Optimization to Manage Supply Chain Disruptions Using the NSGA-II

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Abstract. Disruption on a supply chain provokes lost that can be minimized through an alternative solution. This solution involves a strategy to manage the impact of the disruption and thus to recuperate the supply chain. Difficulty of this management is the diversity of factors such that becomes complex to provide or choice a solution among the possible ones. Depending on the objective(s) to optimize are the strategy to follow and the solution to choice. In this work the Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization NSGA-II is used as the strategy to generate and optimize (minimize) solutions (lost) in front of a disruption. The included objectives are cost, risk and the place of facilities supporting the supply chain recuperation. These objectives are combined to generate possible solutions and to choice one such that it provides a proposal to minimize the disruption impact on a delimited period of time. Advantage of NSGA-II utilization is the provision of a practical formal and computational tool to analyze different scenarios without simplifies the complexity of a standard real supply chain. The illustrative exercise presents recovery scenarios for a crude oil refinery supply chain.

Keywords: disruption management, supply chain, optimization, NSGA-II.

1 Supply Chains and Managing Disruption

A supply Chain (SC), in nature and in human societies incorporates a set of interdependent supply entities, such that the produced for one is consumed by others ones, such that they supply the consumption of thirds, and so on. This supply – consuming process, interactive and some time cyclic, applies to any individual or social activity. An alive organism is example of a supply chain of meals, oxygen and vital stimuli among organs and tissues. Departments of an organization, industrial, financial, educative, etc., chain the supply each provides, such that from this chaining it results the organization offered product: devices, financial plans, education, etc. In turns, this product (good or service) is required by suppliers in order to generate required products to other people and organizations. This supply – consume process occurs to different individual or organizational levels, with different scopes too.

In spite of the general description of before examples, it evidences the complexity of the interaction process in a SC. There are diverse suppliers and consumers, of different

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kinds and sizes, interacting during distinct moments and through diverse circumstances, some times unexpected [17].

SC approach has shown its efficacy to modeling the supply – consume process in nature and the society to bounded scale. Several natural processes to molecular, individual or population level as well as diverse industrial, services, governmental or commercial processes can be suite modeled, to small or medium scale using this approach. Currently, challenge is to achieve such SC process modeling to large scale.

In order to model the SC interactions in a systematic way it is required do it like a process, formalized such a way to set enough flexibility to properly describe complex situation, diverse ones, and such that precise analysis and diagnosis can be made. Complementary, computational tools such that they allow trust solutions and with efficacy and simplicity. All fashioned such that the parameters variations to describe varied modalities are agile and direct.

In the interdependent supply – consume process whenever a chain entity (slave) fails to supply its product, it affects to the consumers. Eventually these affected entities leave to supply their products affecting in turns their consumers. And so on. An entity leaves to provide its products when suffer the lack of needed elements to produce it. This can be due to the fail on the supply of some element(s). Usually the fail inducing disruption is provoked by an unexpected event that affects the process.

A SC disruption has consequences of different magnitude, depending on the strategic position inside the chain of the lack supply product: fail on the gasoline supply in the Sidney airport in 2002 provoked a domino cascade of supply disruptions such that drops lost of hundred of thousand of million dollars. Fail on the blood and oxygen supply from the heart of an alive being to the rest of the organism due to an infarct, if large, get the being collapse and dead.

1.2 Disruption Management

In front of a disruption the look for emergent suppliers and routs is needed to supply the product which supply was interrupted. The look for alternative routs of provisioning sets a process combining diverse circumstances, determined by the location of replacing products. Such emergent processes to deal with disruption have a cost weighted by the urgency to incorporate to recuperate the SC operation.

In nature as well as in human societies to successfully surmount the disruption negative effects, it depends to some extent, on the capacity from the affecters to generate alternative plans and to strategically apply them. An adequate disruption management it includes to take in account, the SC disruptive scenarios, even the low probable or implausible. It means be aware about the risk situations that the entity is exposed as part of the SC. As well, it includes to be anticipated to disruption with viable solutions, of practical implantation; in the case of human SC with a costs assessment too. Complementary, the strategies to take in the interrupted resources: information on emergent providers including their location, answer capacities considering spend time and costs.

In essence, disruption management implies to minimize their negative effects by setting bounds through space, time and any kind of costs. Minimization in a dual vision implies the optimization of the plausible solutions; at least of some of them. This minimization/optimization of the disruption negative-effects/solutions, i. e, the disruption managing, let the survival of the entity being affected, either alive being or social chain; furthermore, the permanence and competence of this SC.

The analysis on optimization/minimization of the solutions/negative-effects to manage SC disruption, natural or social ones, makes evident that this is not a linear process. It combines several factors each with the relevance weight depending on the circumstances. Solutions are not exclusive but can be weighted in different manners. Furthermore, optimization/minimization is multi-objective. Thus, there are several alternatives to optimize solutions, depending on the weighting to each objective throughout the solution.

The disruption administration process in a SC involves parameters and objectives to optimize. In this circumstance the optimization must be a heuristic. The optimization process to minimize negative effects with the disruption is divided in three steps. The fist step covers identification of possible solutions, considering parameters that characterize a disruption in a SC as well as different objectives in consideration. The second step is the process that ranks the objectives, from where the solutions can be generated. The third is the choice of solutions.

Supply chains in petroleum industry is characterized by the product availability in the right place at the right time is an important matter. Supply availability in any kind of industry is necessary for its maximum development, and it is needed the knowledge of the right supplier in some fixed circumstances in order to minimize the lack of product supply. Making a finished product is a hard task, even if the distribution is decentralized because of the difficult of organizing the product delivery. Another problematic is fluctuation in the production demand, which is produced by many factors and circumstances.

The agent based systems can emulate activities performed in industry departments, as well the suppliers, logistic services, etc. Agents can model business policies and simulate different processes in industry. The supply chain dynamic is emulated by simulations of discrete events on agent based modeling.

An adequate SC disruption management is part of the whole planning in industry processes. It includes a transport network of supply raw materials and finished products, as well as risks identification and plans to control these risks once they happen. It is mandatory to have a short term demand projection and the required raw material quantity to cover this demand. It is necessary to manage and select raw materials in order to improve cost and production, and find the best way to storage raw materials.

This work shows the way that a supply chain management in petrochemical industry can be modeled to determine a viable solution to control unexpected events. Disruption management can help in the disruption detection even before they occur if their causes are well controlled, in the worst case, there would be time enough to take adequate measures to correct them. The problem causes can be detected in order to prevent and minimize looses in near future.

2 Optimization Using Multi-objective Evolutionary Algorithms

In most of the real world problems, requires information that of solutions we can obtain is by using heuristic method. A heuristic is a method that search for almost optimum solutions with a reasonable computational cost. Although this methods does not warranties the best solution, because in most of the real world scenarios we are not able of knowing how near of the optimum ours solutions are.

2.1 Basic Genetic Algorithm

Genetic algorithms were developed by John H. Holland in the early 60s [5, 6], motivated by his interest in solving problems in machine learning. Within evolutionary computation, genetic algorithms emphasize the importance of the so called sexual operator over the mutation operator, and uses a probabilistic selection. Standard construction of a Genetic Algorithm involves:

- Randomly generating an initial population.
- Computing fitness value for each individual.
- Perform selection (in a probabilistic way) based on the fitness values.
- Apply genetic operators (crossover and mutation) in order to generate the next population.
- Loop until the maximum number of iterations is reached.

Genetic algorithms do not need specific information in order to guide the search because they are a heuristic technique. A GA can be seen as a black box that can be connected to any particular application. In order to apply a genetic algorithm, the following basic components are required:

- A representation of potential solutions to the problem.
- A method to create an initial population of possible solutions (this is normally done in a random manner).
- An evaluation function that plays the role of environment, classifying the solutions depending on the fitness value.
- Genetic operators that modify the composition of the offspring produced for the following generation.
- Specify values for the genetic algorithm parameters (population size, crossover probability, mutation probability, maximum generation number, etc.)

The traditional representation used to encode a set of solutions is the binary scheme, where a chromosome is composed of a chain with the form $b_{1,} b_{2,} \ldots, b_m$ where each element is called alelo (that could be zeros or ones).

Genetic algorithms have been widely used in multi-objective optimization because of its population-based nature, which allows the generation of several elements of the Pareto optimal set with a single run [4].

The NSGA-II is an approach with $O(kN^2)$ computational complexity (where k is the number of objectives and N is the population size). The NSGA-II uses a selection operator that creates a mating pool by combining the parent and offspring populations and selecting the best (with respect to fitness and spread) N solutions from them. Because of its low computational requirements, its elitist approach, and its parameterless sharing scheme, the NSGA-II is the algorithm chosen to act as our optimizer in the research reported in this paper.

2.2 NSGA-II

The Fast Elitist Nondominated Sorting Genetic Algorithm for Multi-Objective Optimization, NSGA-II [12] successfully combines the following key elements:

1. A fast nondominated sorting approach.
2. A density estimator.
3. A crowded comparison operator.

In the fast nondominated sorting approach, each solution is compared with every other solution in the population to find if it is dominated. First, all individuals in the first nondominated front are found. In order to find the individuals in the next front, the solutions in the first front are temporarily discounted. The procedure is repeated to find all the subsequent fronts.

To get an estimate of the density of solutions surrounding a particular point in the population the average distance of the two points on either side of this point along each of the objectives is adopted. The obtained quantity serves as an estimate of the size of the largest cuboid enclosing the point of interest, without including any other point in the population (the so-called crowding distance).

The crowded comparison operator guides the selection process at the various stages of the algorithm towards an uniformly spread out Pareto-optimal front. Between two solutions with different nondominated ranks, the point with the lower rank is always preferred. Otherwise, if both points belong to the same front, then the point which is located in a region with a lower number of points is preferred (the size of the cuboid enclosing it is larger).

In the algorithm's main loop, a random parent population P_0 is initially created. The population is sorted based on nondomination. Each solution is assigned a fitness equal to its nondomination level (1 is the best level). Thus, minimization of fitness is assumed. Binary tournament selection, recombination, and mutation operators are used to create a child population Q_0 of size *N*. From the first generation onward, the procedure is different. First, a combined population $R_t = P_t \cup Q_t$ is formed. The population R_t will be of size *2N*. Then, the population R_t is sorting according to nondomination. The new parent population P_{t+1} is formed by adding solutions from the first front till the size exceeds *N*. Thereafter, the solutions of the last accepted front are sorted according to the crowded comparison operator and the first *N* points are picked. This is how the population P_{t+1} of size *N* is constructed. This population of size *N* is now used for selection, crossover and mutation to create a new population Q_{t+1} of size *N*.

In the modelling of the supply chain, profit and looses can be calculated for different scenarios. A GA can be used in order to find in which conditions the profit is bigger with the minimum of losses.

3 Modeling and Parameterization to Manage SC Disruption

There are mathematical models for supply chain, its behaviour as well as its performance indicators [14, 15]. The mathematical evaluation functions to SC parameterization are presented below.

Following the model, in this preliminary work, just to show that this approach can be used in real industrial scenarios, SC disruptions are used to generate solutions and some of them will be optimized applying the NSGA-II, using simulated binary crossover [11] in order to handle the parameters involved in SC problems. Figure 1 shows the outline of the way in which our GA works.

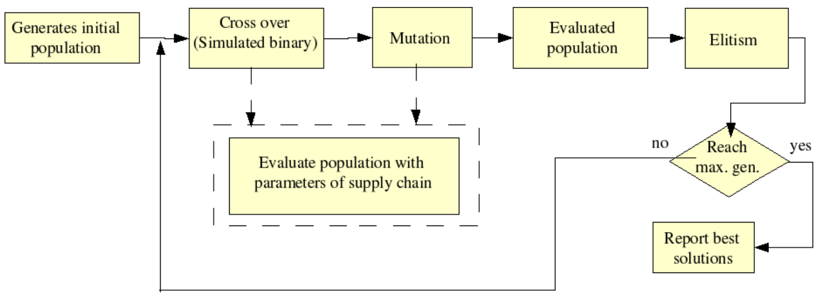

Fig. 1. Flow diagram of a genetic algorithm

In the model, the relationships between providers and clients are taken into account, such that the clients should be satisfied with an opportune and right delivery of the product. Relationships between providers and consumers in different scenarios have been modelled to represent the available scenarios to consumer satisfaction with the product delivery. Special attention is paid on the SC disruption.

As particular instances of the modelling, ad-hoc simulators oriented to a particular industry are implemented. A GA combined with a simulator or with a model of the supply chain where this model plays the role of the chromosome is used. There exist simulators that can estimate the cost and production in the chemical industry with the knowledge of the probability of the disruptions. However, it is not clear what are the best values of the parameters of this simulator to be adopted in order to increase the production while lowering the cost.

3.1 Evaluation Functions for Supply Chain

In order to model the relation between providers and consumers, a reinforcing model proposed by Lawrence et al. [14] is used, they divide SC models based on the underlying optimisation model (facility location) and the risk measure (expected cost). Their models intend to work efficiently in normal conditions as well as with disruptions.

The supply chain is analysed looking for possible disruptions in the provider-consumer network; such a network and possible disruptions is modelled on a virtual supply chain of refineries as follows:

$$\sum_{j\in J} F_j X_j + \sum_{s\in S} q_s \sum_{i\in I}\sum_{j\in J} h_i d_{ij} Y_{ijs} \tag{1}$$

Equation 1 represents disruption cost. There are J refineries open, F is the cost during a time period (e. g. 1 day) the refinery is open, X is a Boolean variable with value 1 if refinery is open and 0 otherwise. The value q represents if in the scenario $s \in S$, a disruption occurs; such that it obligates to take a different path to deliver the product in quantity h; d is the path distance. Y is Boolean too so 1 if this path is used, or 0 if not.

One way to obtain a SC disruption model together with the associated cost is by modeling previous disruption experiences such that the obtained knowledge be applied on later similar situations. However, this is not a preventive way to deal with disruptions. A preventive manner is to set a model considering most of the every eventual disruption so that be prepared with recuperation plans, even to the worst case having maximum cost. This cost can be used as a maximum risk measure to deal with any eventual (minor) disruption. Thus, the maximum cost U should be minimized.

Minimize

$$\mathbf{U} \tag{2}$$

Subject to

$$\sum_{j\in J} F_j X_j + \sum_{i\in I}\sum_{j\in J} h_i d_{ij} Y_{ijs} \le U, \forall s \in S \tag{3}$$

$$\sum_{j\in J} Y_{ijs} = 1, \forall i \in I, s \in S \tag{4}$$

$$Y_{ijs}, X_j \in \{0,1\}, \forall i \in I, j \in J, s \in S \tag{5}$$

In this last modeling the scenarios, the probability of disruption occurrence as well as the cost to each is randomly generated. On this context, cost of recuperation to the SC disruption is optimized.

In the simplified model created each scenario represents two kinds of disruptions: 1) a refinery cannot produce, and 2) an inaccessible path to deliver or receive the product. When a refinery is not producing consumers need to be provided by other refineries, it having an extra cost directly related to the distance from the supply refinery and the amount of product required. If the amount required is low, it is preferable to ask for product from open neighbor refineries such that cost remains low. Each neighbor refinery could provide a small quantity of its production in order to not get rid of product for its own distribution. This is simple estimation illustrative to multi-objective minimization; this one will be the standard deviation of product taken from other refineries for the local distribution. An illustrative scenario with five refineries showing distances among them is in Figure 2: a path disruption occurs between R2 and R5 as well as a production disruption in R4.

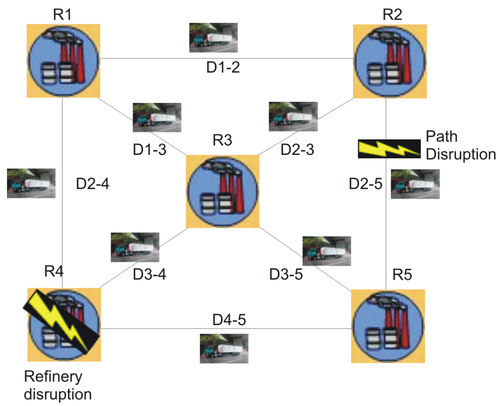

Fig. 2. An illustrative scenario

A general tip during a practical application using a multi-objective GA, is to optimize a low number of objectives simultaneously, such that the computational resources needed can remain manageable, especially when dealing with stochastic variables having a high level of unpredictability. Moreover, when the evaluation of a noisy objective function is used, more care is needed because given the same input parameters, different outputs could be obtained. Multi-objective GAs have a robust behavior because the average performance of a population acts like a noise filter [2, 7]. However, for a general multi-objective optimization, the use of a technique to avoid noisy effects to find a Pareto front with nondominated solutions is needed. To deal with difficult problems, probabilistic selection [8] and partial order [16] techniques have been used. Re-sampling methods have been found to be useful to deal with noise. An additional advantage is to avoid the loss of diversity which is induced by using probabilistic methods [3]. The price to pay is the process time increase. At the moment, because of the bounded number of elements in the SC being modeled, the evaluations time spent is low.

From our perspective, the best thing to do in this case is to fix the values of some SC variables. For that sake, we selected the more stable variables such as the number of refineries, the number of tanks, or the containers capacity. Some other variables, the two or three to be optimized, can be parameterized, e. g. the profit can be handled as a principal objective to be maximized.

4 Test of the Model

To test the model, a randomized parameterization was practiced: the number of disruptions, the probabilities for each disruption as well as the cost associated due to the distances and delivery cost to emergent suppliers is created randomly. Low probabilities to high cost disruptions are assigned. Given certain parameters, the optimization of the profit, number of refineries and product asking to any other refinery could be done.

The remarkable information is that after the algorithm execution, the output shown a consistent behavior by drawing a similar graph like the one in Figure 3. This is a front of Pareto with the set of available optimal solutions. The values do not correspond to a particular input. But the result was the same with same SC model parameterization. These evidences can support the right applicability of NSGA II to optimization practiced having an objective function evaluated in systems with low noise, this means that with the same input parameters, the resultant outputs will be near between them, where near means that the difference is not too much important in practical uses.

There are extreme cases when values change a lot with respect to previous evaluations with the same parameters. These cases are very unlikely. However when this occurs the model can be erratic and the solution could be very different to previous ones.

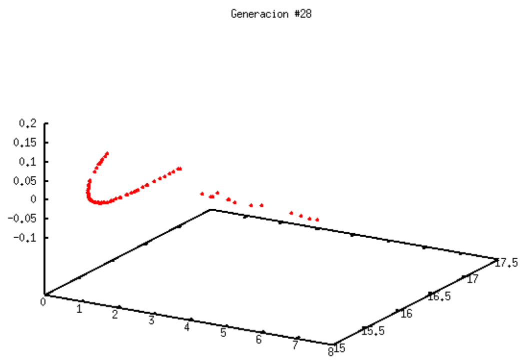

Fig. 3. Optimum values for a specific scenario

5 Conclusions

In the kind of optimization problems, an efficient and reliable algorithm is required to find a set of optimal solutions. This is the reason to use NSGA-II. A possible drawback could be the time required to run many simulations. However, this computational time investment, to assess the decision to build of a new refinery is worth spending, so that we are able to learn if our investment will be quickly recovered.

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References

[1] Bodendorf, F, Zimmermann, R. *Proactive Supply-Chain Event Management With Agent Technology*, International Journal Of Electronic Commerce, 2005.

[2] D. Bueche, P. Stoll, R. Dornberger, and P. Koumoutsakos. Preprint: *Multi-objective evolutionary algorithm for the optimization of noisy combustion processes*. IEEE Transaction on Systems, Man, and cybernetic, 32(4), 2002.

[3] Bui, L. T., Abbass, H. A., and Essam, D. 2005. *Fitness inheritance for noisy evolutionary multi-objective optimization*. In Proceedings of the 2005 Conference on Genetic and Evolutionary Computation (Washington DC, USA, June 25 - 29, 2005). H. Beyer, Ed. GECCO '05. ACM Press, New York, NY, 779-785.

[4] Coello Coello, Carlos A.; Van Veldhuizen, David A. and Lamont, Gary B. *Evolutionary Algorithms for Solving Multi-Objective Problems*, Kluwer Academic Publishers, New York, 2002.

[5] John H. Holland. *Concerning efficient adaptive systems.* In M. C. Yovits, G. T. Jacobi, and G. D. Goldstein, editors, Self-Organizing Systems- 1962, pages 215-230, Spartan Books, Washington, D.C., 1962.

[6] John H. Holland. *Outline for a logical theory of adaptive systems.* Journal of the Association for Computing Machinery, 9:297-314, 1962.

[7] E. J. Hughes. *Evolutionary multi-objective ranking with uncertainty and noise.* In Zitzler et al., editor, Proceedings of the First Conference on Evolutionary Multi-Criterion Optimization, Zurich, Switzeland, 2001.

[8] Evan J. Hughes. *Multi-Objective Probabilistic Selection Evolutionary Algorithm.* Technical Report DAPS/EJH/56/2000, Department of Aerospace, Power, & Sensors, Cranfield University, RMCS, Shrivenham, UK, SN6 8LA, September 2000 .

[9] N. Julka, R. Srinivasan and I. Karimi, *Agent-based Supply Chain Management – 1: Framework*, Computers & Chemical Engineering, Vol 26(12), 1755-1769, 2002.

[10] N. Julka, I. Karimi, and R. Srinivasan, *Agent-based Supply Chain Management –2: A Refinery Application,* Computers & Chemical Engineering, Vol 26(12), 1771-1781, 2002.

[11] Kalyanmoy Deb and Ram Bhushan Agrawal. *Simulated Binary Crossover for Continuous Search Space*. Complex Systems, 9:115-148, 1995.

[12] Kalyanmoy Deb, Samir Agrawal, Amrit Pratap, T Meyarivan, *A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II (2000).* Proceedings of the Parallel Problem Solving from Nature, VI Conference, 2000.

[13] Lau, HCW, Hui, IK, Chan, FTS, Wong, CWY. *Monitoring the Supply of Products in a Supply Chain Environment: A Fuzzy Neural Approach***.** Expert Systems, 2002.

[14] Lawrence V. Snyder, M. Paola Scaparra, Mark S. Daskin, Richard L. Church. *Planning for Disruptions in Supply Chain Networks*, Tutorials in Operations Research Informs, 2006.

[15] Lee Ying Koo Yuhon Chen et al. *Evaluating Refinery Supply Chain Policies and Investment Decisions Through Simulation-Optimization*, Proceedings of the 2006 Winter Simulation Conference, 2006.

[16] Rudolph, G. *A partial order approach to noisy fitness functions.* In Proceedings of the 2001 Congress on Evolutionary Computation CEC2001 (2001), IEEE Press, Piscataway, NJ, USA, pp. 318-325.

[17] Smirnov AV, Sheremetov LB, Chilov N, et al. *Soft-computing technologies for configuration of cooperative supply chain.* Soft-computing technologies for configuration of cooperative supply chain. Applied Soft Computing 4 (1): 87-107 Feb 2004.