any evolutionary process, only the most suited elements in a population (a set of solutions) are to survive and generate offspring, thus transmitting biological heredity to the new generations. In a similar way, GA also starts with a particular initial population and subsequent generations are created using generic operators. Population is a set of strings, each representing a potential solution to the given problem. Each string is called a chromosome and the elements of the chromosome are called genes. For creating the offspring only a promising string is selected so that the generic material is transferred effectively. Generic operators' are applied to the mating pool to create offspring. The set of strings chosen to create offspring is called mating pool. After the creation of a new set of strings, the population is evaluated and only the best elements are chosen for the next generation and finally the search ends with a best possible set of solutions. As Fig. 3 shows the structure of a simple GA, it would involve the following stages:

1) Representation of feasible solution to the problem as chromosomes and generation of the initial population.
2) Evaluation of the population using fitness function.
3) Generation of new population using the generic operators: Crossover (swaps a portion of the two parent chromosomes of the mating pool to create two new chromosomes); Mutation (select two random genes and then exchange their positions); Selection (select the best solutions).
4) Selection of new population using the offspring generated.

GA is a one the most popular EA that is implemented by scholars to optimize hard combinatorial problems and GrSC problems. Several authors have shown the effectiveness of using GA for reverse and closed-loop logistics network optimization and facility location optimization to lead supply chain to be green. Zarei *et al.* [63] designed an effective reverse logistics to collect and recycle end-of-life vehicles (ELVs) and they expressed due to model complexity GA can be used to solve and optimize the problem. In addition, GA applied has been applied for recovery and reverse logistics optimization for green suitcase chain [64], white goods industry [65] and product return in online sale networks [66]. Due to the influence of the reverse logistics activities on forward logistics such as occupancy of warehouse and transportation capacity, researchers have interested to integrate forward and reverse logistics to avoid sub-optimality [67]. In this regards closed-loop supply chain design has been more interested by researchers recently. However they are more complex comparing to forwards and reverse logistics solely. It caused GA has been applied in closed-loop supply chain in so many researches and fields. Kannan *et al.* [68] developed a close-loop supply chain for battery recycling and used GA and GAMS as solving approach. They compared results obtained by GAMS and GA and concluded the GA and GAMS results are close together for small size problems and when the problem would be equal as real case GAMS need more computational time. Mitra [69] has employed GA in inventory management in a deterministic and stochastic closed-loop supply chain. In the same studies, GA has been used for clopped-loop optimization as a solution approach [4], [34], [70], [71] and it is employed to overcome the complexity in forward and reverse integration problems in [72]-[74]. In some studies [75]-[77] such as researchers integrate GA approach with fuzzy theory to overcome uncertainty and some parameter fuzziness. GA has been used by researchers to optimize remanufacturing optimization such McGovern and Gupta [78] that minimize workstations, and ensures similar idle times, as well as other end-of-life specific concerns for balancing in a disassembly line. In the same light, GA has been employed in field of balancing disassembly lines and remanufacturing [79]-[81]. Recently, Li *et al* [82] designed a multi-objective model in reverse logistics to optimize cost and service level simultaneously. They used non-dominated sorting GA (NSAG2) method that has been developed by Deb *et al.* [83]. They can simultaneously address a set of possible solutions in one single run in reasonable time.

IV. Other Meta-Heuristic Algorithm

Besides EAs and SIs algorithms, there are some other meta-heuristics algorithms that are inspired natural processes and events such as simulated annealing (SA) algorithm and Tabu search (TS). The SA's main idea is inspired from annealing technique in metallurgy [84]. It involves heating and controlled cooling to maximize the size of its crystals and minimize their defects. This notion of slow cooling is implemented with the SA algorithm as a slow decrease in the probability of accepting worse solutions as it explores the solution space. Pishvaee et al. developed a mixed integer linear programming model for transportation and opening cost in multistage reverse logistics and applied the SA algorithm to optimal solution. In another research Lee *et al.* [85] used SA to solve two-stage stochastic programming multi-period reverse logistics network model. Also in closed-loop supply chain problems SA algorithm has been employed by [4] that simulate bottles distilling/sale company in Korea. This paper designed the method of calculation for a solution using optimization algorithms with the priority-based genetic algorithm (priGA) and compared with SA result. Gu and Sosale [86] proposed an integrated modular design methodology for reusable, recyclable or remanufacturing products in life cycle engineering. They used SA algorithm for module formation and cluster the components. In GrSC multi-objective problems, multi-objective simulated annealing (MOSA) that proposed by Ulungu *et al.* [87] can be implemented.

Another meta-heuristic algorithm that is formulated by Glover [88], [89] is Tabu Search. TS algorithm is a local search method used for mathematical optimization. TS algorithm checks immediate neighbors in solution space in hope to find an improved solution. SA search and TS methods usually implement one move at each iteration, while genetic methods like GA may generate several new moves (individuals) at each iteration (generation) [90]. Many researchers prefer to employ TS as an effective method to solve mathematical models especially in the field of reverse and closed-loop logistics in GrSC problems such as [67], [91]-[94]. Furthermore, a recycle paper network has been optimized by

Schweiger and Sahamie [95] and they used a hybrid TS for solving the model.

V. Conclusion

In this paper we have discussed on nature-based meta-heuristic algorithms that have been used in GrSC activities. We briefly reviewed kind of activities that should be considered in the supply chain to be green. Typical illustrations are addressed for PSO, ACO, ABC, GSA, GA, TA and SA algorithms, and their applications. A general overview of the state-of-the-art meta-heuristic algorithms in GrSC helps readers to refer proper algorithm in the practical solution in their models in the field. Some of our findings are listed in following:

1) Considering more variable in models to be more similar to the real world and multi-objective optimization instead of single objective to satisfy not only economic goals but also environmental and social objectives, cause GrSC to be complex problems. So that most of these models belong to the NP-hard class. Thus, heuristics and meta-heuristics algorithms are more interesting to be used by researchers in the last decade due to their abilities to find the optimal solution in reasonable computation time
2) The next achievement of this paper is that the number of researches on nature-inspired optimization algorithms for GrSC problems has increased significantly especially after 2000s.
3) Simulation nature-based ideas such as: mutations, recombination and reproduction are well suited for solving complex optimization problems like GrSC issues.
4) An algorithm may solve some problems better and some problems worse than others. Hence, so a proper algorithm should be selected regarding to the problem characteristics, available time for implementation of the model, computational requirement, and required solution quality.

Although GA has been used in a large percentage of early works, PSO and GSA and other swarm-based algorithms have gained more attention of scholars and practitioners since 2005.

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