

AN HYBRID DISCRETE PARTICLE SWARM OPTIMIZATION ALGORITHM FOR SOLVING A SUSTAINABLE REMANUFACTURING SUPPLY CHAIN PROBLEM

Abstract – We propose a hybrid evolutionary algorithm based on discrete Particle Swarm Optimization for solving a novel remanufacturing sustainable supply chain design problem. There is little research being done in mathematical modeling and solutions methods for these problems. The paper describes a NP-hard mixed-integer 0-1 model (MIP) for this remanufacturing sustainable problem in which given a network of three layers, we have to determine the number of remanufacturing facilities to be located at sites chosen from among a given set of candidate sites, to allocate sourcing facilities to remanufacturing facilities and remanufacturing facilities to demand facilities with a given demand. The objective is to minimize transportation, distribution and operation costs of the facilities. The heuristics combine the traditional binary PSO algorithm with greedy-exchange strategies in order to improve the quality of the solutions. We report computational results for instances generated from known data test available in the literature.

Keywords – Keyword 1, keyword 2, keyword 3, additional keywords (6 at most).

1 Introduction

By 2020 the impact of climate change on the world economic will get an equivalent of 20% of the global GDP per year. Under business as use scenarios, the GHG emissions is expected to grow from 40 GtCO_{2e} (dioxide carbon equivalent) emitted per year in 2002 to nearly 53 GtCO_{2e} annually by 2020. Considering the magnitude of the impact for the global economic, many governmental agencies and international institutions are taking action to reduce and control the GHG emissions. GHG emissions it is not the only environmental problem companies are worried about. The efficient waste stewardship is another issue involving the concern for the final destination of products and their components, and what is their impact on the pollution of the air, water and earth besides the costs of treating the disposal in landfill. Notice that by 2013 the total e-waste will reach 73 million metric tons. These products not only need to get back to the supplier, re-use or recycled, some disposal also remain in the earth producing several kind of damages. Several regions and nations set up tighter carbon emission goal in a collaborative action to mitigate the potential damage for the economic and also the health of the people. There are specific rules in some regions like UE, where The European Waste Electrical and Electronic Equipment Directive (WEEE) and End of Life Vehicles Directive, (ELV) are encouraging companies in the automotive industry to collaborate with other businesses and organizations in the supply chain to ensure that products can be disassembled and reused, remanufactured, recycled or disposed of safely at the end of their life. In addition to stronger legal environment restrictions, there are several reasons because an increasing number of companies will be interested into get engaged in sustainable initiatives like the management of reverse flows, going backwards from customers to recovery centers, within their supply chain [1,2]. As pointed out by some authors, huge monetary values "can be gained by redesigning the reverse supply chain to be faster and reduce costly time delays" [3]. According to the same authors, design strategies for reverse supply chains are relatively unexplored and underdeveloped. Returned products are remanufactured if judged cost-effective. Some firms may treat all product returns as defective. Some returned products may be new and never used; then these products must be returned to the forward flow. Some products not reused or remanufactured are sold for scrap or recycling. Remanufactured products are sold in secondary markets for additional revenue, often to a marketing segment unwilling or unable to purchase a new product. In this context, remanufacturing activities are recognized as a main option of recovery in terms of its feasibility and benefits. In this paper is addressed the problem of designing a remanufacturing supply chain network. The problem is a NP-hard combinatorial optimization. We present a particle swarm optimization (PSO) algorithm for solving it.

In the last decades, evolutionary algorithms (EVO) have been widely used as robust techniques for solving a number of hard combinatorial optimization (CO) problems. An EVO is directed by the evolution of a population in the search for an optimum solution to the CO problems. Particle Swarm Optimization (PSO) is an evolutionary algorithm that has been applied with success in many areas and appears to be a suitable approach for several optimization problems [4,5,6]. As pointed out by some authors [7,8], besides this technique has succeeded in many continuous problems, in discrete or binary version there are still some difficulties. We try this aspect in this paper.

In this paper, we present a three-layer facility location model for designing the reverse supply chain that covers remanufacturing activities. In the first section, we provide a literature review with a brief introduction to sustainable and reverse supply chain and particularly to the remanufacturing case. In the second section, we formulate the mathematical model. In the third section, we propose an algorithm based on binary particle swarm optimization for solving this problem and in the fourth section, we present experimental results for a small case as well as for larger sets of data. The last section contains our conclusions and directions for future research.

2 Literature Review

Adopting a friendly sustainable management implies a number of changes for companies from the strategy level to the operational point of view, affecting their people and impacting their business processes and technology. In this regards, [9] Simchi et al. (2007) pointed out, “the strategic level deals with decisions that have a long-lasting effect on the firm. These include decisions regarding the number, location and capacities of warehouses and manufacturing plants, or the flow of material through the logistics network”. They established a clear link between facility location models and strategic decisions of supply chain management (SCM). Supply Chain Management - SCM, and in particular Sustainable Supply Chain Management – SSCM give a good framework to address sustainable issues. Green supply chain management (GSCM) was emerging in the last few years. This concept covers every stage in manufacturing from the first to the last stage of product life cycle, i.e. from product design to recycle. [10] made a carefully literature review and he shows that a broad frame of reference for Green Supply Chain Management (GSCM) is not adequately developed. As a consequence, the author identifies the need for a “succinct classification to help academicians, researchers and practitioners in understanding integrated GSCM from a wider perspective”. Finally he defines GSCM as an integrating environment including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers, and end-of-life management of the product after its useful life. Sustainable Supply Chain Management involves (a) many organizations, (b) many business processes across and within these organizations, and (c) with social, environmental and economic objectives shared by each organization and the entire Supply Chain. As it has been mentioned previously, companies must orchestrate their greening efforts across all Supply Chain processes within and inter organizations, starting with product design and development, procurement and purchasing, manufacturing, packaging, transportation, warehousing and inventory management, demand fulfillment, and end-of-life management, including waste stewardship and reverse logistics [11]. As part of the SSCM, reverse logistics is defined as: “The process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal.” [1]. In a reverse supply chain, the reverse logistics system comprises a series of activities to treat returned products until they are properly recovered or disposed of. These activities include collection, cleaning, disassembly, test and sorting, storage, transport, and recovery operations. Regarding recovery operations, we can find a combination of several main recovery options, like reuse, repair, refurbishing, remanufacturing, cannibalization and recycling [12,13]. Based on previous works, four kinds of basic reverse logistics network can be identified [6,7,14,15]: the directly reusable network (DRN), the remanufacturing network (RMN), the repair service network (RSN), and the recycling network (RN).

In this paper, we focus on the remanufacturing network (RMN). Here, remanufacturing is defined as one of the recovery methods by which worn-out products or parts are recovered to produce a unit equivalent in quality and performance to the original new product and then can be resold as new products or parts. Because remanufacturing activities are often implemented by the original producer such a network is likely to be a closed-loop system. Remanufacturing activities are recognized as a main option of recovery in terms of its feasibility and benefits. It provides firms a way to master the disposal of their used products, to reduce effectively the costs of production and save raw materials.

2.1. The facility location problem for reverse supply chain

As pointed out in [9], strategic decisions involve the number, location and capacities of warehouses and (re)manufacturing plants, and/or the flow of material through the logistics network. Then facility location is one of the strategic problems that is part of a planning process for managing and designing the supply chain network [9]. The greatest benefits of applying SCM are obtained by an extended analysis including organizations upstream -closer to the raw materials- and downstream -closer to the consumer- of the supply chain and then back again so that the unsold products are recycled. But, by extending the focus, what this really does implies more organizations, multiplying the relation between the organizations and getting a more complex supply chain (SC) to manage. Considering this complexity, the focus of the supply chain management literature has been on dyadic networks (supplier units-customer units) [16]. The problem of locating facilities and allocating customers is not new to the operations research community and covers the key aspects of supply chain design [17]. This problem is one of “the most comprehensive strategic decision problems that need to be optimized for long-term efficient operation of the whole supply chain” [18]. Notice that some small changes to classical facility location models are quite hard to solve [19].

The presence of recovery activities (like remanufacturing) brings up some new challenges on the design and management of supply chain. In [2] the authors discussed the new issues that arise in the context of reverse logistics and reviewed the mathematical models proposed in the literature.

Regarding the location problems for the design of reverse logistics networks, [20] presented a two-level distribution and waste disposal problem, in which demand for products is met by plants while the waste generated by production is correctly disposed of at waste disposal units. [21] described a network for recycling sand from construction waste and proposed a two-level location model to solve the location problem of two types of intermediate facility.

Regarding remanufacturing location models, [22] described a small reverse logistics network for the returns, processing, and recovery of discarded copiers. They presented a mixed integer linear programming (MILP) model based on a multi-level uncapacitated warehouse location model. The model was used to determine the locations and capacities of the recovery facilities as well as the transportation links connecting various locations. In [23] is analyzed a closed-loop logistics

network of an electronic equipment remanufacturing company in the USA. They proposed a 0-1 MILP model to determine the location of distribution/remanufacturing facilities, the transshipment, production, and stocking of the optimal quantities of the remanufactured products. In [24] is proposed a model for addressing a recycling network of electrical appliances and computers in Taiwan.

In this paper, we study a three-layer location problem for a RMN. We propose a metaheuristic procedure to solve the problem of design a remanufacturing supply chain network. In our model, reverse flows are considered. We will see that decisions about locations of reverse units are strongly connected. In the next section, we describe the context of the problem and then present the model that we propose.

2.3. The discrete Particle Swarm Optimization algorithm

Particle swarm optimization (PSO) is a metaheuristics based on the social behavior and communication of bird's flock and shoal of fishes [4]. PSO can be considered as an evolutionary algorithm because its way of exploration via neighborhood of solutions (particles) across a population (swarm) and exploiting the generational information gained. But, it has some divergences from other evolutionary algorithms in such a way that it has no evolutionary operators such as crossover and mutation of genetic methods. PSO has the advantage that is ease of use with fewer parameters to adjust. In PSO, the potential solutions (particles), move around in a multidimensional search space with a velocity, which is constantly updated by a combination of the particle's own experience, the experience of the particle's neighbors and the experience of the entire swarm. PSO has been successfully applied to a wide range of applications such as neural network training [25], task assignment [26], and scheduling problem [27, 28]. See [6] for a further discussion on applications. Since PSO is developed for continuous optimization problem initially, most existing PSO applications are resorting to continuous function value optimization [4-6, 29]. Recently, a few researches applied PSO for discrete combinatorial optimization problems [26-28, 33-37]. For the problem addressed in this paper we explore the use of a hybrid discrete PSO algorithm to overcome the feasibility issues of the traditional binary algorithm.

3 A model for a remanufacturing supply chain network

In this paper, the model for designing a sustainable supply chain network belongs to a class of the static, three-echelon, capacitated location models. The remanufacturing supply chain network consists of three types of member i.e., intermediate facilities (sources), remanufacturing facilities and point of sale facilities. At the customer levels, there are product demands and used products ready to be recovered. At the first layer of the supply chain network, there are reprocessing centers that are only used in the reverse channel and are responsible for activities, such as cleaning, disassembly, checking and sorting, before the returned products are sent back to remanufacturing facilities. At the second layer, remanufacturing facilities accept the checked returns from intermediate facilities and are responsible for the process of remanufacturing. As a member of the "forward" channel, remanufacturing facilities are responsible to meet the product demands of the customers. In this paper we address the backward flow of returns coming from sources (intermediate facilities) and going to point of sale facilities through remanufacturing facilities properly located at pre-defined sites. In such a supply chain network, the reverse flow, from customers through intermediate facilities to remanufacturing facilities is formed by used products, while the other ("forward" flow) from remanufacturing facilities directly to point of sales consists of "new" products.

In our model is assumed that the product demands (new ones) and available quantities of used products at the customers are known and deterministic. All returned products (used products) are first shipped back to intermediate facilities where some of them will be disposed of for various reasons, like poor quality. The checked return-products will then be sent back to remanufacturing facilities, where some of them may still be disposed of. The product demands at the customers can be met by point of sale facilities, which receive products from the remanufacturing facilities. In our problem, remanufactured products are considered the same as the new products coming from "traditional" producers in terms of satisfying the customer demands.

We introduce the following inputs and sets:

I = the set of source facilities at the first layer, indexed by i

J = the set of demand nodes at the third layer indexed by j

K = the set of candidate remanufacturing facility locations at the mid layer, indexed by k

h_i = supply quantity at source location $i \in I$

l_j = demand quantity at point of sale location $j \in J$

f_k = fixed cost of locating a mid layer remanufacturing facility at candidate site $k \in K$

g_k = management cost at a mid layer remanufacturing facility at candidate site $k \in K$

c_{ik} = is the unit cost of delivering products at $k \in K$ from a source facility located in $i \in I$

d_{kj} = is the unit cost of supplying demand $j \in J$ from a mid layer facility located in $k \in K$

M = cardinality of J

We consider the following decision variables:

$w_k = 1$ if we locate a remanufacturing facility at candidate site $k \in K$, 0 otherwise

$x_{ik} = 1$ if the remanufacturing facility located at $k \in K$ is serviced by a source facility $i \in I$, 0 otherwise

$y_{kj} = 1$ if the demand of $j \in J$ is serviced by a remanufacturing facility located at $k \in K$, 0 otherwise

The remanufacturing supply chain design problem (RSCP) is defined by:

$$\text{Minimize } \sum_{i \in I} f_k w_k + \sum_{i \in I} \sum_{k \in K} h_i c_{ik} x_{ik} + \sum_{k \in K} \sum_{i \in I} g_k x_{ik} + \sum_{k \in K} \sum_{j \in J} l_j d_{kj} y_{kj} \quad (1)$$

$$\sum_{i \in I} h_i x_{ik} \leq M w_k \quad \forall k \in K \quad (2)$$

$$\sum_{k \in K} x_{ik} = 1 \quad \forall i \in I \quad (3)$$

$$\sum_{j \in J} l_j y_{kj} \leq M w_k \quad \forall k \in K \quad (4)$$

$$\sum_{k \in K} y_{kj} = 1 \quad \forall j \in J \quad (5)$$

$$\sum_{j \in J} l_j y_{kj} \leq \sum_{i \in I} h_i x_{ik} \quad \forall k \in K \quad (6)$$

$$x_{ik}, y_{kj}, w_k \in \{0,1\} \quad \forall i \in I, \forall j \in J, \forall k \in K \quad (7)$$

In this remanufacturing problem, the structure of the reverse supply chain is of three layers and the number, locations and capacity of possible remanufacturing facilities has to be decided. The objective function (1) minimizes the sum of the installation remanufacturing facility costs plus the delivering costs. Constraints (2) warranty that supplying at facility $k \in K$ is delivered to a mid layer remanufacturing facility already opened. Constraints (3) warranty that supplying at facility $i \in I$ must be delivered to only one mid layer remanufacturing facility $k \in K$. Constraints (4) warranty that the demand of a point of sale facility must be serviced by a remanufacturing facility already opened. Constraints (5) ensure that each point of sale facility must be allocated to one remanufacturing.. Constraints (6) ensure that the quantity of products being delivered from a remanufacturing facility is not greater than the quantity of products being supplied by sourcing facilities. Constraints (7) are standard binary constraints.

4 A Hybrid Discrete Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is an evolutionary computation method [1, 2] to solve continuous optimization problems. This is an optimization algorithm based on swarm theory where the main idea of a classical PSO is to model the flocking of birds flying around a peak in a landscape. In PSO the birds are substituted by artificial beings so-called particles and the peak in the landscape is the peak of an objective (fitness) function. The particles of the swarm are flying through the search solution space with a velocity forming flocks around peaks of fitness functions. In a continuous PSO, an individual particle's status i on the search solution space D is characterized by two factors: its position u and velocity v . The position u and velocity v of the i th particle in the d -dimensional search solution space can be represented as:

$$v_{id}^{t+1} = c_1 v_{id}^t + c_2 r_1 (p_{id} - u_{id}^t) + c_3 r_2 (p_{gd} - u_{id}^t) \quad (8)$$

$$u_{id}^{t+1} = u_{id}^t + v_{id}^{t+1} \quad (9)$$

Where c_1 is called the inertia weight factor, c_2 and c_3 are constants called acceleration coefficients, r_1 and r_2 are two independent random numbers uniformly distributed in the range of $[0, 1]$, p_{id} corresponding to the personal best objective value of particle i obtained so far at time t , p_{ig} represents the best particle found so far at time t . Equation (8) stands for

calculating the new velocity of each particle i at time $(t+1)$. Equation (9) stands for updating the position of particle i at time $(t+1)$. Each $v_{id}^t \in [-v_{max}, v_{max}]$ and $u_{id}^t \in [-x_{max}, x_{max}]$, with v_{max} and x_{max} set by users to control excessive roaming of particles outside the search solution space. Particles fly toward a new position according to (9). The process is repeated until a user-defined stopping criterion is reached.

4.1 The Binary PSO Algorithm

In order to manage discrete optimization problems, in [3] they proposed a binary PSO algorithm. The difference between binary PSO algorithm and traditional PSO algorithm is that a formula (9) has been replaced by the following:

$$u_{id}^{t+1} = \begin{cases} 1 & \text{if } rand() < S(v_{id}^{t+1}) \\ 0 & \text{if } rand() > S(v_{id}^{t+1}) \end{cases} \quad (10)$$

Where $S(.)$ is the Sigmoid function and $rand()$ is a random number uniformly distributed in the range $[0,1]$. We use this method in this paper.

4.2 The particle coding method

To find a good coding method corresponding to the optimization problem is the most critical problem [5]. In this paper, the particle's d -dimensional space is divided into three sets u^1, u^2 and u^3 . The length of each set (vector) respectively corresponds to the number of candidate sites to locate remanufacturing facilities $|K|$, the number of the intermediate facilities (sources) times the number of candidate sites and the number of point of sales times the number of candidate sites.

Every component of each vector can take only 1 or 0. If the k th component of u^1 is equal to 1, then the remanufacturing facility at candidate site k must be open, 0 otherwise. A value of 1 in the jk th component of u^2 determines that point of sale j will be serviced by a remanufacturing located at k , 0 otherwise. For u^3 , a value of 1 in the ik th component indicates that intermediate facility i is supplying by the remanufacturing facility located at k . For example, one particle's coding method is as follow [1, 0, 1 | 1, 0, 0, 0, 0, 1 | 0, 0, 1, 1, 0, 0]. This code corresponds to the following remanufacturing supply chain network structure: remanufacturing facilities will be located at candidate sites 1 and 3. The remanufacturing facilities located at 1 and 3 will be supplied by intermediate facilities 2 and 1 respectively. Point of sales 1 and 2 will be serviced by remanufacturing facilities 1 and 3 respectively.

4.3 The feasibility procedure

During the tuning phase of the algorithm, we uncovered a significance number of particle representing unfeasible solution and ending the algorithm with poor solution to the supply chain problem. To overcome this problem, we implemented a feasibility procedure. The procedure takes the unfeasible particle and generates a new feasible particle taking into account capacity restrictions (2), (4) and (6). Remember that this is not a trivial procedure because we need to maintain a flow balance constraint for each facility opened. This is, the flow of products arriving to the facility k already opened must be equal to the number of products that this facility k is delivering to the demand facilities. On the other hand, you have the hard constraints that every source facility must be serviced by only one facility, and the same occur by the demand side, in which every demand facility must be serviced by only one facility.

4.4 The single exchange heuristics

For every feasible particle we implemented a single exchange procedure in order to improve the quality of the solution. The procedure works as follows: For every feasible particle, we take at random one of the facilities already opened, then we take at random one of the facilities closed and we switch it to open. We exchange the entire cluster of source and demand facilities serviced by the opened facility to the new opened facility. If we improve the cost of the solution, we validate the switching, otherwise, we maintain the older solution.

4.5 Other considerations

We initialize our algorithm with a size swarm of 30 particles. The maximum number of iterations was also set to 30. We used these setting parameters because we consider the problems already solved in the literature are small, then we stressed the heuristics. The acceleration coefficient c_2 is set to 2 and c_3 to 1. The inertia coefficient start with a value of 0.9 and it decreases till get 0.4 depending on the number of iterations performed. The initial swarm is composed of just feasible solutions. Each particle is generated randomly using the following procedure: firstly we generate the remanufacturing facilities to be located at candidate sites according to a random number distributed in the range $[0,1]$; then for each point of sale j we generate the remanufacturing facility k that will service it and, finally for each intermediate facility i we generate the

remanufacturing facility k that will be supplied by facility i . The velocity vector v_{id}^t is generated randomly in the range $[-4,4]$ previously described as in the continuous method. At every iteration, the algorithm uses the code method described earlier and updates the position vector u_{id}^{t+1} according to (9). The velocity vector v_{id}^t is updated at each iteration according (8). The fitness function is like (1). It is straightforward to calculate its value from u_{id}^{t+1} . In every iteration we check for updating the best position of a particle and the global best position of the swarm. Notice that we do not explore swarm neighborhood structures, i.e. the way information is distributed among its members.

4 Some Numerical Results

We implemented a computer program on Scilab for testing our algorithm described above. All test examples presented in the next sections are solved on a Pentium PC 2.1 MHz, and 1Gb memory. Since there is no benchmark model available in the literature for the proposed model, we generated test problems from available data set of well known related supply chain problems [38-40]. These are data sets corresponding to networks of up to $10 \times 10 \times 15$. The data set for the test problems given in Table 1 is available with the authors and because of restriction in the number of paper the authors have not given the full data in this paper. In order to validate our DPSO solutions we used GAMS on integer linear programming model described in previous section and it was solved for some instances using Cplex Solver 8.2 as the integer linear program solver. Every test problem was running 5 times and we present an average value of the objective function in Table 1. As we can see in Table 1, for the instances problems we used the GAP obtained is quite small. Both methods (GA and GAMS) quickly converge on mentioned RSCP instances and their running times are not reported here.

Table 1 – Computational Results. First column indicates the problem instance; z^* is the optimal solution; $z(\text{DPSO})$ is the solution value obtained by the heuristics.

Parameter	z^*	$z(\text{DPSO})$	GAP(%)
Li	1740	1790	2,9
Lu&Bostel1	3427	3427	0
Lu&Bostel2	3279	3279	0
Lu&Bostel3	3190	3190	0

5 Conclusions

In this paper, we introduced a novel remanufacturing sustainable supply chain network design problem. This is a NP-hard problem and it address the design of a remanufacturing supply network, that consists of three types of member i.e., intermediate facilities (sources), remanufacturing facilities and point of sale facilities. At the customer levels, there are product demands and used products ready to be recovered. The problem was formulated as a mixed integer 0-1 linear programming problem (MIP) and solved using a hybrid discrete PSO algorithm coded in Scilab. The algorithm considers a traditional binary PSO algorithm, a feasibility procedure and finally a single exchange heuristics. We conducted a preliminary experimental study on instances generated from related remanufacturing supply chain problems. The traditional binary PSO algorithm generated a significance number of unfeasible solution. The capacity and flows balance constraints proved to be the hardest constraints of the problem in term of the number of unfeasible solutions generated and the procedure to generate a feasible solution. To improve the quality of the solution obtained, we introduce a single exchange heuristics. This heuristic looks for one facility already closed and it tests to exchange it with one facility already opened. If the switch gets a better solution then we validate the exchange, otherwise we retain the previous solution. To validate our algorithm we used GAMS to obtain optimal objective values on the MIP. Preliminary results are good but it is necessary to perform further experiments on larger instances to conclude regarding the overall performance of the algorithm.

7 References

- [1] D.S. Rogers, R.S. Tibben-Lembke. Going backwards: reverse logistics trends and practices, **Reverse Logistics Executive Council**, (1998).
- [2] M. Fleischmann, P. Beullens, J.M. Bloemhof-Ruwaard, L.N. VanWassenhove. The Impact of Product Recovery on Logistics Network Design. Working paper of the **Center for Integrated Manufacturing and Service Operations**, 2000/33/TM/CIMSO 11, (2000).
- [3] D. Joseph D, V. Blackburn. R. Daniel. G. Guide, C. Souza, L.N. Van Wassenhove, Reverse Supply Chains for Commercial Returns, **California Management Review**, 46(2000).

- [4] J. Kennedy and R. C. Eberhart. Particle Swarm Optimization. **Proceedings of the IEEE International Conference on Neural Networks**, (1995), 1942-1948.
- [5] J.Kennedy, R.C.Eberhart, Swarm Intelligence, **Morgan Kaufmann Publishers**, (2001).
- [6] R. Poli, Analysis of the Publications on the Applications of Particle Swarm Optimisation, **Journal of Artificial Evolution and Applications**, (2008), 1-10.
- [7] A. P. Engelbrecht. Fundamentals of Computational Swarm Intelligence. **Wiley**, (2005).
- [8] M. Fatih Tasgetiren, L. Yun-Chia, A Binary Particle Swarm Optimization Algorithm for Lot Sizing Problem, **Journal of Economic and Social Research**, 5 (2004), 1-20.
- [9] D. Simchi-Levi, P. Kaminsky, E. Simchi-Levi, Designing & Managing the Supply Chain, 3rd ed. **McGraw-Hill/Irwin**, (2007).
- [10] S. Srivastava, Green Supply-Chain Management: A State-of-the-Art Literature Review, **International Journal of Management Reviews**, 9(2007), 53-80.
- [11] N. Tohamy, Green Journey Needs a Roadmap, **Supply Chain Management Review**, 1(2009), Available from: <http://www.scmr.com/toc-archive/2009/20090101.html> (accessed 16 July 2009)
- [12] M. Beaulieu, R. Martin, S. Landry, Logistique à rebours: un portrait nord-américain. **Logistique & Management**, 7(1999), 5-14.
- [13] R. Dekker, E.A. Van Der Laan, Gestion des stocks pour la fabrication et la refabrication simultanées: synthèse de résultats récents. **Logistique & Management**; 7(1999), 59-64
- [14] M. Fleischmann, J.M. Bloemhof-Ruwaard, R. Dekker, E. Van Der Laan, J. Van Nunen, L.N. Van Wassenhove, Quantitative models for reverse logistics: a review, **European Journal of Operational Research**, 103(1997), 1-17.
- [15] M.C. Thierry, M. Salomon, J. Van Nunen, L.N. Van Wassenhove. Strategic issues in product recovery management. **California Management Review**, 37(1995), 114-35.
- [16] T.Y. Choi, Z. Wu, Taking the leap from dyads to triads: Buyer-supplier relationships in supply networks, **Journal of Purchasing and Supply Management**, 15(2009), 263-266.
- [17] M.S. Daskin, L.V. Snyder, R.T. Berger, Facility Location in Supply Chain Design, In: **Logistics Systems: Design and Optimization**, Edited By A. Langevin and D. Riopel, Kluwer, (2005), 39-65.
- [18] F. Altıparmak, M. Gen, L. Lin, T. Paksoy, A genetic algorithm approach for multiobjective optimization of supply chain networks, **Computers & Industrial Engineering**, 51(2006), 197-216.
- [19] R.Z. Farahani, M. Hekmatfar, Eds., Facility location: concepts, models, algorithms and case studies. **Springer-Verlag**, (2009).
- [20] J.M. Bloemhof-Ruwaard, M. Salomon, L.N. Van Wassenhove, The capacitated distribution and waste disposal problem. **European Journal of Operational Research**, 88(1996), 490-503.
- [21] A.I. Barros, R. Dekker, V. Scholten, A two-level network for recycling sand: a case study. **European Journal of Operational Research**, 110(1998), 199-214.
- [22] H.R. Krikke, A. Van Harten, P.C. Schuur, Business case OCE: Reverse logistics network re-design for copiers. **OR Spektrum**, 21 (1999), 381-409.
- [23] V. Jayaraman V, V.D.R. Guide Jr. R.A. Srivastava, A closed-loop logistics model for remanufacturing. **Journal of the Operational Research Society**, 50(1999), 497-508.
- [24] L. Shih, Reverse logistics system planning for recycling electrical appliances and computers in Taiwan, **Resources, Conservation and Recycling**, 32(2001), 55-72.
- [25] F. Van den Bergh, A. P. Engelbrecht, Cooperative learning in neural networks using particle swarm optimizers, **South African Computer Journal**, 26(2000), 84-90.
- [26] A. Salman, I. Ahmad, S. Al-Madani, Particle swarm optimization for task assignment problem, **Microprocessors and Microsystems**, 26(2002), 363-371.
- [27] A. Allahverdi, F.S. Al-Anzi, A PSO and a Tabu search heuristics for the assembly scheduling problem of the two-stage distributed database application, **Computers & Operations Research**, 33(2006), 1056-1080
- [28] M. F. Tasgetiren, Y.-C. Liang, M. Sevkli, G. Gencyilmaz, A particle swarm optimization algorithm for makespan and total flowtime minimization in the permutation flowshop sequencing problem, **European Journal of Operational Research**, 177(2007), 1930-1947.
- [29] R. Poli, J. Kennedy, T. Blackwell, Particle swarm optimisation: an overview, **Swarm Intelligence Journal**, 1(2007), 1-10.
- [30] J. Wen, C. Meng, Optimization of Logistics Distribution Network Based on Improved Particle Swarm Optimization, **Proceedings 2008 Fourth International Conference on Natural Computation**, 7(2008), 659-663.
- [31] J. Jun, W. Chang, The Discrete Binary Version Of The Improved Particle Swarm Optimization Algorithm, **International Conference on Management and Service Science -MASS '09**, (2009), 1-9.
- [32] A.R. Guner, M. Sevkli, A Discrete Particle Swarm Optimization Algorithm for Uncapacitated Facility Location Problem, **Journal of Artificial Evolution and Applications**, 2008, (9 pages. doi:10.1155/2008/861512).
- [33] J. Kennedy, R. C. Eberhart, A discrete binary version of the particle swarm algorithm. **Proceedings of the IEEE International Conference on Computational Cybernetics and Simulation**, (1997), 4104 - 4108.
- [34] M.F. AlHajri, M.R. AlRashidi, M.E. El-Hawary, A Novel Discrete Particle Swarm Optimization Algorithm for Optimal Capacitor Placement and Sizing, **Canadian Conference on Electrical and Computer Engineering - CCECE 2007**. 1 (2007), 286 - 1289.

- [35] M.A. Khanesar, M. Teshnehlab, M.A. Shoorehdeli, A novel binary particle swarm optimization, **Proceedings 2007 Mediterranean Conference on Control and Automation**, (2007), T33-001.
- [36] G. Wei, Kai-Sheng-Huang, Guan-Yi-Chen, A hybrid Approach for Logistics Center Location, **Proceedings 2007 IEEE International Conference on Automation and Logistics**, (2007), 2830 – 2835.
- [37] T. Li, Research on Location of Remanufacturing Factory , **Proceedings 2011 International Conference on Management Science and Industrial Engineering (MSIE)**, (2011), 1016 – 1019.
- [38] N. Li, Research on Location of Remanufacturing Factory Based on Particle Swarm Optimization, **Proceedings of IEEE MSIE 2011**, (2011), 1016-1019.
- [39] G. Kannan, P. Sasikumar, K. Devika, A genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling, **Applied Mathematical Modelling**, 34 (2010), 655–670.
- [40] Z. Lu, N. Bostel, A facility location model for logistics systems including reverse flows: The case of remanufacturing activities, **Computers & Operations Research**, (2005), 89-100.