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Metaheuristics in Logistics and Supply Chain Management

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The modeling of logistics systems is performed to seek the best possible system configuration to minimize costs or maximize operational performance, in order to meet or exceed customer expectations. Classically, analytic system analysis of this type has been performed using optimization, simulation, or heuristics. However, in the past two decades, a newer class of techniques, metaheuristics, has emerged as a capable method for quickly providing near-optimal solutions for problems that exact optimization cannot solve. This article outlines recent advances in metaheuristics development, and considers the ability of these advanced techniques to resolve various logistics and supply chain problem types. Specifically, the article discusses the ant colony optimization, genetic algorithm, simulated annealing, and tabu search metaheuristics. The capabilities of these metaheuristic techniques to examine supply chain risk and disruptions, intermodal operations, customer service trade-offs, backhaul strategies, and simultaneous facility location and vehicle route problems are proposed. The article concludes by describing how faculty can bring these techniques into the classroom to ensure their students enter the logistics and supply chain field with a current and relevant understanding of the state of the art in supply chain design techniques.

Keywords: supply chain network design; logistics system design; optimization; simulation; metaheuristics; heuristics; ant colony optimization; simulated annealing; genetic algorithm; tabu search

INTRODUCTION

The modeling of supply chain and logistics problems has traditionally relied on three primary methods: optimization, simulation, and heuristics (Ballou 1989). Over the last several decades, however, optimization has been the preferred method to mathematically model and generate optimal solutions for complex supply chain problems (Shapiro 2001; Harrison 2004; Croxton and Zinn 2005; Ragsdale 2011). Similarly, simulation is increasingly applied in cases where the stochastic nature of supply chain problems and the ability of various supply chain practices and configurations to deal with these variations is a principal interest (Goldsby et al. 2006; Nyaga et al. 2007; Defee et al. 2009). Since 2000, 33% of the analytic works published in the *Journal of Business Logistics* have applied optimization, whereas 59% applied simulation methods. However, only 15%[1] of articles applied heuristics, despite the fact that heuristic development has accelerated rapidly in recent years. This imbalance in the use of analytic modeling methodologies may limit the field's ability to resolve critical logistics and supply chain issues; especially for those problems suited to methods beyond the beaten path of optimization and simulation. In particular, next-generation heuristics, called metaheuristics, offer the ability to analyze complex problems, like those presented by cross-functionally focused supply chain research, that often are too complex to be solved in reasonable time frames by optimization methods. These new metaheuristic techniques are positioned to provide valuable insight to important supply chain problems needing analytic examination.

This article is concerned with these metaheuristics, and strives to inform the reader about the types of techniques available, some supply chain problems suited to their application, and ways these techniques can be brought into the classroom. This article first discusses the analytic context within which metaheuristics exist. Second, the advantages and disadvantages of the key metaheuristic algorithms within two primary classes of the method, including descriptions of recent algorithmic developments in each class are reviewed. Third, the article reviews a group of complex supply chain problems that appear as though they may benefit from reconsideration using metaheuristics methods. Finally, the article concludes with a discussion of teaching approaches for metaheuristics in academic settings.

METAHEURISTICS WITHIN THE ANALYTIC METHOD

Problem complexity is a major issue when selecting an analytic method to evaluate supply chain alternatives. Traditionally, researchers and practitioners prefer closed form analytic methods that evaluate equations and functions to solve problems (Borwein and Crandall 2010). Optimization seeks the best problem solution by minimizing or maximizing a specific objective function. As seen in Figure 1, optimization is one of the three main analytic methods used to solve a variety of problems. Each method possesses differing strengths and weaknesses, the specific comparison of which is not the focus of this article. However, an excellent overview of these general classifications appears in a group of articles by Bowersox and Closs (1989), Powers (1989) and Ballou (1989). Regarding optimization problems, they are guided by

[1]The cumulative percentage of articles exceeds 100% due to the use of multiple methodologies in some articles.

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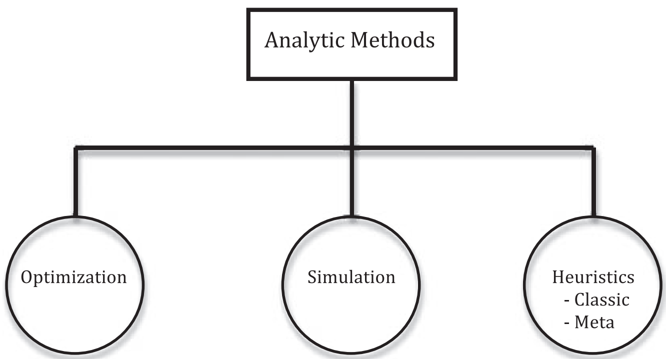
Figure 1: Analytic methods.



sets of decision variables that are manipulated to achieve an optimal solution within the confines of a set of constraints that prohibit variables from taking on infeasible values (Hillier et al. 2000; Ragsdale 2011). However, due to the size, complexity, and often the nonlinear nature of some problems, closed form approaches yielding exact methods for solving a problem are not always available. The widely employed simplex method, for example, is limited in the size and structure of the problems it can solve.

Therefore, supply chain professionals often must turn to computer simulation (when variability is a primary concern) or other forms of mathematical modeling that do not rely on closed form expressions. However, simulation does not provide an optimal solution and performing enough replications to begin to approach optimality is impractical, and even then, knowledge of achieved optimality is not assured, even if it was found.

Therefore, heuristics methods have traditionally been relied upon to generate solutions to large and complex optimization problems. The application of heuristics to problems, such as facility location problems, vehicle routing problems, and resource allocation problems is well established (Zanakis and Evans 1981; Ballou and Agarwal 1988; Laporte 2007; Daskin 2008; Pereira and Tavaras 2010). Although numerous classification schemes for heuristics exist, there is general agreement that there are two primary categories, heuristics and metaheuristics.

Heuristics

Heuristics, sometimes called "rule-of-thumb" algorithms, are sets of steps, taken in sequence, to resolve a combinatorial optimization problem (Shapiro 2001). Basic heuristics used in common logistics problems such as the vehicle routing problem can be described as either construction heuristics or local improvement heuristics (Bräysy and Gendreau 2005). Construction heuristics build a feasible solution using iterative steps based on some criteria such as minimizing cost. The most common examples include the savings algorithm (Clarke and Wright 1964), sweep algorithm (Gillett and Miller 1974), and various versions of Solomon's (1987) insertion heuristic. In contrast, local improvement heuristics start with an initial solution and iteratively improve on it by considering neighboring solutions. Common local improvement heuristics in network routing and location problems include the 2- and 3-opt heuristics (Lin 1965), Lamba-exchange (Osman 1993), and various ejection chain procedures (Bräysy 2003). Although heuristics can build solutions or iteratively improve feasible solutions, their solution capabilities are limited by problem size and complexity. In addition, they may terminate at a "local" optimal solution, ignoring better solutions in different regions of the solution space. They are also often specific to a narrow problem type. However, despite these issues, and the fact that they do not always solve problems to optimality, their solutions are often near-optimal, and generally arrive at their solutions much quicker than optimization. However, in the past 20 years, a new, improved class of heuristics has developed, called metaheuristics that have rapidly closed the solution quality gap between optimization and heuristics, and also possess properties making them particularly well suited to logistics and supply chain research.

Metaheuristics

Metaheuristics are defined as solution methods that orchestrate an interaction between basic local improvement heuristics and higher level strategies aimed at escaping from local optimums in a solution space (Glover and Kochenberger 2003). Metaheuristics differ from the classic heuristics in that they "… perform a much more thorough search of the solution space, allowing inferior and sometimes infeasible moves, as well as recombinations of solutions to create new ones" (Cordeau et al. 2002, 516). They are often considered a part of the evolutionary or artificial intelligence class of optimization methods, and are used successfully in many fields of science (Coppin 2004). As metaheuristics conduct a more thorough search, they have quickly become the preferred method for generating solutions to complex real-world problems that exact methods are incapable of solving (Glover and Kochenberger 2003). Given the reality that supply chain problems generally exhibit significant real-world complexity, metaheuristics are particularly well suited to examining supply chain issues. This article focuses on metaheuristics due to their domination of heuristics in solving problems, and because they have incorporated within their scope classic heuristic techniques, many of which form the basic building blocks of metaheuristics.

There are several distinct advantages and disadvantages of using metaheuristic methods in comparison to other analytic methods. First, many logistics and supply chain problems are too large or complex for traditional optimization methods to guarantee an optimal solution. Large vehicle routing problems and facility location problems (selecting 20 warehouse locations from hundreds of potential locations) results in almost infinite combinations to evaluate and cannot be solved in real time with any exact closed form algorithm (Kariv and Hakimi 1979; Lenstra and Rinnooy Kan 1981), because they are classified as NP-hard combinatorial optimization problems (Daskin 1995). Further, mathematically deriving sharp lower bounds for such large problems is difficult, and exact algorithms such as branch-and-bound are too slow to converge and are inadequate for the problem

(Cordeau et al. 2002). However, metaheuristics have the ability to find a "near-optimal" solution to the problem in reasonable amounts of time. While some argue that metaheuristic solutions are inferior because they cannot be proven to be mathematically optimal, metaheuristic techniques can provide solutions within scant percentages of optimal, and offer insight into complicated problems that simulation or linear programing cannot fully analyze.

In addition to handling large problem sizes, metaheuristics can also generate solutions to complex problems when the constraints or objective function are not continuous or differentiable, such as when transportation price functions for less-than-truckload and truckload shipments change with distance and quantity shipped (Galbreth et al. 2008), nonlinear conditions that challenge optimization. In addition, results from complex optimization problems are sometimes weakened due to data aggregation (Simchi-Levi et al. 2000) or by constraint relaxation performed when the original problem is too complex for optimization. Metaheuristics are often able to generate realistic solutions to the real problem while preserving the original inputs, without aggregation and retaining system constraints as they genuinely exist (Lourenco 2005).

In addition to size and complexity, metaheuristics provide a robust method that can be adapted to problems with different solution characteristics. This capability is important when confronted with supply chain problems, constraints, and conditions that may change frequently. The modular design of metaheuristic algorithms also make them easy to update and re-run when the real-world intrudes and changes occur (Lourenco 2005). In addition, as metaheuristics conduct a search of all feasible solutions to a problem, they have the ability to find alternate, optimal solutions and provide the user with alternatives. This is especially helpful in logistics problems that may have several alternate solutions, each providing equivalent optimal outcome (cost, distance, speed, etc.). As such, metaheuristics can provide a variety of solutions to multi-objective problems, allowing the results of these solutions to be used to develop an efficient frontier diagram (McMullen and Tarasewich 2006), so the user can identify trade-offs in objectives such as customer service or logistics cost. By comparison, optimization methods generally terminate once the first optimal solution is observed, limiting the ability to assess possible trade-offs.

However, metaheuristics are not without their disadvantages. Users applying metaheuristic methods generally must be able to code the algorithm as there are limited off-the-shelf software system (such as Excel) with embedded metaheuristic algorithms. Similarly, establishing control or "tuning" parameters for metaheuristic algorithms is not an exact science, increasing the difficulty of the method. In addition, some variations of metaheuristics may be too complicated to code or have too many tuning parameters for practitioners to readily apply (Cordeau et al. 2002). Finally, the nature of metaheuristics as search algorithms means that they may give up some of their speed advantage when more exhaustive search parameters are employed. For strategic decisions and experimental research, this is less of a concern as the frequency of needing a solution will be low. For more immediate needs, for example, a real-world dynamic emergency vehicle routing problem where every second counts, several extra minutes of solution time may make the method impractical to use, even though a better solution may be found.

Past metaheuristic applications

The application of metaheuristic techniques to logistics and supply chain issues in the literature is extensive and growing rapidly as the supply chain field has expanded. Within the logistics management literature particularly, the application of metaheuristics is more limited despite the seemingly good match of the techniques to the problems logisticians face. Within the past 20 years, techniques such as ant colony optimization (ACO), simulated annealing, genetic algorithm, and tabu search have all been applied in the logistics management journals. Abdinnour-Helm (2001) applies simulated annealing and tabu search to a hub and spoke transportation network, demonstrating that modern metaheuristics outperform older techniques. Pankratz (2005) performs similar analyses, noting the quality of solutions offered by genetic algorithms (GA) in solving dynamic vehicle routing problems. Gonzalez and Fernandez (2000) and Berry et al. (1998) employ similar techniques (GA) in addressing distribution problems. Bell and Griffis (2010) revisit the work of Ballou and Agarwal (1988), updating for newer metaheuristic techniques, showing they outperform the state of the art techniques of 20 years before. While these studies appear in the logistics management literature, far more study on logistics and supply chain issues has appeared in journals that extend beyond logistics management. The Appendix lists 128 articles appearing in major journals and employing metaheuristic techniques to address logistics and supply chain problems. A brief summary of the problem types most commonly addressed is presented next.

The most common logistics and supply chain problems addressed with metaheuristic methods is vehicle routing. A variant of the traveling salesperson problem, where multiple vehicles serve a set of customer locations, vehicle routing is of obvious interest to logistics and supply chain researchers and professionals. Fifty-six of the 128 articles (44%) in the Appendix are focused upon the vehicle routing problem and its extensions. Extensions to the basic problem include time windows (Bräysy and Gendreau 2005), pickup and delivery (Van Der Bruggen et al. 1993), split deliveries (Archetti et al. 2008), transshipment (De Rosa et al. 2002), backhauls (Duhamel et al. 1997), intermodal shipping (Verma et al., 2012), and disaster relief (Yi and Kumar 2007). Facility location problems, of primary importance to logisticians and supply chains have been extensively examined as well, including extensions focused upon multimodal freight networks (Yamada et al., 2009), design for service operations (Pedersen et al. 2009), dynamic facility and inventory location (Javid and Azad 2010), and containerized shipping (Shintani et al. 2007). Supply chain scheduling issues are another area that regularly employ metaheuristics, with extensions addressing issues related to preventative maintenance (Ahire et al. 2000), container sequencing in ports (Vis and Carlo 2010), seaport berth scheduling (Golias et al.

2009), port crane scheduling (He et al. 2010), and air cargo load scheduling (Tang, 2011). The last topic reflecting significant research includes facility layout and resource allocation, with extensions concerned with intermodal trailer assignment (Feo and González-Verlarde 1995), container to rail car assignment (Joborn et al. 2004), and ship, berth, crane assignment (Imai et al. 2008). The Appendix provides a more comprehensive list of previous research, listing topic areas, methods employed, and outlets.

PRIMARY METAHEURISTIC METHODS

Within the category of metaheuristics, various classifications of metaheuristic approaches have been proposed. However, the dominant classification views metaheuristics as being based upon either local search, or population search techniques (Cordeau et al. 2002).

Local search metaheuristics, sometimes also called neighborhood searches, explore solution spaces by moving from existing solutions to potentially more promising solutions in their immediate region or neighborhood. In this manner, feasible solutions are considered, until either numbers of iterations, or search time are exhausted. The two primary local search metaheuristics include simulated annealing and tabu search (Cordeau et al. 2002).

Simulated annealing

Simulated annealing is an established and widely published local search metaheuristic that applies a search strategy analogous to the metallurgical practice of cooling or annealing metals (Kirkpatrick et al. 1983; Cerny 1985). When metals such as steel are cooled too quickly or slowly, they do not achieve the desired physical properties such as hardness or malleability. On observing this phenomenon, physicists and early computer scientists realized that the search for an optimal solution might similarly benefit from being allowed to go from a high "temperature" state with associated radical changes in a current solution to one that concentrates only on conservative local changes later in the search (Metropolis et al. 1953). Therefore, at the beginning of a simulated annealing search, a high-temperature setting affords a higher probability that a seemingly inferior solution is temporarily accepted, something sometimes called hill-climbing (Henderson et al. 2003). This allows the search to move into new solution regions and avoid being trapped at a local optimal solution. The expectation is that by moving away from a local optimum the search may discover an even better, distant, solution. However, as the search progresses the temperature is slowly decreased using a cooling rate and the probability of accepting an inferior solution is decreased. The search conducts a predetermined number of iterations that consider new solutions at each temperature level, and then ends when the temperature reaches a predetermined stopping criteria or terminating temperature (Azencott 1992; Aarts and Lenstra 1997; Henderson et al. 2003; Dreo et al. 2006, 1–46).

Simulated annealing has real advantages over other methods. It is easy to use on problems with a large number of constraints and new constraints can easily be added as the problem environment changes (Dreo et al. 2006, 1–46). In addition, the method is shown to generate generally good solutions and alternate solutions can be saved during the search, to help analyze multimodal instances when alternate optimal solutions exist. Although, simulated annealing has primarily been applied to supply chain problems with discrete data sources such as vehicle routing, production sequencing, and facility location problems with a combinatorial nature, it has also been adapted for use on continuous problems (Henderson et al. 2003).

Like all techniques, simulated annealing also has disadvantages. First, selecting the proper cooling schedule and tuning the various parameters of the algorithm is an inexact science and can be time consuming. In addition, improper tuning can result in long-solution times for large-scale problems, resulting in frustrated users (Dreo et al. 2006, 1–46). Simulated annealing continues to be improved in the literature and offers an excellent choice for finding and studying large-scale supply chain problems. Recently, multi-objective versions of simulated annealing have been offered by Briant et al. (2008) and Sitarz (2009). In addition, Goodson et al. (2012) have recently offered a version of simulated annealing that considers stochastic demand. Pseudo-code for creating a simulated annealing search program and the detailed steps for the algorithm are available in the literature (Eglese 1990; McMullen and Frazier 2000; Bell 2003; Henderson et al. 2003; Aarts et al. 2005), and advice for applying the algorithm for the first time is offered by Dreo et al. (2006, 1–46).

Tabu search

The second local search metaheuristic, tabu search, may be the most effective and prevalent metaheuristic for combinatorial problems like the vehicle routing problem (Tarasewich and McMullen 2002; Gendreau 2003; Cordeau and Laporte 2005). The initial tabu search algorithm was created by Glover (1986), and it incorporates heuristics analogous to human memory into the search for improved solutions (Dreo et al. 2006, 47–74).

Like other local search heuristics, tabu search conducts an iterative search from a current (initial) solution and identifies the potential neighboring solutions that can be achieved in one step from the current solution. The neighboring solution that achieves the best improvement of the objective function value is selected as the next move in the search, even if it is worse than the current solution(s). This property keeps the search from becoming trapped at a local optimal solution. However, once a move is accomplished, future moves back to previous solutions are considered taboo (called tabu in the literature). To keep the search from cycling back to previous solutions, a list of tabu moves is kept and updated in the short-term search memory. The search is prevented from executing any of these recent tabu moves, which guides the search to avoid local optimal points, and into unexplored areas in pursuit of better solutions (Dreo et al. 2006, 47–74). Keeping and storing such tabu lists in a computer's memory also requires the use of tables to sort and identify tabu solutions (Woodruff and Zemel 1993; Taillard 1995).

Beyond the tabu list, the metaheuristic also incorporates explicit and attributive memory mechanisms (Glover and Laguna 1997). The explicit memory keeps track of elite solutions that are within a threshold percent level of what the optimal solution is believed to be. These elite solutions are kept in memory in order to expand or guide the search, and at times are used to avoid revisiting regions, rather than specific solutions, during a search. Attributive memory keeps track of how specific attributes of a solution are changed from one move to another. More advanced features of the tabu search metaheuristic create a long-term memory that makes it adaptive and responsive (Glover and Laguna 1997). For example, intensification heuristics can be added to the search to encourage it to return to areas in the solution space that have been successful at finding good solutions. Contrasting diversification heuristics can also be added to the search to force the search into regions that have not been highly explored by the search (Dreo et al. 2006, 47–74).

Tabu search has distinct advantages for finding near-optimal solutions to complex supply chain problems, such as being able to quickly and efficiently evaluate a neighborhood of local solutions (Cordeau and Laporte 2005). However, the true advantage of tabu search rests in its ability to self-adjust parameters and change the search toward an optimal solution based on its more advanced long-term memory procedures (Glover and Laguna 1997). Although tabu search offers excellent speed and accuracy in finding solutions, its disadvantages relate to its complexity and limited flexibility of coding and applying the method (Cordeau et al. 2002) .

The use and development of improved versions of tabu search in the literature continues to accelerate. Recent versions of tabu search with multi-objectives and continuous problems have been developed by Caballero et al. (2007) and Jaeggi et al. (2008), and a version for a dynamic transportation problem was offered by Kergosien et al. (2011). A step-by-step description of the tabu search algorithm for a facility location problem is offered by Sun (2005), and pseudo-code for the algorithm is provided by Lodi et al. (2004). Tips and advice for those who want to code and apply tabu search to a supply chain problem for the first time is provided by Gendreau (2003).

Other local search metaheuristics

Several other local search metaheuristics have been used successfully. The greedy randomized adaptive search procedure (GRASP) developed by Feo and Resende (1989, 1995) uses an initial construction heuristic and multiple restarts to conduct a search and is easily adapted to new problems, and has fewer parameters to tune in comparison to other metaheuristics (Dreo et al. 2006, 169–170). The variable neighborhood search (VNS) aims for simplicity and uses systematic changes in a neighborhood of solutions including both local and random changes (Hansen and Mladenovic 2003). First developed by Mladenovic (1995) and Mladenovic and Hansen (1997), VNS has been applied to a wide variety of problems, including vehicle routing, scheduling, facility location, pipeline design, and others. Finally, other local search metaheuristics such as guided local search (Tsang and Voudouris 1997), reactive search optimization (Battiti and Tecchiolli 1994), and spiral optimization are continuing to be developed by researchers (Tamura and Yasuda 2011).

Population search

Population search metaheuristics differ fundamentally from local search metaheuristics. Rather than search solution regions by moving from contiguous point to contiguous point, population searches evaluate pools of solutions for their quality and characteristics, whereas maintaining a list of generally beneficial solutions (Cordeau et al. 2002). Knowledge and structures from these previous solutions are then used to create new solutions. In cases where these new solutions improve upon existing solutions they replace the worst current, ‘‘good’’ solution, and the process is repeated until either numbers of iterations or search time are exhausted. The two primary types of population metaheuristics are GA and ACO.

GA

One of the best-known metaheuristic approaches, GA, is based on biological evolution, and the competitive selection and survival of species through adaptation and the inheritance of traits. GA can be traced to the early study of Holland (1962), Fogel et al. (1966), and Rechenberg (1973), and were extended by De Jong (1975) and Goldberg (1989). Although many dissimilar types of evolutionary algorithms and evolutionary computing have been developed since the original study of these pioneers, the term genetic algorithm coined by Holland (1962) has been retained to describe the entire class of algorithms (Dreo et al. 2006, 75–122).

The classic genetic algorithm searches for an optimal solution by translating the search for an improved solution into a process analogous to evolution. In GA, a single feasible solution is similar to an individual in biologic terminology, and a group of solutions is a population. In a computer search, GA select a set of individuals (current solutions) from an initial population to create offspring (new solutions) and eliminates other, lesser, individuals from the population in successive cycles or generations (Dreo et al. 2006, 75–122). By manipulating the population in each generation an improved population is created in the next generation with the overall goal of creating an offspring that is perfect, or optimal.

Similar to other metaheuristics, genetic algorithm has the advantage of not requiring a linear formulation to generate solutions. In addition, GA have the advantage of not requiring extensive knowledge of the constraints and rules of the actual problem. Rather, it quickly converges on improved solutions, which can then be translated into a vector of decision variables representing a solution to the actual problem (Reeves 2003).

However, GA do have disadvantages. First, as with nature, GA make no guarantee of perfection (optimality). In addition, the development of a fitness function to evaluate the new offspring solutions in a genetic algorithm search can be difficult (Dreo et al. 2006, 75–122) and as can be imagined, is a critically important issue. There are no universal methods for cross-over and mutation to create new offspring that will work successfully with every problem type, and researchers often have to develop special selection operators, population sizes, and other parameters to find the best possible solution (Reeves 2003; Potvin 2009).

Recently, new versions of genetic algorithm using insertion methods and construction methods have been developed by Christiansen et al. (2011) and Wang and Chen (2012) that improve solution quality. In addition, a method with dynamic mutation rates has recently appeared in the literature (Chan et al. 2008), as has an extension called a memetic algorithm, which replaces mutation with neighborhood or local search based procedures (Potvin 2009; Bontoux et al. 2010).

ACO

ACO is another promising metaheuristic technique, which emulates the quasi-intelligent actions of ant colonies in their pursuit of food by, using the accumulated knowledge of an entire colony of ants, making it a "population" based metaheuristic. The method was first developed by Dorigo (1992), and is the newest of the four primary metaheuristics discussed in detail. A version of ACO for the vehicle routing problem was previously described in detail in the *Journal of Business Logistics* by Bell and Griffis (2010).

In the ACO, artificial ants travel through a network that reflects the real situation being modeled to find solutions. As simulated ants move through the network pursuing their goal (food in real colonies), they deposit pheromones on the paths (arcs) in the network. Over time, the shortest paths (arcs) on a route accumulate more pheromone, because the ants can travel a shorter route more frequently given a constant speed (Dorigo et al. 1999; Tarasewich and McMullen 2002). Ants venturing into the network generally choose those paths with the strongest pheromone trails. An important property of the problem is that the pheromones on the paths evaporate over time, lowering the desirability of a less visited trail to subsequent ants. In addition, ants randomly ignore the trails with the strongest pheromone trail (the shortest existing paths) and instead take a different path in search of food. If this path ends up being shorter still, they are able to update the pheromones more quickly and following ants will begin to prefer this new, shorter path. In this way, the ACO heuristic learns by following a pseudo-random proportional process and the ants as a colony are able to converge on improved or even optimal solutions (Dorigo and Gamberdella 1997).

ACO has distinct advantages and disadvantages. First, ACO fits nicely with any problem that can be made analogous to a routing or traveling salesman problem. In addition, as a population search metaheuristic, ACO builds knowledge about previously explored routes and trails, and stores this knowledge using the pheromone component of the problem. This makes ACO a good method for a dynamic supply chain problem where a solution might have to be adjusted due to disruptions or changes in the network (Dorigo and Stutzle 2003).

However, ACO also has disadvantages as well, including the difficulty of tuning several parameters that do not have a proven theoretical basis for their values. This makes the use of ACO experimental in nature, and it can require significant time investments by the user to test and correctly set parameters for a particular problem. In addition, updating pheromone trails and the related probabilities on each arc in a network has to be continually accomplished, potentially increasing coding difficulty and computation times (Dreo et al. 2006, 123–152).

Additional descriptions of the ACO appear in the literature (Tarasewich and McMullen 2002; Dorigo et al. 2006; Bell and Griffis 2010). Recent extensions of ACO with improved pheromone management procedures have been presented by Morin et al. (2009) and Yu et al. (2009). A discussion of application principles that provides advice for newcomers can be found in Dorigo and Stutzle (2003).

Other population search metaheuristics

In addition to genetic algorithm and ACO, other population-based metaheuristics are available in the literature. Scatter search is a method first introduced by Glover (1977), and although not as well known as tabu search, it continues to be used and extended as a method for solving difficult problems. In addition, particle swarm optimization is a relatively new metaheuristic developed by Kennedy and Eberhart (1995), and it has recently been applied to vehicle routing with time constraints (Xu et al. 2011). Finally, other new population-based search methods such as heuristic concentration (Rosing and ReVelle 1997), Harmony Search (Geem et al. 2001), and the firefly algorithm (Yang 2008) have also appeared in the literature and may be future methods for analyzing complex supply chain problems.

SUPPLY CHAIN APPLICATION AREAS FOR METAHEURISTICS

Metaheuristics have been applied to a number of supply chain-related issues to date, including vehicle routing (Shyu et al. 2004; Reimann and Laumanns 2006; Reimann and Ulrich 2006), production (Bautista and Pereira 2007), network routing (Bean and Costa 2005), space planning (Bland 1999), job sequencing (McMullen 2001), and product design (Albritton and McMullen 2007). Table 1 provides counts of the types of supply chain related problems, which have been examined using metaheuristics, and the type of metaheuristics employed. The Appendix provides a more thorough list of the papers referenced in Table 1 and lists the exact problems resolved.

However, despite this volume of research, examination of these works reveals that often the practical management perspective that is central to readers of the *Journal of Business Logistics* is absent in the works referenced in Table 1 and the Appendix. A thorough consideration of the Appendix reveals opportunities exist to increase the managerial relevance of analytic supply chain research, and that metaheuristics possess a variety of properties well suited to the complexity of modern supply chains. As shown in Table 1, the most common uses in the logistics-specific literature address vehicle routing and facility location modeling tasks.

Although these areas hold obvious potential as application areas for metaheuristics, research should not be limited to these two areas. The following section describes additional potential application for metaheuristics.

Table 2 identifies a variety of potential supply chain topics suited to examination using metaheuristic techniques. Although any of the metaheuristic techniques previously identified might be potentially useful, these recommendations are based upon examination of analogous problems already present in the literature, but lacking in supply chain realism and depth. Rather than describe each of the examples presented in Table 2, a limited group of those most interesting prospects is proposed.

One supply chain issue that has garnered great attention in recent years is that of supply chain disruptions. The impact of supply chain disruptions are readily observed in the routes that vehicles take, the suppliers available to serve supply chains, and the demand offered by customers. Regarding problem types (Table 2), vehicle routing and service level optimization show clear relationships with these issues. This synthesis of metaheuristic methods suggests that the ACO may hold great potential to research supply chain disruptions. ACO, like the ants they emulate, readily adjusts to changes in system states. Just as real ants quickly discover ways to work around obstacles dropped in their way, and find food (resources) recently made available, the ACO metaheuristic has proven its ability to solve similar supply chain-like problems. When a supply chain that has relied upon a set route to deliver product is suddenly disrupted, like when hurricane Irene washed out roads in Vermont in 2011, ACO may be extremely well positioned to quickly offer alternate solutions to maintain operations.

Table 1: Articles using metaheuristic methods for supply chain topic areas

Topic areas	Number of papers*	Methods	Number of papers*
Vehicle routing	56	Tabu search	52
Facility location/network design	21	Genetic algorithm	46
Production/ops scheduling	17	Simulated annealing	23
Resource allocation and layout	14	Ant colony	8
Vehicle scheduling	9	GRASP	5
Quantitative method development	4	Other	9
Product mix/assortment	4		
Vehicle fleet sizing	3		
Product design	3		
Forecasting	2		
Labor scheduling	2		
Product market selection	1		
Purchasing	1		
Project scheduling	1		

Notes: *One hundred twenty-eight papers were identified. One hundred thirty-eight topic areas and 143 methods were listed due to the use of multiple methods and multiple topic areas in some papers. A detailed list of the articles and the journals reviewed is included in the Appendix.

GRASP, greedy randomized adaptive search procedure; ops, operations.

Another area of increasing research interest, returns management, presents an exciting opportunity to employ metaheuristics. Although application of GA and tabu search have been used to examine returns processing on a limited basis (Hahn et al. 2004; Min et al. 2008), a broader view of the value of returns management is warranted (Mollenkopf and Closs 2005). Such examination using metaheuristic methods might include decisions about combined forward and reverse supply chain network design, or analysis of the flow and routing of returns products in different stages of the product lifecycle. Similarly, the combinatorial nature of the role of returns management when making trade-offs in customer service, process design, and supplier selection decisions offers an area for further analysis using metaheuristic techniques.

One of the most interesting areas for metaheuristics might be what is classified as hybrid problems. Hybrid problems are those that simultaneously solve more than one problem type. For example, a facility location problem needs to consider a large number of relevant variables (e.g. land cost, freight volumes, demand served, tax rates, employee availability, and transportation rates). Regardless of which technique is selected, metaheuristic or not, it is confronted with a complex problem, given the magnitude of the data and the range of assumptions that are necessary. In the facility location example, as soon as the location is selected, subsequent issues must consider how to route vehicles (and the products they carry) from to the supplier or customer locations. Such routing is typically considered to be a completely separate problem, handled at a later time, using the selected location as an unchangeable input. However, there is a recursive relationship between these two problems. Given the difficulty optimization techniques have with either of the problems, with all the complexity of a modern supply chain, incorporating both types of problems simultaneously may quickly exceed the present computational abilities of exact optimization methods. However, with metaheuristics these complexities can be incorporated, and the most recent techniques, like those discussed herein, hold the promise to be able to find improved, even near-optimal solutions, to the combined (hybrid) problems. It may not be overstating the issue to propose that metaheuristics, at least until exact optimization methods and computing power increases significantly, may be the only way to truly consider real supply chain problems represented by the hybrid problem type described in Table 2.

Specifically, metaheuristics offer the potential to examine facility location and vehicle routing problems simultaneously with tabu search or simulated annealing, whereas also considering and testing differing managerial strategies to find ways to create value with practical solutions. In addition, there is evidence that tabu search may have potential to resolve purchasing and routing problems together as well and initial work in this area shows great potential for supply chain level cost

Table 2: Potential metaheuristics application to supply chain problems

Problem type	Potential metaheuristic application	Metaheuristics—problem match	Practical supply chain application
Vehicle routing	Ant colony optimization	Flexibility, speed, and solution quality suited to short planning horizons of dispatch operations	Potential to address SC disruptions and complex cross-dock operations given ants adaptive ability
	Tabu search	Memory functions facilitate efficient search of solution space; able to accomplish problem specific steps	Long-range transportation planning and routing, including decisions to outsource some or all of transportation
Facility location modeling	Tabu search	Shown to generally produce best metaheuristic solutions independent of problem type	Useful in SC design for new facilities and intermodal transportation net works
	Simulated annealing	Demonstrated ability to provide high quality solutions on capacity-constrained facility location problems	Ability to resolve capacity constraints provides advantages for adjusting existing SC networks, an issue for most SC systems
Facility/warehouse layout	Genetic algorithm	Demonstrated ability to handle complex problems for placing resources and using physical space	Plan aisle location and materials handling equipment placement in a warehouse; crane placement on loading docks
	Simulated annealing	Has ability to be modified for dynamic problems that consider parameter changes	Apply to dynamic layout problems with changes in product mix and demand
Service level optimization	Ant colony optimization	Demonstrated ability to find feasible solutions to multiple objective routing problems	Analyze the trade-off in customers service levels against cost and profit objectives of routing or network design
	Genetic algorithm	Ability to analyze trade-offs in multiple objective problems	Address the customer service and cost trade-offs in a JIT distribution system in a multiproduct, multi-channel supply chain
Fleet sizing	Ant colony optimization	Ability to efficiently use resources such as time, labor, and equipment in routing and design problems	Analyze backhaul strategies for vehicle routing when minimizing fleet size is the priority
	Simulated annealing	Proven ability on fleet sizing and resource allocation problems	Determine the number of vehicle, rail cars, or containers for a supply chain, and how to allocate them to customers or regions
Crew scheduling	Genetic algorithm	Demonstrated ability to resolve problems with moveable resources, like vehicle operators	Apply to truck, aircraft, vessel scheduling in cases where stable crew assignments might degrade performance through familiarization
	Tabu search	Ability to deal with multiple objectives in a complex scheduling problem	Driver and crew scheduling for vehicles loading docks and warehouses
Returns management	Genetic algorithm	Demonstrated ability optimize complex network designs given multiple constraints and flows	Use to find the best approach for collection, repair, resale, disposition of returned product
	Tabu search	Has the ability to generate a large number of solutions to analyze trade-offs in decision making	Analyze distribution channel discounts and pricing policies for returned and perishable items

Continued.

Table 2: (Continued)

Problem type	Potential metaheuristic application	Metaheuristics—problem match	Practical supply chain application
Carrier bid optimization	Simulated annealing	Demonstrated potential to manage portfolios of various types	Select suppliers with varying performance and multi-objective selection criteria, including risk minimization and less common characteristics
	Genetic algorithm	Ability to look at complex combinatorial pricing and allocation problems	Manage transportation procurement auctions and supplier bid pricing with varying purchaser objectives and pricing points
Hybrid problems	Tabu search, simulated annealing	Ability to solve combined location and routing problems	Simultaneous warehouse/plant location decisions with routing of goods to/from those locations
	Genetic algorithm, tabu search	Ability to solve combined inventory and routing problems	Simultaneous inventory level/multiple location /vehicle routing determination in SC network
	Tabu search	Ability to solve combined purchasing and routing problems	Simultaneous sourcing/routing decisions in a supply chain
	Genetic algorithm, tabu, ant colony optimization	Ability to create multi-echelon network designs	Simultaneous decisions about the number and location of plants, distributors, retail outlets in a SC

Note: JIT, just-in-time; SC, supply chain.

savings in comparison to solving the problem separately (Chiang and Russell 2004). GA as well have shown potential in solving hybrid problems similar to the multi-echelon inventory problems that also consider simultaneous facility location determination (Zhao et al. 2008; Moin et al. 2011).

METAHEURISTICS IN THE CLASSROOM

Given their practical benefits, teaching metaheuristics in classrooms is encouraged. However, there are at least three different levels of knowledge that the content can achieve. Similar to Bloom et al.'s (1956) taxonomy on the cognitive domain, a taxonomy of outcomes, including familiarization, understanding, and mastery related to teaching metaheuristics are described.

With regard to familiarization, it is important for undergraduate students to be aware of what metaheuristics are, and where they fit within the range of analytic techniques available to them. Discussions of the advantages and disadvantages of alternative analytic techniques, such as optimization, simulation, and metaheuristics should make the student conversant in the reasons why one method or another is appropriate to problems they may encounter in their professional lives. Similarly, it is important to address the types of problems that are best suited to each of these methods with particular focus upon problem types more and less suited to metaheuristics techniques. Discussions for familiarization of these techniques should include the general manner in which they solve problems, but should be limited to interaction with already-developed examples.

When seeking to achieve a deeper level of understanding, higher level students will need to go beyond simple familiarization. In particular, the hands-on interaction with the methods should necessitate a deeper involvement on the student's part, so that they may, through a trial and error process, see how the metaheuritics are transformed from conceptual techniques into software code that can be used to resolve a basic problem. Depending upon the student's computer programing skill level, this may take different forms, with the possibility that segments of code may be provided for the students to work from in cases where software coding skills are limited.

Students needing to master metaheuristics is likely limited to PhD students, and master's students in more analytically focused degree programs. These students need to be able to do more than simply code established metaheuristics into software and ensure functionality. These students should be able to expand beyond existing techniques, making modifications to the metaheuristics to achieve new ends, extend the scope of the metaheuristics, and improve upon their utility in areas and problems of specific interest to the student. Overall, metaheuristics are an interesting topic for students of all levels, and appropriately communicated, can provide these students with valuable knowledge that is important to their professional development in the logistics and supply chain field.

CONCLUSION

Metaheuristics' potential has developed rapidly in the past 20 years, well beyond their initial development as novel strategies for applying heuristic approaches. Although the oldest metaheuristics are nearly 50-years old, the last 20 years has seen a veritable explosion of techniques. The metaheuristics described herein represent those with already-demonstrated ability to solve problems related to, or specifically drawn from, the supply chain domain. However, as previously mentioned, newer techniques continue to emerge, often inspired by nature, and accordingly named. Emerging metaheuristics, such as harmony search (Geem et al. 2001), glow worm optimization (Krishnanand and Ghose 2009), artificial bee colony (Karaboga 2005), intelligent water drops (Shah-Hosseini 2007), firefly algorithm (Yang 2008), monkey search (Mucherino and Seref 2008), and the cuckoo search (Yang and Deb 2009) may in the future hold even more potential for complex supply chain applications, and logistics and supply chain researchers pursuing the best possible solutions to their research problems should stay connected with their development.

In the near term though, existing metaheuristic algorithms already hold the potential to revolutionize how supply chains are designed, managed, analyzed, and improved. In particular, these metaheuristics appear capable of addressing the cross-functional complexity of modern supply chains, including the large size, multiple parameters, multiple objectives, and the often nonlinear aspects of such problems. Metaheuristics are likely to continue to provide value for supply chain researchers and practitioners into the future through examination of more complex hybrid problems, in ways that conventional optimization is unlikely to be able to approach for quite some time.

APPENDIX

Authors	Journal	Year	Applicable area	ACO	GA	GRASP	SA	Tabu	Other
Verma et al.	TRE	2012	Vehicle routing					X	
Keskin et al.	TRE	2012	Facility location/network design					X	
Qi et al.	TRE	2012	Vehicle routing		X				
Archetti et al.	TS	2011	Vehicle routing					X	
Chen et al.	TRE	2011	SC scheduling					X	
Xu et al.	TRE	2011	Vehicle routing						X
Gul et al.	POM	2011	SC scheduling		X				
Verma et al.	TS	2011	Vehicle routing		X				
Hohn et al.	MS	2011	SC scheduling		X				
Tang	TRE	2011	SC scheduling		X				
Lin and Liu	TRE	2011	Resource allocation and layout		X				
Meng and Wang	TRE	2011	Purchasing		X				
Yu and Yang	TRE	2011	Vehicle routing	X					
Javid and Azad	TRE	2010	Facility location/network design				X	X	
Li et al.	TRE	2010	Vehicle routing					X	
Prescott-Gagnon et al.	TS	2010	Vehicle routing					X	
Sungur et al.	TS	2010	Vehicle routing					X	
Xie et al.	TRE	2010	Resource allocation and layout					X	
Ishfaq and Sox	TRE	2010	Facility location/network design					X	
Klibi et al.	TS	2010	Facility location/network design					X	
Soltani and Sodjadi	TRE	2010	Vehicle scheduling				X		X
Vis and Carlo	TS	2010	SC scheduling				X		
Lee et al.	TRE	2010	Resource allocation and layout			X			
He et al.	TRE	2010	SC scheduling		X				
Chang et al.	TRE	2010	Resource allocation and layout		X				
Barcos et al.	TRE	2010	Vehicle routing	X					
Bell and Griffis	JBL	2010	Vehicle routing	X					
Huang and Lin	TRE	2010	Vehicle routing	X					
Scmid et al.	TS	2009	Vehicle routing						X
Zhang et al.	TRE	2009	Vehicle routing					X	
Pederson et al.	TS	2009	Facility location/network design					X	
Cortes et al.	TS	2009	Vehicle routing						X
Ballestin and Leus	POM	2009	Project scheduling			X			
Yamada et al.	TS	2009	Facility location/network design		X			X	
Zegordi and Beheshti	TRE	2009	Vehicle scheduling		X				
Karlaftis	TRE	2009	Vehicle routing		X				
Liu et al.	TRE	2009	Vehicle routing		X				
Golias et al.	TRE	2009	SC scheduling		X				
Dong and Song	TRE	2009	Resource allocation and layout		X				

Continued.

APPENDIX (Continued)

Authors	Journal	Year	Applicable area	ACO	GA	GRASP	SA	Tabu	Other
Archetti et al.	TS	2008	Vehicle routing					X	
Desaulniers et al.	TS	2008	Vehicle routing					X	
Ohlmann et al.	TS	2008	Vehicle routing					X	
Braysy et al.	TS	2008	Vehicle routing				X		
Belloni et al.	MS	2008	Product design		X		X		
Imai et al.	TRE	2008	Vehicle scheduling		X				
Cha et al.	TRE	2008	Vehicle scheduling		X				
Lee et al.	TRE	2008	SC scheduling		X				
Imai et al.	TRE	2008	Resource allocation and layout		X				
Chen and Ting	TRE	2008	Facility location/network design	X					
Berman and Huang	TS	2007	Vehicle routing						X
Ak and Erera	TS	2007	Vehicle routing					X	
Berman and Huang	TS	2007	Vehicle routing					X	
Prins et al.	TS	2007	Vehicle routing					X	
Tang et al.	TRE	2007	Labor scheduling					X	
Xia and Dube	POM	2007	Forecasting				X		
Rodriguez et al.	TRE	2007	Facility location/network design				X		
Shintani	TRE	2007	Facility location/network design		X				
Yi and Kumar	TRE	2007	Vehicle routing	X					
Archetti et al.	TS	2006	Vehicle routing					X	
Gendreau et al.	TS	2006	Vehicle routing					X	
Ichoua et al.	TS	2006	Vehicle routing					X	
Keng et al.	TS	2005	Vehicle routing					X	
Cordeau et al.	TS	2005	Resource allocation and layout					X	
Spada et al.	TS	2005	Vehicle routing				X		
Kimes and Thompson	JOM	2005	Assortment				X		
Zhong and Cole	TRE	2005	Vehicle routing						X
Braysy and Gendreau Pt I	TS	2005	Vehicle routing	X	X		X	X	
Braysy and Gendreau Pt II	TS	2005	Vehicle routing	X	X		X	X	
Jula et al.	TRE	2005	Vehicle routing		X				
Pankratz	IJPDLM	2005	Vehicle routing		X				
Huang, et al.	JOM	2005	Product design		X				
Kim et al.	MS	2005	Market selection		X				
Audet et al.	MS	2004	Assortment						X
Lapierre et al.	TS	2004	Facility location/network design					X	X
Joborn et al.	TS	2004	Resource allocation and layout					X	
Gutenschwager et al.	TS	2004	Vehicle scheduling				X	X	
Bent and VanHentenryck	TS	2004	Vehicle routing				X		
Ragsdale	DS	2004	SC scheduling		X				
Sexton et al.	DS	2003	Quantitative methods		X				
Rosa et al.	TS	2002	Vehicle routing					X	
Bard et al.	TS	2002	Vehicle routing			X			
Jin et al.	POM	2002	SC scheduling		X				
Bertsimas and Demir	MS	2002	Resource allocation and layout		X				
Bennell and Dowsland	MS	2001	SC scheduling				X	X	
Gopalakrishnan et al.	MS	2001	SC scheduling					X	
Abdinnour-Helm	IJPDLM	2001	Facility location/network design				X	X	
Lourenco et al.	TS	2001	Labor scheduling		X			X	
Ichoua et al.	TS	2000	Vehicle routing					X	
Budenbender	TS	2000	Facility location/network design					X	
Ahire et al.	DS	2000	SC scheduling				X		
Cooper and Giuffrida	MS	2000	Forecasting				X		
Wolfe and Sorensen	MS	2000	Vehicle scheduling		X				
Gonzalez and Fernandez	IJPDLM	2000	Vehicle routing		X				
Sumichrast et al.	DS	2000	SC scheduling		X				
Premkumar et al.	DS	2000	Facility location/network design		X				
Guertin et al.	TS	1999	Vehicle routing					X	

Continued.

APPENDIX (Continued)

Authors	Journal	Year	Applicable area	ACO	GA	GRASP	SA	Tabu	Other
Jiefeng et al.	MS	1999	Facility location/network design					X	
Alrefaei and Andradotter	MS	1999	Vehicle scheduling				X		
Rego	MS	1998	Vehicle routing					X	
Glover et al.	MS	1998	Facility location/network design					X	
Balas and Vazacopoulos	MS	1998	SC scheduling						X
Bard et al.	TS	1998	Vehicle routing			X			
Bhattacharyya and Koehler	DS	1998	SC scheduling		X				
Bhattacharyya and Pendharkar	DS	1998	Quantitative methods		X				
Miller	MS	1998	Quantitative methods		X				
Berry and Murtagh	IJPDLM	1998	Facility location/network design		X				
Cao and Glover	MS	1997	Vehicle routing					X	
Duhomel et al.	TS	1997	Vehicle routing					X	
Taillard et al.	TS	1997	Vehicle routing					X	
Toth and Vigo	TS	1997	Vehicle routing					X	
Midgley et al.	MS	1997	Assortment		X				
Xu and Kelly	TS	1996	Vehicle routing					X	
Balakrishnan and Jacob	MS	1996	Product design		X				
Franca et al.	TS	1995	Vehicle routing					X	
Hooker and Natraj	TS	1995	Vehicle routing					X	
Feo and Gonzalez-Velarde	TS	1995	Resource allocation and layout			X			
Pakath and Zaveri	DS	1995	SC scheduling		X				
Gendreau et al.	MS	1994	Vehicle routing					X	
Laguna	MS	1994	Facility location/network design					X	
Aneja and Parlar	TS	1994	Facility location/network design				X		
Borin et al.	DS	1994	Assortment				X		
Kray	TS	1994	Vehicle scheduling		X				
Yow-Yuh et al.	DS	1994	Resource allocation and layout		X				
Laguna and Glover	MS	1993	Resource allocation and layout					X	
Van Der Bruggen	TS	1993	Vehicle routing				X		
Friesz et al.	TS	1992	Facility location/network design				X		
Chung and Silver	DS	1992	Quantitative methods		X				
Abramson	MS	1991	Vehicle scheduling				X		

Notes: Notation for journals: DS, *Decision Sciences*; IJPDLM, *International Journal of Physical Distribution and Logistics Management*; JBL, *Journal of Business Logistics*; JOM, *Journal of Operations Management*; MS, *Management Science*; POM, *Production and Operations Management*; TRE, *Transportation Research: Part E*; TS, *Transportation Science*. Abbreviations: ACO, ant colony optimization; GA, genetic algorithms; GRASP, greedy randomized adaptive search procedure; SA, simulated annealing; SC, supply chain.

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