SIMULATION AND EMULATION OF MANUFACTURING SYSTEMS BEHAVIOUR

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Abstract
Current manufacturing systems must operate under resource constraints. Simulation can help to improve the operation of such manufacturing systems. This paper describes the principles of computer simulation and emulation used for the modelling of behaviour of real production systems. Simulation as the technology of 21st Century is used for the analysis of dynamics of manufacturing system. Emulation approach is used for the analysis of a control system and control rules used for the control of a real manufacturing system. The evolution principles and algorithms were used by the optimization of manufacturing system performance. Especially Genetic Algorithms (GA) were used to optimize the parameters of manufacturing system. The paper presents the comparison of results gained through classical optimization algorithms and GA.

Keywords
computer simulation, emulation, production control, optimization, genetic algorithms.

Introduction

Design and operation of current logistic and manufacturing systems is very complex task. The designer of such systems has to evaluate many variants of manufacturing systems influenced by sets of endogenous and exogenous factors.

One way how to simplify the design process of manufacturing systems is the utilization of computer simulation. Recent effort of researchers on this area is focused on the integrated approach connecting simulation and emulation with the evolutionary optimization methods.

Effective manufacturing nowadays requires global optimization of all processes. As the research and practice showed there exists only narrow set of methods enabling study and optimization of dynamics of complex manufacturing systems.

It is especially difficult to optimize complex systems behaviour with hundreds of factors by classical optimization methods. There exist a plenty of classical and recent optimization approaches and methods. Evolutionary algorithms and especially Genetic Algorithms (GA) have shown their computing power by the solution of comprehensive practical optimizations.

The complex systems are usually designed on the basis of narrowed criteria. If the project is too expensive, there will be obviously done some adjustments whether to realize such a project at all. It is very difficult to speak about total optimization of the system parameters by uncertain future demand, time pressure, financial limitations, unavailable modern software tools, etc.

That is why it is obvious, that already in the design phase of manufacturing systems there exist shortages that do not allow the full use of systems possibilities. The supervisors have to solve, besides own operating activities, the problems of supplementary system changes too. Computer simulation ap-
pears as very advantageous for the solution of the above described problems.

Nowadays “uncertain” situation at the domestic and foreign markets, known but hard “treated” problems in the production presents a new challenge for designers of manufacturing systems. The simulation is often used as a method of the “last resort” [1]. If the problem cannot be solved by using of other methods the simulation is used.

**Principles of computer simulation**

The simulation can be considered as a statistical experimentation method. It works on a similar theoretical basis as the estimation methods in the mathematical statistics. The basic principle of simulation (Fig. 1) resides in a simplified representation of a real (conceptual) system, which we are interested in (simulation target). The analyst does, after verification and validation of a simulation model, a set of simulation experiments. The experimentation with simulation model, aided by a computer, allows examining the variants of system’s behaviour in a longer time period and in assumed conditions. New knowledge gained through such simulation experimenting is used for the optimization of a real (conceptual) system.

Simulation is a very powerful tool often used in the design phase of manufacturing systems. Performance of various layout alternatives can be studied using simulation. Moreover using computer animation, the operation of the whole factory can be viewed before implementation of various production control strategies.

Simulation enables to test designed manufacturing system by given, virtual experimental conditions.

Simulation, as the experimental method, is time consuming and expensive. Any change of manufacturing systems conditions requires new simulations and evaluations of their results.

The simulation is not able to solve automatically all production problems. It does not offer directly explanation of behaviour of the analysed system and the analyst needs certain experience to be able to interpret achieved results. The trial and error method is often used by experiments. Even in case the experiments design and planning increases probability of optimum finding, common current simulation systems don’t offer direct single run optimisation approach. Optimisation systems are complicated, not user friendly and usually very expensive.

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**Fig. 1.** The basic principle of simulation.  
*Source: The Authors.*
Modelling of large systems, hierarchical models of the entire enterprises require high computing power which is multiplied by the utilisation of 3D animation with virtual reality features. It is difficult to interpret the comprehensive tables with statistical results, even for experienced analysts. Optimisation in this case is only theoretical desire of analysts.

Simulation can be used for the support of a decision making on all organizational levels of the factory (see Fig. 2).

Many of the published works were oriented on the modelling and simulation of various production control strategies, both in traditional and lean production environments.


Gregor et al. [5] have analysed FMS working in CIM environment.

Many authors were busy with push / pull control problems. Agarwal and Babu [6] have studied the effects of variations in Master Production Schedule (MPS), Bill of Materials (BOM) structure, inventory supports, lot sizing, capacity planning, scheduling rules and shop floor conditions in a typical Material Requirements Planning (MRP) based production system with the simulation support.

**Modeling and simulation of production systems**

The Central European Institute of Technology in co-operation with the University of Žilina has developed a comprehensive holistic solution for the design and testing of mobile robotic systems and intelligent automatic handling systems. This solution consists of many subsystems, e.g. simulation-emulation software platform ELLA 3.0, monitoring and control system WATCH, modular production system, pattern...
recognition subsystem, quality control system with laser measurement and control units, etc. All above mentioned subsystems are subsequently integrated in what is currently called Zilina Intelligent Manufacturing System (ZIMS).

ZIMS [12] represents a mixed virtual and real environment which enables to design and develop advanced intelligent solutions for industry. Figure 3 shows picture of current ZIMS state. It integrates many enterprise areas like: product design, Rapid Prototyping, product properties simulation and testing, new technology design, layout design and optimization, material flow optimization, handling, simulation, etc.

![Fig. 3. ZIMS – innovative environment. Source: Gregor et al. [12].](image)

Material transportation and handling system belongs among the most decisive parts of effective production systems [11]. Future production systems will require Intelligent Automatic Handling System (IAHS) equipped with industrial robots, autonomous mobile robotic systems, etc. [18]. Recent development on this area showed the growing interest in AGVs (Automated Guided Vehicles). There exists a plenty of solutions for automatic transportation and handling of material in production, e.g.: inductive AGVs, through magnetic type controlled AGVs, radio frequency controlled AGVs, mechanically (hanged systems) controlled AGVs, AGVs with artificial intelligent control, etc.

**Automated guided vehicles**

The Central European Institute of Technology has developed for industrial purposes a family of low cost, autonomous AGVs supplied with the complex monitoring and control system. Figure 4 shows the family of low cost AGVs, developed in CEIT.

The part of this complex solution is a special simulation system for the design and emulation of AGVs.

![Fig. 4. The family of AGVs. Source: CEIT.](image)

It enables to design all parts of AGV, e.g. mechanical, electrical, sensors, actuators, etc., including AGV control system, in virtual reality environment. The developed virtual control system is after validation transferred into real AGV control.

**Software development for simulation and emulation of production systems**

One of the most important areas of development in the framework of ZIMS is the development of a software platform for the simulation and emulation of production systems behaviour (see Fig. 5). This platform is being developed in ELLA 3.0 framework [16]. It consists of simulation, statistics, optimization, visualization and emulation, parts.

![Fig. 5. Wheeled robot with a distance meted and a virtual camera. Source: CEIT.](image)

Currently as the new generation of AGV system in Central European Institute of Technology was developed, the simulation, statistics and visualization parts of this platform are ready and tested in practice.

The aim of using simulation platform in AGV system designing lies mainly in:

1. Detailed visualization of designed AGV system to the future user – presentation of AGV functionalities and virtual training of using, setting up and modifying of the AGV.

The visualization environment is created in 3D space (with full support for stereoscopic displaying).
User can be in touch with the designed system, watch it working, be virtually trained how to change AGV settings and find out all possible functionalities of AGV system in virtual space [7].

2. Simulation of AGV system – support in design and implementation of AGV system in real manufacturing conditions [15].

This creates support in designing of the AGV system. It allows user in pre-production phase to:
- analyse early AGV system design,
- set proper placement for magnetic tape,
- optimize the place of the rechargers,
- determine number of necessary AGVs,
- define settings of the AGVs (speed, reach of the scanner, ...),
- show statistics about complex AGV system,
- create variant solutions.

Basic frontend of simulation platform is shown in Fig. 6. The battery consumption simulation belongs among innovative functionalities of simulation platform. Each vehicle consumes power from batteries during the simulation and as the placement of rechargers is not set proper, the AGV vehicle could stop. Exact actions could be defined to solve this problem (time for AGV replacement, battery replacement, technician requirement, etc.).

![Fig. 6. Simulation platform frontend. Source: CEIT.](image)

The AGV system is not working in manufacturing system alone, as in real conditions. The question of interactions with the rest of manufacturing and logistics system is very crucial [8]. To solve this problem, the simulation platform is able to define zones of interactions. The analyst can determine frequency of stopping the AGV, and time of stop for chosen zones.

These settings might be estimated by experts or could be processed from statistics of AGV monitoring system with methods described later in this article (if applicable).

### Simulation and optimization of material handling system

Figure 7 presents the simulated production system. The main target of simulation was productivity improvement through the material flow optimization and costs reduction.

![Fig. 7. The simulated production system. Source: CEIT.](image)

The following example shows results from conducted simulation study. After simulation targets were defined a required data about current state of simulated production system were collected and worked out. The collected experimental data for all significant processes were analysed through CHI-square test. The CHI square test criteria was as follows [14]:

\[
\chi^2_o = \sum_{i=1}^{k} \frac{(E_i - O_i)^2}{O_i},
\]

where \(\chi^2_o\) – calculated CHI-square value, \(k\) – number of histogram classes, \(E_i\) – experimental data frequency, \(O_i\) – model (theoretical) data frequency.

In case the calculated value of CHI-square is lower in comparison with CHI-square critical value, the found theoretical distribution is a good fitness of collected experimental data.

The fitted theoretical distribution found as the approximate replacement of the experimental data for simulation is shown in Fig. 8.

After statistical analysis of input data was conducted a simulation model of production system was developed and validated. The set of pilot runs was realised with the target to determine the number of required simulation runs, the length of warm up period, sensitivity of simulation model to random number, etc.
The minimum number of simulation runs was estimated through the following expression [10]:

$$N = \left( \frac{t_{n-1,1-\alpha/2} \cdot S_n}{e} \right)^2,$$

(2)

where $N$ – minimum number of simulation runs estimated for a required precision of simulation results, $S(n)$ – point estimation of $\sigma$ from $n$ replications of simulation runs, $e$ – error level between parameter estimation and its mean value $\mu$, $t_{n-1,1-\alpha/2}$ – critical value of $t$-distribution.

The calculated value of $N$ was determined as 29 simulation runs.

The batching in a single run method was chosen to eliminate the autocorrelation influences in simulation model. Its principle is shown in Fig. 9.

The batching in a single run method is based on the idea of realization of one long simulation run which is warm up period cut only one time after the beginning of simulation. Simulation run is then divided into $k$-similar batches. Average value of given random variable is calculated for any batch. Finally a point estimation of required parameter is calculated as the total average of random variable from batch averages according to the following formula:

$$\bar{X} = \frac{1}{k} \sum_{i=1}^{k} X_i,$$

(3)

The determined borders of confidence interval of average value of tracking random variable are often used as a stop rule for a single simulation run.

$$\mu \in \left( \bar{X} - \frac{t_{1-\alpha/2,k-1} \cdot s}{\sqrt{k}} , \bar{X} + \frac{t_{1-\alpha/2,k-1} \cdot s}{\sqrt{k}} \right).$$

(4)
Optimization with evolutionary principles

Simulation optimization gives structural approach to set the optimal value of the input factors, where the optimum is measured by the function of output variables (parameters) from simulation model. As the optimal value of the optimization function cannot be measured directly, but as a result of simulation runs, it is necessary to have the simulation model built to use simulation optimization. Simulation model is a function (which exact form is not known), which evaluates set of inputs. That means the time period to perform the simulation run is very time consuming in comparison to the optimization itself (setting the input factors for the next run).

Even if the simulation run is quite simple, optimization could take long time to perform due to big amount and variety of types of input variables and due to the fact, that we know only a little about the objective function [9].

These facts aim the research in this area into use of heuristics based on genetic algorithms, that means optimization techniques which can perform optimization effectively and quick without further information about the objective function (reaching results which are close to the optimum, not the optimal solution).

Despite the fact, that the research in heuristics is not done, they are effectively used in practice mainly for its reliability in searching for near-optimal results (mathematical, combinatorial tasks, transport problems, robot management). GA searches the space of possible solutions (combining direct and stochastic search), working on the set of possible solutions – population (input factors stored in unique form) in several cycles – generations (developing subset of solutions) using the nature selection methods: inheritance and natural selection, which helps individuals to evolve [17].

Exact and particular settings of these methods determines the effectiveness and speed of GA optimization. Therefore the possibility, will and effort are important to use simulation not only for “what if” analysis, but also for real use of simulation for optimizing real production and logistics systems [13].

Considering the character of Genetic algorithms (see Fig. 11), identified advantages of GA in comparison with common used optimization algorithms are:

- possibility to parallel enumeration of objective function,
- easy implementation of simulation run results statistical comparison,
- easy implementation of simulation run results approximate estimation, without real need to perform simulation run,
- suitability for use in applications, where exact form of objective function is not known (discrete-event simulation).

Optimization solution – GASFOS

As mentioned above, GA is perfect for using in simulation where the exact form of objective function is not well known. To perform simulation optimization using GA, special software is being developed at the University of Žilina. GASFOS is standalone application, which allows to vary settings of genetic algorithms, input factors and simulation runtime. The structure of created software is shown in Fig. 10.

Simulation results

The following part presents chosen results from a comprehensive simulation study. Figure 12 shows the progress of product throughput time and its smoothing average values. As it is evident the throughput time progress shows stability (see smoothed values).

Figure 13 shows the result of autocorrelation analysis of throughput time values. The obtained correlogram shows only very weak correlation among the values of single throughput times.

Figure 14 and Fig. 15 show results of performed experiments in manufacturing system. The aim was to analyze influence of order deviation to manufacturing system control. Two different manufacturing forecasts were used, 8 types of product were manufactured and order deviation was set to 0%, 10%, 25% and 50%.

First forecast required 8 setup processes of production line in one week (smaller batches are manufactured more often), forecast 2 required 5 setup processes (bigger batches, less number of setup processes).

Results of the experiments show, that the first forecast is much more independent from change of order by customer. The manufacturer is able to fulfil most of the demanded order using first forecast even with 25% deviation from expected amount.

An experiment has been performed to obtain the external performance of GA in comparison to Simulated Annealing algorithm. The results achieved were compared as well as the number of necessary simulation runs for achievement of these results. In Fig. 16 the maximum values obtained by Simulated Annealing algorithm was specified as well as the average value of the generation of solutions obtained by GA in the course of simulation runs.
Fig. 10. GASFOS software structure. 
Source: CEIT.
One simulation run was considered as one generation in Simulated Annealing so it was necessary to approximate the curves to make them comparable (GA performed 4 simulation runs within one generation).

As we can see, in this case the results of GA and Simulated Annealing algorithms are comparable; GA converges to the semi-optimal solution evenly. Since genetic algorithms work based on probability and estimation, the chance to find solution with high-value of objective function relatively quick is high. To compare the speed of reaching the semi-optimal solution (Simulated Annealing, GA), another graph was made. As we can see from Fig. 17, GA converges...
to the optimum evenly, from the second simulation run even performs better than Simulated Annealing algorithm.

Fig. 17. Ability to reach maximum.
Source: CEIT.

The results of experiments show that genetic algorithms are without problem ready to use in simulation optimization. Since the early stage of GASFOS development, it is remarkable that the software reaches high values of objective function so quickly in the beginning of optimization.

This feature was found as a crucial for simulation, since the goal for simulation optimization is to perform minimum number of simulation runs, which are computationally most challenging component of simulation optimization. Weakness which is known so far is mainly the early convergence of GASFOS, which deny looking up for the higher values of objective function. In the simulation, however, it is required a satisfactory outcome, not an optimal one, so this weakness is only relative disadvantage.

Future research

Future research will be oriented on the design of a holistic simulation and emulation environment supported by immersive technologies. The new directions of research are supposed in the following areas: parameterisation of simulation model, genetic algorithms modules, emulation environment.

Conclusions

The current global business environment requires high flexibility from the designers of advanced manufacturing systems. CEIT in co-operation with the University of Žilina have developed a new approach for the design, simulation and emulation of manufacturing systems based on Digital Factory. Such solution enables designers to develop manufacturing systems which will be able to work effectively during their life cycle. This new approach is the first step done in Žilina in the area of the design and building of Intelligent Manufacturing Systems. Currently new research environment is under development (ZIMS) which integrates all important subsystems in a holistic production system. Simulation and emulation systems became a significant part of ZIMS used in the design of manufacturing system and its control system. Such development environment, based on recent research, supported by virtual reality and immersive technologies presents a quit new direction in Digital Factory research. This innovative solution is fully available to the students, researchers and professors of the University of Žilina. It enabled to develop a concept of Learning University – new innovative learning system where professors and their students together solve applied research projects for industry.

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References


