Modeling and Optimisation of Distribution Networks Using Hybrid Genetic Algorithms: A Comparative Study

Romeo M. Marian, Lee H.S. Luong and Son Duy Dao

Abstract— **This paper focuses on the second stage of a three-stage, integrated methodology for modeling and optimisation of distribution networks based on Hybrid Genetic Algorithms. The methodology permits the use of any combination of transportation and warehousing costs for a deterministic demand. This paper analyses and compares the variation of overall costs when the number of facilities varies and indicates how to minimize them.**

The distribution network directly and critically affects costs, efficiency and service level - the essential performance operation indicators for supply chains.

The paper concentrates on Capacitated Location Allocation of distribution centers, a large scale, highly constrained, NP-hard, combinatorial problem.

The Hybrid Genetic Algorithm used has a classical structure, but incorporates a special encoding of solutions as chromosomes and the integration of a Linear Programming/Mixed Integer Programming module embedded in the generation, crossover and pseudo-mutation operators.

A complex and extensive case study – 25 production facilities, 5 to 10 distribution centres and 25 retailers (up to 520 variables intricately connected with a significant number of constraints) – is described, demonstrating the robustness of the Hybrid Genetic Algorithm and the optimization approach.

Index Terms— **Distribution network, Capacitated Location Allocation Problem, Optimisation, Hybrid Genetic Algorithms.**

I. Introduction

The distribution network directly and critically affects the structure, complexity, costs and overall efficiency associated with operating a Supply Chain (SC), as well as the service level, the two critical factors in any SC [1]. This directly influences the aptitude of participants in a SC (whether is under control of a single or a conglomerate of companies) to enter or stay competitive in a market. An aspect of the utmost importance is the escalating complexity of distribution networks. As SC become increasingly large and complex, a general trend today, due mainly to globalization [2], designing the distribution network becomes vital [3], [4]. Due to sheer size, capacity of classical tools to solve and optimise LA problems in real distribution networks was exceeded. For this reason, development of new tools and implementations were and are necessary.

The paper presents a framework developed for the optimisation of distribution networks in SC, especially as the Location-Allocation (LA) of distribution centres (DC) or warehouses are concerned. The size of DC/warehouses is limited – thus, the problem becomes a Capacitated Location Allocation (CLA) problem.

The CLA problem is a large scale, highly constrained, NP-hard, combinatorial problem [5]. Genetic Algorithms (GA) have been chosen in this research for the design and optimisation of the distribution network for their remarkable capacity to successfully work with problems with huge solution spaces [6].

Various GA have been developed, as shown briefly in the next section, to solve a plethora of LA - like problems. Some of them were successful, at least to a certain degree, to tackle - in general - restricted variants of the problem. This becomes obvious when the run-time of a genetic algorithm starts clocking hours of CPU and indicates that particular methodology has attained its limits, mainly due to the general foe of combinatorial optimisation, the combinatorial explosion.

The approach presented in this paper to tackle the CLA problem differs from others through the use of an integrated methodology, flexible enough to accommodate most realistic assumptions and, at the same time, computational-resource conscientious, to avoid combinatorial explosion. The methodology presented here is a development of algorithms of similar complexity presented in [7], [8] and an extension of the work in [3], [4].

A complex case study, of considerable size and a complex cost structure, achieved excellent run times. It demonstrates the robustness of the Hybrid Genetic Algorithm (HGA) and its capacity to tackle problems of considerable size and the expandability of the HGA to even larger and more complex problems.

II. Literature Review on Optimisation of Location-Allocation Problems

The LA problems received considerable attention in the last 50 years due to their immediate practical applicability. A wide variety of methodologies and techniques were employed, alone or in diverse combinations in attempting to find good solutions.

LA problem were treated in depth in recent years [9], [10]. Variations of the problem appear in numerous papers. Different definitions of variants of LA problems make in fact difficult to compare results between different problems. The literature review presented here shows mainly the

Manuscript received December 2010; revised February, 2011.

Romeo MARIAN, PhD is Senior Lecturer and Program Director at School of Advanced Manufacturing & Mechanical Engineering, University of South Australia, Australia (e-mail: romeo.marian@unisa.edu.au).

Son Duy DAO is postgraduate student at School of Advanced Manufacturing & Mechanical Engineering, University of South Australia, Australia (corresponding author, e-mail: daosd001@mymail.unisa.edu.au).

Professor Lee Luong is Head of School of School of Advanced Manufacturing & Mechanical Engineering (email: lee.luong@unisa.edu.au)

diversity of problems and approaches used to tackle them.

The initial LA problem has been generally further complicated to integrate different aspects relating to production and distribution [11], product returns [12], facilities restricted to being located along a line, while the destinations that will be served by them are generally located off the line [13], etc. It is, however, important to highlight that LA problems are combinatorial problem and any complication of the model generally has a detrimental effect on the size of the problem that can be, eventually, solved.

MIP has been used extensively, directly [14] or in combination with other techniques – e.g GA [12] in tackling LA problems with various degrees of success.

Artificial intelligence techniques have also been used in optimising LA problems, standalone, or in combination with other AI or mathematical optimisation techniques.

A hybrid heuristic based on the Simulated Annealing method, Tabu list, and improvement procedures are proposed to resolve the un-capacitated single allocation hub location problem [15]. This algorithm is compared with a GA [16]using similar sets of data.

GA have been applied in the optimisation of LA problems. The extreme variety of LA and LA-like problems led to the development of various GA and combinations of GA with other mathematical tools.

A multi-phase mathematical approach for the design of a complex SC network is presented in [17]. The proposed approach is based on GA, the analytical hierarchy process (AHP), and the multi-attribute utility theory (MAUT) to satisfy simultaneously the preferences of the suppliers and the customers at each level in the network. Even if the model is very comprehensive, it is likely to be limited to distribution network of reduced size. A network of 3-4-4-2 facilities illustrates the application of the approach.

A LA problem involving reverse logistics is presented in [12]. It addresses the problem of determining the number and location of centralized return centres (i.e. re verse consolidation points) where returned products from retailers or end-customers are collected, sorted and consolidated into large shipments destined for manufacturers' or distributors' repair facilities. The paper proposes a nonlinear MIP model and a GA that can solve the reverse logistics problem involving product returns. The model and algorithm were validated by an example of 30 customers, 10 potential sites for collection and 5 potential sites of centralised return (although the actual number of sites for collection and centralisation is smaller). The solution times tend to indicate potential combinatorial explosion issues.

From this literature review it can be seen that the LA problems are of an extremely diverse nature. Also, GA are important candidates when it comes to select optimisation tools. Due to the extreme variety of the problems and implementation of algorithms, it is difficult to compare or classify them.

Most of the algorithms above are limited in either one or more of the following: size of solution space, realism of the modelling of the problem – this includes decoding chromosomes to meaningful solutions - versatility and capacity to be customised for more or less related problem, and, probably the most important, robustness [18].

For solving realistic and versatile CLA, avoiding simultaneously all limitations presented above, a new methodology and optimisation tool was necessary and are presented in the next sections.

III. METHODOLOGY TO OPTIMISE THE DISTRIBUTION NETWORK

The complexity and contradictory nature of optimisation criteria requires the problem to be optimised in stages.

The main tool for the optimisation of the CLA problem in this research is a HGA, chosen for the versatility of GA to implement optimisation criteria, their flexibility to be adapted to extremely diverse types of problems (hybridised with LP/MIP tools) and their capacity to work in extremely vast solution spaces [19].

It is challenging to work with solutions with variable size. In case of the CLA problem, one of the parameters to be optimised is the number of DCs (complete definition of the problem in the next section). As a result, and to still do a proper optimisation for the number of DCs as a variable, the optimisation is initially done for a set number of DCs. After a local optimum/near optimum set of solutions has been found for that particular number of DCs (in the first stage), the algorithm is run for a different number of DCs (second stage). This approach can quickly point out towards the most promising zone of the solution space (as number of DCs is concerned) and permits to determine a global optimum.

The major steps of the first two stages are as follows

First stage:

- Determine the optimal (local optimum - minimal cost to operate the distribution network) result using HGA for a set number of DCs and a deterministic demand:
- Set number of DCs to be opened and operated;
- Determine the location of DCs;
- Allocate PFs to each DC;
- Allocate flow of merchandise from each PF to each allocated DC;
- Allocate DCs to each R;
- Allocate flow of merchandise from each DC to each allocated R;

Second stage:

- Determine the global optimum (minimum cost) by varying the number of DCs, for a deterministic demand;
- Repeat the first stage for a different number of DCs;
- Determine optimal result in each case;
- Select the solutions that offer global minima of costs;

An important aspect in practice is the stochastic character of many variables playing a role in any SC and in the distribution network in particular. To capture the stochastic nature of the SC in the final results of the optimisation, a third stage is proposed.

Third stage:

- Verify robustness of the solutions – by modelling and simulating the distribution network and by varying different parameters and using stochastic input values - so as to improve the realism of the results. Test when uncertainty is present in the various components of the supply chain and its actors, primarily:
  - Stochastic demand;
  - Variable/stochastic transportation costs;
  - Stochastic variation of different costs in opening/operating the DC, etc.;

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

- Determine, in the new conditions, actual service levels, costs, potential bottlenecks, etc. in realistic settings;

If the final results of a realistic, stochastic SC, are not satisfactory and not within the accepted levels in practice, different parameters and inputs of the problem can be used (e.g. multiply the demand, the storage capacity, transportation costs, etc. by a safety factor) and the optimisation process can be re-run for the new values.

This approach offers the maximum of flexibility to adapt a method, initially developed for a deterministic set of constraints into a more realistic one, involving stochastic data and settings.

This paper only focuses on the second stage of the research, the first stage being extensively detailed in [3], [4].

IV. THE MODEL OF THE CAPACITATED LOCATION ALLOCATION PROBLEM

In general Location Allocation problems require locating a set of new facilities - DCs in this case - such that transportation costs from facilities to customers are minimized [20].

Due to the extreme variety of LA problems presented in the literature, it is necessary to define the model used in this work. The CLA problem, as considered in this work, (Fig. 1. presents a case), is defined as follows [3], [4]:

Considering known:

1. Number, location and production capability in a given time frame of Production Facilities (PF);
2. Number, location and demand in a given time frame of product users or retailers (R);
3. Demand;

Determine:

- Number, location and capacity of DCs (Note: the number of DCs is set in the first stage of optimisation and is varied/optimised in the second stage);
- Allocation of DCs to production facilities;
- Allocation of the flow of products from each PF to the relevant DC;
- Allocation of retailers to DCs;
- Allocation of the flow of products from each DC to the relevant Rs;

So that:

- The overall operating costs are minimized;
- A pre-set level of service is maintained;

Conditions:

1. It is assumed, initially, that demand can be fully satisfied and all production can be sold;
2. The capacity of DCs is limited, selected from a modular set of capacities;
3. Capacity conditions – capacity of DCs as selected cannot be exceeded;
4. Each DC is allocated to at least one PF and at least a R;
5. In a given time frame, flow of products IN equals the flow of products OUT of a DC;
6. A single type of product is considered;
7. The products move strictly from PF to a DC and from the DC to a R;
8. The cost of opening a DC for each particular size of DC is known;
9. The cost of operating a DC for each particular size of DC is known;
10. Transportation costs and structure are known;

Fig. 1. presents a typical graph of a distribution network, including facilities (as vertices) and connections between them (as edges), as considered in LA problems. In this case, PF1 sends products to DC1, PF2 sends products to DC1 and DCj, etc. DC1 receives products from PF1 and PF2 and distributes it to R1, R2 and R3, etc (directed graph).

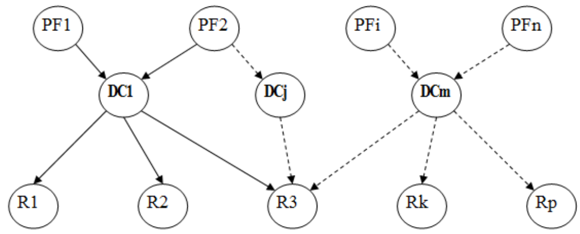

Fig. 1. Distribution network for *n* PF, *m* DC and *p* R.

This model is general enough to cover most of real-life problems, and at the same time it permits the optimisation of the CLA problems with a single general methodology

V. STRUCTURE OF THE GENETIC ALGORITHM

The structure of the HGA is classic, but a special attention has to be attached to handling the numerous and various constraints of the problem and between different genes of the chromosome.

The issue of constraints becomes critical for this problem and for the development of the HGA. The probability to obtain a legal and feasible chromosome by random generation of genes or simply by using any completely random operation (as part of a Genetic Operator (GO)) on genes is quasi-nil. If special measures are not implemented, any genetic operator is very likely to produce an illegal chromosome or offspring.

Also, due to the size of the chromosome and complex relations between genes, the number of operations needed to be performed within any GO has to be minimised. At the same time, the stochastic character of the HGA has to be preserved. Rejecting, repairing and penalty strategies to handle constraints were comprehensively explored at the beginning of the research and discarded as inadequate for the present problem. Instead, modified GO developed for the particularities of the CLA problem are used. This was necessary as no suitable GO, could be found in the literature.

The HGA is designed to work only with feasible chromosomes, to avoid the need to repeatedly check the feasibility of the chromosome during the running of the algorithm (operation prone to combinatorial explosion). As a result, all operators are designed to filter the potential candidates in any operations on genes. To ensure feasibility of the solutions, the genetic operators are hybridised with LP/MIP tools – essentially, a low-level optimisation is done using LP/MIP. Actual selection to use either of them depends on the particular conditions of the problem. LP/MIP filter potential candidates and retain, at each step, only the ones guaranteed to lead to a gene that satisfies all constraints and will, in turn, produce a feasible chromosome. Thus, any random operation within the chromosome is applied only on suitable candidates - guided search using LP/MIP during the application of any operation [19], and the resulting gene/chromosome is guaranteed feasible. Three major GO are hybridised with LP/MIP: random generation of chromosomes, the crossover and the

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

pseudo-mutation (PM).

A major, conceptual, difference between a classic, complete GA and the HGA used to optimise the CLA problem in this case, is the absence of a mutation operator per se, replaced with a pseudo-mutation [4], which successfully replaces the mutation operator in its function. The pseudo-mutation is applied to the population after evolution, i.e. after the selection process has taken place

VI. CASE STUDY

The case study mainly focuses on the second stages of the methodology to optimise the CLA problem.

The distribution network is composed of 25 PFs, 10 DCs and 25 R. All components of the network are placed on an array of 100 x 100 cells. The x and y coordinates of the cells in which PFs and Rs are located are given in Table 1, where PFX(i), PFY(i) – x and y coordinates of PFi and RX(i), RY(i) – x and y coordinates of Ri, the annual output of PFs (PPi) and also the annual demand of Rs (PRi).All output can be sold, all demand can be satisfied, so the sum of the annual output of PFs equals the sum of annual demand of Rs.

TABLE 1. CASE STUDY DATA

i	Production facilities – positions		25 Retailers - positions		Output of Prod. Facilities	Demand of Retailers
	PFX(i)	PFY(i)	RX(i)	RY(i)	PP(i)	PR(i)
1	59	85	41	83	6420	2820
2	96	24	66	75	7140	6240
3	94	59	49	50	3840	8160
4	25	22	62	17	7260	4080
5	41	26	62	72	4080	7920
6	42	42	59	69	7860	7260
7	27	75	46	18	4920	2700
8	8	67	65	36	4080	4500
9	32	58	49	48	7740	7680
10	75	15	60	100	3180	6060
11	95	20	17	52	5700	8040
12	98	2	96	44	8160	6480
13	55	51	82	13	5220	3420
14	85	7	56	12	2400	6360
15	34	74	70	11	5220	7680
16	61	12	98	76	5040	2400
17	89	68	5	75	7500	7680
18	89	79	39	61	3780	2880
19	71	28	85	94	5340	2520
20	29	52	88	41	4020	5640
21	15	56	4	45	7980	4920
22	92	66	38	35	7080	3540
23	37	11	16	75	5040	7260
24	63	66	54	13	4080	7920
25	7	78	34	47	6540	5460

Additionally, the following assumptions are considered:

- The output of each PF is to be transported in 5 equal installments (i.e. monthly installments) to DCs. This demonstrates the HGA can be applied also when production is seasonal;

- Each R has a demand of products to be delivered as requested – i.e. the capacity of the DC has to accommodate the peak production of PFs;

- All products are produced, delivered and sold within a standard period (e.g. one year);

- The structure of the costs takes into consideration economies of scale. DC capacities and costs are presented in Table 2. The opening costs of a DC are compounded and allocated as annual costs depending on the capacity of the DC. On the other hand, the operating costs for a DC are allocated as costs per actual unit transiting the DC:

TABLE 2. STRUCTURE OF COSTS

DC capacities (units)	Opening costs per unit of capacity	Operating costs per actual unit through DC
10000	$1	$ 0.5 /actual unit
20000	$ 0.75	$ 0.4 /actual unit
50000	$ 0.6	$ 0.3 /actual unit
100000	$ 0.4	$ 0.2 /actual unit

- Transportation is considered by trucks, and the cost is allocated as $ $0.2*10^{-3}$ per actual unit transported and per unit of distance (Manhattan distance);

VII. IMPLEMENTATION

The algorithm has been successfully implemented in a computer program coded in Microsoft Visual Basic 6, not compiled. The machine used to run the program was a notebook with a Core 2 Duo 2.4 GHz processor and 4 GB DDR RAM.

The costs are implemented as separate subroutines and can be easily modified and adapted to suit any particular practical cost structure and allocation and actual transportation rates. This makes the case study and its implementation, even if developed for a scenario and not a real case from practice, easily transferable and customisable for problems encountered in practice.

The whole HGA has been tested for the settings presented above (25 PFs, 10 DCs and 25 Rs), and the complex cost structure (DC opening and operating costs, transportation costs from PFs to DCs and from DCs to Rs and economies of scale). For a population of 100 chromosomes evolving through 150 generations:

- the initial population (up to 100 chromosomes) is generated in less than one second;
- the evolution through one generation takes typically under 2 seconds;
- the evolution of a population of 100 chromosomes over 150 generations takes typically under 5 minutes;
- the PM rate is 8%;
- the output of the algorithm is recorded in a *.txt* file, from which the information is processed further;
- the size of the output .txt file is in the order of 200 MB, which corresponds to about 750 000 pages of raw data;
- the output of the HGA gets stabilised after about 100 generations;

The implementation proves to be very fast and with plenty of potential for expansion – i.e. the possibility to tackle significantly larger problems.

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

A typical evolution of the results of the HGA is presented in Fig. 2: evolution of the average and minimum values of costs for each generation.

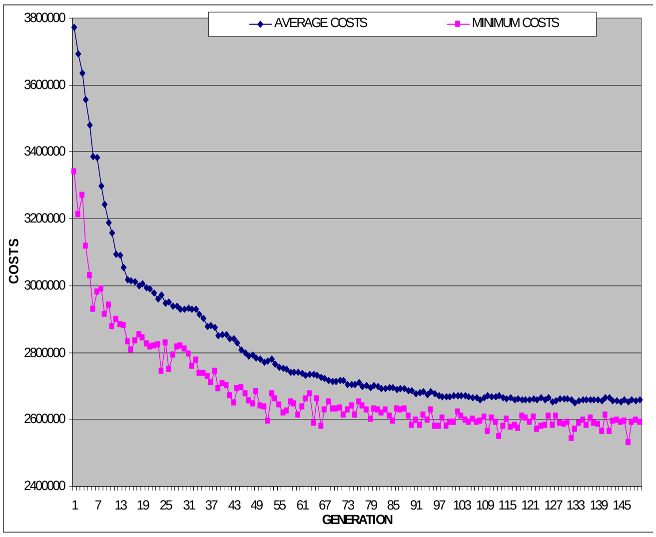

Fig. 2. Typical evolution of the results of the HGA

VIII. A COMPARATIVE STUDY - APPLICATION OF THE HGA TO VARIOUS CONFIGURATIONS OF THE DISTRIBUTION NETWORK

The HGA permits the testing of different scenarios and variations applied to the distribution network. The structure of the costs (including different costing policies), the number of DCs, different sets of constraints applied to the allocation of DCs to PFs and Rs to DCs, ... etc.

Table 3 presents the results of series of runs of the HGA for a different number of DCs in the network. All parameters were kept constant – a population of 100 chromosomes evolving over 150 generations. The only change involved the number of DCs.

Specifically, for each number of DCs, set from 10 to 5, the HGA has been run 10 times and the minimum values of the costs over the distribution network have been recorded in Table 3. (minimum of minima – minim minimorum MM - and average of the minimums, FA – final generation).It also contains the average of start cost averages (SA) – defined as average over the 10 runs of the averages of costs of the population of solutions in the first generation of each run. The minimum and average values across various numbers of DCs in the network have been represented in Fig. 3.

The ratio between FA and SA (optimisation ratio FA/SA) is consistently around 30% for the number of DCs from 10 to 5. This means that, by modelling the network and running the algorithm, the totality of costs in the supply chain can be reduced by about 30%. It is worth considering these figures in light of some statistics: grocery industry in US can save about $ 30 Billion, or 10% of the annual operating costs by using more efficient supply chain strategies [1]. In case this algorithm is applied, savings can be of the order of 30% for the portion of SC where results are applied.

A number of conclusions can be drawn from examining Table 3. and Fig. 3, and the context in which results were obtained:

- the MM and FA values are very close to each other (less than 3% and 1.5 %, respectively). This can be attributed to the number of DCs per PF, which has been kept constant over the experiment (max 5), the capacity of the algorithm to find consistently good solutions, just slight variation of the costs if the number of DCs vary and the structure of the opening/operating costs for DCs;

Table 3. COMPARATIVE STUDY OF DISTRIBUTION NETWORK OVERALL COSTS.

	Cost					
	No. of DCs					
Run no.	**10 DCs**	**9 DCs**	**8 DCs**	**7 DCs**	**DC6**	**5 DCs**
1	2582699	2650427	2709175	2621674	2555249	2661262
2	2671802	2600410	2596027	2639483	2621090	2629925
3	2595235	2548232	2725879	2664019	2645709	2576142
4	2643025	2631391	2564001	2517838	2592724	2583852
5	2668349	2611887	2538922	2629772	2634023	2561923
6	2592083	2594487	2591196	2591397	2651871	2608955
7	2609241	2693317	2509232	2598378	2626243	2777139
8	2609381	2605224	2551041	2568115	2754417	2678564
9	2628396	2585734	2699229	2563010	2617379	2652160
10	2642547	2717553	2679737	2616710	2618132	2667405
(SA)	3764934	3771158	3764992	3755449	3745062	3720276
(MM)	2582699	2548232	2509232	2517838	2555249	2561923
(FA)	2624276	2623866	2616444	2601039	2631683	2639732
(FA/SA)	0.697031	0.695772	0.69494	0.692604	0.702708	0.709553

- even if the differences small, it seems that the optimum number of DCs for this problem is 7 or 8. The final number should be determined after additional constraints are considered (robustness of distribution network);

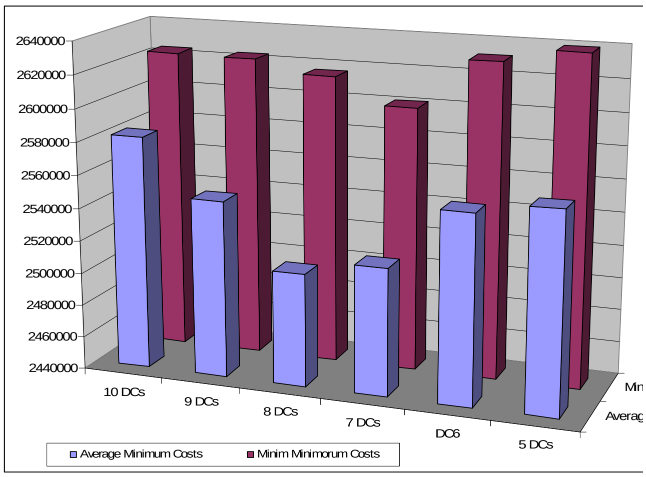

Fig. 3. Minimum and average values across various numbers of DCs

It is important to highlight that the runtime is proportional with the number of DCs, being reduced to about 150 s for 5 DCs in the distribution network.

Considering the observations above, significant savings could be achieved by further tweaking variables and constraints and their adaptation to real situations. As an example, the number of DCs per PF could be modified and their number could be optimised in this context. Also, different structures of costs and cost allocation could further improve the results of operating the distribution network

IX. CONCLUDING REMARKS AND FURTHER WORK

The papers presented an integrated methodology to model and optimise distribution networks in SC using a Hybrid

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Genetic Algorithm. This methodology allows working with deterministic demand and is being developed for stochastic demand. The optimisation criterion for the problem is the cost, considering the service level set to 100%.

The proposed model of the CLA problem is able to encode, in an explicit and compact manner, in an array, all relevant information about the location of DCs, allocation of DCs to PFs and Rs to DCs and flow of products for each active pair PF-DC and DC-R. Also, any realistic cost structure and allocation for warehousing and transportation costs can be modeled.

The HGA is a combination of a Genetic Algorithm and LP/MIP tools. LP/MIP are used extensively during the generation of the initial population of chromosomes and during crossover and pseudo mutation. They are intimately embedded in the structure of the genetic operators and coordinate the generation of genes of the chromosomes to ensure feasibility. LP/MIP module ensure all constraints are satisfied, whereas the stochastic character of any operator is preserved.

The necessity to use LP or MIP becomes obvious only when the constraints are set for a particular problem. In the case study presented here, an MIP approach has been used, but there might be situations when LP suffices.

The HGA developed and presented here has been extensively tested, for various combinations of the input parameters. The evolution of the output is consistently convergent towards the optimum.

It is important to point out the possibility to adapt the HGA for a very large palette of real situations. Especially the flexibility in defining the costs permit the exploration of different business models and allocation of costs, economies of scale, seasonal production, inverse logistics, multi-products, etc.

Further work is being conducted in:

- Generalisation of the model and HGA for multi-echelon supply chains, with good results;
- Possibility to add the time dimension to the encoding, so that a much more detailed history of the system can be built and studied and the scheduling can be considered at that stage;
- Testing of a yet more complex cost structure, to balance the economies of scale, characteristic to having fewer and larger DCs with the associated risks;
- Improvement of the crossover operator, to preserve more of the parents' genetic information, especially as the second part of the chromosome is involved.

After the full implementation of the HGA and after obtaining the results from running the algorithm, the robustness of the distribution network will be assessed using a simulation software package (Automod or Arena), for different, preset levels of uncertainty and the level of service will be determined in each case.

The computer code developed to implement the HGA, managed to achieve excellent times for the optimisation of the CLA problem. The capacity of the algorithm to work and consistently produce good results in those conditions proves its robustness. The results lead to the justified assumption that the technique can be safely extrapolated for most practical - size CLA problems with complex cost structures.

REFERENCES

[1] Simchi-Levi, D., P. Kaminsky, and E. Simchi-Levi, Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies (3rd Edition). Third Edition ed. 2008, New York: McGraw-Hill Publishers.

[2] Fahimnia, B., R. Marian, and B. Motevallian, Analysing the Hindrances to the Reduction of Manufacturing Lead-Time and Their Associated Environmental Pollution. Int. J. Environmental Technology and Management, Inderschience publishers., 2009 10 (1): p. 16-25.

[3] Marian, R.M., L.H.S. Luong, and R. Akararungruangkul, Optimisation of Distribution Networks Using Genetic Algorithms - Part 1 - Problem modeling and automatic generation of solutions. International Journal of Manufacturing and Technology Management, , 2008a. 15(Special Issue on: Latest concepts and approaches in logistics engineering and management): p. 64 - 83.

[4] Marian, R.M., L.H.S. Luong, and R. Akararungruangkul, Optimisation of Distribution Networks Using Genetic Algorithms - Part 2 - The Genetic Algorithm and Genetic Operators. International Journal of Manufacturing and Technology Management, , 2008b. 15(Special Issue on: Latest concepts and approaches in logistics engineering and management): p. 84 - 101.

[5] Perez, M., F. Almeida, and J.M. Moreno-Vega. Genetic algorithm with multistart search for the p-Hub median problem. in 24th Euromicro Conference, 1998. Vasteras

[6] Fahimnia, B., L. Luong, and R. Marian. Optimization of a Two-Echelon Supply Network Using Multi-Objective Genetic Algorithms in 2009 World Congress on Computer Science and Information Engineering. 2009.

[7] Lai, K., T., et al., An Optimisation Framework for the Design of Multi-echelon Production-distribution Networks using Genetic Algorithms. Asian International Journal of Science and Technology (AIJSTPME) in Production and Manufacturing Engineering,, 2008. 1 (2): p. 17 - 29.

[8] Marian, R.M., L.H.S. Luong, and K. Abhary, A Genetic Algorithm for the Optimisation of Assembly Sequences. Computers and Industrial Engineering, 2006. 50: p. pp 503-527.

[9]Gen, M. and R. Cheng, Genetic algorithms and engineering design. Wiley Series in Engineering Design and Automation, ed. H. Parsaei. 1997, New York: John Wiley & Sons, Inc.

[10] Gen, M. and R. Cheng, Genetic algorithms and engineering optimisation. 2000, New York: Wiley.

[11] Jayaraman, V. and H. Pirkul, Planning and coordination of production and distribution facilities for multiple commodities European Journal of Operational Research, 2001. 133: p. 394-408.

[12] Eben-Chaime, M., A. Mehrez, and G. Markovich, Capacitated location-allocation problems on a line Computers & Operations Research, 2002. 29(5): p. 459-470.

[13] Silva, M.R. and C.B. Cunha, New simple and efficient heuristics for the uncapacitated single allocation hub location problem. Computers & Operations Research, 2009. 36(12): p. 3152-3165.

[14] Min, H., H.J. Ko, and C.S. Ko, A genetic algorithm approach to developing the multi-echelon reverse logistics network for product returns. Omega, 2006. 34,(1): p. 56-69

[15] Chen, J.-F., A hybrid heuristic for the uncapacitated single allocation hub location problem. Omega, 2007. 35(2): p. 211-220.

[16] Topcuoglu, H., et al., Solving the uncapacitated hub location problem using genetic algorithms. Computers & Operations Research, 2005. 32: p. 967-984.

[17] Sha, D.Y. and Z.H. Che, Supply chain network design: partner selection and production/distribution planning using a systematic model. Journal of the Operational Research Society 2006. 57(1): p. 52-62.

[18] Hoffmann, C.M., The problems of accuracy and robustness in geometric computation. IEEE Computer, 1989. 22(3): p. 31-41.

[19] Marian, R.M., L.H.S. Luong, and K. Abhary, Assembly Sequence Planning and Optimisation Using Genetic Algorithms. Part I: Automatic Generation of Feasible Assembly Sequences. Applied Soft Computing, 2003(2/3F): p. 223-253.

[20] Zhou, J. and B. Lui, New stochastic models for capacitated location-allocation problems. Computers and Industrial Engineering, 2003. 45: p. 111-125.

[21] Simchi-Levi, D., P. Kaminski, and E. Simchi-Levi, Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies 2003 New York McGraw-Hill Publishers.

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)