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Genetic algorithms in supply chain management: A critical analysis of the literature

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Abstract. Genetic algorithms (GAs) are perhaps the oldest and most frequently used search techniques for dealing with complex and intricate real-life problems that are otherwise difficult to solve by the traditional methods. The present article provides an extensive literature review of the application of GA on supply chain management (SCM). SCM consists of several intricate processes and each process is equally important for maintaining a successful supply chain. In this paper, eight processes (where each process has a set of sub-processes) as given by Council of SCM Professionals (CSCMF) are considered. The idea is to review the application of GA on these aspects and to provide the readers a detailed study in this area. The authors have considered more than 220 papers covering a span of nearly two decades for this study. The analysis is shown in detail with the help of graphs and tables. It is expected that such an extensive study will encourage and motivate the fellow researchers working in related area; to identify the gaps and to come up with innovative ideas.

Keywords. Genetic algorithms; supply chain management; inventory management; soft computing.

1. Introduction

Maintaining an efficient supply chain has always been a focus of attention of scientists and researchers since decades. In fact, the entire economy of a country more or less depends on an efficient and well-managed supply chain processes. However, with the growing competition all round the world; the SCM models are also becoming more complex day by day. Consequently, researchers are focusing on efficient and robust techniques for dealing with SCM. In this article, a review on the application of GA, one of the most popular techniques, for dealing with different aspects of SCM is presented. The popularity of GAs for solution of SCM can be attributed to its capability to evolve solutions, handle ambiguity, and execute optimization [1]; its competence to tolerate imprecision, uncertainty, and partial truth to attain tractability and robustness on simulating human decision-making behavior with low cost [2, 3].

Moreover, GA has been applied quite successfully to a wide range of problems occurring in diverse SCM domains, for example, forecasting [4], job-shop scheduling [5], economic lot-size scheduling [6], economic lot-size model [7], vendor-managed replenishment system [8]. Therefore, it is quite natural to assume that for SCM processes and sub-processes, GA has always been an option for dealing with SCM models.

The present study is an extension of paper presented by authors [9] that focuses on GA applications to SCM. Here the authors have provided a much more detailed analysis including figures, charts, and graphs. The articles reviewed for this study cover almost two decades; from the late 1990s until the present time. Through this review the reader can easily visualize how GA has evolved for solving the different aspects of SCM.

The rest of the research article is prepared as follows: Subsequent to the introduction in section 1, the genetic algorithms and supply chain management are briefly described in sections 2 and 3 respectively. The methodology, section 4, describes the critical analysis of the literature and reviews of existing studies and section 5 briefed discussion part and future trends of the study. Finally, Summary drawn from the present study is provided in the last section 6.

2. Genetic algorithms

GA is an evolutionary algorithm first proposed by John Holland and his colleagues in 1975. Based on Darwin's theory of survival of the fittest, it is one of the most popular search technique used for solving optimization problems. It is a derivative free, direct search algorithm used to find true or approximate solutions to optimization and search problems [10]. Some pioneering work in GA can be found in

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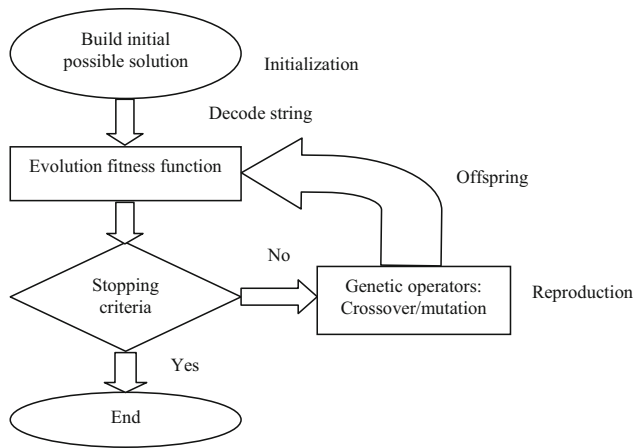


Figure 1. Interconnection of GA stages.

[11–19]. The working of GA begins by initialization of the population of n chromosomes within the given range. The second step is to decide a fitness function that helps in assessing the fitness of every single chromosome in the population. After this phase, GA operators (crossover plus mutation) are activated, which help in generating the new population. The procedure is repeated iteratively till a stopping criterion is met. An interconnection of GA phases is shown in figure 1.

2.1 Computational steps of GA

- (1) Build initial population of randomly generated solutions.
- (2) Evaluation of the fitness function of individual solutions in the population.
- (3) Generate new population by repetition of subsequent phases as follows:
 - Selection: Pick a pair of parent solutions from a population corresponding to their fitness. The one having a superior fitness value is more likely to be selected.
 - Crossover: Perform crossover with the help of a predefined crossover probability to produce new child solution.
 - Mutation: Perform mutation by means of a predefined mutation probability.
- (4) Adopt newly build population for an additional run of the algorithm.
- (5) Check whether the stopping criterion has been reached. If yes, then terminate; otherwise go to step 2.

Several variants of GA are available in literature, including binary and real encoded; unconstrained and constrained; and single objective and multiobjective, depending on the type of problem being dealt with, the suitable variant may be applied.

3. Supply chain management

SCM is a set of approaches of managing upstream and downstream interrelationship with suppliers and its clients to deliver high-quality customer value at lowest possible price as a whole supply chain [20, 21]. Its aim is to manufacture as well as allocate the products and services in the right amount, to the right location, also at the right time so as to reduce cost while retaining customer satisfaction [4], figure 2 shows the SCM linkages.

4. Methodology

In the present study, 220 articles are considered where GA has been applied for dealing with different aspects of SCM. The authors have mainly concentrated on refereed articles. The main keywords; “Genetic algorithms” and “Supply chain management” are searched for in major databases. The other keywords include the GAs applications to SCM process and sub-processes “Inventory Management, Material Planning”, “Supply Chain Planning, Production Planning”, “Logistics Network Design/Planning, Vehicle Routing/Assignment”, “Sales Forecasting, Bullwhip Effect”, “Supplier relationship management”, “Product development and commercialization”, “Returns management”, “Customer service management”, and “Customer relationship management”. The papers are segregated as per the area, and analysis is done to find out where and how GAs are applied. Graphs and charts are drawn so that the reader can easily visualize in which areas of SCM have GAs been used most frequently and in which areas some more work is to be done.

The present study is inspired by [22], main difference being that in the present paper the authors have focused on GA, while in [22], besides GA, the soft computing approaches such as fuzzy logic and neural network are also considered. The main similarity between [22] and the present study is that in both the studies eight processes of SCM as given by Council of SCM Professionals (CSCMF) are considered. These processes are given as follows:

- 4.1 Manufacturing flow management (MFM)
 - 4.1a Inventory management/material planning
 - 4.1b Supply chain planning
 - 4.1c Production planning
- 4.2 Order fulfillment (OF)
 - 4.2a Logistics network design/planning
 - 4.2b Vehicle routing/assignment
 - 4.2c Other issues
- 4.3 Demand management (DM)
 - 4.3a Sales forecasting
 - 4.3b Bullwhip effect

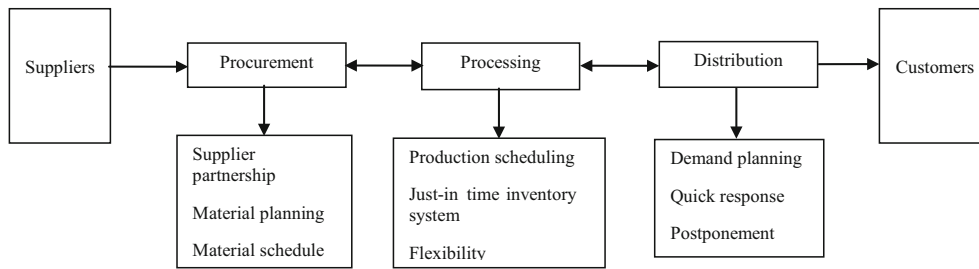


Figure 2. Supply chain management linkages.

- 4.4 Supplier relationship management (SRM)
- 4.5 Product development and commercialization (PDC)
- 4.6 Returns management (RM)
- 4.7 Customer service management (CSM)
- 4.8 Customer relationship management (CRM)

These processes are explained one by one in a sequential order in the following subsections.

4.1 Manufacturing flow management (MFM)

Manufacturing flow management (MFM) is the SCM process comprising all actions required to transport merchandises over the company in addition to attaining, employing, and bringing about manufacturing flexibility in the supply chain [23]. A framework on manufacturing flow in SCM is shown in figure 3. Figure 4(a), (b), and (c) shows the number of research articles breakup yearwise of MFM process, which includes Inventory management/Material planning, Supply chain planning, and Production planning, respectively.

As shown in figure 5, the first research article in relation to application of GA in MFM was presented in 1991 [5]. Till 2003, there are only a few studies, with less than two publications per year. This scenario however changed after 2004, where we can see a firm increase in the quantity of research articles, touching a highest in 2014. This indicates that additional work can be expected in the coming years. The researcher's curiosity can be acknowledged by means of the distribution of these research articles dealing with sub-processes. As shown in figure 6, Production planning has gained scholars' foremost interest. Predominantly, there are 55 numbers of studies pointing on Production planning that constitute 59% of total number of research papers in the MFM.

4.1a Inventory management/material planning: In SCM, Inventory management is a combined method for the planned controlling of inventories, over the whole inter-connection of cooperating enterprise, starting with the supply source to the end worker [24]. The order distribution studies were solved by [25, 26] with the help of a heuristic methodology and a multicriteria GA in a demand-driven

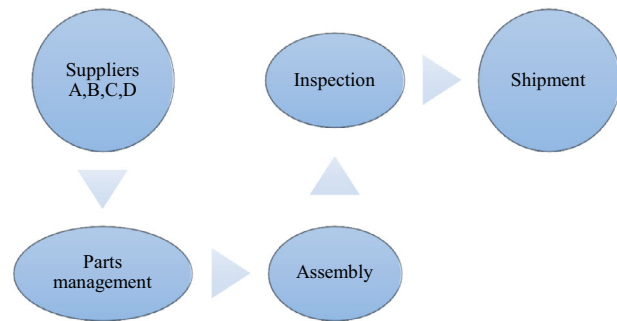


Figure 3. Manufacturing flow in SCM.

collaborative supply chain; afterward, the economic lot-size scheduling issues were dealt by GA heuristic approach [6, 7]. In [6], GA is used for determining a fuzzy economic lot-size scheduling issue and in [7] GA is used to solve a joint economic lot-size model for integrated inventory control of a four-stage supply network in view of backlogged shortage. Vendor-managed inventory (VMI) issues are also discussed in various papers. In [8], GA and machine learning technique is used for modeling in addition to optimizing a vendor-managed replenishment system, while in [27] a two-echelon supply chain is studied for optimum operational parameters of VMI system using GAs; furthermore, in [28], a GA-neural network technique is suggested to lessen spare parts logistics overhead to deal the bill of material (BOM) configuration design issue.

Reference [29] presents a parameter-tuned GA to deal with multiproduct economic production quantity model, including space constraint, discrete delivery orders as well as shortages. Afterward, [30] used GA to optimize the emission inventory for a chemical transport model. In [31], GA is used with fuzzy arithmetic operations for simulation of VMI problems; in [32], a GA for VMI control system of two-level supply chain composed of a single vendor and a single retailer economic order quantity model is proposed; and in [33], a parameter-tuned GA is presented to optimize two-echelon continuous review inventory practices efficiently. In [34], authors proposed hybrid metaheuristics algorithms (HMHAs), which included GA, harmony search

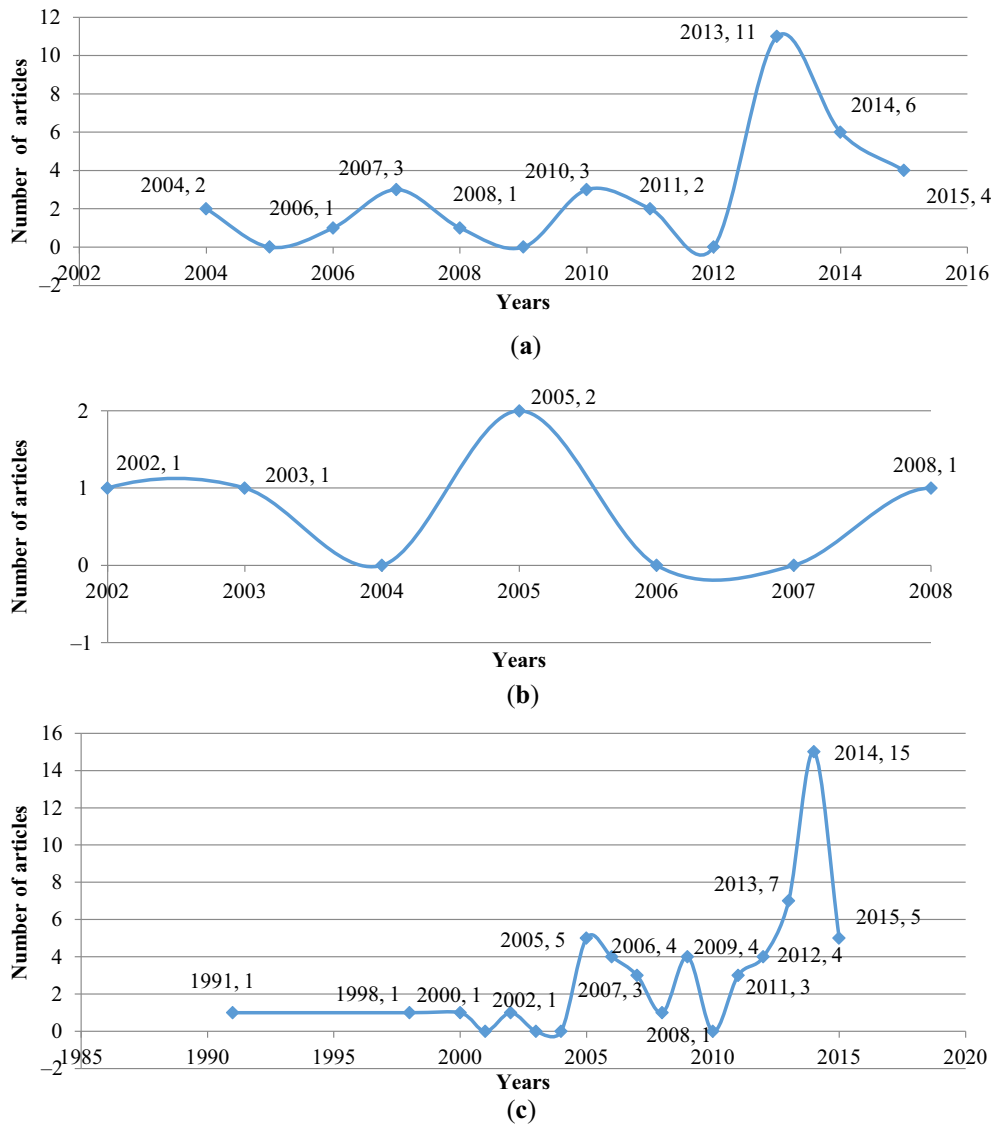


Figure 4. (a) Number of articles in inventory management/material planning sub-process of MFM, (b) number of articles in Supply chain planning sub-process of MFM, and (c) number of articles in production planning sub-process of MFM.

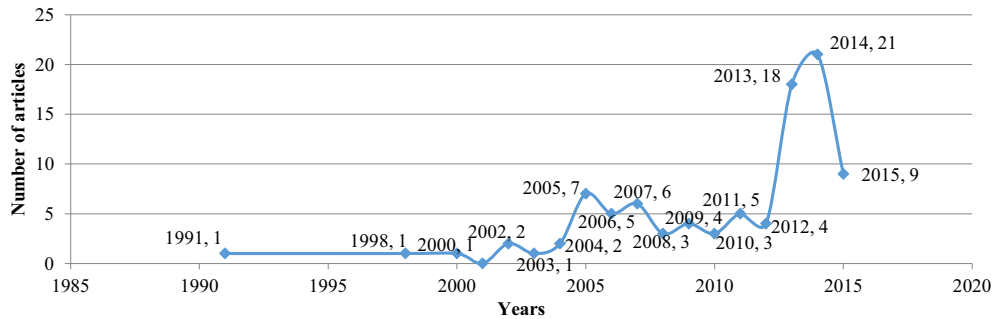


Figure 5. Total numbers of articles in sub-process of MFM.

(HS), particle swarm optimization (PSO), simulated annealing (SA), variable neighborhood search (VNS), and bees colony optimization (BCO) methods to solve the

three-inventory problem, joint replenishment economic order quantity (EOQ) problem, newsboy problem, and stochastic review problem, in certain and uncertain

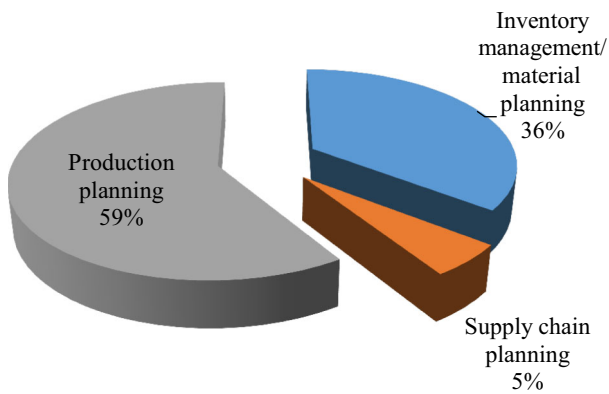


Figure 6. Distribution of articles in sub-processes of MFM.

environments such as stochastic, rough, and fuzzy environments with six different applications. In [35], authors offered a hybrid method of GA and fuzzy simulation (FS) to deal with inventory management issues alongside stochastic replenishments plus fuzzy demand. In [36], authors designed GA with varying population size method for a deteriorating item with time-varying demand and shortages of two-warehouse production inventory model; in [37], GA is proposed for supply chain inventory optimization with the best possible surplus stock level. In [38], the authors used GA to analyze a bi-objective inventory routing problem where the transportation cost along with the delivery cost is measured independently.

In [39], authors proposed a modified multicriteria optimization GA (MCOGA) established on the procedure for order distribution in collaborative supply chain. In [40] GA is used to optimized the two-stage collection distribution (TSCD) model with capacity constraints at both stages and results are compared with the standard operations research software LINDO for small problems. In [41], GA method including fuzzy simulation via contractive mapping is proposed to a vague production inventory model under volume flexibility; in [42], GA is used for optimization of VMI of multiproduct economic production quantity (EPQ) model with multiple constraints; in [43], an adaptive GA is proposed that produces good-quality solutions to the time-dependent inventory routing problem (TDIRP). In [44], emphasis is laid on developing a fuzzy-rough (Fu-Ro) multi-objective decision-making imperfect production inventory model with GA.

Reference [45] presents a research on multiproduct, multiperiod continuous review inventory models based on a GA approach; [46] proposed a GA for an EOQ model of an item with imprecise seasonal time; [47] used GA for optimizing VMI of multiproduct EPQ model with multiple constraints. Authors in [48] used soft computing techniques in fuzzy-rough environment for a multi-objective multi-item inventory control problem. In [49], GA is used to solve a VMI system in a two-echelon supply chain used hybrid algorithm. Later in [50], a nondominated sorting genetic

algorithm-II (NSGA-II) with tuned parameters is used for optimizing a hybrid VMI and redundancy allocation problem in SCM.

In [51], problem of green VMI of multi-item multi-constraint EOQ model under shortage solved by a hybrid genetic and imperialist competitive algorithm is considered; [52] deals with the problem on inventory-based multi-item lot sizing by using a biased random key GA approach. In [53], a bi-objective VMI model with trapezoidal fuzzy demand is solved by two parameter-tuned multi-objective evolutionary algorithms, NSGA-II and nondominated ranking genetic algorithm (NRGA). In [54], an evolutionary algorithm (NSGA-II) for a new multi-objective location-inventory model is proposed.

4.1b Supply chain planning: Supply chain planning, in most enterprises, is the management of supply-facing and demand-facing activities to lessen disparities in a complete supply chain [55]. A supply chain planning framework is shown in figure 7. Reference [56] used GA to develop optimum resolutions through a two-stage optimization method for collaborative supply chain planning; afterwards, [57] showed that GA approach can be applied in multi-plants supply chain, an optimum or near-optimum result with very high probability for integrated process planning and scheduling by means of decreasing total tardiness; in [58], the authors recommended that the evolutionary search method can be a noble substitute for the same problem discussed in [57]; furthermore, [59] presented a knowledge-based model for resource planning with several strategic as well as operational requirements of regional M-SMEs, later [60] considered a GA-based supply chain model to incorporate production as well as supply sourcing decisions.

4.1c Production planning: Production planning is an essential apprehension that together directly and indirectly makes a difference to the performance of the facility [61]. A classification framework on production planning in SCM is shown in figure 8. The first article in relation to application of GA in SCM was presented in 1991 [5], where a GA that can deal with the optimization of the job-shop problems is proposed; later, in [62], multi-objective GA (MOGA) is used for more convincing job-shop scheduling problems. The study in [63] shows that constrained GAs can also be used in scheduling problem. This GA uses a novel chromosome representation that takes into account machine as well as worker's assignments to jobs; subsequently, in [64], the general capacitated lot-sizing problem was resolved by at first using GA. The study in [65] suggested an adequate heuristic for optimizing sequence of customer orders.

Reference [66] presents an approach to solve a production and distribution problem based on a hybrid GA; the study in [67] shows a methodology to resolve distributed scheduling problems based on an adaptive GA with dominated genes. In [68], an approach is proposed to solve a due date-assigned distribution network problems based on multicriteria

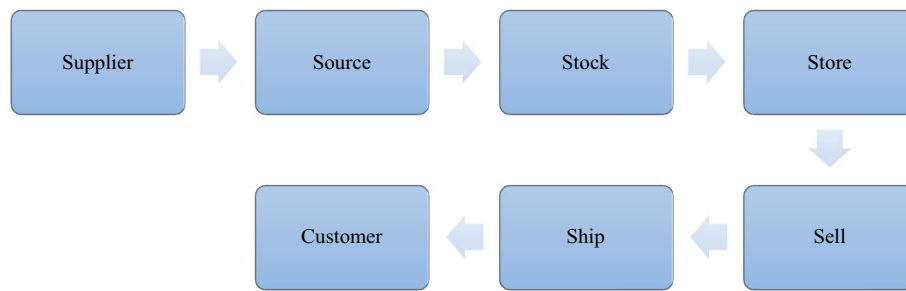


Figure 7. Supply chain planning framework.

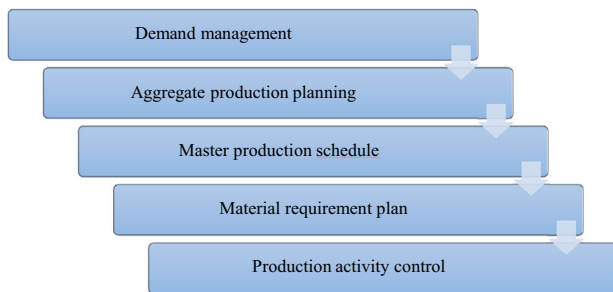


Figure 8. Productions planning in SCM.

genetic optimization. In [69], machine assignment problem is solved by a GA-based method. In [70], work is dedicated to simulation-based sequencing along with lot-size optimization, which shows that the GA is a dominant technique to determine good results for a production and inventory system. In [71], a GA-based approach is proposed, which solved iteratively a resource-constrained operations machines assignment problem and flexible job-shop scheduling problem; [72] presents optimization of a distributed scheduling problem in flexible manufacturing systems (FMS) based on GAs with dominant genes and [73] presents a GA-based approach for solving distributed FMS scheduling problems subject to maintenance; [74] proposed a GA with an mixed-integer linear programming (MILP) solver to studied the influence of flexible lead times on a paper producer, [75] applied GA for effective search of solutions for economic lot-scheduling problems; in [76], the authors analyzed batch manufacturing problems, where GA has been suggested to deal with job-shop problems; in [77], an efficient algorithm for a job-shop environment using GA is proposed to optimize lot streaming for product assembly; [78] proposed a study for distributed production scheduling environment using a modified GA-based approach; [79] solved lot streaming in a job-shop scheduling problem through GA and in [80] a hybrid chaos-based fast genetic tabu SA (CFGTSA) algorithm-based approach is proposed for performance optimization of a legality-inspired supply chain model, and in [81] GA approach is proposed to solve assembly job shop with part sharing.

The hybrid flow-shop scheduling solved by an adequate GA on the value of an optimum schedule, including multiprocessor task problems is shown in [82], while in [83] a modified GA (MGA) is presented where the objective is to minimize the total make span; [84] presented a GA-EDD algorithm using the earliest due date (EDD) dispatching rule for scheduling dual flow shops; while in [85], a modified GA is proposed for making manufacturing process plans in multiple parts manufacturing lines; [86] presented GA as well as Tabu search for solving the aggregate production planning (APP) model aimed at a two-phase production systems problem; [87] deals with the combinatorial explosion of alternatives associated with the consideration of different production scenarios as a computing efficient alternative using GA.

In [88], research on production scheduling with mold maintenance consideration based on a GA approach is presented. In [89], multi-objective GA is used for multi-criteria study of the production scheduling of a Brazilian garment company. Afterward, in [90], planning algorithms for automatic job allocations is proposed based on group technology and GA.

Reference [91] addresses in the first part of the article modeling of the problems and discusses how the chromosome illustration of the real-coded GA (RCGA) can manage much flexibility of operations in the FMS and the second part of the article discusses the effectiveness of this hybrid approach to solve several test-bed problems. In [92], a method for optimizing the process planning with GA in enterprise resource planning (ERP) analyzed the factors relating to production planning decisions in ERP, where GA played undoubtedly a role of enhancing system performance.

Reference [93] demonstrates an interactive fuzzy-based genetic algorithm (FBGA) approach for solving a two products and two periods APP with some vulnerable managerial constraints such as imprecise demands, variable manufacturing costs, and in [94] a hybrid variant consisting of linear search, GA, and SA is proposed to capture the optimal solutions with respect to the vagueness factor and level of satisfaction for industrial production planning problems. Reference [95] presents an interactive MOGA

method for solving the multiproduct, multi-period APP with forecasted demand, related operating costs, and capacity; in [96], a GA is developed to deal with the capacitated lot sizing in addition to scheduling problem with sequence-dependent setups, setup carryover, together with backlogging.

Reference [97] presents greedy rolling horizon search (GHRS) technique for solving production planning problem in supply chain networks. Although this paper does not use GA as the main algorithm, comparative analysis of GHRS is done with GA. Results show that GHRS performs better than GA. In [98], an alternant iterative GA is proposed to integrate production planning and scheduling for a mixed batch job-shop environment; in [99], a two-level soft drink production problem is solved using GA and mathematical programming approach, while in [100], a controlled elitist nondominated sorting GA (NSGA) and NSGA-II is used for multiobjective process planning and scheduling (PPS); in [101], PPS problem is solved using hybrid multiobjective algorithm combining the properties of vector-evaluated genetic algorithm (VEGA) and pareto-dominating and -dominated relationship-based fitness function (PDDRRFF). Reference [102] presents a literature survey, classification, and analysis to solve scheduling problems on FMS by using GAs; in [103], job process planning and scheduling (PPS) in batch production is solved using a GA-based approach.

Reference [104] presents an improved GA approach for joint optimization of production planning and supplier selection incorporating customer flexibility; reference [105] demonstrates the application of hybrid GA on test bed scheduling problems, and reference [106] presents a process plan modeling framework for multiple parts process planning in serial-parallel flexible flow lines using GA. Reference [107] presents a solution method based on GA with fixed and variable length chromosomes for multiple parts process planning in serial-parallel flexible flow lines. In reference [108], a multiobjective job-shop scheduling problem is solved using a dispatching rule-based GA with fuzzy satisfaction levels.

In reference [109], reentrant flow-shop scheduling problem with time windows is solved using hybrid GA-based on auto-tuning strategy. Reference [110] presents a GA approach for coordinated scheduling of the transfer lots in an assembly-type supply chain, while in reference [111] an integrated discrete PSO and extended priority-based hybrid GA is proposed for multistage production distribution under uncertain demands. In reference [112], unequal individual GA with intelligent diversification is used for lot-scheduling problem in integrated mills using multiple-paper machines; in [113], integrated PPS is optimized by an object-coding GA. In [114], a flow-shop sequence-dependent group scheduling problem is solved by minimizing make span

using a hybrid GA combining features of random sampling search with GA.

4.2 Order fulfillment

An order that completely fulfills customer requirements within its completion is termed as a “perfect order” [115]. Order fulfillment (OF) is one of the vital parameters to reflect client service performance. A pictorial cycle on OF in SCM is shown in figure 9. Figure 10(a), (b), and (c) shows the number of research articles breakup yearwise for a process that includes logistics and networks planning, vehicle routing, and other issues, respectively.

As shown in figure 11, the quantity of research papers relating to OF increase gradually, through some rise and fall, between 1998 and 2009. By contrast, a histrionic growth can be observed from 2010 to 2014. As shown in figure 12, out of the 90 papers on OF in SCM, 52% of the studies concentrated on logistics network design/planning problem; however, the other studies focused on vehicle routing and other issues.

4.2a Logistics network design/planning: To improve a long-standing optimal supply chain, one of the best comprehensive tactical decisions has been recognized as the network design problems [116]. Reference [117] proposed GA to solve network design problem that can be relatively common in nature; references [118–124] proposed to solve dynamic logistics network design as well as planning problem, such as multistage logistic network design and optimization.

Reference [118] discussed a spanning tree-based GA (st-GA) approach to find the best production/distribution design in multistage logistic network. Reference [119] used

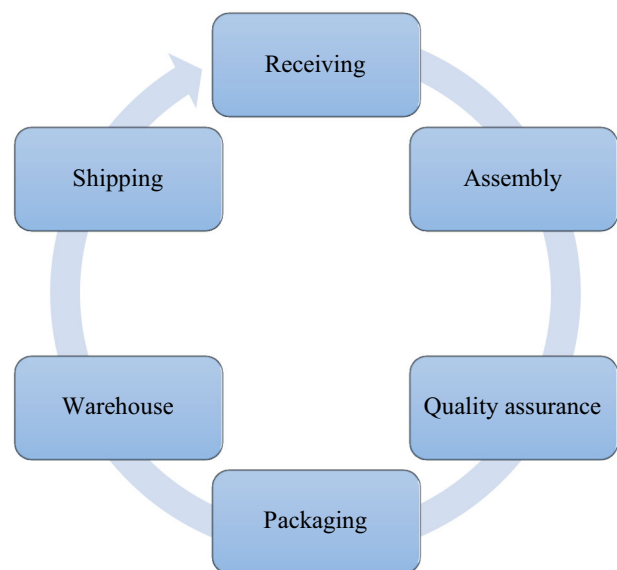


Figure 9. Order fulfillment cycle.

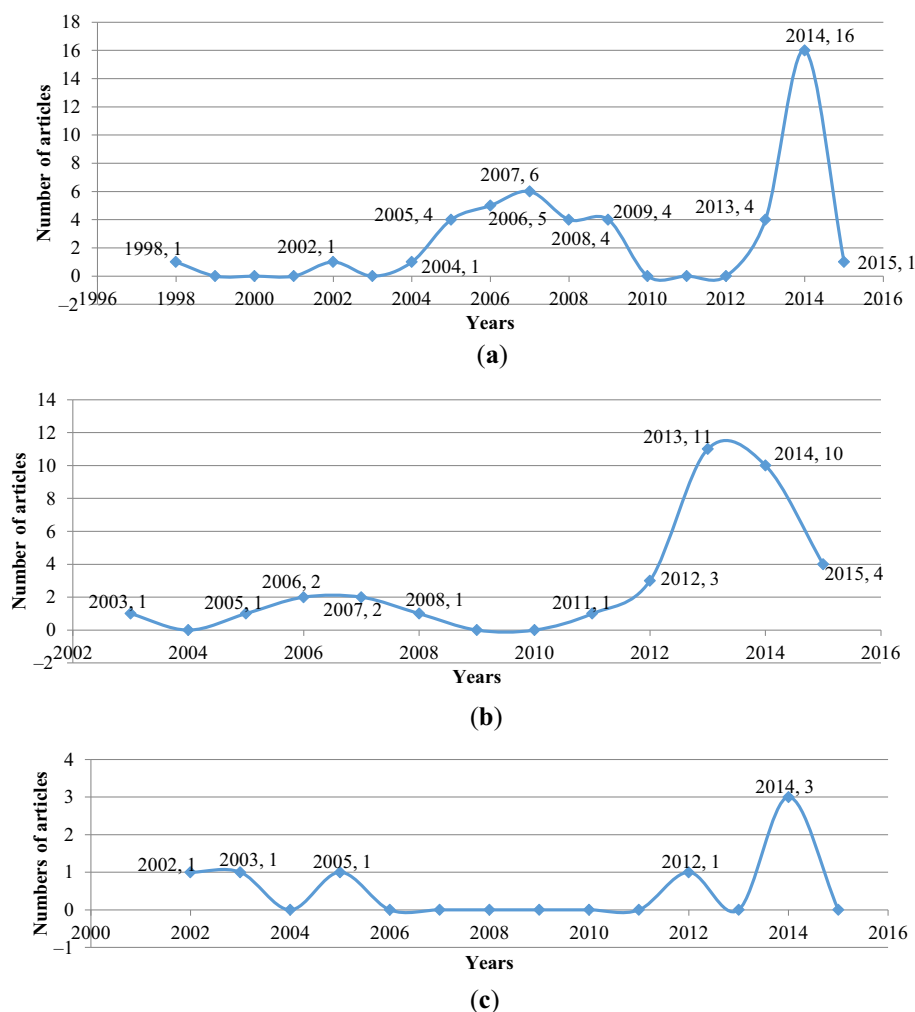


Figure 10. (a) Number of articles in logistics and network design sub-process of OF, (b) number of articles in vehicle routing sub-process of OF, and (c) number of articles in other issues sub-process of OF.

an enhanced GA based on the Prüfer number in addition to the adequate capacity coding to optimized unbalanced multistage logistics systems. In [120], st-GA is used in random fuzzy environment for multiobjective supply chain networks optimum model and its applications to the Chinese liquor industry; in [121], researchers determine the optimum solution of the continuous network design problem (CNDP) using two global approaches composed of GA as well as SA; and in [122] researchers applied a hybrid nondominated sorting GA (NSGA) to optimize the total cost along with service level aimed at just-in-time (JIT) distribution in a supply chain. In [123], researchers solved single-source, multiproduct, multistage supply chain network (SCN) design with steady-state GA (ssGA); later, in [124], researchers proposed a GA-based heuristic method for a two-stage supply chain distribution problem related with a fixed charge.

Authors in [125] solved distribution network problems by multi-criteria genetic optimization; in [126], authors used GA in distribution network problems for optimization

of OF. References [127, 128] show freight transportation planning; [127] use GA and probability theory, which affects the determination of the tactical model, and in [128], authors solved nonlinear fixed charge transportation issue using the spanning tree-based GA method; afterwards, in [129], authors solved multitime period production/distribution planning problem with the application of a novel method named hybrid spanning tree-based GA (hst-GA); and in [130], the authors suggested a fuzzy-GA that solved integrated production/distribution planning model in the SCM; references [131, 132] deal with logistic process optimization. In [131] weighted fuzzy optimization is used for logistic systems and in [132] the online reoptimization of a logistic scheduling problem is solved with the help of GA along with ant colony optimization (ACO). In [133], the authors suggested vehicle transshipment planning in seaport terminal. References [134, 135] present a study on network design problems; whereas in [134], the authors suggest a knowledge-based method that assists in procurement decision making, and in [135], the authors

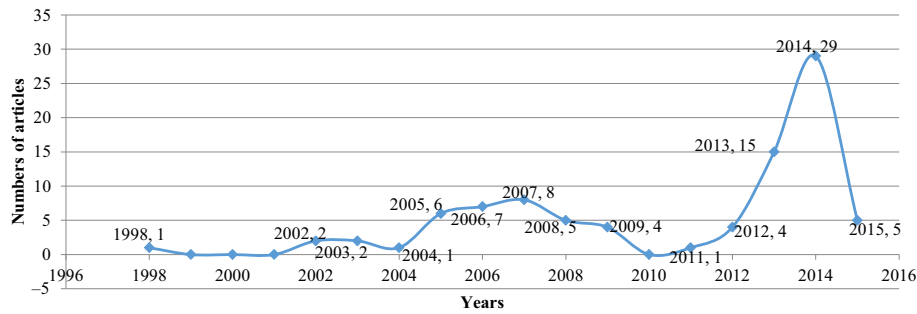


Figure 11. Total numbers of articles in sub-process of OF.

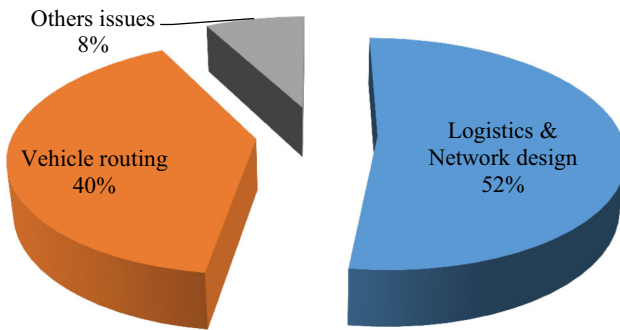


Figure 12. Distribution of articles in sub-processes of OF.

determined the set of pareto-optimal solutions for multi-objective supply chain network (MO-SCN) design problem using a GA-based approach.

Reference [136] presents a GA method for freight transportation planning to reduce overall shipment costs. Subsequently, authors in [137] employed GA for solving the problem of container shipping and repositioning. In [138], the authors unite GA and a set of constructive heuristics for the distribution of ready-mixed concrete. References [139, 140] provide a study on third-party logistics (3PLs) services integration; researchers in [139] proposed a hybrid GA-based heuristic optimization/simulation modeling method for the design of a delivery setup of 3PLs; researchers in [140] suggested a GA-based heuristic that involves genetic operations along with simplex transshipment algorithm 3PLs.

In [141], the authors applied GA to attain improved cooperation, together with superior collaborative work in a collaborative SCN. Authors in [142] suggested interval hierarchical OD demand based on an interval GA, which is for discrete logistics network design model; in [143], authors provided a continuous equilibrium network design model of stochastic demand and supply solved by Monte Carlo simulation-based GA. In [144], the authors employed a multi-objective GA (MOGA) for the resolution of the consequential NP-hard combinatorial optimization problems. In [145], the authors customized Pareto-based multi-objective evolutionary algorithm and NSGA-II to determine the compromise

solutions for a readily adapted three-level logistic network design. Later in [146], the authors used priority-based GA for combined closed-loop logistics network design along a fuzzy-random programming.

In reference [147] transportation problem is solved using fuzzy guided multi-objective evolutionary algorithm model, and in [148] two-way approximation GA is presented for supply chain distribution network of bi-level programming model. In [149], the authors have used a hybrid PSO and GA for closed-loop SCN design in large-scale networks; in [150], optimization of closed-loop SCN is presented with crisp and fuzzy objectives by a GA approach; in [151], a fuzzy reverse SCN design is presented using hybrid algorithms; and in [152], authors optimize the green agricultural products SCN using a transforming quantum-inspired GA. Reference [153] presents optimization of defective goods supply chain costs using GA.

In reference [154], authors used GA for design of SCNs with supply disruptions; in [155], the authors used GA for optimization of a multistage SCN. In reference [156], response surface method (RSM) and GA are used for optimization of logistics cost and inventory design of an organizations logistics network. In [157], GA is used for presenting an optimization model for reverse logistics network under stochastic environment. Authors in [158] solved emergency logistics scheduling using greedy-search-based MOGA; reference [159] presents a case study of automotive wiring harnesses based on optimization of reverse logistics network by GA. In [160], authors have applied GA on reverse logistics for optimization of network site for e-commerce; authors in [161] proposed GA for optimization of logistics network of import crude oil in China, and in [162], GA is used for design of multiproduct/multi-period closed-loop reverse logistics network. In [163], NSGA-II and NREGA are proposed for bi-objective optimization of a problem of multiproduct, multi-period, three-echelon supply chain under uncertain environments.

4.2b Vehicle routing/assignment: The vehicle routing problem (VRP) is made up of a number of customers, each needing a fixed mass of goods to be transported. Vehicles dispatched from a single work shop must transport the

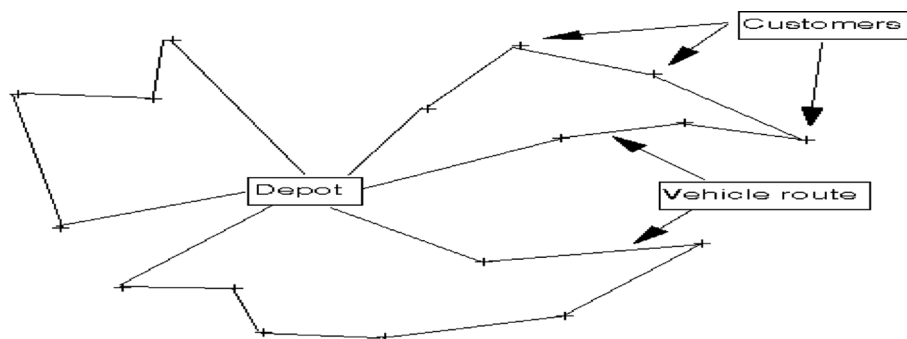


Figure 13. Route of vehicle in a depot (source: <http://people.brunel.ac.uk/~mastjjb/jeb/or/vrp.html>).

merchandises required, and then come back to the work shop. The problem is to fix distribution routes and give nominal cost [164]. Vital VRP have picked logistics administrators and researchers' consideration after 2000. A pictorial route of vehicle in a depot is shown in figure 13. Many GA-based papers are available in literature for dealing with VRP. In [164], the authors used GA for the first time in 2003 for VRP; in [165], the authors proved that a GA-based methodology is competent to determine superior solution to fulfill the growing pressures on readily adapted and speedy transportation services. References [166–168] show that, in a simple supply chain, a hybrid GA (HGA) is extra encouraging in reducing transportation charge; in [166], the authors proposed an HGA for the finite horizon economic lot along with delivery scheduling; in [167], authors offered a critical literature review on different heuristic shortest-path algorithms, and in [168], for logistics distribution centers, location problem authors used integrated GA, FS algorithm, and Tabu search algorithm to seek better approximate solution.

References [169, 170] presented promising results on VRP along with pickup and delivery sequence constraints; in [169], the authors proposed a cluster along with search heuristic to deal with the VRP with delivery as well as pickup, and in [170], the authors developed a simple GA to solve multidepot VRP (MDVRP) by integrating three hard optimization problems; in [171], authors offered a novel kind of geometric shape-based genetic clustering algorithm for multi-depot VRP, and in [172], an improved savings heuristics along with GA for bi-objective VRP with forced bi-backhauls (BVFB) is proposed. References [173, 174] present a hybrid approach that merge a GA with an iterated local search (ILS) to deal with the location-routing problem (LRP) efficiently. In [175], authors proposed an effective hybrid GA, including progressive diversity control method for a large class of time-constrained VRP.

Reference [176] presents a new niche cellular GA algorithm to solve the VRP with time window, and in [177], a hybrid GA is applied to the capacitated VRP (CVRP); in [178], the authors suggested improved GA to solve the VRP along time window by applying an optimized crossover

operator; in [179], the authors recommended a hybrid genetic and immune algorithm to deal with the VRP along with limited capacity. Authors in [180] introduced an adaptive evolutionary approach that apply a GA in an adaptive tactic for real-time VRP with dispatching; in [181], the predictability of GA performance is examined on the VRP using information-theoretic fitness landscape measures; in [182], authors propose a new way to calculate the adaptive probability in the cross operator with an improved GA.

In [183], authors proposed a hybrid GA for the multi-depot open VRP, and in [184] the authors worked on enhancing localized GA for large-scale capacitated VRP solution by introducing selective search version of the automated problem decomposition strategy, a faster genotype-to-phenotype translation scheme, and various search reduction techniques; reference [185] presented a work on traffic volume and vehicle utilization, which are closely related to the cost of vehicle traffic, a vehicle scheduling model with the minimum fuel cost, and fixed cost is established. According to the requirement of real-time and complicity of the vehicle scheduling, a cloud-adaptive GA is proposed by combining cloud model theory with GA.

In [186], a GA is proposed to deal with the bi-objective VRP with time windows simultaneously, considering total distance and distance balance of active vehicle fleet. A new complex chromosome is used to present the active vehicle route. In [187] GA is used for solving the dynamic VRP, while in [188] authors solved the periodic VRP with time windows by a hybrid generational GA and in [189] VRP is solved with the help of a new MOGA: called fitness-aggregated GA (FAGA).

In [190], the authors solved a multi-depot open VRP using a hybrid GA; in [191], authors solved multi-objective VRP with time windows, with the help of partially optimized cyclic shift crossover for MOGA. Reference [192] presents optimization of warehouse order-picking routes using vehicle routing model and GA. Reference [193] proposed FAGA for the solution of multi-objective VRP with time windows; in [194], authors used fuzzy cost coefficients and hybrid GA to solve VRP; in [195], authors present a parallel multi-start NSGA-II algorithm for multi-

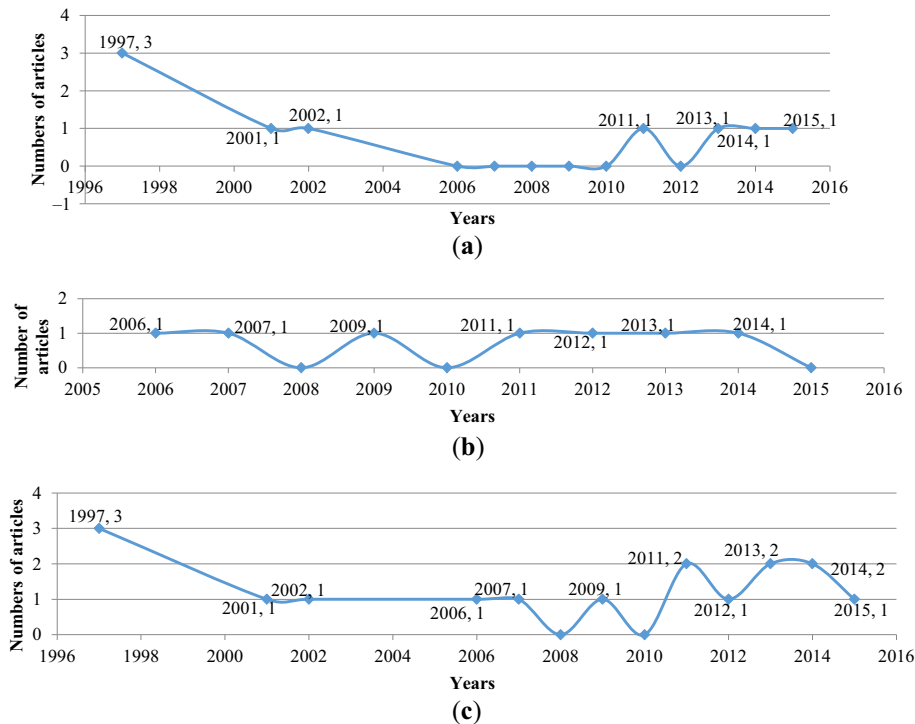


Figure 14. (a) Number of articles in sales forecasting sub-process of DM, (b) number of articles in bullwhip effect sub-process of DM, and (c) total numbers of articles in sub-processes of DM.

objective energy reduction VRP; in [196], authors solved multi-depot heterogeneous VRP with simultaneous pickup and delivery time windows using an improved GA. Reference [197] presents a survey of GAs for solving multi-depot VRP. In [198], authors present a GA approach for two-level vehicle routing with cross-docking in a three-echelon supply chain.

4.2c Other issues: Authors in [199] developed a new balanced star spanning forest formulation including GA to deal with the balance allocation problem, which is known to be NP-hard, and in [200], authors employ a GA aimed to determine pareto-optimal solution for dealing with problems in a small portion of interval; reference [201] regulates the optimum arrangement of shipping choices to reduce overall logistics costs using a genetic or evolutionary algorithm (GA-EA).

Reference [202] used GA for optimizing replenishment policies of single-warehouse multiretailer system; reference [203] proposed GA for solving and modeling supply chain facility location problem; in [204], authors solved the economic manpower shift planning problem with the help of GA, and in [205], the capacitated facility location problem is solved using hybrid firefly-GA.

4.3 Demand management

Demand management (DM) comprises all the demand activities, including market sensing, market creating,

marketing, and demand capturing. It has two major sub-practices: sales forecasting and bullwhip effect [206]. Figure 14(a) and (b) show graphically the number of articles corresponding to sub-practices of DM, namely, sales forecasting (9 articles) and bullwhip effect (7 articles). Figure 14(c) shows total number of research articles in sub-processes of DM and figure 15 shows the distribution of articles in sub-processes of DM.

4.3a Sales forecasting: Sales forecasting models perform a substantial part in marketing of goods and services planning [1] and it is one of the main tactical exercises in managerial decision-making practices for DM [207]. In [4], the authors used GA in SCM for computerized causal forecasting system, while in [208], authors presented a forecasting algorithm made up of two loops: the genetic forecasting loop and the pattern learning loop. Reference [209] presents a combination of two techniques, fuzzy theory and GA for the solution of forecasting problems. In [210], authors proposed genetic fuzzy predictor ensemble for forecasting a time series problem. In [206], authors solved sales forecasting system based on fuzzy neural network problem with generated initial weights by GA; in [1], authors extracted the rule base of the fuzzy expert system and K-means genetic fuzzy system (KGFS) in building a sales forecasting expert system using GA.

In [211], GA is used for optimizing neural network for coal sales prediction in some large coal enterprise; reference [212] established a novel forecasting model integrating decision tree (DT) algorithms and GA to construct a

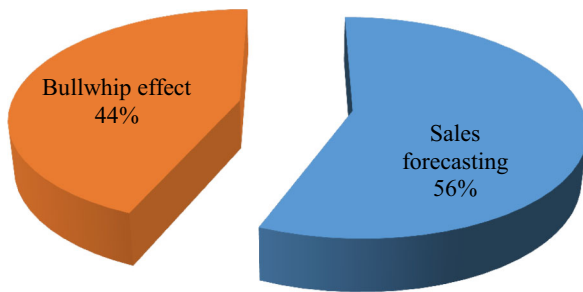


Figure 15. Distribution of articles in sub-processes of DM.

sales predictions system based on historical data and the most optimized decision tree. In [213], authors proposed a GA to optimize backpropagation (BP) neural network structure on car sales forecasts.

4.3b Bullwhip effect: A phenomenon through which a slight discrepancy in the demand from end customer effects massive deviations as it drives upstream is called bullwhip effect [214]. Reference [215] suggests that the GA can minimize the bullwhip effect with random customer demand, combined with deterministic and random lead times.

Authors in [216] showed that GAs can minimize the bullwhip effect with the optimal ordering policy of difficult supply chains. Reference [217] investigates whether GAs can adequately minimize the bullwhip effect in an efficient-responsive supply chain.

In [218], GA and control engineering (PI and PID controllers) are used as tools for the bullwhip minimization in supply chains; in [219], GA is used to minimize the bullwhip effect and to find optimal ordering quantity in a multistage supply chain. In [220], a parallel GA is proposed to reduce the bullwhip effect and cost in an automotive supply chain. In [221], evolutionary multi-objective meta-heuristics is used for optimizing of bullwhip effect and net stock amplification.

4.4 Supplier relationship management

SRM is an exercise involved in dealing with finest vendors and finding new ones, at the same time as minimizing costs, accomplishing procurement predictable along with

repeatable, bring together buyer understanding, and take out the profits of supplier partnerships [222]. Some pioneering work in SRM can be found in [223–226]. A pictorial classification of the different steps of supplier relationship management in SCM is shown in figure 16, and figure 17 shows the number of articles in SRM.

Reference [227] used for optimization of incentive system to achieve competence of supply chain allies to make sure the long-standing tactical relations with a GA technique, whereas in [228] GA is applied with budget constraints for a stochastic demand multiproduct vendor selection model; in [229] two MOGA are applied to find a set of pareto-optimal solutions that can develop additional solutions for the green partner selection using weighted sum tactic. In [230], authors solved a stochastic demand multiproduct supplier selection model along with budget constraints applying GA. In [231], authors applied GA-based gray goal programming model for evaluation and selection of the suppliers, and in [232], authors selected GA parameters for solution. The authors also analyzed the sensitivity of the multiple supplier–multiple buyer collaborative supply chain model parameters to understand how variations in the model parameters affect the related total costs. Reference [233] presents a case study using a GA for supplier selection decision enhancement.

4.5 Product development and commercialization

The product development and commercialization (PDC) practices need adequate planning along with execution all through the supply chain, and if managed in the approved manner can deliver a sustainable competitive benefit [234]. A pictorial classification framework on product development and commercialization in SCM is shown in figure 18 and figure 19 shows the number of articles in PDC.

In [235], a hybrid multi-objective (GA-MCDM) approach is presented for selecting the best portfolio alternative for new product development in the pharma industry. Reference [236] presents an adaptive GA for task allocation optimization in collaborative customized product development. In [237], authors proposed an approach for optimal affective product design using mined rules based

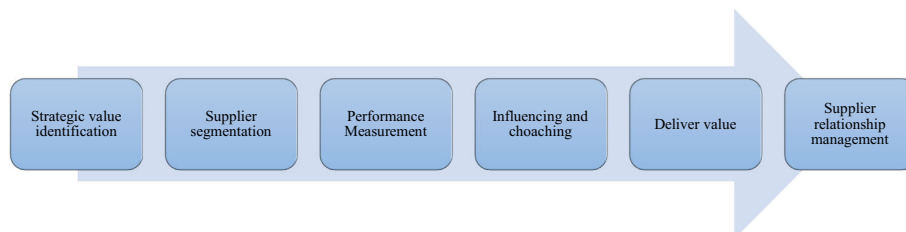


Figure 16. Different steps of SRM in SCM.

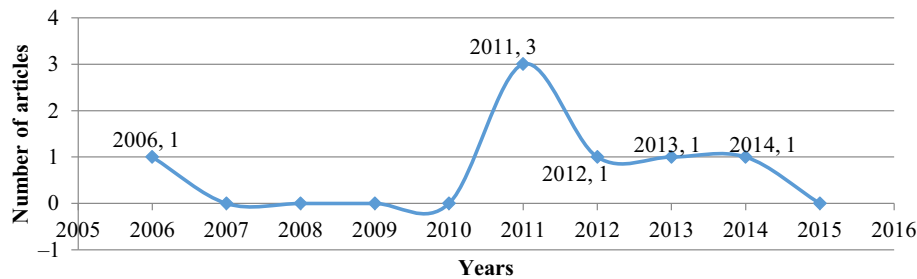


Figure 17. Number of articles in SRM process.

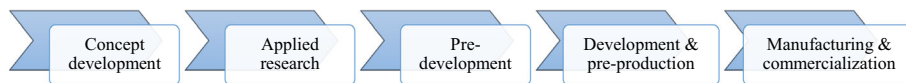


Figure 18. Product development and commercialization steps.

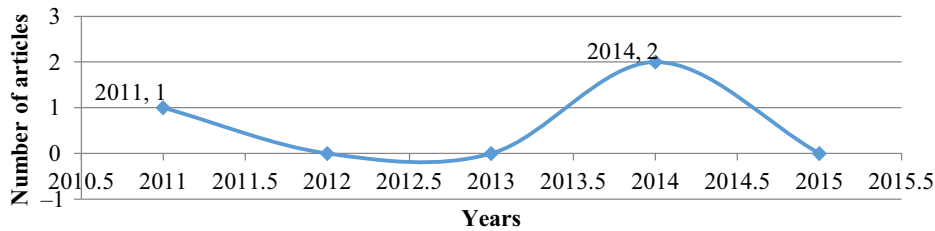


Figure 19. Number of articles in PDC process.

on guided-search GA. It seems that there are very few research papers addressing this process.

4.6 Returns management

Returns management (RM) is the SCM practice by which activities associated with returns; reverse logistics, gate keeping, and avoidance are managed within the enterprise through crucial associates of the supply chain [238]. The number of articles in PDC is shown in figure 20.

References [239, 240] give GA-based method to deal with reverse logistics problem of handling reverted goods, where [239] presented a mixed-integer, nonlinear programming model along with a GA that can deal with these problems containing equally spatial plus temporal consolidation of reverted produces; reference [240] presents a mixed-integer, nonlinear programming model including GA that can settle the reverse logistics problem; in [241], the authors established an optimum solution to deal with the reverse logistics network design problems, in order to search for the optimal solution of this a mixed-integer nonlinear programming model (MINLP); in [242], authors proposes a mixed-integer

programming model and a GA to solve the similar issues from third-party logistics service providers' viewpoint.

In reference [243], authors proposed a hybrid qualitative and quantitative methodology by means of fuzzy cognitive maps along with GA to model as well as estimate the competence of radio frequency identification (RFID)-enabled reverse logistic activities; in [244], authors presented a GA that can deal with the stochastic network design problem in a closed-loop supply chain; subsequently, [245] used GA and artificial immune system to present an optimization model for product returns; in [246], a competent hybrid genetic-simulated annealing algorithm (HGSAA) is proposed to deal with the NP-hard problem, of a location-inventory-routing problem; in reference [247], authors researched on spare part returns in stochastic deteriorating manufacturing system under a condition-based maintenance policy using simulation-based GA approach; and in [248], the authors proposed an improved adaptive GA (IAGA) to solve optimization of location inventory routing problems (LIRPs) considering the cost of the returned products and the retailers' time-satisfaction degree into account; in [249], an optimization model for product returns is solved using GA and SA.

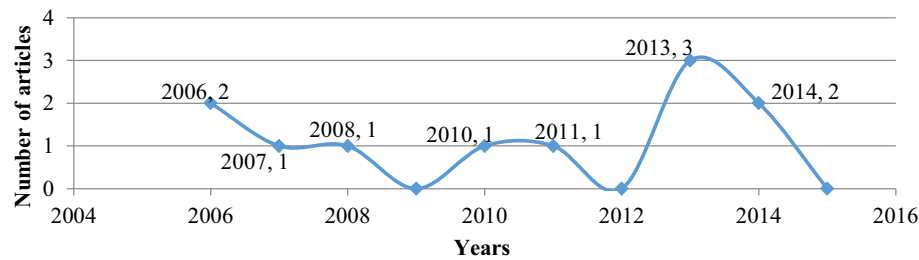


Figure 20. Number of articles in RM process.

Table 1. Annual distribution of number of papers in respective subject processes.

Years	MFM	OF	DM	SRM	PDC	RM	CSM	CRM	Total
1991	1								1
1997			3						3
1998	1	1							2
2000	1								1
2001			1						1
2002	2	2	1						5
2003	1	2							3
2004	2	1							3
2005	7	6							13
2006	5	7	1	1		2			16
2007	6	8	1			1			16
2008	3	5				1			9
2009	4	4	1						9
2010	3					1			4
2011	5	1	2	3	1	1			13
2012	4	4	1	1					10
2013	18	15	2	1		3			39
2014	21	29	2	1	2	2			57
2015	9	5	1						15
Total	93	90	16	7	3	11			220

4.7 Customer service management

CSM deals with a service-focused process of managing tie up between clients and service provider [250]. We could not find any relevant paper in this area.

4.8 Customer relationship management

CRM is a widely practiced model for managing a firm's relations with customers, consumers, in addition to sales scenarios [251]. Here also the authors could not find any paper on CRM where GA is used.

5. Discussions

- Distribution of articles as per main processes and sub-processes of SCM

- As shown in table 1, several research papers have contributed to seven broad categories of SCM processes. The MFM is the most popular process targeted by GA applications. The research papers about OF are slightly more common than the papers regarding DM. It is clear therefore that papers for those three major SCM processes are considerably more than those in other SCM processes.
- Pie diagram given in figure 21 shows the percentage of papers concentrating on the major processes of SCM. It shows that out of total research papers reviewed for this study, MFM contributes 42% of the total distribution and is the most popular process in SCM where GA is used. MFM is closely followed by OF, having 41% papers with GA application. Remaining 17% papers consist of papers focused on DM (7%) and other issues such as SRM, PDC, RM contributes 10% to this distribution.

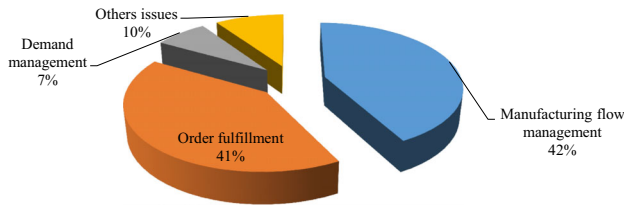


Figure 21. Proportion of articles in SCM major processes.

- Table 2 provides a break up in detail for the connection between researchers and respective SCM research area on yearly basis. The number of research articles and the researchers working for GAs applications in SCM-related areas has steadily increased since 2000.
- As shown in table 3, out of the surveyed 220 papers, 93 are concerned with the MFM, in which sub-processes include inventory management/material planning (33), supply chain planning (5) and production planning (55). While 90 out of remaining 127 papers concerned with the OF, based on available practices from the literature, include sub-processes logistics & network design (47), vehicle routing (36) and others issues (7), for tackling the problem. Subsequently, 16 papers utilize DM practices, which include sales forecasting (9) and bullwhip effect (7). Finally, the remaining 21 papers are based on the processes concerned with SRM (7), PDC (3), and RM (11).
- The graph in figure 22 shows that there has been a considerable increase in the number of articles since 1991, where GA is applied for dealing with

different aspects of SCM. In 2014, the number of articles with GA application in SCM touched 57.

• *Publication of articles in leading journals*

- As presented in table 4, 23 papers were published by *Expert Systems with Applications*, while 15 of total papers were published by *Computers and Industrial Engineering*, and 12 articles by *International Journal of Production Economics*. *European Journal of Operational Research*, *Journal of Intelligent Manufacturing*, *Computers & Operations Research*, *Journal of Advanced Manufacturing Technology* and *Journal of Intelligent Manufacturing* as well the key journals acknowledged by scholars.
- From the publication point of view, we see that almost all the major journals have covered articles belonging to SCM. As shown in table 4, the top contributor is a journal focused on computer science (*Expert Systems with Applications*), on computer science and industrial engineering/operations research (*Computers and Industrial Engineering*, *Computers & Operations Research*), and well-established journals in the Operations Management and Manufacturing areas (*International Journal of Production Research*, *European Journal of Operational Research*, *International Journal of Production Economics*, *Journal of Intelligent Manufacturing*, *Journal of Advanced Manufacturing Technology*); contributions can be also retrieved in more traditional journals from several disciplinary areas, such as Informatics and Computer Science Intelligent Systems Applications

Table 2. Annual summaries of articles in respective subject processes.

Years	MFM	OF	DM	SRM	PDC	RM	CSM	CRM
1991	[5]							
1997			[208–210]					
1998	[62]	[117]						
2000	[63]							
2001			[206]					
2002	[57, 64]	[118, 199]	[4]					
2003	[59]	[164, 200]						
2004	[25, 26]	[125]						
2005	[56–69]	[127, 129, 133, 134, 165, 201]						
2006	[6, 70–73]	[119, 126, 135, 136, 139, 166, 167]	[215]	[227]		[239, 240]		
2007	[7, 8, 27, 74, 75, 76]	[128, 130, 131, 137, 138, 140, 168, 169]	[216]			[241]		
2008	[28, 58, 77]	[120, 122, 132, 141, 170]				[242]		
2009	[78–81]	[121, 123, 124, 147]	[217]					
2010	[29–31]					[243]		
2011	[32, 33, 82, 83, 85]	[171]	[1, 218]	[228–230]	[235]	[244]		
2012	[84, 86–88]	[172–174, 202]	[219]	[231]				
2013	[34–44, 89–95]	[142, 144–146, 175–178, 180–186]	[212, 220]	[232]		[245–247]		
2014	[45–50, 96–109]	[143, 148–162, 179, 187–194, 203–205]	[211, 221]	[233]	[236, 237]	[248, 249]		
2015	[51–54, 110–114]	[163, 180, 195–198]	[213]					

Table 3. GAs applied to respective subject processes.

Processes	Genetic algorithm
MFM	93
OF	90
DM	16
SRM	07
PDC	03
RM	11
CSM	0
CRM	0
Total	220

(*Information Sciences*), Industrial engineering (*Industrial Management and Data Systems*), Soft computing (*Applied Soft Computing*, *Applied Mathematical Modelling*, (*Applied Mathematics and Computation*), Mechanics and Materials (*Applied Mechanics and Materials*), Artificial Intelligence (*Engineering Applications of Artificial Intelligence*), Operations Management (*International Journal of Physical Distribution & Logistics Management*), Manufacturing Technology (*Journal of Manufacturing Technology Management*).

- *Types of GA variants used*

Depending on the nature of the problem formulated, different variants of GA have been used. It is observed that in most of the papers a hybrid variant of GA is used, where hybridization is done with fuzzy logic, support vector machine, machine learning, local search methods, etc.; besides, GA has also been hybridized with other algorithms such as Tabu Search and SA. Since several SCM problems can be modeled as multi-objective optimization problems, multi-objective GA has been used for solving such cases. Parallel variants of GA have been used in two cases; while in some other cases, new operators are proposed or a study is done on the effect of change of parameters.

- *Future trend*

With the growing competition in today's environment, the mathematical models of SCM are becoming more and more

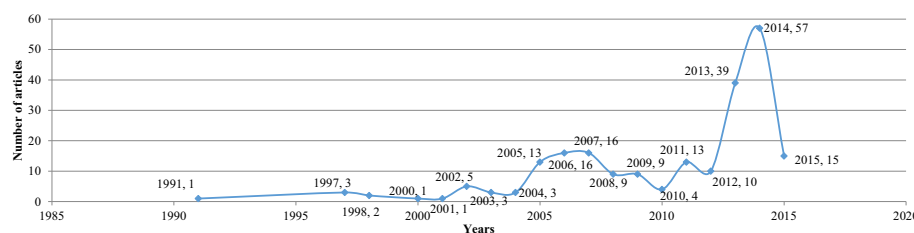
Table 4. Research articles published by main journals.

Journals title	No. of articles
Expert Systems with Applications	23
Computers and Industrial engineering	15
International Journal of Production Research	12
European Journal of Operational Research	10
Journal of Intelligent Manufacturing	12
Computers & Operations Research	7
International Journal of Production Economics	7
Journal of Advanced Manufacturing Technology	6
Information Sciences	5
Industrial Management and Data Systems	3
Applied Soft Computing	3
Applied Mathematical Modelling	3
Applied Mechanics and Materials	3
Engineering Applications of Artificial Intelligence	3
Applied Mathematics and Computation	2
International Journal of Physical Distribution & Logistics Management	2
Journal of Manufacturing Technology Management	2
Others	100
Total	220

complex. For example, in order to make the problem more realistic, problems are being formulated as multi-objective. This trend can be seen in the recent papers where the researchers have considered bi-objective or multi-objective models. Consequently, researchers are concentrating on developing multi-objective variants of GA. Secondly, the focus is also on developing efficient GAs for integer and mixed programming problems that may be linear or nonlinear.

6. Summary

Since its development in 1975, GAs have emerged as a powerful tool for dealing with problems arising in various fields. It is remarkable that despite the presence of several other soft computing techniques [252–255], GAs have maintained their

**Figure 22.** Number of articles in SCM using GA.

own fan following and are widely used scientists and researchers in various fields [256–259]. GAs has particularly shown their efficiency in case of optimization models. This is one of the reasons why GAs has frequently been used for in SCM as many of the problems here can be formulated as optimization problems. The popularity of GA can also be attributed to the availability of fast computers and freely available GA tool boxes. The purpose of this paper is to familiarize the reader with the application of GA on the eight processes of SCM as given by Council of SCM Professionals (CSCMP), namely, Manufacturing flow management (MFM), which includes Inventory Management/Material Planning, Supply Chain Planning and Production Planning; Order fulfillment (OF), which has Logistics Network Design/Planning, Vehicle Routing/Assignment and Other issues as sub-processes; Demand management (DM) having Sales Forecasting and Bullwhip Effect as sub-processes; Supplier relationship management (SRM); Product development and commercialization (PDC); Returns management (RM); Customer service management (CSM); Customer relationship management (CRM). It is seen that in all the areas except CSM and CRM, GA has been applied successfully. The authors have tried to cover as many papers as possible; however, there is a possibility that some useful paper might have been overlooked.

Acknowledgments

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