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Optimal Supply Chain Redesign using Genetic Algorithm

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Abstract

Supply chain redesign involves decisions regarding the timing, amount and location attributes of the investment and disinvestment in facilities, production, purchase of raw materials, sale of products, loans and bonds for raising capital, signing of contracts for material purchase and sales, such that the profit is maximized. In this work, we use genetic algorithm to obtain the supply chain redesign plan while maximizing the profit. Genetic algorithms (GA) are best suited for unconstrained problems and we present a novel formulation of the supply chain redesign problem in an unconstrained fashion. To demonstrate this new and unconstrained formulation, we solve the problem which we previously presented (Naraharisetti et al., 2006), where we developed a novel MILP model for supply chain redesign and solved it using Cplex.

Keywords: capacity, planning, distribution, genetic algorithms, optimization

1. Introduction

With the advent of globalization, new markets are opening up in various parts of the world and organizations are venturing into these markets in order to exploit new opportunities and maximize the share holder value. One way to achieve this is through efficient asset management of their supply chains. The assets in the supply chain include the production and inventory holding facilities, raw materials and products in inventory, technological know-how and financial assets such as, capital from loans and bonds and contracts for material supply. Organizations invest in potential profit-making assets and disinvest assets that are yielding reduced profits. While doing this, they must also consider various issues such as the logistics costs, the regulatory factors on import and export at the current and new locations, among others. Hence, a mathematical model that considers these issues and gives a plan such that the share holder value is maximized is of utmost importance to the industry and has not been addresses in the literature.

2. Background

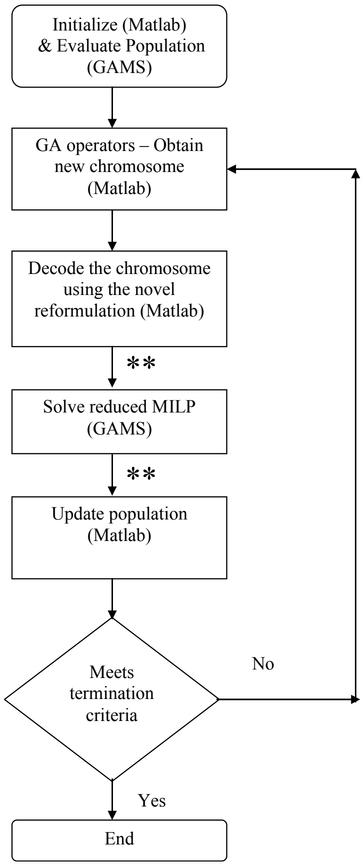
We previously presented (Naraharisetti et al., 2006) an MILP model considering such issues as investment, disinvestment, relocation, regulatory factors, transportation cost, contracts for strategic material supply, and loans and bonds for raising capital, among others. To the best of our knowledge, we were the first to consider the issues of disinvestment, relocation and contracts for strategic material supply. This model was implemented in GAMS 21.7 and solved using Cplex 9.0 to a gap of 9% in 24 hrs. It can be seen that the computational time is large for an academic example. Considering the size of the problems in the industry, an MILP model may not be able to give a feasible solution in reasonable computational time. Hence, it is important that we seek alternative optimization techniques. However, genetic algorithms have been primarily designed to handle unconstrained problems. Hence, a reformulation of the model is required because the problem under consideration is heavily constrained.

3. Genetic Algorithms for constrained problems

Considering the large number of constraints involved in our model, the crossover and mutation operations often generate infeasible strings. There are several methods of handling these infeasibilities and some of them are to: a.) reject infeasible strings, b.) penalize objective value when infeasible strings are generated, c.) repair the infeasible strings and d.) generate strings such that they are always feasible. The strategies of rejecting the infeasible strings or penalizing the objective function perform poorly because the given problem is heavily constrained. We worked on a strategy which is based on generating most of the decision variables in a string in the feasible region and repairing the infeasibilities in the others, which is partially similar to Michalewicz and Janikow, 1991. In their work, they handle the constraints by generating the decision variables in the feasible region. This is achieved by modifying the GA from case to case. In our strategy, we would only need to write the evaluation function from case to case and the GA remains the same. In this paper, we will elaborate on this new and innovative way of remodelling a heavily constrained problem and highlight the relative advantages and disadvantages of solving an MILP model directly in GAMS vis-à-vis by solving the MILP with the aid of GA.

3.1. Reformulation of MILP

While modeling the supply chain redesign problem as an MILP, the binary variables for the strategic part of the problem are 1.) plant expands, 2.) plant is disinvested, and 3.) technology upgrade takes place. In addition, we use 0–1 continuous variables to represent whether a.) plant exists, and b.) plant existed in the past and is currently disinvested. Since the horizon is divided into H number of predetermined time periods in an MILP, 3H binary variables and 2H continuous variables are required for each facility. In the reformulation, the 0-1 continuous variables can be replaced by two variables a.) time at which the plant begins to exist, and b.) the duration for which a plant exists. Similarly, technology upgrade can be represented by just one variable i.e., time at which the technology upgrade occurs, instead of the H binary variables used in MILP. Also, we use 'n' variables to define the number of expansions allowed at a given facility and another 'n' variables to define if the n^{th} expansion at the facility occurs. Hence, we will only have 2n variables instead of H variables to model capacity expansions for a given facility. It can thus be seen that 3H binary variables and 2H continuous variables are represented by 3 + 2n variables in the reformulation. Since, the number of expansions allowed is usually about 3 or 4 in the planning horizon, the total number of variables in the reformulation would be only about 9 to 11 for a given facility. This is far less than the 120 (H=40) binary variables and 80 continuous (0–1) variables required in an MILP. The 9 variables can then be decoded to a feasible set of binary and continuous variables using a decoding procedure. The binary and continuous variables thus obtained are then passed to the MILP solver, where these are fixed and the smaller MILP (tactical decisions are still in MILP) is solved to a gap of 1% and the objective is passed to the GA. The 0–1 continuous variables and binary variables are constrained due to the construction lead time, assumption that a facility once disinvested cannot be purchased back, the limit on the number of times a facility expands, and limits on technology upgrade. It can thus be seen that the 0–1 continuous variables and binary variables which are constrained in the MILP, are modelled in an unconstrained fashion by this reformulation in GA. In our work, we use GAMS-Cplex as the MILP solver and implement GA in Matlab. The MILP model is solved using Cplex 9.0 in GAMS 21.7 on a Windows XP based HP workstation with an Intel Xeon (Dual) 3.6 GHz processor and the GA is implemented in Matlab 7.0.1. The strategy is shown in Fig. 1.



	MILP	MILP+GA
Binary Variables	2220	400 in MILP 1820 from GA (Chromosome length = 183+1)
0–1 continuous variables	2160	2040 from GA
Constraints	26,390	26,390
Variables	18,134	18,134
Non-zeros	103,302	103,302
CPU time (hrs)	24	96 (13-15s for each reduced MILP)
NPV ($ bn)	8.31	7.93
Gap	9%	11%

Table 1. (above) Computational statistics for full MILP model in GAMS and the MILP+GA strategy.

Figure 1. (left) Illustration of the strategy of obtaining important decision variables from GA in Matlab and obtaining the objective by solving an MILP with fewer binary variables in GAMS.

**The GAMS-Matlab interfacing by Ferris, 1998.

3.2. Case study

We consider a multi-echelon supply chain network consisting of two material suppliers who supply five raw materials and one intermediate, four production facilities (three existing and one future possible) producing one intermediate and five products, and five distribution centers (three existing and two future possible). In addition, each production facility has two input inventory holding facilities and two output inventory holding facilities. The production facility that can potentially be disinvested and the facility that can be newly invested in are in two different nations. Hence, the problem can be considered to be that of relocation from one nation to another. The features that we include in our model are inflation, depreciation, regulatory factors, contracts for material supply, loans and bonds for raising capital for investments, possibility of a shutdown for maintenance or when there is no raw material, among others. To solve this problem, we consider a planning horizion of ten years divided into forty time periods and worked on a discrete time formulation. The computational statistics are presented in Table 1.

3.3. Results & discussion

The MILP model implemented in GAMS had 2220 binary variables. The same implementation when done in GA enables the division of the set of the binary variables into strategic (1820) and tactical (400) binary variables. The strategic binary variables are obtained from the GA and the tactical binary variables are left in the MILP. The strategic binary variables are constrained and hence a reformulation of these constraints is required so that the GA produces only feasible set of the binary variables. The reformulation results in only 183 variables and this reduction in the number of variables has great potential in reducing the computational time. In addition to the 1820 binary variables, 2040 out of the 2160 continuous (0–1) variables are also obtained from the GA and fixed in GAMS. This leads to a small computational time of about 15s to reach a gap of 1% for the reduced MILP.

Table 2. Comparison of the capacity (Ktons/quarter) profiles obtained by the complete MILP with the best solution of GA-reduced MILP (PF-production facility). TU-technology upgrade.

	Capacity (period) from GAMS (TU of PF1=31)	Capacity (period) from GA-GAMS (TU of PF1 at 33)
PF1	6000(1-9); 8000(10-25); 12900(26-40)	6000(1-11); 8000(12-32); 12500(33-40)
PF2	6000(1-7); 0(8-40)	6000(1-10); 0(11-40)
PF3	6000(1-8); 12510(9-31); 15220(32-40)	6000(1-9); 11330(10-32); 13330(33-40)
PF4	0(1-8); 7970(9-31); 14175(32-40)	0(1-10); 8000(11-40)

The capacity profiles of the production facilities for the solution obtained from GAMS and those obtained by GA-GAMS (the best plan) are given in Table 2. Furthermore, Table 3 shows the comparison of two more chrosomes from the population in GA. It can be seen that the primary differences between the two profiles are the time at which the technology upgrade takes place and the times at which the expansions occur. However, it is interesting to note that in both the cases the capacities of the production facilities are similar for PF1 and PF2. PF3 manufactures an intermediate and a product. This intermediate is used as raw material by PF2 and PF4. A new chromosome should at the same time give expansions at both PF3 and PF4, else it will result in a lower profit. To obtain a solution as good as GAMS, the child chromosome should be produced such that the entire set of decisions would give a good objective. Since the problem is constrained and there are flows of intermediate materials in a chemical supply chain network, it probably would not be possible to obtain a better solution than GAMS. However, GA has the potential to fare better when the size of the problem is too big for a full scale MILP. The full MILP can be solved by a decomposition procedure when the problem is large and we intend to pursue it as future work and compare it with GA.

Table 3. Comparison of the capacity (Ktons/quarter) profiles of the solutions (ranked 2 and 3; rank 1 is presented in table 2) obtained by the GA-reduced MILP (PF-production facility).

NPV ($ bn)	Capacity (period) PF1	Capacity (period) PF2	Capacity (period) PF3	Capacity (period) PF4
7.56 (TU of PF1=33)	6000(1-11) 8000(12-32) 12500(33-40)	6000(1-10) 0(11-40)	6000(1-9) 11330(10-32) 13330(33-40)	0(1-10) 8250(11-40)
7.52 (TU of PF1=33)	6000(1-11) 8000(12-32) 12500(33-40)	6000(1-15) 0(16-40)	6000(1-9) 11330(10-32) 13330(33-40)	0(1-12) 7700(13-40)

4. Conclusions

We have developed a novel reformulation of the constraints that involve the binary and 0–1 continuous variables and have used GA in conjunction with GAMS to obtain a population of good solutions for the supply chain redesign problem. It can be seen that by using this novel reformulation, we are able to achieve objective values >96% of that achieved by solving the complete MILP in GAMS. Even though the objective value is lower, we obtained a population of solutions which can further be analyzed. It is observed that the network structure for all the members in the population is similar and their objectives are different because of small differences in the time at which capacities expand or relocate. Hence, a direct inference would be the low sensitivity of the objective value to the changes in implementing the decisions.

References

1. P. K. Naraharisetti, I. A. Karimi and R. Srinivasan, 2006, Capacity Management in the Chemical Supply Chain, International Symposium on Advanced Control of Chemical Processes - ADCHEM, 2-5 April, Gramado, Brazil.
2. Z. Michalewicz, C. Z. Janikow, 1991, Handling Constraints in Genetic Algorithms. Proceedings of the Fourth International Conference on Genetic Algorithms, July, San Diego, USA.
3. M. C. Ferris, 1998, Interfacing optimization and visualization software, Computer Sciences Department, University of Wisconsin, Madison, Wisconsin, USA.