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AI-BASED OPTIMIZATION FOR FLEET MANAGEMENT IN MARITIME LOGISTICS

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ABSTRACT

This paper outlines the features of an automated Decision Support System (DSS) developed to optimize the logistics of maritime transportation for a large chemical company. The paper focuses on the design and implementation of an optimization module to complement a DSS architecture including dynamic databases, decision heuristics, and dynamic process simulation, for the systematic generation of cost-effective fleet configurations capable of meeting the company's production requirements.

1 INTRODUCTION

Experiential knowledge plays a key role in the effective management of complex industrial processes. The development of an automated Decision Support System (DSS) involves not only the accurate modeling of the logical steps followed by the industry experts, but also the ability to capture unspoken criteria of choice among decision alternatives, which highly depend upon the particular situation at hand. This paper presents the key issues and the major steps undertaken as part of an on-going project in transportation logistics for the automation of an integrated Decision Support System (DSS) to optimize the logistics of maritime transportation for a large chemical company, which runs multiple operations in geographically distributed production sites. The DSS, previously developed as part of the same project, is an interactive tool capable of generating alternative logistic configurations in an expert-assisted way and to test their performance through simulation.

In the existing architecture, a set of decision heuristics provides the general framework for the systematic definition of a family of logistic configurations. The identification of a particular solution within the family depends upon the customization of the heuristic algorithms and criteria built into the corresponding DSS module. The heuristic module contains the algorithms and criteria for flow grouping, route definition and vessel selection, to systematically generate product transportation scenarios once a set of decision parameters has been fixed for the specified case. The proposed optimization module uses Artificial Intelligence (AI) techniques based on Genetic Algorithms (GAs) to suggest specific values for the case-dependant parameters, which customize the algorithms and criteria built into the decision heuristics to suit the particular situation (problem) at hand. Based on such customization, the logical flow of the heuristic decision steps automatically generates a tentative configuration of transportation routes and resource allocation, which can be tested for actual effectiveness in the process simulation environment. The feasibility and effectiveness of each configuration needs then to be tested in the real context of the whole product movement strategy. It is the simulation module which provides the context for this performance test. The outcome of the simulation test is fed back to the GAs where it serves as guideline for the generation of improved sets of customization parameters (Bruzzone, Giribone, and Revetria 2002, Giribone, Orsoni, and Revetria 2002). The same procedure is iterated until the optimal logistic configuration is found. During this iterative process, in the search for the optimum solution, the impact of each logistic configuration can be tracked over time in the dynamic simulation environment to assess their long, medium, and short term impact on performance. Performance is here intended as the combined performance of the logistic and of the production divisions of the company.

2 THE ROLE OF HEURISTICS IN THE DECISION PROCESS

The complex nature of fleet management in maritime logistics involves highly interdependent decision processes, which lead from a list of product transportation requirements specified by the Production Division, to a corresponding set of fully configured ship missions capable of meeting such transportation requirements in a cost effective way. In particular, the information pertaining each product transportation requirement includes the monthly product quantity and the corresponding ports/plants of origin and destination. The fully configured ship missions are specified in terms of product aggregations, transportation routes, resources (ships) allocation and estimated departure times (slots) for each of the ports involved in the mission (Bruzzone et al. 2002).

While several approaches can be pursued for the optimization of the entire product transportation network (e.g. Artificial Intelligence techniques, Linear Programming, Simulation, etc.) none of them can address the whole problem alone. The closest problem formulation which finds analytical solution is the Vehicle Routing Problem (VRP), however, the fleet management problem, as proposed in this paper, is far more complicated than the conventional VRP (Golden 1991, Toth and Vigo 2001): there is not a fixed vessel capacity (ships are only available in a range of commercial sizes which vary according to their product abilitation), and the quantities of products to be shipped to and from the various destinations are known only in terms of cumulative monthly (product) flows. In addition, safety regulations impose compatibility constraints on the products to be loaded on the same ship. Therefore, a direct application of the VRP solving algorithm is not a viable approach in this case. The computational class of the problem is NP-Complete and it can only be optimized using heuristic approaches. Until the most recent past, the company's way to deal with the logistic fleet management problem was "expert-centered", which means that it relied on a combination of semi-quantitative techniques and experiential rules in order to ensure the feasibility and effectiveness of the solution. In such an approach the judgment of the subject matter expert appears to be the most value-adding contribution. Building from this experiential knowledge base the proposed approach and, particularly, the heuristic module provides a formalization of the logical steps actually followed by the experts in the formulation of a logistic fleet configuration.

The simulation module performs feasibility (i.e., ability to complete all the required transportation missions within the specified deadlines) tests and cost-effectiveness tests on a well defined scenario (Bruzzone and Kerckhoffs 1996): the proposed logistic configuration. In order to provide actual support in the decision making process a specialized module is required for the definition of product transportation missions capable of meeting the needs of the processing plants. In response to these perceived needs a decision heuristic module was designed, as a step by step tool, which starting from an exhaustive list of transportation requirements (representative of the whole company's transportation needs) enables the user to group product movement orders into product transportation missions, to specify the corresponding transportation routes, and to associate one or more vessels of given type and size to each defined mission. In its original design the heuristic module can be used either as an interactive tool, by industry experts (manual operation mode), or as a semi-automated, propositive, tool by less experienced users. When run as an interactive support the heuristic module enables the user to manually select the product flows which define the individual missions and evaluates the effectiveness of each mission in terms of navigation distance, percentage utilization of vessel capacity, and cost. When run as a semi-automated tool, the heuristic module lists a number of feasible solutions on a by-mission basis ranking them by overall distance, effective use of vessel capacity, and cost. Based on such ranking the user may select one or more of the proposed plans for further testing through simulation. Finally, the resource requirements of the chosen plans are spread over a weekly calendar, subject to a reality check on the actual availability of such resources, on the current status of on-going transportation missions, and on the current production/raw materials stock available at the chemical plants, to ensure the feasibility of each mission. In order to perform such reality checks, the heuristic module interacts with dynamic databases which are constantly updated with current information respectively from the simulation module (status of on-going missions) and from the production plants (production/raw materials currently in stock.) The full automation of the decision process built into the heuristic module can only be obtained running it in an "optimizer" mode in conjunction with the GAs-based optimization module, which links the performance outcomes of the simulation model, on a selection of proposed logistic configurations, to the corresponding settings of the case-dependant parameters required for the customization of the decision heuristics. The full automation of the decision process built in the heuristic module entirely depends upon the automated choice of such case-dependant parameters. The specification of such parameters univocally determines the outcome of the heuristic module, which is bound to produce a deterministic configuration of routes definition and resource allocation from the systematic application of the built-in criteria and algorithms, at each decision step. While such parameters in the interactive and in the semi-automated operation modes are specified by the user, leading to logistic configurations which are as good as the experience and knowledge of the user, in the automated optimizer mode they are specified by the GAs, thus excluding the need for user intervention. The procedure is automatically iterated until no further improvement is found in the performance measures.

The major advantage of using GAs in the optimization process is that the search for the optimum solution begins from an entire "population" of scenarios and, thus, from multiple points in the space of the possible solutions, which highly increases the chances of finding the actual optimum, rather than a sub-optimum (Goldberg 1989). In addition, GAs are based on stochastic rather than deterministic rules, which further improves the effectiveness of the search (Goldberg 1989, Koza 1992).

3 THE CASE-SPECIFIC PARAMETERS IN THE DECISION PROCESS

The logical flow of decision steps required to define the set of ship missions capable of meeting the production requirements specified by the production division is represented in Figure 1.

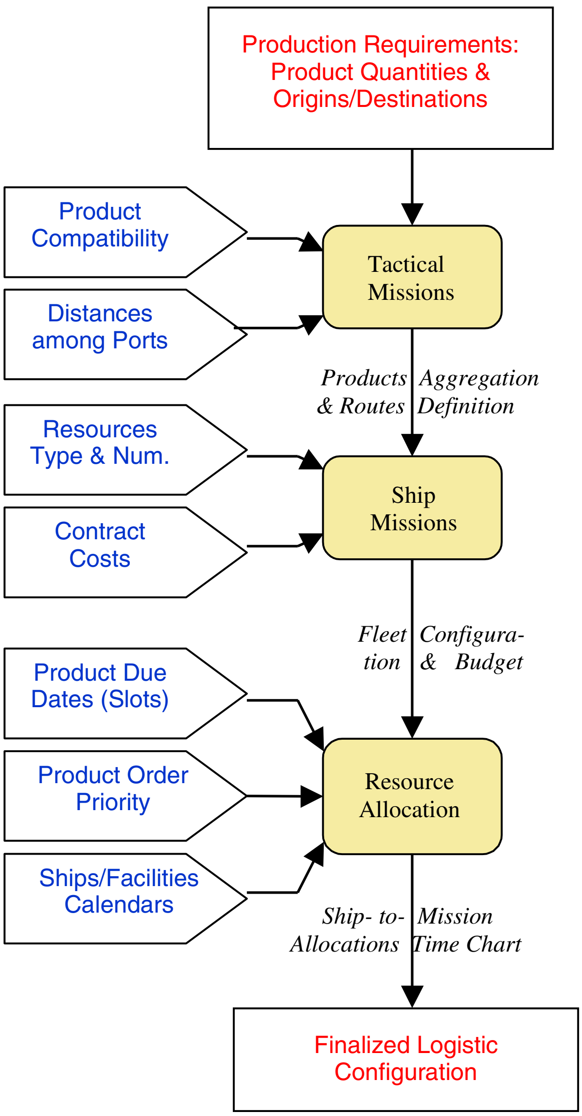

Figure 1: Logical Flow of Decision Steps

Specifically, the first step involves the formulation of a first attempt solution, by simple aggregation of the product flows into tactical missions. Product flows are monthly transportation requirements specified in terms of total amount (tons), ports of origin and destination. Tactical Missions are entities, which identify the lists of ports to be reached, their sequence, and the amounts of the different products to be loaded and unloaded in each port. Flow grouping, Time Grouping, and Sequencing are the corresponding heuristics sub-modules which lead to the definition of Tactical Missions. The Flow Grouping heuristic requires the specification of two decision parameters for product aggregation purposes: the first one is the "distance coefficient" which constrains the area of the search for compatible flows to the one which makes the aggregation cost efficient in terms of added navigation distance. Product aggregation into missions starts from the maximum product flow in the list of transportation requirements (i.e., the current maximum not yet aggregated into a mission) and expresses the extension of the cost-efficient aggregation area in terms of distance from the segment $(OD)_{max}$. The length of $(OD)_{max}$ represents the distance between the ports of origin and destination for the identified maximum flow. The maximum distance from such segment for a port to be included in the mission's sequence can be expressed as the product of the distance coefficient and the length of $(OD)_{max}$. The second decision parameter to be set for Flow Grouping purposes is the "coefficient of unused capacity" which measures the tolerance on capacity utilization as a percentage of the capacity already committed (i.e., the maximum capacity committed as a result of prior aggregations within the same mission) on each leg of the mission's route (a leg is the portion of a route between two subsequent ports). This parameter is used to assess the convenience of flow aggregation based on its impact on overall capacity utilization.

The Time Grouping heuristic enables to allocate monthly ship capacities to each group of product flows previously defined. Each flow is analyzed in terms of monthly fluctuations from the average on the temporal horizon of interest: the "uniformity level" parameter discriminates which portion of the flow can be allocated a fixed monthly capacity (corresponding to either Time Charter or COA contracts), and which portion needs to be treated as contingency and thus dealt with through occasional ship hires (corresponding to Spot contracts). The uniformity level expresses the percentage of the monthly average which is accepted as tolerance on the monthly fluctuations for the purposes of allocating a fixed ship capacity. Once the uniformity level is specified, each product flow can be split into a "uniform" and a "residual" component, which are separately handled in the subsequent decision steps. The Sequencing heuristic completes the definition of the Tactical Missions by specifying the most effective order in which the ports involved in each mission need to be reached. Each Tactical Mission needs to be further specified in terms of its constitutive Ship Missions: in other words it is necessary to allocate commercial ship types and capacities to handle the cumulative monthly capacities previously committed as part of the Flow Grouping and Time Grouping decision steps. The ship class (i.e., vessel type and capacity) is assigned according to the nature of the product(s) to be shipped and according to production sustainability considerations (e.g. plants' storage capacity and production/consumption rates). In particular two decision parameters need to be specified in order to make flow sustainability assessments in relation to the number of ships allocated and their types. These assessments involve stock-out and over-stock risk analyses on the storage capacities available at the production sites. A first decision parameter is the “Impact Factor” which is used to adjust the impact of location and facility-specific factors affecting the ship’s cycle time on a mission. Each Port and Terminal for instance are characterized by a Port/Terminal Factor which is a function of the nationality of the port and of its average traffic level (Fleming 1997). Such factors affect the duration of the wait times and operation times of the ship in that particular port (Frankler 1987). The second decision parameter is a boolean variable which abilitates either an optimistic or a pessimistic “sustainability hypothesis” regarding the storage capacity of the origin/destination plants for a given product. The optimistic hypothesis allocates the entire storage capacity to the flow for risk analysis purposes, whereas the pessimistic hypothesis allocates to the flow a fraction of the whole capacity proportional to the corresponding percentage of the total flows insisting on the same storage facility. Once flow sustainability has been verified for a given set of ship classes, the Ship Mission is defined and specific resources need to be assigned choosing the corresponding ship contracts and fixing their estimated arrival/departure time slots to/from each of the mission’s specified ports. The selection of a particular type of contract, either Time Charter, COA or Spot, for a given ship mission is based upon Cost Factors which are contract-specific and reflect the current market trends in terms of daily cost of hire per unit capacity (ton) as well as the number and types of ships already hired by the company. Knowing the due dates (i.e., acceptable time slots) of each product flow, the speed of each allocated ship and the types of operations that they need to perform in each port, it is possible to determine the estimated arrival/departure times of each ship to/from each port, and thus check for possible dock/facility accessibility conflicts when spreading the different Ship Missions over a timetable. A set of four decision parameters need to be specified in order to enable Conflict Resolution, in case of overlapping time slots. In the first place it is necessary to specify the Priority Factor for each of the flows present on board, which is a function of the potential production losses caused by the late arrival of the ship. The second and third decision parameters are the Ship’s Cost Factor and the Penalties Weight Factor which directly depend upon the daily cost of the ship, as specified by the contract, when used within the terms of the contract and beyond the terms of the contract, respectively. The last decision parameter for conflict resolution purposes is the Time-Frame Factor which accounts for the nearest due date (time slot) of each of the flows on board. As explained in the following, the decision parameters identified in this section will be the objects of GAs-based optimization for the purposes of generating feasible and cost-effective fleet configurations. The decision heuristics module performs preliminary feasibility tests at each decision step to ensure that the applicable process constraints are not violated in the proposed solution: once a product flow is chosen for aggregation on a tactical mission, the tool verifies the compatibility among the products on board of the same ship, the ship classification (oil, gas, chemical) and the availability of arrival/departure docking facilities and equipment (Nevins et. al 1998, Thiers and Janssens 1998). If one or more constraints are violated a warning is flagged, otherwise a first attempt solution is created. Further iterations of the procedure will try to improve the quality of the solution by optimizing ship and dock utilization using real-time information (estimated arrival time, estimated departure time, docks schedule, resource schedule, etc.). The output configuration is tested through simulation in order to evaluate its performance and its robustness: the heuristic results are obtained under a set of assumptions, which may be far from realistic because each step of the actual process is strongly influenced by the effects of stochastic variables. Simulation allows the users to estimate not only the performance of a particular solution, like an analytical model, but also the corresponding confidence level. The robustness of the simulation results will be a measure of the effectiveness of the proposed solution.

The output of the simulation model is fed back either to the expert or to the genetic algorithm (depending on whether the system is run in interactive or automated mode) for further improvement of the proposed solution; in the automated mode the mechanism of solution improvement is of key importance towards the optimization process because the whole system is run in closed loop.

4 THE GA-BASED OPTIMIZATION MODULE

The automated optimization of the route definition and resource allocation process is based upon heuristic algorithms which enable the formulation of a complete product movement scenario, once a set of scenario-specific parameters have been fixed. Such parameters, highly dependent upon the particular situation at hand, for instance the geographic area of interest, the temporal horizon of interest, the monthly distribution of product flows and any contingent need that may arise, which in the current company practice, are typically estimated by operations managers based on their experiential knowledge about the process and based on their personal judgment. Variations in the choice of such parameters significantly impact the outcomes of the heuristic algorithms and thereby the logistic scenario suggested by the system. For instance, for the purposes of product flows aggregation in tactical missions, the choice of a particular distance coefficient, limiting the maximum distance of a port to be included in the mission, highly influences the number of product flows which can be considered for aggregation and also the overall length/ duration of the mission. These constraints, in turn, drive the number and the capacity of the ships required to perform the specified mission, and thereby influence the choice of the corresponding types of contracts. If the distance coefficient was arbitrarily set to a default value not entirely supported by specific knowledge about the process for the particular case to be addressed, it would lead to the definition of a logistic configuration of routes and resource allocation which could be sub-optimal in terms of overall service costs. Another interesting example of case-specific parameter is the uniformity level in the context of the Time Grouping heuristic algorithm (Section 3). A high flow uniformity level, and thus a very tight tolerance on the monthly fluctuations of each product flow leads to a high utilization of the ship capacity allocated to the uniform component of the flow, however it may generate an excess of monthly residual flow components to be managed as contingencies. Such situation may lead to a logistic configuration far from optimal, depending on the contingent price of the capacity unit (ton) for the ship type and capacity class required. The setting of the uniformity level needs to be chosen considering simultaneously all the company transportation requirements and cannot be fixed to a default value, for an efficient utilization of the fleet.

In order to minimize the problems associated to bad parameter settings, this research proposes the development of an optimization module based upon GAs. The main function of the GAs-based optimization module is to support the choice of such parameters settings considering the particular type and amounts of product flows and the present performance objectives, in relation to the vessels already available (under contract), and the current costs of new hires, by contract type and capacity class.

5 INTERACTIONS AMONG GAS, HEURISTICS, AND SIMULATION

The interactive use of AI techniques and simulation constitutes a hybrid approach, which the authors have extensively applied to address complex decision making issues in supply chain management. The approach has successfully supported the development of DSSs typically combining either artificial neural networks (ANNs) or genetic algorithms (GAs) with simulation in a variety of industrial contexts (Giribone and Bruzzone 1997, Bruzzone and Signorile 1998). The choice among the possible AI techniques highly depends on experiential knowledge in the area of application and on the specific optimization problem within such a context. GAs are capable of handling relatively complex combinatorial problems and to manage large numbers of process variables without any training on historical data.

Each iteration can be seen as an evolutionary step in which the least efficient solutions are discarded. The next iteration is an attempt to improve the remaining solutions through mutation and cross-over techniques.

Although both ANNs and GAs show a good optimization potential in their combination with simulation, the logistics of fleet management seems to be better addressed using GAs, given the lack of historical data relevant to the specific optimization areas and the large number influencing factors which affect the choice of the decision parameters.

GAs present several advantages in their application to optimization problems: their search for the optimum begins from an entire population of solutions, and thus from multiple points in the space of the possible solutions, thereby increasing the chances of finding the actual optimum rather than a local sub-optimum. Moreover, GAs base their search on stochastic rather than deterministic rules, which further increases the effectiveness of the search.

In the proposed DSS architecture the GAs-based optimization module is interfaced to the simulation module through a heuristic module which contains all the criteria and algorithms required for the specification of the logistic configuration. The heuristic module consists of multiple sub-modules which represent the logical steps that logistics managers would follow to determine the means and the resources required to satisfy the plants production requirements. Each sub-module has built in constraints and requirements which are typical of the real system.

Specifically, these are compatibility constraints (i.e., among products for aggregation, between product and ship, between product and dock equipment, capacity constraints, and dock accessibility constraints (space-wise and time-wise). The need for this intermediate structure is determined by the complexity of the problem which, as mentioned before, recalls a complex version of a nested VRP, in which neither the size of the vessel, nor the route, nor the type of product is fixed. Such problem complexity leads to the need to narrow the areas of optimization, while searching for a global optimum across the entire set of product flows. While each decision step is taken simultaneously for the whole set of product flows, the outcomes of each step necessarily influence the decisions taken in the following step, creating a chance for sub-optimization in an application context in which decisions are so highly interdependent. It is in such respect that verification of the logistic strategies through simulation becomes of vital importance to test the performance of the individual choices not just from the perspective of the single ship mission, but from the perspective of the whole product movement plan. These interactions among the different DSS modules are shown in Figure 2.

The optimization module consists of a set of GA-based modules, which are fed with specific data characterizing the optimization context and return a first attempt set of decision parameters. Once the settings of such parameters have been finalized, the heuristic module univocally generates a routes configuration and resources allocation plan, which is then tested for feasibility and cost effectiveness through simulation. The overall cost of the first at tempt solution, as calculated by the simulator, will be used as guideline in the GAs-based optimization module for a new iteration.

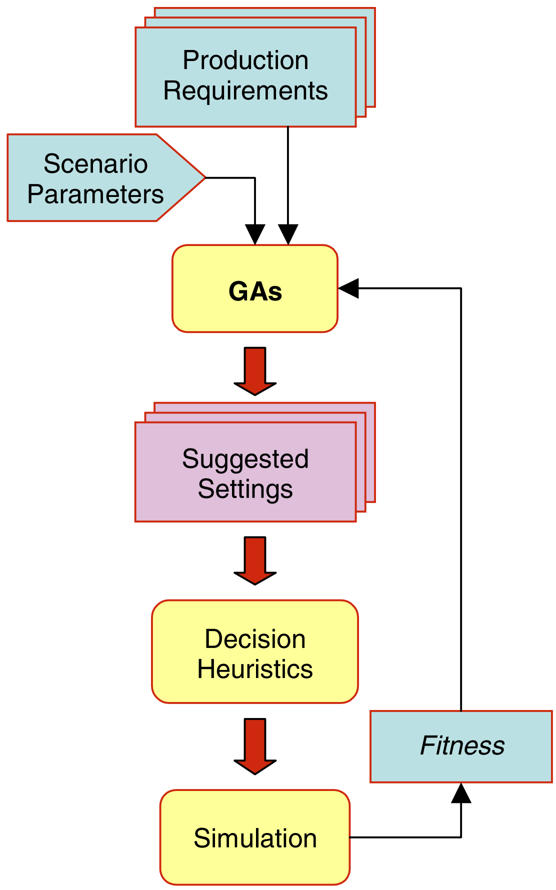

Figure 2: Logical Flow of the Optimization Process

6 STRUCTURE OF THE GA-BASED MODULE

As mentioned in the previous section, GAs search for the optimal configuration starting from a population of first attempt solutions. This population consists of individuals (e.g. strings of characters) whose chromosomes represent a potential solution of the optimization problem (e.g. a logistic configuration). The genes of such chromosomes, instead, define the set of optimization parameters described in Section 3 of this paper. The encoding proposed for the implementation of GAs in this particular application context involves the following genetic coding of the chromosomes, explained in Table 1 (A1, A2, A3, A4, A5, A6, A7, A8, B1, B2, B3, B4).

Any individual of this kind contains the complete set of information for the customization of the heuristic algorithms. This information, along with the specification of a particular scenario, enables the automatic generation of a consistent logistic configuration of routes and resource allocation. The target function evaluated by the simulation for such a logistic solution measures the individual's "fitness" and constitutes a starting point for GAs-based optimization.

Table 1: Genetic Encoding of Optimization Parameters

A1	Distance Coefficient (Flow Grouping) Float 1.0 → 2.5, step 0.2 (8 combinations)
A2	Unused Capacity Coefficient (Flow Grouping) Float 0.0 → 127.0, step 16 (8 combinations)
A3	Uniformity Level (Time Grouping) Float 0.0 → 127.0, step 16 (8 combinations)
A4	Impact Factor Coefficient (Ship Selection) Float 0.5 → 2.0, step 0.1 (16 combinations)
A5	Sustainability Hypothesis: Optimistic [0] versus Conservative [1] (Ship Selection) Boolean 0/1 (2 combinations)
A6	Cost Factor for Time Charter (Contract Selection) Float 1.0 → 1.3, step 0.1 (4 combinations)
A7	Cost Factor for COA (Contract Selection) Float 1.0 → 1.3, step 0.1 (4 combinations)
A8	Cost Factor for Spot (Contract Selection) Float 1.0 → 1.3, step 0.1 (4 combinations)
B1	Flow's Priority Factor (Conflict Resolution) Float 1 → 1280, step 80 (16 combinations)
B2	Ship's Cost Factor (Conflict Resolution) Float 1 → 1280, step 80 (16 combinations)
B3	Penalties'Weight Factor (Conflict Resolution) Float 1 → 1280, step 80 (16 combinations)
B4	Time-Frame Factor (Conflict Resolution) Float 1 → 1280, step 80 (16 combinations)

The initial structure of a genetic program is the initial population of strings. Each string in the initial structure is randomly chosen out of a uniform probability distribution. A specified target function serves the purposes of systematically measuring the "fitness" of each individual in the initial structure as well as the fitness of all the successive generations proposed by the GAs.

For the purposes of this study the target function is defined as a multi-objective function combining in a weighed sum the following performance measures:

- *Total Product Movement Costs*
- *Total Fleet Costs* (extended to all ships' hire and operation costs)
- *Total Costs of Unmet Performance Targets* (penalties associated to unmet delivery/pick-up dates and production losses related to stock-out and over-stock conditions at the processing sites)
- *Percentage Utilization of Time Charter Ships Capacity* (Average Utilized Capacity versus Available Capacity)

It was chosen not to specify the actual weights associated to each component of the target function since different users and different situations may privilege some measures of performance over others. Simulation-based testing on a population associates a value of fitness to each individual through the specified target function. The individuals are then ranked according to their fitness. Only the best fit individuals are allowed to reproduce according to a reproduction rate (i.e., percentage of the population which "survives" the fitness test) which is specified in the GAs. The mechanism of GAs reproduction is shown in Figure 3. The individuals selected for reproduction are randomly paired and a cross-over is performed on each pair exchanging randomly selected portions of the respective genetic heritage at randomly selected points.

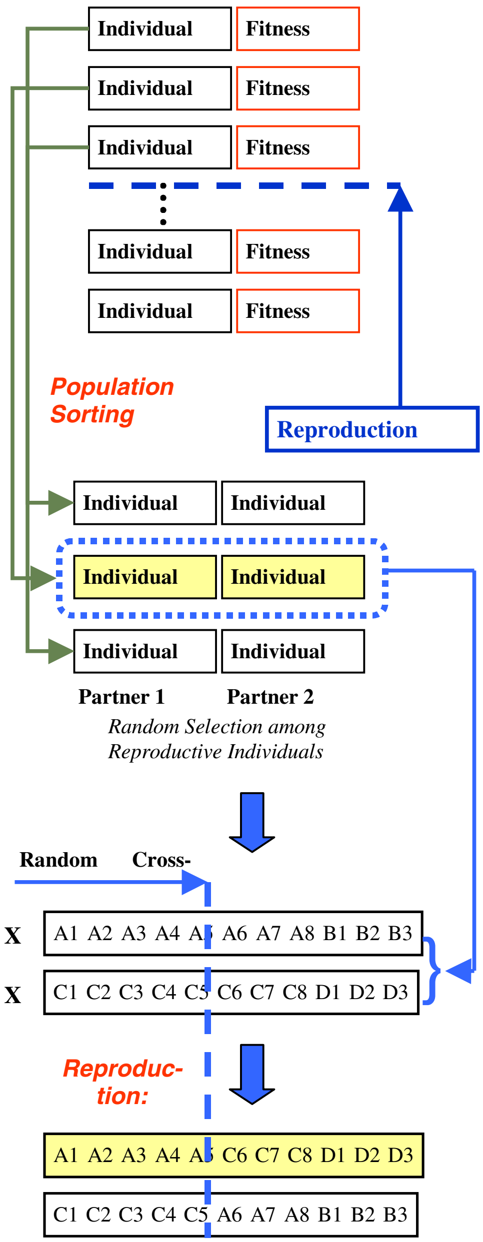

Figure 3: GAs Reproduction Mechanism

Once a new generation is obtained through reproduction another genetic operator takes care of individual mutation according to a specified mutation rate. As represented in Figure 4, mutation consists of performing random changes on a random number of genes of the selected individuals. This way the new generation is complete and it can be tested through simulation in order to get their fitness assessed prior to their joining the remaining of the previous population. For the purposes of this work the population size was set to be equal to 20 (e.g. 20 individuals in the initial structure), the total number of generation was set to 200, fixing a reproduction rate of 50% and a mutation rate of 5%. These preliminary settings represent reasonable first attempt values, however they are expected to be fine-tuned with use and experience.

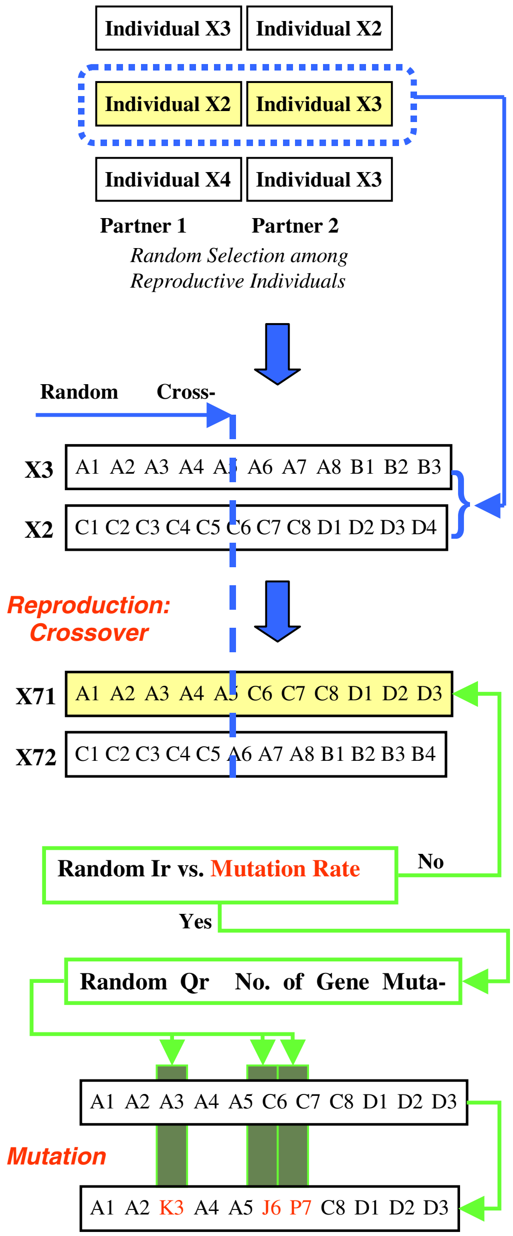

Figure 4: GAs Mutation Mechanism

7 CONCLUSION

This paper introduced a GA-based optimization module to automate an interactive DSS for the logistic management of maritime transportation in the chemical industry. The paper focused especially on the functional requirements of the optimization module, on the structure of the corresponding GAs, and on the issues related to its implementation in the DSS. Specifically, the paper addressed the interactions between the optimization module and the decision heuristics for the purposes of automated scenario generation and optimization. In the proposed architecture the decision heuristics provide a general framework to systematically generate a family of logistic solutions. Case-specific customization of the heuristic algorithms and criteria particularize the solution to address a specific problem. A GA-based module was introduced to expedite the optimization process by automating the choice of the case-specific parameters. While this optimization approach has been outlined with respect to a specific industrial context, the concept of using GAs in combination with heuristic approaches can easily be generalized to address the optimization of interdependent decision processes under multiple levels of uncertainty.

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