4th International DAAAM Conference
"INDUSTRIAL ENGINEERING – INNOVATION AS COMPETITIVE EDGE FOR SME"
29th - 30th April 2004, Tallinn, Estonia

GA MODEL OF ON-LINE OPTIMIZATIONS OF PRODUCTION COSTS OF CONTINUOUS PROCESSES

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Abstract: In modern industry, which consists of many different more or less computer-aided processes, there is almost lack of integration between different subsystems. Manufacturers continue to refine how they plan the production to meet the demands and manage fast growing dynamics. In this regard, we have seen the evolution to MRP, MRP II and ERP. However, even those with extremely sophisticated planning systems often have major difficulties in executing in the plant in a way that meets market demands cost-effectively. Planning system in major commercial ERP solutions such as SAP, Baan, Oracle, PeopleSoft consists of many small special parts of software for planning of different resources: material requirement, capacity usage, human resources, cash flow and time management.

In the capital-intensive process industries, linear programming and other optimizations methods are more typical approaches to planning. Optimizations methods such as genetic algorithms, genetic programming or evolution programming bring a great opportunity to solve complex optimizations problems in such environment.

In modern production plants where complexity is soaring, very highly trained personnel are needed. The new methods enforce new kind of skills and special knowledge. Through optimizations and decision support, it leverages investment in plant equipment and information systems.

Key words*: Genetic Algorithm, Constraint Planning, Material Requirement Planning, Master Production Scheduling, Capacity Planning, Enterprise Resource Planning*

1. PROBLEM DESCRIPTION

Global economy bring a great pressure on every single manufacturer who strives to meet performance targets, including higher plant throughput, better customer service, higher product variety, shorter cycle times, lower inventory levels, increased return on assets, and higher profits. This really translates to an enterprise's ability to demonstrate agility. Unfortunately, the logical goals of agility create direct conflicts in day-to-day operations.

Concurrent pressures from stockholders, customers, and market competition are squeezing manufacturing plants in terms of efficiency and profitability. Such time pressure leads to new challenges; production on demand which has increased the number of products; as a result, smaller order quantity must gear up to handle extra loads, customers are now penalizing the suppliers not only for deliveries that are late, but also for those that are too early or incomplete.

The flexibility not only on the production line but also on every business process is becoming a must for surviving. The production cycle must be shrinked but is just one small time interval in the whole customer order life cycle as was reported by Jezernik [13] and many others [21, 25]. There are a lot more processes and parameters nowadays, which cross the company's boundaries.

Most of decisions at different business stages must be served by accurate data because the wrong decision can have a great impact on the whole business in one time period. Typically, at the moment of customer's demand without the view on capacity utilization, material requirement and inventory, acceptance of order and delivery date cannot be handled in a proper way.

Realistic systems are rarely deterministic if either the dependencies or boundary conditions are well known. Mathematical models [17, 18, 26] have a great degree of uncertainty with numerous parameters with questionable dependencies.

Aluminum processing is a typical mass not interrupts industry with great dependency on small changes in the whole process because the rules of changes and algorithms are mostly unknown to the conventional mathematical methods and there are not the best methods for solving complex tasks in real production system.

In special situations the simplified models are a good decision for solving problem in a single point in the line of business processes. Unfortunately we cannot control the impact between many different processes. What does the low price of material goods mean in the aluminum producing process when the process of casting and melting is frequently stopped because of bad quality?

Controlling the material flow, capacity usage, and production cycle time can be of special advantage in case of malfunction. Production process it self is complex enough without all co-processes, which are obviously part of one business process.

What does the shortest operation time mean when we have a long set-up time? What are worthy the high efficiency of capacity usage with constantly long supplier's delivery times and unpredictable delays in the supply chain?

Synchronizing tasks for closely connected processes can be a great opportunity for gaining business at higher efficiency. At the crisis time we need a different scenario for immediate use ever changing conditions and with major parameter – speed. Polajnar et al. [20] reported that only speed could bring a company predominant position on the market.

ERP or MRP II systems provide planning based on current transaction from the market and purchasing, manufacturing execution systems, shop floor control, and data collection system track actually happening at the point of production. Optimizing engine is needed to synchronize customer's expectation and company environment with production execution system.

MPS system can be used for planning and forecasting the future trends on the market and in production process as well. The real situation with many dynamic changes of plan cannot be planned correctly with the system like MPS. The methods of operational research come in place, which provide a search mechanism for reaching contradictory business goals and the best economic results with minimal costs.

2. TRENDS AND SOLUTIONS IN MODERN INDUSTRY

Industry specific solutions are based on developing a good idea, manufacturing philosophy or modelling. Some of them are become on industry trend in specific industry or philosophy whit specific view on manufacturing processes or ideas for future; JIT, Lean Manufacturing, CIM, Virtual Company, TQM, BMS, Fractal Company and a lot of others [2, 19].

Some of them have had a great success in many companies. It is very difficult to find out the right reason of success or disaster by implementing one of the ideas in practice, the priorities of some different aspects in production, integration of business processes, quality control, material flow. New information technology brings up new models and concepts such as Biological Manufacturing or Fractal Company. Polajnar [19] reported that fractal in such company represent work unit whit his own space of activity.

The high technology it self does not give the guarantee for success since it is not advantageous when it is not used in a proper way. The company must build up its own strategy when the well-known models and philosophy can be of great help.

2.1 Simulation and optimization as bridge between planning and production

In the manufacturing the software architecture simulation and optimization bridge the gap between the planning system and the shop floor system. ERP or MRP II provides planning and management information based on current transaction from the market and purchasing manufacturing execution systems, shop floor control, data collection systems track which actually happening at the point of production.

Quality decisions depend on accurate information and the information on current state is almost late when the decision for future is in question. With accurate information and parameters the model of current state in the manufacturing process can be well described

Mathematical models are derived from mental models and are closely related (Resinovič et al. [21]). With company strategy and market demands the model of goal state can be developed but for reaching the right way it must be found with simulation and optimization engines.

Cebulj [8] reported that production planning and scheduling systems must synchronize the market demand and materials data from planning systems with the current plant status. The scheduler is an "optimizing" engine to execute plans as well as possible.

Synchronization is a combination of co-ordination and timing. With comprehensive modelling and what-if capability, a scheduling system can sequence and synchronize the plant operations [15].

2.2 Balancing Priorities

Since business goals are often at odds, a company must make trade-offs between them. For example, four common goals in plants are lower WIP inventory, higher percentage of customer deliveries on due date, higher machine utilization, and lower cycle times (Figure 1). One traditional method for improving due date performance is to build up inventory, an obvious conflict; and striving for high capital equipment utilization also forces negative impacts elsewhere in the equation.

Transaction oriented ERP systems organize large quantities of data, the scheduling and synchronizing systems add business rules, models and decision-tree logic which helps the people make better decisions. The sequences of tasks guarantee that model can reflect the real plant conditions very closely. In reality, there are a lot of exceptions such as machine breakdown, material quality side problem, absence of qualified staff on one side and changing minds of customers about product configuration, quantity, or due date. A good system must be able to resynchronize itself with the reality of the plant - usually at least daily which keeps the schedule and the plant operation in perfect synchronization [7].

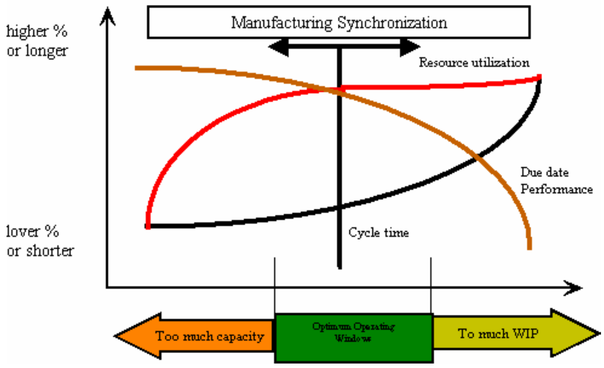

Figure 1: Scheduling techniques can help find out the best trade-offs between the conflicting goals inherent in striving simultaneously for agility, reliability, and resource utilization

The real strange of good scheduling systems consists of the ability to handle a lot of data and look only on sinful combination which make a good filter on data and serve the user with accurate and ready information.

2.3 Optimization methods

In (Figure 2) a wide variety of optimization methods are presented which were developed across the time and classified in problems areas.

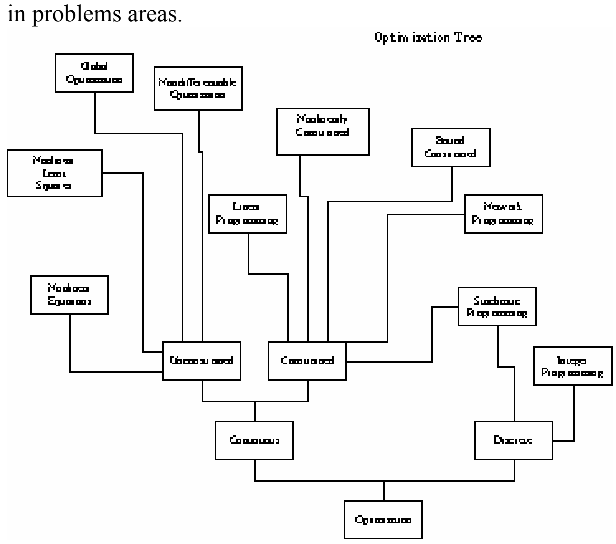

Figure 2: Optimization tree as guide to the field of numerical optimization

Methods have been developed from the problem point of view and are specialized for different kind of problems [6, 10]. A well-defined problem is needed for using each of those constraints methods in an efficient way, numeric model, goal variable and constraints. Depending on decision between "best solution" and reasonable response time the way of optimization flow is taken.

In real world the cost of optimal solution is almost too high so the solution near to optimal must be accepted for real time business decision. Accurate information is mostly more important than precision of the solution itself. Optimization model and results become useful only when they can be verified by different optimization methods. That does not mean that the quality of solution with different methods is the same.

2.3.1 Linear programming and simplex method

The basic problem of linear programming is to minimize a linear objective function of continuous real variables, subject to linear constraints [7] give detailed description of linear programming problems with examples). The standard form for describing and analyzing algorithms is

$$\min\{c^T x : Ax = b, x \geq 0\}, \qquad (1)$$

Where $x \in \Re^{\Re}$ is the vector of unknowns, $c \in \Re^{\Re}$ is the cost vector and $A \in \Re^{mx\Re}$ is the constrain matrix. The feasible region described by the constraint matrix is a polytope, or simplex, and at least one member of the solution set lies at a vertex of this polytope.

The simplex method generates a sequence of feasible iterates by repeatedly moving from one vertex of the feasible set to an adjacent vertex with a lower value of the objective function $c^T x$. When it is not possible to find an adjoining vertex with a lower value of $c^T x$, the current vertex must be optimal, and termination occurs.

The linear programming consumes a lot of computer cycles and in large models also a heavy traffic of data occurs. Another problem of this method is that it does not predict the actual decrease in the objective function $c^T x$, which can lead to solution in local minimum, or that solution moves in wrong direction from the point where another vertex can be encountered.

2.3.2 Multi-Resolution Methods and Graduated Non-Convexity

Often a function surface can be very un-smooth, having many sharp local minima, making it hard to find the overall global minimum (Figure 3). For instance, the response of a correlation mask over a noisy image tends to be noisy - the only way to be sure to locate the best match is to search through every pixel location. However, in some situations it is much easier to locate the minimum of a smoothed version of the function surface, which can then give a good starting point to locate the minimum of the original function.

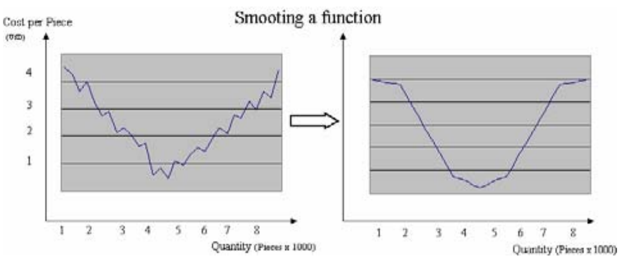

Figure 3: Smoothing a function can help find the minima

Notice that it is very inefficient to generate the function surface and then smooth it - far too many function evaluations would be required [16]. Instead, we need a new function, based on the original, which will generate a smoother surface with the major minima in similar locations to the original. In the correlation example this can be achieved by smoothing (and possibly sub-sampling) both the mask and the target image. Correlating the smoothed mask over the smoothed image will tend to give a cleaner response with minima close to the main minima of the original mask. In this case care must be taken that the desired global minimum hasn't been smoothed out of existence, which can happen if the important mask features have a high spatial frequency.

Multi-Resolution methods work by applying an algorithm to smoothed versions of an image (or data set). The result at one level of smoothing is used to seed the algorithm working with less smoothing, repeating until the solution is found on the un-smoothed original image.

A function f(a) is said to be convex over a region R if, for two points $x, y \in \Re$, the following holds

$$tf(x) + (1-t)f(y) \geq f(tx + (1-t)y), (0 < t < 1) \qquad (2)$$

Geometrically, in the n+1 dimensional space the line segment joining the points (x,f(x)) and (y,f(y)) never goes below the function surface (a,f(a)).

Such a function will have at most one minimum, which can be found by applying a local minimizer to any starting point in R.

2.3.3 Genetic Algorithms

Genetic Algorithms attempt to minimize functions using an approach analogous with evolution and natural selection. The key features are:

A point in the search space is encoded as a chromosome.

A population of N chromosomes/search points is maintained, rather than just a single point.

Combining existing solutions generates new points.

Optimal solutions are evolved by iteratively producing new generations of chromosomes in which good solutions are combined (bred) and bad ones discarded.

Usually a chromosome is a string of bits formed by concatenation of the bit strings representing each of the n parameters $a = (a_1, ..., a_n)$. The number of bits used to encode each parameter will depend on the desired tolerance.

Two chromosomes are combined by. Two parent chromosomes are each cut at a random location and the opposing sections rejoined to form two children:

abcdefghijklmnop ⇨ abcdeFGHIJKLMNOP
ABCDEFGHIJKLMNOP ⇨ ABCDEfghijklmnop

In addition, a small amount of mutation is introduced, randomly changing bits in the chromosomes. Goldberg [9] named combination of two operation Selection + Mutation = Continual Improvement and Selection + Recombination = Innovation. The algorithm starts by creating a first generation of N chromosomes scattered randomly about the search space. Each new generation is produced as follows

- Decode each chromosome to obtain a and evaluate f(a).
- Rank the chromosomes by their function evaluation
- Use some breeding strategy to combine good chromosomes and discard bad ones, allowing the better chromosomes to breed with a greater probability. This generates a new set of N individuals.
- Apply a small amount of mutation to the chromosomes.

The assumption is made that combining small sub-sections of the chromosomes, each of which will tend to improve the function evaluation of any full chromosome containing them, can form the optima. Thus these good building blocks will tend to be reproduced and will propagate through the population. Eventually all the current generation of individuals should end up in the global optimum.

For functions of the form where each is continuous with upper and lower bounds a straightforward bit string encoding of a is sufficient for the chromosomes. However, permutation problems (such as the Traveling Salesman Problem) are much harder -

Simulated Annealing algorithms are likely to give better results.

Under the right conditions Genetic Algorithms have been shown to converge to good solutions remarkably quickly and have the advantage that the rate of convergence varies in accordance with the complexity of the search space.

3. MODELING ALUMINIUM PRODUCTION WITH GENETIC ALGORITHM

Genetic Algorithm (GA) is optimization method with great power when a large space of solutions must be discovered. The main problem areas for GA so far are non-deterministic problems which means that way to the optimal solution is not known which is specially true in complexity of production and business processes [11].

The main goal of these models is to reach optimal production plan with consideration of dynamic conditions such as customer orders, inventory, capacity utilization and quality of raw material and products [14, 23]. For easier representation of results and clear model representation it consists of four optimizing phases:

- data preparation and initial of global variables,
- searching for optimal production plan on bases of customer orders,
- time scheduling and costs optimization,
- inventory optimization,
- costing capacity optimization with consideration of raw material quality.

The optimization process is managed with decision tree logic where each optimization task is one node with different attributes. Al-Attar [1] reported about model, which transforms the resource optimization problem into a sequence optimization problem. These attributes help us to control process with particularly rules to rich most accurate goal at different time. Because of lack of time we can execute different phases of optimization out of job time and save the phase optimization results, which can be used as, input when the time for decision is very limited. Values of attributes can be changed on global level and used in particular tasks, which provides a great possibility of various simulations.

3.1 Data preparation and modelling

The purpose data modelling is to provide fast integration path to the operational data from enterprise resource planning system and convert them in proper format. Data in genetic algorithm must be converted into numerical ones, which are used as genes composed in string of them called chromosomes.

The model must describe the characteristics of plant, how the various resources work, time frames, rules, or conditions. There are two different types of data; static data that does not change often (technology, machine parameters, etc.) and dynamic data which changes frequently (orders, customer requirements, market constraints, etc.) [22].

Static data includes all plant data that does not change very often, such as information about the resources (machines, tools, people, materials), as well as basic production processes (routing and operation definitions). Static data also include calendars of work shifts and Bills of Materials.

Dynamic data changes frequently, based on customers, suppliers, orders, shop floor transactions, inventory, due dates, etc. Dynamic data is acquired in enterprise software and imported frequently in scheduler system. The connection between those systems is very important and time consuming.

3.2 Definition of cost function

Decision either we are looking for maximum, minimum or target value of specific function is crucial and must be accepted at the very beginning of modelling a problem case. The whole model can be built from different perspective e.g. the profit can be defined by function based on minimum costs or by searching for maximum incomes [4, 5].

The tree layer architecture of optimization engine offers the possibility for fine-tuning of cost function and precision of result. The highest level is decision tree logic with control tasks and values of attributes witch can be also used in decision rules. The second level is genetic optimization engine with parameters, chromosomes and genes. Depending on the goal function the engine evaluates the generation of genes and uses methods such as mutation, adaptation and crossover. The third level is programmed logic which can be used for tiny tuning for almost every element of optimization i.e. goal function, constraints, computing derived variables.

In our case we decide that major goal function will be searching for maximum income based on production plan, available capacity and customer orders. The main cost function is to find optimal production program which can be realized with regard to fixed customer order amount constrained with aluminium metal quantity, capacity availability and order delivery dates. Cost function for reaching maximal profit can be defined as follow:

$$\max\left(\sum_j (c_j - b_j).Q_j - C\right) \tag{3}$$

Where

c_j - net selling price product or family products

b_j - production costs of product or family of products

Q_j - produced quantity of product or family of products

C - fixed costs of operation.

Meško [17] used similar model for multi phased business process.

In such a way we simulate environment where numerous combinations of selling prices (c_j), production costs (b_j) and quantities (Q_j) are explored with genetic algorithm and optimal solution is proposed.

Next optimization phases have different goal functions to provide minimal production costs in different production stages. Capacity planning is based on production time for machine and workers [16]

$$\min\left(\sum_i (t_m * C_m + t_w * C_w)\right) \tag{4}$$

Where

t_m - machine time on work center per work order

t_w - work time on work center

C_m - machine cost on specific work center i

C_w - machine costs on work center i

Inventory handling and material flow is the next very important segment in aluminium producing process, which is optimized in separate phase where the goal is to reach the minimal material costs. The next equation is the principal presentation of economic handling of material as reported by Ljubič [14]:

$$C_M = \sum_i \frac{C_o + Q_i C_i}{M_i} + \sum_j \frac{C_o + Q_j C_j}{M_j} \tag{5}$$

Where

C_M - material costs including purchase and warehouse costs

Co - purchasing costs

Q_i, Q_j - quantity of product i and quantity of raw material j

C_i, C_j - warehouse costs for product i and raw material j

M_i, M_j - sum requirement for product i and raw material j.

Material intensive production such as aluminium production is very sensitive to small changes of production parameters while it has big impact on economic balance on same production program. The quality of products and raw materials has a great impact on casting and melting of aluminium alloys. Because there is always one interval of concentration of specific element in the alloy we can search for most cost efficient composition of elements, which can be described as follow [16]

$$\min(\sum_i P_i \sum_j ((q_j \pm dq_j) * c_j)) \qquad (6)$$

Where

P_i - quantity of product i

q_j - raw material consumption as norm

dq_j - allowed tolerance of raw material j in alloy i

c_j - cost price of raw material

These base goal functions are starting points which are used as main direction for optimization flow, more precisely defined functions can be specified inside these ones which means the flexibility of model.

3.3 Optimization parameters setting

Parameter values are used for testing different strategies for choosing pair of genes on which crossover operation is executed. The number of generations, which are created during the evolution cycle, must be defined at the start of optimization process and initial value must be large enough to ensure improvement of cost variable.

Tests indicate that 50 generation is quite enough to reach good optimization results in our problem types. With stopping criteria it is possible to break the optimization process when the cost variable remains almost static for a given consecutive number of generations or when the predetermined level of cost function is reached.

The influence on optimization strategy is achieved with parameters values, which define relations between the gene crossover, adaptation and mutation and probability of each one. Most of these parameters can be used to enlarge the search space and variety of solutions. The greater probability for mutation, crossover and adaptation tells the genetic algorithm to search for more possible solutions. Parameter "keep best individuals" is used to speed up the searching process but good solution can be overlooked.

Problem modelling with different chromosome types can be crucial for quality of solution i.e. the probability for find up optimal planning solution for groups of products (families) is much more higher than possibility to reach good solution on much larger number of single products. In the problem case the best solution was achieved with three and more variable non-sequence chromosomes where each of them has different number of genes.

3.4 Constraints definition

Optimization separated in many optimization phases has separated constraints and bound conditions for each of costs functions. Basically, each gene value is constrained with minimum and maximum values and non-sequence chromosomes are constrained with sum of all genes in one chromosome.

Unfortunately constraints can be just rarely defined as a fixed number, most of conditions are represented as expression, which defines the interval for such constraint. In real state situation the conditions are almost always in correlation i.e. increased production capacity decreases the delivery time, decreased set-up time and production costs per unit increases the material flow and so on.

Calculation of cost variable from gene values must be defined first. In first optimization step this is maximal profit and genes are quantities of products. Scale of weights is defined and low costs are allocated to genes, which have bad impact on cost function. When we are looking for many good solutions it is a good idea not to "kill off" all bad genes in one generation. Such kind of constraints definition give us the opportunity to build up different searching strategies for different purposes i.e. in some cases the speed is more important than precision.

4. ANALISYS OF OPTIMISATION RESULTS

With good scheduling program it is possible to handle much more load than it was before, instead of investing in expensive new equipment [12]. The plant was able to leverage greater productivity and higher throughput from existing resources.

Model for reaching greater productivity is based on operational data and must be verified with different methods. The optimization phases have been simplified with the sense to provide the clear model where results of optimization can be easy interpreted. Other reason is the possibility to solve the same optimization problem with different methods.

On some stages the classical methods of linear programming [24] are very efficient and enable easy interpretation of the results. The main goal of using different methods for this particular model was to verify the model rather than valuation of methods itself. The choice of right method is closely connected to problem space.

In general the evolution engine of genetic algorithm is much more time consuming process when small problem space must be discovered for optimal solution but is very efficient to find up the near to optimal solution in second or third generation. The real power becomes obvious when the complexity of model gets out of control i.e. when the cost functions can no more be expressed with mathematical equations or when the number of variables is very large [3].

Modelling problem with non-sequence chromosomes leads to more controlled optimization when chromosomes represent different groups of products, machines types, quality classes and groups of raw material. With such model some unreasonable results are automatically eliminated from searching space and the optimization process is much faster.

Variable non-sequence chromosomes were used for testing another variation of problem model the system with hundred equations and four hundred unknowns. Calculation of cost variable and constraints in each generation evaluates the generated genes and gives us best results. In this model the cost prices of products become variable and the evolution engine finds itself the relation between the quantity of product and it price (Figure 4).

Method	Simplex Algorithm	GA 1 Chromosome	GA 4 Chromosome
Results	173.320.000	157.486.079	190.331.241

Figure 4: The results of searching the optimal production plan in specific point of time and production stage, which was achieved with different searching method

Wide variety of possible simulations stays open for discovering. Much more than on calculation methods they have impact on the way of modelling the optimization process. Evolution methods have shown on a new great possibility for making production process more efficient in any particular state. Optimizing engine provides a new view to end user, which could simulate different paths or different results, before it makes a final decision.

Coclusion

Leading ERP systems already have integrated planning systems such as MRP, MPS, CRP, which give us the powerful tool for planning different resources in different time intervals, from strategic to operational level [2, 4, 14]. Almost all have some simulating tools included.

But the way that we can simulate the whole business behavior is maybe more important than most precisely predicted states – too late. First of all, we are looking for reason, which can cause bad business results, or opportunities, which can give more value at same price.

With one kind of modelling and with one way of thinking we can easy miss the real cause or opportunity. Modelling and searching for different solutions using evolution methods can give us totally new view on existing state and show up the reason for bad results. This is a way of learning and collecting knowledge.

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