The Processual Programming Essentials – Criticism and New Options

▪

Ion Gh. Roșca
Ph.D. Professor
George Moldoveanu
Ph.D. Professor
Octavian Thor Pleter
Candidate Ph.D. Lecturer
Cosmin Dobrin
Ph.D. Senior Lecturer
Academy of Economic Studies, Bucharest

Abstract. *The Process Programming Basics: Priorities, Heuristic or Genetic Algorithms? This paper analyzes methods to optimize process programming, starting with the heuristic algorithms, then reviewing the current method previously advanced by the authors, the quantitative priorities, and finally approaches the problem with an innovative and promissory concept: the genetic algorithms and the "total costs and risks" optimization criterion, which is an alternative to both optimization with constraints and optimization with Lagrange multipliers. This new method emulates natural systems, thus borrowing from their robustness and adaptability. The method proves particularly useful in a turbulent and changing environment, requiring a realistic simulation model and also parallel processing in a high power computing grid.*

Key words: operations management; aggregate programming; master scheduling; multidisciplinary optimization; genetic algorithms.

▪

JEL Classification: C61, D81, L23, M11.

The heuristic algorithms have been very popular with the operations management literature and practice, until the priority quantitative measures took their place (which we have advanced and sustained). It is the time though for the next step in our opinion, which may well be the genetic algorithms within the biologic rational model, used as a better representation of the artificial world.

1. The research objective and the criticism of the current situation

The objective of the research is to provide more efficient methods for aggregate programming, master scheduling and operational programming. Thus, the aggregate programming is an operational management tool aimed at balancing processing or supply (Q_t^S) with the demand level (Q_t^D), by introducing additional costs such as: inventory cost, overtime cost, inactivity cost, shortage cost, hiring and firing cost etc. (C_i).

The managers act to achieve:

$$\min f = \sum_{L=1}^{n} C_i$$

where:

n is the number of additional costs used in the decision making process.

However, the aggregate programming has limits, which are not enough revealed by the users in practice, such as:

- Both the demand forecast, and the aggregate programming use equal time intervals (months, quarters), and not with a small time step (on-line), which may generate methodical errors, greater time intervals incurring proportionally bigger errors; for instance, a Q1 demand dated 1st of January is quite different from one dated 31st of March.
- The inventory and other costs are considered variable, i.e. proportional with the quantity of products. Both the variable and the fixed costs are abstract, all costs being in fact combinations of variable and fixed.
- In practice, the shortage is a hybrid between the two ideal hypotheses, reporting and lost sales.
- The high productivity variance is ignored, using the average productivity of an employee, taken as constant. In reality, the productivity varies from an employee to another, from a shift to another and within a week, month or year even for the same employee. For instance, it is notorious the case of the automotive industry, where the daily productivity is lower in the third shift, as well as in the days of Monday and Friday, and in the months of December, January and June, for all shifts.
- There is no account for the working days within each month, equal months and equal quarters being considered.
- The methods are adequate for undifferentiated products (commodities such as sugar or wheat). For the majority of products, which are differentiated, even though the fabrication cycle takes the same amount of time for every variety, there is an important reduction in productivity if the demand is fragmented over a wide span of differentiation variables.
- Many applications assume that *D* manufactured units are enough to satisfy the demand *D*, ignoring a percentage of rejected units, which may be important in some industries, such as microelectronics, due to the silicon raw material imperfections. In fact, $\frac{D}{1-\frac{\text{rejections}[\%]}{100}}$ units should be produced to satisfy the demand *D*.
- The methods ignore the fact that some clients are dominant in the total demand, and a negotiated sequencing of deliveries may be used by the manufacturer to flatten the demand curve. Other methods of flattening are also used by the managers, whereas the aggregate programming methods assume the natural demand, taken as ineffable.
- It is assumed that the number of workplaces changes with the number of employees, which does not hold true for the majority of the real manufacturers. The hiring and firing costs should include these workplaces adjustment costs as well. Moreover, often the additional workplaces have access to less productive assets, thus the production vs. number of employees is not always a linear function.
- Many classical applications do not account for the reductions in costs as an effect of producing quantities multiple of the optimum batch dimension (for instance, in the steel industry the steel quantity should be a multiple of the charge mass).
- The classical methods may not work for those industries where the produced quantity is not strictly controllable (e.g. in agriculture, horticulture, fishing and extractive industries).
- Many methods do not account for a good practice of organizations during the gaps in demand: vacations for employees. If the vacations are uniformly distributed all year long, the methods are correct, but the managers usually take the opportunity to concentrate vacations in the demand gaps.
- Applications do not allow for the experience curve, which severely limits the productivity of a freshly hired workforce as a consequence of a peak demand.
- Although the methods accept the shortage hypothesis, assessing the cost of shortage is a problem with uncertain and variable solutions. The current management avoids the shortage by overestimating this cost, because it has been noticed that the deficit hits hard the very loyal customers segment.
- As a summary of some of the previous points, we may notice that classical aggregate programming methods assume all *the functions which model the processes as linear*. In practice, many of these functions are in fact non-linear and the managers are compelled to adjust the results with their experience, flair and intuition. On the other hand, computing with non-linear functions lead to discouraging calculus complexity.

In the step subsequent to the aggregate programming, the master scheduling (calendar central plan), which constitutes a planning norm strategy, has as an objective function:

$$(\max/\min)f(x)=\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{p}q_{ij}^{k}\times x_i\times C_i$$

where:

q_{ij}^{k} is the quantity of goods, works, services etc. of the type *i*, with the attribute *j*, processed in the time interval *k*;

x_i is the price used to express the value of products, works, services of type *i*;

C_i is the efficiency criterion, which may be expressed as the unitary profit, when we search to maximize the function, or alternatively as the unitary penalty due to failing to meet the contractual obligations with respect with terms, quality or quantity, when the maximum of the function is sought;

p is the number of programmed time intervals;

m is the number of priorities used by the decision making factor in the programming process;

n is the number of products works and services programmed and considered by the manufacturer.

The realities in the Romanian organizations suggest the use of the loss minimizing functions from not meeting the contractual obligations.

However, the question is what instruments are adequate for this purpose, and we need to focus on them further.

To the level of the master scheduling, the multicriterial decision theory, and the vague sets theory provide the possibility to align criteria such as the traditional customers' priority, the maximum profitability activities, direct exports, high value products, reduced adaptation costs (reaction speed to change). However, after the global and detailed alignment between resources and objectives, after the load and workforce utilization factors calculations, after determining the breakeven point, the assumed master schedule must respond primarily to the requests made by the clients and not to the manufacturer's preferences.

To the level of the structural (operational) *subunits*, the instrumental resources provided by the "priority rules", the programs are fed to a leading processing center, which may control a larger system. Thus, the rule "first come, first served" in the processing center (FIFO) is a democracy rule in operations programming, typical to superior systems (with a high degree of organization). Yet, the activity first to arrive in the actuator center may be undesired in the following stream. We stand definitely for the "pull" concept here, and not for the "push". In these circumstances, we may resort to another rule, such as the "shortest activity", which frees operators promptly, but all clients have to be served, internal as well as external.

From the test we have accomplished, we drew the conclusion that a very useful rule is the following: "first to be processed is the product with the least time reserve for the current operation". However, none of the recommended, "rational" rules is able to solve all the demands of the processing system, in all cases. A prioritization of those in practice may be done through the estimation of the mean processing time, and the advance or the delay time. Also, we suggest more ways of implementing, such as:

i) singular;

ii) additive combinative;

iii) multiplicative.

The later implementation method leads to the greatest benefits, but requires a large effort, which makes it inoperative. Yet, the singular implementation method proved during the experiments enough benefits.

The ordinance instrument layout provided by the priority rules is enhanced by the procedural or the heuristic algorithms, generously offered by operational research.

This instrument layout is not an universal solution though, because it has enough limitations, such as:

- it operates with restricted realities (the case of Johnson, Next-Best, Branch and Bound algorithms);
- it uses static data, which in reality are dynamic, such as: operator and machine release times, internal delivery terms etc. (the case of sequential upstream-downstream programming);
- the use of objective functions to minimize the final term of execution, the immobilization time for the work in progress, the delay or advance factors, which are difficult to operationalize, with lots of efforts in practical cases.

The conclusion is that this operations management instrument layout, although useful sometimes, fails to reveal its practical utility, especially in the current, turbulent environment, with low predictability and high volatility, with the need to a real-time strategic response.

2. The first advance: priorities and not deadlines

Our experience in the field allow us to formulate the priority as a numerical measure resulted from calculations, including the intermediate deadlines or the final fabrication ones, the size of the asset immobilization and the incurring loss thereafter, the time of the execution cycles etc. We reached a practical format for the priority measure:

$$p_{ivt} = T_{livi} - d_{devans,ivt}$$

where:

p_{ivt} is the numeric (quantitative) priority measure for the product i, structural subunit v and operation t;

T_{livi} is the time interval to the deadline of supplying the product i;

The $d_{devans,ivt}$ is a function of the lead time, which is expressed in working days or calendar days as well; putting it in mathematical form:

$$d_{devans,ivt} = f(d_{cicluproces})$$

The resulted numbers are grouped on subunits and are ordered in strictly increasing strings. At the end of these relatively simple calculations, which work on sets like the number of parts of a product, augmented by the number of operations, the numeric priorities measures are recorded in the programs. For instance, the priority 20.8 is recorded in the January master schedule, the third decade operational plan, for the subunit which processes the product i. An alternative method from the literature to quatify the priorities is the following:

$p_{ivt} = T_f - T_c - \alpha \times d_{cilcuproces,ivt}$

where:

T_c represents the calendar date for which the "priority" is determined;

a is the coefficient to increase the processing cycle time.

If the numbers resulted from calculations are negative, they mean delays, with the highest delay having priority, whereas if the numbers are positive, they are advance times, and the lowest advance having priority. We recommend caution on the d_c, which is dynamic even in narrow intervals, and it leads to restructuring the priority system, especially by its action on the resources of all types. This dimension has the greatest implications upon the priority measure, as our simulations suggested.

In practice, it is essential for implementing the priority numerical measures to codify the products, the structural subunits and to set up a data bank with the quantitative measures which will supply the operation programs.

Practical considerations

The formulas presented above rely on a linear model and work with static measures. In reality though, the measures are rather dynamic. Thus, the lead time is a variable with respect to the level and the structure of the processing capacity. This is a general situation in operations management. Another overused static model is the breakeven analysis, with fixed costs and unitary price, and yet these fluctuate with the quantities of goods or services purchased by the customers, particularly in killing competition environments.

To narrow the gap between the theory and practical calculations, we suggest a proportion between the demand of every resource and its corresponding supply, at the level of each processing link, according to the following relationship:

$$\frac{\frac{1}{K_{nv}}\sum_{i=1}^{nv}\sum_{j=1}^{mv} Q_{ij,v}^{k} \times t_{ij,v}^{k}}{\frac{1}{K_{nv+1}}\sum\sum Q_{ij,v+1}^{k} \times t_{ij,v+1}^{k}} = \frac{F_{tdispv}^{k}}{F_{tdispv+1}^{k}} = C$$

where:

K_{nv}, K_{nv+1} represent the coefficients of fulfillment of the norm in the links *v*, and *v*+1 respectively;

$t_{ij,v}^{k}$, $t_{ij,v+1}^{k}$ is the time required to process the products *i* with the priority *j*, in the link *v*, and *v*+1 respectively;

F_{tdispv}^{k}, $F_{tdispv+1}^{k}$ are the available time resources in the link *v*, and *v*+1 respectively, in the time interval *k*;

C – constant which, under circumstances of ideal efficiency, is going towards 1.

The other notations are similar to the ones used previously. To be noted that the relationship above would generate equality between priorities and calendar dates, but this is a desired rather than an effective situation. Moreover, the contigency and not the configurative concept is used in reality, to generate answers efficiently and effectively.

All these considerations lead to a new idea, that of studying and at a later stage implementing, of the genetic algorithms, in the context of our recent advances, reflected in both literature and business practice.

3. The next generation methods: TCR and heuristic algorithms

3.1. The total costs and risks - an alternative optimization criterion

The use of the *total costs and risks* function (*TCR*) represents an attractive alternative to the use of arbitrary constraints in the optimization process. The function is expressed directly in currency units (for instance •), being additive and allowing the aggregation in complex systems optimizations, with as many hierarchy levels as desired.

The implementation of the multidisciplinary optimization based on the total costs and risk criterion (*TCR*) has been presented in a number of papers (Moldoveanu, Pleter 2006, 2007, Pleter, 2004). As this method is a clear advance in the line of rationalization of the decisional system, we may attempt its implementation in the operations management too.

The multidisciplinary optimization is a non-linear optimization model to minimize an objective function or a comprehensive cost function (comprising as many variables and criteria as possible concerning the phenomenon under analysis, corresponding to all relevant aspects from all disciplines, both technical and economical). To add up more simple single-disciplinary cost functions, which make up the multidisciplinary cost function, these have to be expressed in comparable units, for instance in the same monetary units. Thus, the *TCR* is different from the classical optimization approaches: the optimization with constraints, and the optimization with Lagrange multipliers, which are used to introduce the constraints as penalizing costs. *TCR* allows the problem to be treated as an optimization without constraints, like the Lagrange method up to a point, but it avoids its problem with the multipliers, which are non-dimensional variables, lacking obvious significance in the problem space, with subsequent arbitrary choice based on trial and error. *TCR* approaches constraints in a more natural way. In fact, in nature there are no definite, net constraints. These are rather the result of abstract thinking. In nature, the limits of a system may be better modeled as costs and risks in every scenario. For instance, if we wish to optimize the trajectory to exit a building, instead of putting a constraint that the trajectory passes through the location where the door is placed, we may do an exhaustive model: passing through the door costs close to zero (just the energy to press the handle to open and then to close the door) and the risks are also nil. The exit through the windows at the ground floor costs more and poses some risks, the exit through the windows at the upper floors poses risks which may be quantified as the probability of injury multiplied by the costs of injury integrated on the entire life time of the subject. The exit through the wall is costly (breaking the wall) and presents the risk of injury and loss of time. Under normal circumstances, this example seems insignificant, but let us assumes, that we run a multidisciplinary optimization to evacuate a building collapsing in fire, by more individuals, through a single exit door. In these circumstances, the outcome will include more evacuation routes, even the riskier ones. As obvious from this example, we need to simulate the building as accurately as possible. *TCR* may be applied only on accurately simulated environments, but nowadays engineering is based on such thorough simulation, even with buildings.

The risks are translated into costs, by the method used in the financial management (the probability of the undesired event multiplied by the resulted damage). The name “total costs and risks” indicates just that, that an exhaustive and complete definition of the problem is required, in both space and time dimensions (for instance, we need to account for the costs and risks over the entire life span of the elements which generate them). Consequently, we are not working with draft or approximate reality any more, but the computation power of the current high power computing grids, as well as the fitness of the genetic algorithms to parallel computing, lead to the conclusion that such a natural modeling method, without constraints and Lagrange multipliers may be implemented, as the above-mentioned papers have ascertained.

The multidisciplinary optimization of a subsystem *k* will consequently pursue the minimization of the following function:

$$TCR_k = \sum_i C_{i,k} + \sum_j p_j \times R_{j,k} = \min$$

where:

TCR_k represents the value of the total costs and risks for the subsystem *k*;

$C_{i,k}$ are the costs generated in the subsystem *k* in the considered scenario;

$R_{j,k}$ are the estimated damages to the subsystem *k*;

p_j are the probabilities of damage occurrences as a function of the scenario considered.

The most interesting feature of the *TCR* function is the additivity, which is adequate to its implementation to complex systems. Thus, the multidisciplinary optimization for a system made of *N* subsystems will be carried on through minimization of the cumulated objective function:

$$TCR = \sum_{k=1}^{N} TCR_k = \sum_{k=1}^{N} \left(\sum_i C_{i,k} + \sum_j p_j \times R_{j,k} \right) = \min$$

The idea to use the *TCR* method in programming and planning processes is believed to be useful because the thorough analysis in time and space yields “routes”, “ways” or variants to reach a planning strategic goal.

The programs are clear examples of equal achievement lead us to the idea to use the *TCR* method, as an alternative to the instrumentation recommended in the economic theory and practice.

Besides avoiding some simplified assumptions described earlier, a *TCR* simulation environment could include valuation of the options in the delivery contracts, quantifying the risks of serious consequences with respect to non-delivery to certain clients within certain time limits, as well as all other risks and threats for all contracts pending.

After the optimization calculus, the best aggregate planning and master scheduling solution would be generated, and yet another crucial asset would emerge: if any initial condition would change (for instance a contract cancellation), the optimization process would continue with a gradual approach to the new optimum.

3.2. The genetic algorithms (GA) - a challenging proposition

“The genetic algorithms are search methods based on the natural selection and genetic mechanisms, abstracted from the algorithms used by living beings to adapt to a large variety of environments in perpetual change. We looked for the robustness of the natural systems; they are robust in an efficient and effective manner.” (Goldman, 1989).

Based on research of Charles Darwin (1871), Holland (1975) and Goldberg (1989) we tried a GA approach to the economic processes, where the operations management is a generous research field, particularly in the areas “research space”, “crossover and mutation operators” (Moldoveanu, Pleter, 2007, Moldoveanu et al., 2007, Pleter, 2004). Moreover, based on Goldberg book, we started studies to implement GAs with simple “fitness” functions, through cost efficient procedures (Moldoveanu, Pleter, Dobrin, 2007), the immediate perspective being that of “computer implementation”, the authors looking for a computing grid to demonstrate the power of the method. Some encouraging conclusions may be underlined:

i) in nature there is no “optimum”, just “better”;
ii) in nature as well as in economy, the objective function changes dynamically with the environment;
iii) the genetic algorithms are performing very well if the objective function keeps changing during the process.

From our simulations using the crossover and mutation operators, better adapted individuals (solutions) emerged, with further good probability of perpetuation (enhancement).

The population of a generation $i+1$ (each individual being represented by a finite string of symbols called *genome*, coding a possible solution in the given space of a problem) is more adapted than the previous generation i, although some $i+1$ individuals may be less adapted than those in i, a consistent and robust approach to economic improvement.

The process repeats itself forever with new “generations” of solutions, but we may choose to stop it when the best solution found is fair and the benefits of the search are obvious.

References

Aprahamian, F., Bertrand, A., Besancenot, D., Ferrari, J.B., Huynh, K. (1999). *Microéconomie*, Bréal, Rosny Cedex

Darwin, C. (1859). *On the Origin of Species by Means of Natural Selection* (http://www.talkorigins.org/faqs/origin.html)

Darwin, C. (1871). *The Descent of Man, and Selection in Relation to Sex* (http://www.zoo.uib.no/classics/descent.html)

Goldberg, D.E. (1989). *Genetic Algorithms*, Addison-Wesley, Boston

Goldratt, E. M. (1997). *Critical Chain*, North River Press, Great Barrington, MA

Holland, J. (1975). *Adaptation in Natural and Artificial System, University of Michigan*

Moldoveanu, G. (2005). *Analiză şi comportament organizaţional*, Editura Economică, Bucureşti

Moldoveanu, G. (1999). *Managementul operaţional al producţiei*, Ediţia a doua, Editura Economică, Bucureşti

Moldoveanu, G., Dobrin, C. (1999). *Managementul operaţional al producţiei*, Editura ASE, Bucureşti

Moldoveanu, G., Dobrin, C. (2007). *Turbulenţă şi flexibilitate organizaţională*, Editura Economică, Bucureşti

Moldoveanu, G., Mincu, C. (1993). *Conducerea operativă a producţiei*, Centrul Editorial-Poligrafic ASE, Bucureşti

Moldoveanu, G., Pleter, O.T., „Capabilitate vs. Performanţă Managerială”, *Simpozionul Internaţional „Management şi Competitivitate”*, Academia de Studii Economice, Bucureşti, 2004

Moldoveanu, G., Pleter, O.T., „Optimizarea multidisciplinară în managementul serviciilor”, *Simpozionul „Abordări moderne în managementul şi economia organizaţiei”*, Academia de Studii Economice, Bucureşti, 2006

Moldoveanu, G., Pleter, O.T., „Multidisciplinary Optimization in Services Management”, *Economie teoretică şi aplicată* nr. 5/2007, Bucureşti

Moldoveanu, G., Roşca, I., Pleter, O.T., „Improving Organizations By Replacing The «Mechanical» Model With The «Organic» One”, în *Studii şi cercetări de calcul economic şi cibernetică economică,* 2007, Academia de Studii Economice, Bucureşti

Pleter, O.T. (2005). *Administrarea afacerilor*, Ediţia a II-a, Editura Cartea Universitară, Bucureşti

Pleter, O.T, Ştefănescu, I.B., Constantinescu, C.E., „Simultaneous 4D Trajectory Optimization Using Genetic Algorithms”, *Proceedings of ICNPAA*, Budapest, 2006

Russell, R.S., Taylor III, B.W. (2000). *Operations Management*, 3rd Edition, Prentice Hall