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Approaches to the Problem of Control after Model in Technical and Economic Systems

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Abstract

The paper presents a study on tackling the settlement pattern in both the technical and economic systems. It highlights the software packages commonly used for systems simulation that occurs in addition to technical factors the human factor.

Key words: *adjustment as a model, economic processes simulation*

Introduction

A systems model ***M*** can be seen as a mathematical relation ***F*** between input set ***X*** and output set ***Y*** (see figure 1).

$$Y = F(X, H, Z) \tag{1}$$

where ***H*** is the impact of external environment (a restricted set of external factors) and ***Z*** is the feedback.

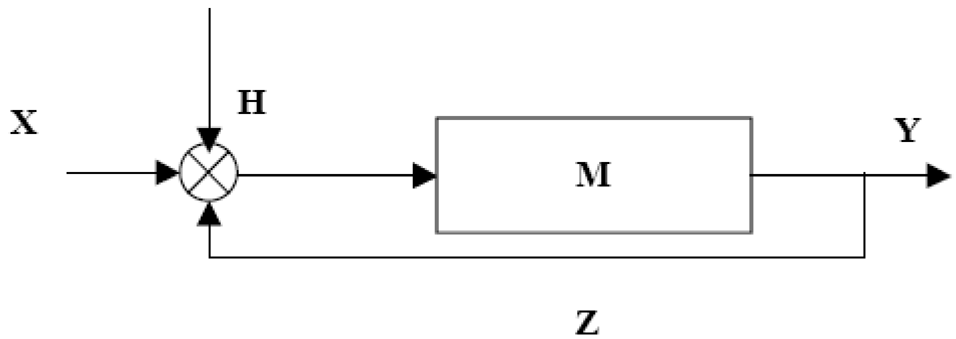

Fig. 1

We can divide the systems in two groups:
- Technical systems;
- Social systems.

Economical and financial systems are social systems. In technical systems ***H*** is the disturbance and in social systems ***H*** is the human factor.
The next ***Y*** (Y_i) depends on the past ***Y*** (Y_{i-1})

$$Y_i = G(Y_{i-1}) \ , \tag{2}$$

with a probability p_i .

In complex systems, having many factors, difficult to be defined, the simulation methods are used for the model description.

Approaches in Technical Process Control

Classical feedback control does not need to know something about the subject of automation, while in feed-forward control, in that it implements a channel to the entrance (the source of disturbance) to the system output, should have a model of the process. Moreover, for a system to intervene before the disturbance can modify the output, it is essential that the model capture the dynamic of the process.

In order to maintain the system in the field restrictions were imposed two approaches:
- optimal approach,
- direct approach.

The two approaches differ in how to use the model process.

Optimal Approach

In case of optimal approach, process model is used to produce the controller model to minimize or maximize an objective function (function that takes both the technical performance and elements of economic performance). Objective function is present in the controller reference.

This approach is known as Model Based Predictive Control (***MBPC***).

The steps in ***MBPC*** algorithms are:
- prediction, based on the model, the evolution of the output on a given period (see block called predictor in Figure 2),
- calculate a sequence command that minimizes the objective function (of system performance) in terms of imposed restrictions (stage optimization).

Each stage of calculation is an optimization problem acting on the sampling period, the prediction horizon and the command horizon, which causes a substantial calculation effort. [23] One way to lower computing effort lies is the use of linear functions around an operating point.

On the other hand models of the process insufficiently studied (not very accurate) lead to problems of robustness of the system.

A number of companies are implementing ***MBPC*** using different technologies (eg for the optimizer) which leads to different software packages.

Several software packages used in industrial applications are:
- Dynamic Matrix Control algorithm, traded by Aspen Technology company under the name ***DMC-PLUS;***
- Model Predictive Heuristic Control algorithm, met in software packages ***IDCOM*** and ***SMC – IDCOM*** traded by Aspen Technology company;
- Hierarchical Constraint Control algorithm ***HIECON*** and Predictive Functional Control algorithm ***PFC*** traded by Adersa;

- Predictive Control Technology algorithm ***PCT*** and Robust Model Predictive Control Technology algorithm ***RMPCT*** traded by Honeywell. [38].

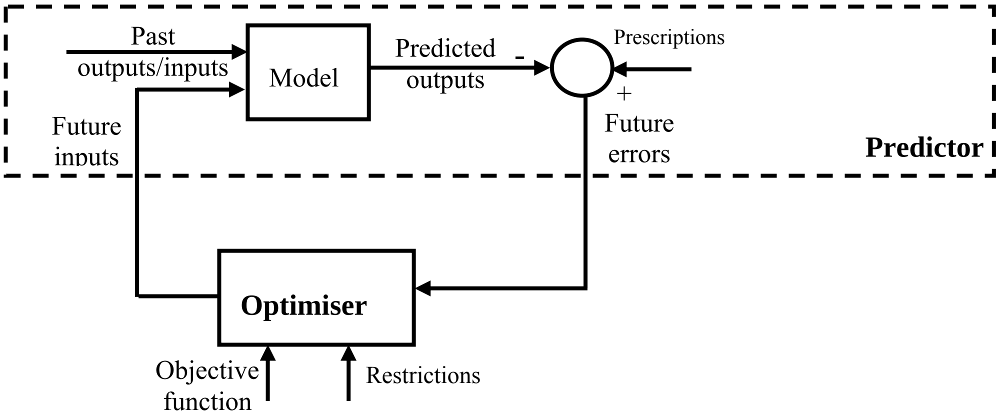

Fig. 2

It requires some considerations on the software packages listed:
- On the reference trajectory, in ***DMC***, deviations of the output to the prescribed value are penalized in the optimization stage. Other algorithms like ***IDCOM, HIECON*** and ***PFC*** let the user to determine not only what should the output reach, but how to get there.
- ***PFC*** and ***IDCOM*** allow the penalty of error only in a few points of the prediction horizon called points of coincidence (in order to reduce the effort calculation).
- ***RMPCT*** maintain the output in an area, specified by the user, and not force it for a certain trajectory. It can set the hill, through a parameter defined as the ratio of time in which it wants the system output return to the limit area and the response of the system in open loop.
- ***HIECON*** and ***IDCOM*** calculate a single value of the command, which reduces the computing effort, but reduces performance in closed loop. On the other hand it establishes a point of coincidence where the output is forced to be identical to the reference. [28]
- The allocation of priorities, in the sense that certain variables can overcome the field restrictions, is different in different software packages. Thus in ***DMC***, these priorities are determined by the parameters of the weighting function objective and in ***HIECON*** and ***SMC-IDCOM*** priorities are set by the user.

From the historical ***MBPC*** was implemented on the basis of linear models [6, 7, 10, 26 and 29] then, the development of computer and deepen the study process has allowed the non-linear models [1, 27 and 31].

Direct Approach

In the case of direct approach, the model is used to design the controller so that the process output follows a prescribed path. Reference, in this case no longer contains the goal but a path. This approach is known as Internal Model Control ***IMC***.

An ***IMC*** system has inside the controller a model of the process $G_m(s)$, connected in parallel with the process $G_P(s)$ (Figure 3), allowing comparison of the process output y with the model output y_m. [24]

In the figure were used : r - prescription, e - error, c - command, d - disturbance measured, y - system output, y_m - model output, $\overline{d}$ - reaction, $G_p(s)$ - the process transfer function, $G_m(s)$ – the model transfer function, Q (s) - the transfer function of the primary controller.

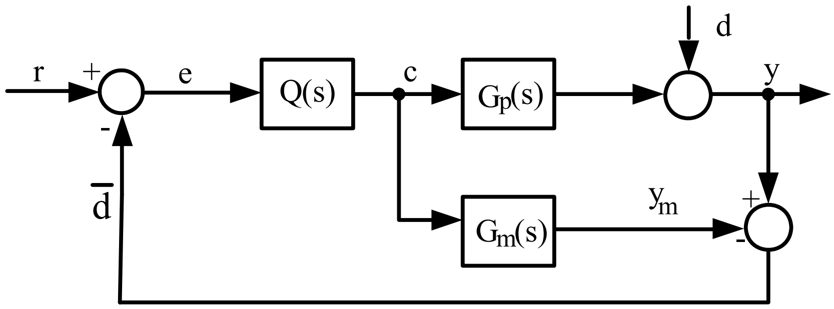

Fig. 3

In the case of a **perfect model**, the model and the process has the same function transfer,

$$G_{\mathrm{m}}(\mathrm{s}) = G_{\mathrm{P}}(\mathrm{s})$$

leading to

$$\overline{D}(s) = (G_P - G_m)\cdot C(s) + D(s), \tag{3}$$

where $\overline{D}(s)$ is the Laplace transform of $\overline{d}$. Hence, $\overline{D}(s) = D(s)$ and the reaction $\overline{d}$ is equal to the disruptive effect of d at the process output.

If the regulator process and elements are stable, then the system will be globally stable.

In the case of an **imperfect model** (model not just because the simplifying assumptions, inability to fully modeling system, etc.), the output depends on the two system inputs

$$Y(s) = G_0(s)\cdot R(s) + [1 - G_0(s)]\cdot D(s) \ , \tag{4}$$

where

$$G_0 = \frac{Q\cdot G_{\mathrm{P}}}{1 + Q\cdot(G_{\mathrm{P}} - G_{\mathrm{m}})} \ . \tag{5}$$

Because the error stationary system to be zero is necessary as a static factor of proportionality regulator to be equal to the inverse proportionality factor model:

$$Q(0) = \frac{1}{G_{\mathrm{m}}(0)} \ . \tag{6}$$

Another approach, requires that the transfer function $Q(s)$ is equal to the inverse transfer function of the model:

$$Q(\mathrm{s}) = \frac{1}{G_{\mathrm{m}}(\mathrm{s})}. \tag{7}$$

Such y track without error dynamic the reference r and remain insensitive to the disturbance d. The Internal Model Control ***IMC*** is proposed in the paper [12] being addressed in many other works for example [14, 15, 25, 3].

In crisis situations, meaning that the process is insufficiently known and modeling it will only be about recourse to a system of regulation that would allow both as process control and model identification. The structure of the system says it is adaptive (***IMC*** with adaptive structure). The model contains a number of parameters that are calculated (estimated) during the operation system [8, 20 and 32].

Approaches in Economic and Financial Process Simulation

Optimization aims to determine a set of controllable quantities entry to establish Extreme (maximum or minimum) an objective function.

It calls the simulation system as the objective function values can not be determined otherwise. For example, we can not establish an analytical expression of the objective function or the costs involved in obtaining experimental the objective function values are prohibitive. Another reason would be that applying a set of input values, whose effect does not know him, could evolve a system to catastrophic damage.

On the other hand justified the cost of economic studies for the establishment of a model simulation because it is less than 1% of the cost required to implement a project, the project is very difficult to fit (as amended) and higher expenses [13].
Simulation approach is in many ways, but we can fix two classes:

- those without class model, based on the court system;
- the class of simulation methods based on a system model.

Methods based on instances generate new solutions based only on the current state.

Model based methods establish a solutions probability distribution in the space acceptable solutions, through which seeks optimal solution.

Among solution searching methods based on instances may highlight [11, 13]:

- Ranking & Selection,
- Response Surface Methodology,
- Gradient-Based Procedures,
- Random Search,
- Sample Path Optimization,
- Metaheuristics Methods.

And methods based on the model were imposed:

- Swarm Intelligence,
- Estimation of Distribution Algorithms (EDAs),
- Cross-Entropy (CE) Method,
- Model Reference Adaptive Search.

In this second category, because the procedure uses a memory (for solutions) may be framed the **tabu search** algorithm.

This algorithm creates a list of tested solutions which specifies different attributes (depending on the purpose of optimization) by removing solutions from the list or by adding, based on performance criteria on attributes. [17]

Swarm Intelligence, uses agents interacting locally with one another and with their environment, one a centralized control structure. Exemple algoritms: Ant colony optimization, Particle swam optimization, Stochastic diffusion search. [4, 11]

Estimation of Distribution Algorithms (EDAs), uses a population of candidate solutions to the problem with a probability distribution over solution space. The goal is to progressively improve a probability distribution on the solution space based on samples generated from the current distribution. [21, 22]. Example algoritms: Compact Genetic Algorithm, Popunation based incremental learning, Univariate Marginal Distribution Algorithm, Estimation of Multivariate Normal Algorithm.

Cross-Entropy (CE) Method, is a Monte Carlo method for rare event simulation using cross entropy to measure the distance from the optimum. In the first step ***CE*** generate a random data sample and next update the parameters of the random mechanism based on the data to produce a better sample. [9, 30, 34, 35.]

Model Reference Adaptive Search, use parameterized family of distributions, and minimize distance to desired distributions. As in **EDAs**, updates a parameterized probability distribution, and like the **CE** method, uses the cross-entropy measure to project a parameterized distribution (however, the projection used relies on a stochastic sequence of reference distributions). The convergence can be established only in the case of Monte Carlo version. [18, 19].

Simulation models do not contain only model system investigated but also a software package (for example *GoldSim*, *Arena*), in which it builds model and generate a code (through which it will conduct exercises). However the model does not necessarily require the use of a software package, may use a general programming language (such as *Fortran, C + +, Java*) or a language simulation (such as *Siman V, GPSS*).

The number of papers that mention the various simulation packages on discrete-event simulation at the 2007 Winter Simulation Conference is presented in figure 4. [33].

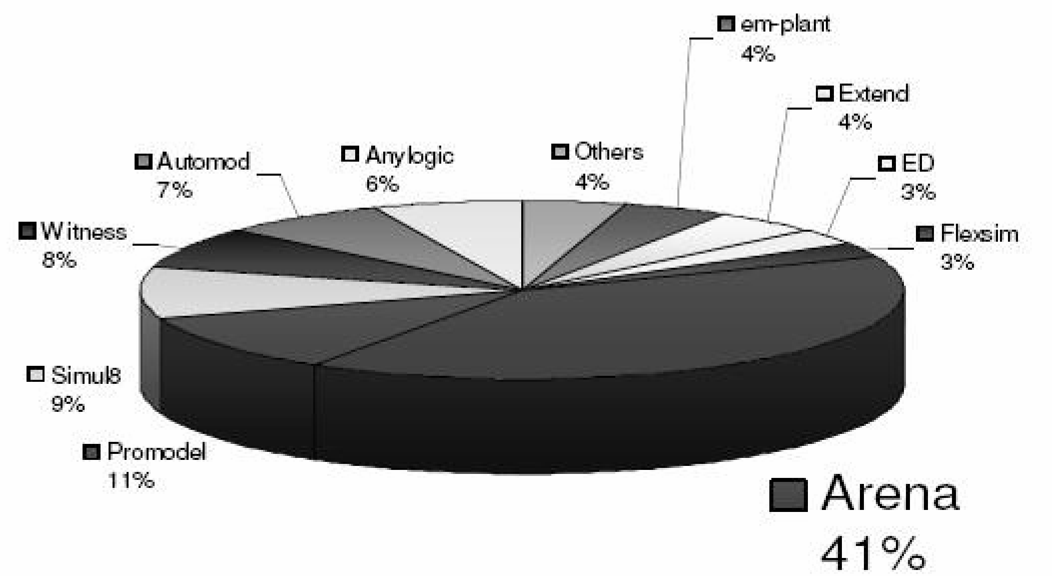

Fig. 4.

Another simulation software survey, which contains the responses to a questionnaire developed by James Swain, provided by the vendors is in [36].

Certain simulations tools are used for simulation both technical and social systems [16]:

- **SWARM**;
- **RePast** (**Re**cursie **P**ours **A**gent **S**imulation **T**oolkit);
- **AnyLogic**;
- **StarLogo**;
- **AgentSheets**;
- **SDML** (**S**trictly **D**eclarative **M**odeling **L**anguage);
- **MAGSY** ;
- **MIMOSE** .

To adopt a package of simulation we can target based on table 1.

Table 1.

Year	SWARM	RePast	Ascape	AgentSheets	SDML	EXTEND
2005	10800	334	127	227	80	21000
2004	14000	721	249	864	1350	26000
2003	15100	630	271	1510	283	30000
2002	15500	679	308	1030	206	32800
2001	15800	634	324	549	1500	35300

In Table 1 are the results of search on the Internet (with Google) of the references to the different packages of simulation in different years. [2] For example SWRAM, in the fall of 2005, is cited 10800 times on the Internet.

The author's choice of the simulation tools is (for training): **SWARM, AgentSheets, EXTEND** [2].

Conclusions

Approach in technical process control and methods of identification and simulation of economic processes are given in the paper.

We highlight software packages that can be used to simulate technical processes in which occurs the human factor.

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Abordări comune şi abordări specifice a problemei reglării după model în sisteme tehnice şi în sisteme economico - financiare

Rezumat

Lucrarea prezintă un studiu privind abordarea problemei reglării după model atât în sisteme tehnice cât şi în sisteme economice. Se evidenţiază pachetele software frecvent folosite pentru simularea sistemelor în care intervin pe lângă factorii tehnici şi factorul uman.