EVOLUTIONARY MULTI-AGENT SYSTEM FOR MULTIOBJECTIVE BALANCING OF PRODUCTION LINES

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Abstract: This work introduces a new evolutionary approach to search for a global solution to multiobjective optimisation problem in the Pareto sense. Novelty of the proposed method consists in application of an evolutionary multi-agent system (EMAS) instead of classical evolutionary algorithms. Decentralisation of the evolution process in EMAS allows for intensive exploration of the search space and effective approximation of the whole Pareto frontier. In the paper the intended application of the proposed technique as a core of a decision support system for balancing of production lines is described.

Keywords: multiobjective optimisation, multi-agent systems, evolutionary computation, balancing of production lines.

1. INTRODUCTION

Tendency to consolidation at the global level comes out not only in the sphere of economy or finance but also in organisation of production and consumption of goods. Having met with a support of tremendous development of computer and telecommunication technologies, the tendency has triggered new forms of management activities within the scope of resource allocation, production, commerce, as well as accumulation and use of information. As characteristic in the question one may call electronic commerce, virtual enterprises, data warehouses and so on.

Realisation of such global activities needs new methods and algorithms allowing for, even approximately, determination of acceptable conditions of cooperation of interrelated units that operate in different areas, conditions and with respect to different goals. A group of cooperating firms having flexible production systems that are connected with a transportation network, common storage and recycling subsystems can serve as an exemplary complex of that characteristics. Each firm remains a subject of particular limitations and applies distinct performance indices. It is hard to imagine that optimal conditions of functioning such a group can be precisely determined. But at the same time, the necessity of elaboration of the area of compromise that encompasses conditions of cooperation acceptable for all sides is obvious. Searching for such a compromise based on some analytic model and using classic solving methods occurs to be fruitless due to large number of dimensions, different types of variables (continuous, discrete, binary), possible non-linearities, discontinuities of formulas (also performance functions) of the model.

In the above context, a need for a computational method arises that deals with multiobjective models in order to obtain some approximation of the Pareto frontier, and moreover:

- is to a large degree independent on analytic shape of the model,
- allows for approximation of non-coherent Pareto frontiers,
- allows for small changes of the model during computation.

Evolutionary algorithms possess at least some of this characteristics – a detailed survey on evolutionary multicriteria optimisation techniques may be found in Fonseca and Fleming (1995) or Coello Coello (1999).
In the paper a new technique is proposed, which combines elements of evolutionary computation with selected features of multi-agent systems. The core of this technique is an evolutionary multi-agent system (EMAS) that incorporates evolutionary processes into a multi-agent system (MAS) at a population level (Cetnarowicz et al., 1996). It means that besides interaction mechanisms typical for MAS (such as communication) agents are able to reproduce (generate new agents) and may die (be eliminated from the system). A decisive factor of an agent’s activity is its fitness, expressed by amount of possessed non-renewable resource called life energy. Selection is realised in such a way that agents with high energy are more likely to reproduce, while low energy increases the possibility of death. By means of communication agents acquire information, which allows for determination of the (non)domination relation with respect to others. Then dominated agents transfer a fixed amount of energy to their dominants. This way nondominated agents should represent successive approximations of the Pareto set (Kisiel-Dorohinicki et al., 2001; Kisiel-Dorohinicki and Socha, 2001).

The paper is organised as follows. Section 2 comprises analysis of the line balancing problem from two points of view: formulation of it as the multiobjective optimisation problem and supporting its solution using a computerised model based on this formulation. Overview of a Pareto frontier is proposed as a heart of the matter. The subsequent sections are devoted to the appropriate solving method. Section 3 and 4 presents MAS and their consecutive sub-types: mass MAS and EMAS. Special mechanisms that allow EMAS for approximating the Pareto set are described in section 5. Section 6 is a tentative report on usefulness of the method.

2. BALANCING AS A DECISION PROBLEM

Decision making and lots of other tasks of human activity described by many non-comparable factors may be mathematically formulated as multiobjective optimisation problems. The term “multiobjective” (multi-criteria) indicate that classical notion of optimality becomes ambiguous since decisions which optimise one criterion need not optimise the others. The notion of Pareto-optimality is based on (non)domination of solutions (which corresponds to the weak-order of vectors in the evaluation space) and leads to selection of multiple alternatives (the Pareto set).

Let the problem variables be represented by a real-valued vector:

\[ x = [x_1, x_2, \ldots, x_N]^T \in \mathbb{R}^N \] (1)

where \( N \) gives number of the variables. Then a subset of \( \mathbb{R}^N \) of all possible (feasible) decision alternatives (options) can be defined by a system of:

- inequalities (constraints): \( g_k(x) \geq 0 \) and \( k = 1, 2, \ldots, K \)
- equalities (bounds): \( h_l(x) = 0, l = 1, 2, \ldots, L \)

and denoted by \( D \). The alternatives are evaluated by a system of \( M \) functions (outcomes) denoted here by vector \( F = [f_1, f_2, \ldots, f_M]^T \):

\[ f_m : \mathbb{R}^N \rightarrow \mathbb{R}, \quad m = 1, 2, \ldots, M \] (2)

The key issue of optimality in the Pareto sense is the domination relation. Alternative \( x^a \) is dominated by \( x^b \) if and only if:

\[ \forall m \quad f_m(x^a) \leq f_m(x^b) \quad \text{and} \quad \exists m \quad f_m(x^a) < f_m(x^b) \] (3)

A solution to the multiobjective optimisation problem (in the Pareto sense) means determination of all nondominated alternatives from \( D \) set. In a general case such alternatives create a set of continuum power called sometimes the Pareto frontier.

So generally presented, the optimisation problem must be specified for the concrete line balancing problem. Firstly, it may have two issues depending on whether the problem concerns design of a production line or just production planning. Secondly, which trade-offs are crucial can be appropriately described by real data and adequately analysed. There can be: time trade-offs (operating versus batch change, waiting [other overhead], disturbance times), cost trade-offs (investment [also people training] versus operating cost [and its components, like cost of maintenance, storage, transportation, etc.], the trade-off between capacity and flexibility, skilled and non-skilled labour (level of automation), etc. The analysed trade-offs can be put into the model as criteria or constraints. Moreover, they can introduce some kinds of non-linearities. As for the model variables, they are very often defined as binary or integer ones.

Let us discuss some aspects of the decision process that uses the above characterised model, and especially the role of a human being involved in it – a decision maker. If the assumption of a human decision maker sovereignty is sustained the model may serve him for:

- learning the decision problem by an overview of the Pareto frontier,
- filling in details of particular alternatives oriented towards a tentative or final choice.

Learning by the overview of Pareto frontier can be organised in several ways. The scalarisation methods used as a core of decision support systems can be used in a step-by-step process based on a dialogue with a decision maker. Approximation and presentation of Pareto frontier in the whole would be also an interesting means in order to understand a decision problem. Unfortunately, classical computational methods are ineffective for majority of (real) decision problems. The corresponding models are too big or formulas
applied too complicated to assure appropriate fluency of a decision maker’s course of analysis. Moreover, it can occur that some formulations must be rejected in the face of numerical instability of available solvers.

Summarising the above consideration, the decision situation that arises in the case of the line balancing problem can be sketched out as it is shown in fig. 1. The main idea is to enrich real management activities by suggestions that are elaborated in the special decision support sub-system. The suggestion is in fact an optimally balanced production programme generated on the basis of the computerised model of the technological process under management. The model represents all firm aspects of the process, while the decision maker tries to relate generated programmes to the out-of-model sphere known to him. It is achieved by a kind of scenario analysis that ends up in designation of some variant for implementation. The computerised model means all software that gathers and stores information about the process, prepares the optimisation problem, solves it, and finally is able to present results to the decision maker or export the chosen variant to the management sub-system.

In the course of the paper just a part of the software — a solver is discussed. The special method that comes from the borderland of evolutionary computation and decentralised intelligence is proposed. It is oriented towards approximation of the Pareto frontier and meets well conditions imposed by the assuming manner of taking a decision. The method is to employ an evolutionary multi-agent system in the role of the solver.

3. MASS MULTI-AGENT SYSTEMS

The multi-agent system consists of the set of agents \( ag \in Ag \) and some environment \( env \) they are living in:

\[
\text{mas} \equiv \langle \text{Ag}, \text{env} \rangle
\]  

(4)

The environment may have spatial structure and contain some information and/or resources, which may be observed by the agents.

4. EVOLUTION IN mMAS

Even though at first sight evolutionary algorithms and agent technology have nothing in common, the literature describes many examples of such hybrid systems. In most such cases an evolutionary algorithm is used...
by an agent to aid realisation of some tasks connected with learning or reasoning (Liu and Qin, 1997; Denzinger and Fuchs, 1996), or to support coordination of team activity (Gordin et al., 1997; Haynes and Sen, 1997). The key idea of an evolutionary multi-agent system is the incorporation of evolutionary paradigms into mMAS at a population level (Cetnarowicz et al., 1996), which is the opposite approach.

Following neodarwinian paradigms, two main components of the process of evolution are inheritance (with random changes of genetic information by means of mutation and recombination) and selection. They are realised by the phenomena of death and reproduction, which may be modelled as actions executed by agents:

→ the action of death results in the elimination of an agent from the system,
→ the action of reproduction is simply the production of a new agent from its parent(s).

Inheritance is to be accomplished by an appropriate definition of reproduction, which is similar to classical evolutionary algorithms. The set of parameters describing basic behaviour of the agent is encoded in its genotype, and is inherited from its parent(s) – with the use of mutation and recombination. The proposed principle of selection corresponds to its natural prototype and is based on the existence of non-renewable resource called life energy. The energy is gained and lost when the agent executes actions. Increase in energy is a reward for ‘good’ behaviour of the agent, decrease – a penalty for ‘bad’ behaviour (which behaviour is considered ‘good’ or ‘bad’ depends on the particular problem to be solved). At the same time the level of energy determines actions the agent is able to execute. In particular, low energy level should increase possibility of death and high energy level should increase possibility of reproduction.

EMAS may be considered as a new search and optimisation technique utilising a decentralised model of evolution. Such a model enables the following (Cetnarowicz et al., 1996):

- local selection allows for intensive exploration of the search space, like in parallel evolutionary algorithms,
- the way phenotype (behaviour of the agent) is developed from genotype (inherited information) depends on its interaction with the environment,
- adaptation of the population size is possible when appropriate selection mechanisms are used.

What is more, explicitly defined living space should facilitate implementation in a distributed computational environment.

Let us consider a generic optimisation problem – eq. (1–3), i.e. searching over some space of feasible solutions D according to some criteria (utility, goal, fitness). It ought to be stressed that most EMAS realisations take form of mMAS, and the whole discussion of the previous section refers also to them. In the presented approach (Kisiel-Dorohinicki et al., 2001) a state of an agent reflects directly the single solution to the problem (denoted by $x \in D$). At the same time a decisive factor of an agent’s activity in EMAS is its fitness, expressed by amount of possessed life energy (eng). The state of agent $ag \in Ag$ in EMAS may be thus defined as a pair:

$$\text{stat} = \langle x, \text{eng} \rangle$$  \hfill (7)

Then the action of death of this agent may be described as:

$$\text{die} : \langle Ag, \text{env} \rangle \rightarrow \langle Ag \setminus \{ag\}, \text{env} \rangle$$  \hfill (8)

At the same time the action of reproduction is:

$$\text{rp} : \langle Ag, \text{env} \rangle \rightarrow \langle Ag \cup \{ag^*\}, \text{env} \rangle$$  \hfill (9)

where the state of the new (offspring) agent $ag^*$ is:

$$\text{stat}^* = \langle x^*, \text{eng}_0 \rangle$$  \hfill (10)

where: $x^*$ – the potential solution to the problem inherited with mutation from $x$, $\text{eng}_0$ – initial energetic level.

### 5. EMAS FOR MULTIOBJECTIVE OPTIMISATION

In order to find the approximation of Pareto frontier for a given multicriteria optimisation problem, the agents of EMAS must act according to the energetic reward/punishment mechanism, which prefers nondominated agents. This is done via so-called domination principle, forcing dominated agents to give a fixed amount of their energy to the encountered dominants. This may happen, when two agents communicate with each other and obtain information about their quality with respect to each objective function. Thus this mechanism consists of several actions of communication and the action of energy transfer (fig. 2) and may be compactly described as:

$$\text{tr} : \text{mas}_{x_1, x_2} \rightarrow \text{mas}_{x_1, x_2}$$  \hfill (11)

where states of agents $x_1$ and $x_2$ change according to domination principle:

$$\text{stat}_1 = \langle x_1, \text{eng}_1 \rangle, \text{stat}_1^* = \langle x_1, \text{eng}_1 - \Delta \text{eng} \rangle$$

$$\text{stat}_2 = \langle x_2, \text{eng}_2 \rangle, \text{stat}_2^* = \langle x_2, \text{eng}_2 + \Delta \text{eng} \rangle$$

and $x_2$ dominates $x_1$.

![Fig. 2. Domination principle: transfer of energy between dominated and dominating agent](image-url)
The flow of energy connected with the domination principle causes that dominating agents are more likely to reproduce whereas dominated ones are more likely to die. This way, in successive generations, non-dominated agents should make up better approximations of the Pareto frontier.

6. EXPERIMENTAL STUDIES

To prove applicability of the proposed method to real problems (e.g. production line balancing), its features and operation profile must be analysed and evaluated. Before comparative study with other solving methods is done, the following issues must be considered that can lead to possible improvement of the method.

**Types of problems covered.** Both representation of solutions and variation operators should reflect the problem to be solved. Binary coding (typical for genetic algorithms) seems to be the most suitable for combinatorial problems while real coding — for continuous model variables.

**Dimensionality.** A large number of decision variables and criteria functions does not pose a problem for evolutionary optimisation techniques, only a suitable size of population and agent space should be selected. What is more, the evaluation of agents (domination principle) has linear complexity with respect to the number of criteria in consideration.

**Stopping condition.** It may be based on the convergence rate of successive approximations of the Pareto frontier $P$, which may be defined as an average distance of new non-dominated solutions $x \in P(t + \Delta t)$ from previous approximation $P(t)$ where the distance of a particular solution $x$ from the set $P$ is specified as the least Euclidean distance from elements of $P$ in the evaluation space:

$$d(x, P) = \min_{x^P \in P} \sqrt{\sum_{i=1}^{M} (f_i(x) - f_i(x^P))^2} \quad (12)$$

Unfortunately this method is computationally demanding and may significantly slow down the solving process, and thus other approaches based on the dynamics of the population size must be proposed.

**Quality of approximation.** Precision of the approximation of the Pareto frontier depends obviously on the population size and may be influenced this way. A harder problem is to ensure the uniform distribution of nondominated agents (solutions) along the frontier.

**Incoherent or discontinuous Pareto frontier.** For a problem with an incoherent (discontinuous) Pareto frontier controlling the distribution of nondominated agents occurs even crucial, e.g. for discovering the gaps of certain dimension. The mechanism of crowd (Kisiel-Dorohinicki and Socha, 2001) is the proposed solution to the problem.

**Dynamic changing of the problem.** The proposed method naturally allows modification of the problem during solving process that can be valuable features for some kind of applications.

Various experiments were conducted to fulfil the topics listed above. Some of them are reported next together with tentative conclusions.

As the most illustrative the convergence rate (as defined above) for a simple optimisation problem is presented in the first chart of figure 3. As one may expect the distance between successive approximations is quite big at the beginning of the solving process, and decreases during further operation of the system. The dashed vertical line is the time point of possible termination of the process because of weak activity of the search (small changes between successive approximations of the frontier).

The second chart of figure 3 shows the number of agents during the solving process. The fall at the beginning of the search means that the worst agents die out. Then a new population is created based on the remaining individuals and, as they are able to gain more energy, the size of the population grows. When most agents in the population become comparatively

objeectives:

$$f_1(x) = -(25(x_1 - 2)^2 + (x_2 - 2)^2 + (x_3 - 1)^2 + (x_4 - 4)^2 + (x_5 - 1)^2)$$
$$f_2(x) = (x_1 - 1)^2 + (x_2 - 1)^2 + (x_3 - 1)^2 + (x_4 - 4)^2 + (x_5 - 1)^2 + (x_6 - 1)^2$$

constraints:

$$x_1 + x_2 - 2 \geq 0 \quad -x_1 + 3x_2 + 2 \geq 0$$
$$-x_1 - x_2 + 6 \geq 0 \quad 4 - (x_3 - 3)^2 - x_4 \geq 0$$
$$x_1 - x_2 + 2 \geq 0 \quad -4 + (x_5 - 3)^2 + x_6 \geq 0$$
$$0 \leq x_i \leq 10, \quad i = 1, 2, \ldots, 6$$

Fig. 3. Distance between successive approximations of the Pareto frontier and dynamics of population size as a base for a stopping condition
good the population size begins to stabilise. One may notice that this reflects the weak activity of the search, and thus might constitute a base for a formulation of the stopping condition – of course in a general case this still needs to be carefully investigated. When the conditions of the decision problem are altered (fig. 4) the system is able to adapt to this change increasing intensity of the search. Considering the dynamics of the population size this may be observed as a repeated increase in the number of agents.

Eventually figure 5 presents the obtained approximation of the Pareto frontier consisting of several disjoint areas. The introduced mechanism of crowd (Kisiel-Dorohinicki and Socha, 2001) makes the distribution of the points fairly uniform over the frontier, which may allow for estimation of possible discontinuities.

$$f_1(x, y, z, t) = - (x - 2)^2 - (y + 3)^2 - (z - 5)^2 - (t - 4)^2 + 5$$

$$f_2(x, y, z, t) = \frac{\sin x + \sin y + \sin z + \sin t}{1 + (\frac{\sin x}{5})^2 + (\frac{\sin y}{5})^2 + (\frac{\sin z}{5})^2}$$

Yet the preliminary results show significant advantages over classical evolutionary techniques regarding adaptation to a particular problem, which is mainly performed by the system itself.

Further research should concern the effectiveness of the proposed approach, especially in the case of difficult problems (many dimensions, multimodal or discontinuous criteria, etc.). Among the above, trials with problems of production lines balancing are prepared.

8. REFERENCES


