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Procedia CIRP 52 (2016) 257 – 261

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Changeable, Agile, Reconfigurable & Virtual Production

An approach to determine simulation model complexity

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Abstract

Discrete event simulation (DES) is an essential tool for planning, operating and evaluating manufacturing systems. Estimation of simulation model complexity provides several advantages in the planning phase of a simulation project. For this purpose some measures of the simulation model's complexity are indispensable. The paper presents an approach to determine the complexity of DES models by combining several parameters describing simulation models. The potentials of the proposed approach are examined via industrial cases.

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016

Keywords: manufacturing; simulation; complexity

1. Introduction

In the last couple of decades manufacturing systems are becoming complex to fulfil the requirements of the increasing production quality and flexibility demands. Determining the complexity of manufacturing systems supports to understand and control the non-linear behavior of them and conclusively makes them more productive and predictive [1]. Analysis and evaluation of manufacturing systems' behavior and their performance became essential in the recent years. Digital enterprise technologies helps decision and in structure or performance analysis of manufacturing systems. One of most effective tools of these technologies is discrete event simulation (DES) [2]. A simulation model is a digital representation of an actual system [3]. DES is applied to model a system as it changes over time by representing the changes of the state variables at separate points in time [4]. Manufacturing simulation imitates several aspects of the real system such as the behavior and the layout of it. Simulation model complexity affects heavily the model building phase of a simulation project. Moreover preliminary estimation of simulation model complexity provides several advantages in the planning phase of a simulation project. For this purpose some measures of the simulation model's complexity are indispensable.

1.1. Complexity generally and in manufacturing systems

There is no universal and absolute definition for the word "complexity" and does not exist a widely accepted definition of it either [5], however the expression "complex" is used in several scientific fields. "Complexity" is typically used in association with systems. A system which consists of partly interacting and partly interdependent components is more complex if more component exist in it, and if more connections represented among the components.

In the field of production systems the complexity can be classified by physical and the functional domains. Physical complexity is divided to static and dynamic complexity. Static complexity is also named as structural complexity and related to the system's physical configuration that is not modified in time. It also refers to the interconnections and interdependencies of the static components. Dynamic complexity is also termed operational complexity and refers to the uncertainty of the system's behavior [5], [7].

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016
doi:10.1016/j.procir.2016.07.072

In the classification of the functional domain two groups are distinguished: time-independent and time-dependent complexity. In this domain complexity is defined as a measure of uncertainty in achieving the functional requirements.

1.2. Simulation model complexity

The correct association between digital and the physical world is essential to design and control a production system by digital technologies [6]. DES models consist of similar components and logical connections as the real system does, hence approaches determining the complexity of manufacturing systems are applicable for creating also various measures for simulation model complexity. Several approaches are published for measuring manufacturing system complexity. Section "Literature review" presents a selection of the existing manufacturing complexity modelling and measuring approaches.

1.3. Granularity, complexity

The representation of the real world in a DES model is heavily affected by the aims of the simulation experiment. Huge amount of information describe a production system completely and this information is inherently kept in the production system itself. The components of the system, the information of their attributes and the interactions and the interdependencies of them are available, measurable or calculable. The modelling objectives determine the set of data used to create a conceptual model that is a base of the simulation model construction and is formal description of the observed attributes of the production system. In this exposition simulation objectives filter data of the production system, see Fig. 1.

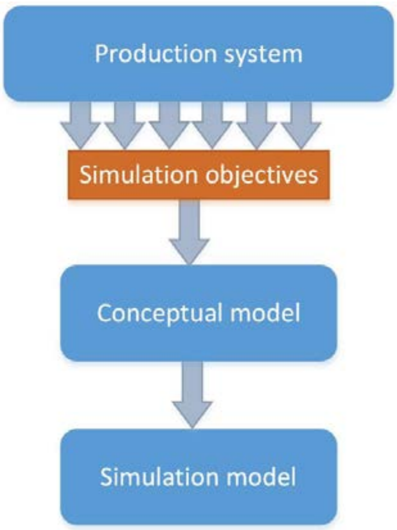

Fig. 1.: Considered information flow to simulation model construction

Simulation objectives also determine the required granularity of the model. In [14] granularity is defined as the varying levels of detail of the system. In terms of simulation granularity is related to the volume of information provided by the conceptual model.

2. Literature review

In the past years several approaches applying different methods have been published for determining and modelling manufacturing model complexity. Majority of them apply methods from axiomatic design theory, information theory, non-linear dynamics, or the combination of them [5], [7] [8].

In the domain of manufacturing several approaches based on "Axiomatic design theory" define complexity as a measure of uncertainty of fulfilling the aims of the functional requirements of the system [9], [10]. According to this approach the main goal of the design and control of manufacturing systems is the optimization of the productivity alongside reduced system complexity, following the philosophy of the "Design-Centric Complexity" (DCC) theory.

Shannon's notion of entropy is related to the uncertainty of the occurrence of an event in the series of events [11]. Information entropy is applied by several approaches in manufacturing in order to determine the complexity of a production system. In [12] the proposed method targets to measure the static complexity of a production system by considering the sum of individual entropies across the different states. Kolmogorov's complexity measure and the Lempel-Ziv complexity measure are also applied for manufacturing domain in [8].

In [13] Alfaro presents a methodology derived from non-linear dynamic systems (NLDS) theory to describe the system's sensitivity to its initial conditions applying Lyapunov exponents and the bifurcation diagrams.

3. Novel approach

In the proposed approach simulation model complexity is divided to three different measures according to the classification of manufacturing complexity in the physical domain in [5].

In the domain of static complexity structural and software (computational & algorithmic) complexity are considered. Regarding the two main domains of structural and software complexity two main categories of measures are defined in the novel approach:

1. Structural complexity measure.
2. Software complexity measure.

3.1. Structural complexity

Structural complexity in simulation models refers to the complexity of the physical layout of the modelled system and the existing physical connection among the represented elements, practically the possible material transportation routes. Regarding the number of the modelled objects and the connections two measures of the layout were defined:

1. M_1: highlights the number of the modelled objects,
2. M_2: determines the number of the connections among the modelled objects.

The applied software (Tecnomatix Plant Simulation 12 (64-bit), Version 12.0.3) provides several predefined manufacturing objects that are applicable for building a simulation model and also supports user defined object creation. Tecnomatix Plant Simulation and most of the recent production simulation software offers hierarchically structured object-oriented model building. In this representation the nodes of the structure graph of the model are the modelled objects or further graphs (sub-graphs) see an example on Fig. 2.

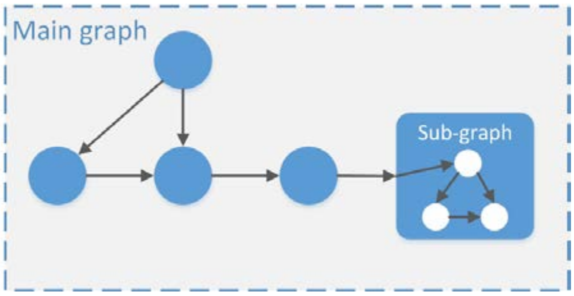

Fig. 2.: Graph of the physical structure of a simulation model (example)

The edges of the structure graph are the physical connections between the modelled objects. In the domain of structural complexity the presented approach considers the object oriented nature of the used simulation software and explores all the graphs and sub-graphs.

The proposed approach considers the modelled objects as sets of attributes. Each attribute is a value with a specific data format. The complexity measure calculated by the novel approach indicates the effort of the model building. 3 different measures are defined to highlight complexity of an object by means of its attributes. Besides hierarchically structured model building object-oriented programming also offers object inheritance that supports reducing model building effort. We considered this in m_{5n}. The measures of the attributes of the objects are the following:

1. m_{3n}: stands for the total number of attributes of object n. The object considered more complex if it has more attributes
2. m_{4n}: indicates the number of the manually changed attributes of object n. The object considered more complex if it has more manually changed attributes.
3. m_{5n}: equals the number of the attributes of object n that are not inherited from the parent object. The object considered more complex if it has more non-inherited attributes.

To calculate the overall measures of the simulation model we applied the following equations:

$$M_3 = \sum_{i=1}^{n} m_{3n} \tag{1}$$

$$M_4 = \sum_{i=1}^{n} m_{4n} \tag{2}$$

$$M_5 = \sum_{i=1}^{n} m_{5n} \tag{3}$$

where n is the number of modelled objects.

3.2. Software complexity

3.2.1. Algorithmic complexity

Software (computational & algorithmic) complexity is considered as the operation and control logics of a production system that is presented in the simulation model by program codes securing the accurate operation of the model. Although program code can be realized in any programming language the algorithmic complexity of it is measurable. In the novel approach we applied McCabe's cyclomatic complexity measure [16]. The calculation of this measure is applicable for structured programs:

$$v = \pi + 1 \tag{4}$$

where π is the number of predicates in the flow graph of the program.

In the presented approach we created a source code parsing method that identifies and counts the predicates of the code. The method recognizes the predefined strings of characters that indicate the predicates in the text of the source code, see an example on Fig. 3. and Fig. 4.

Fig. 3.: Example of a program block

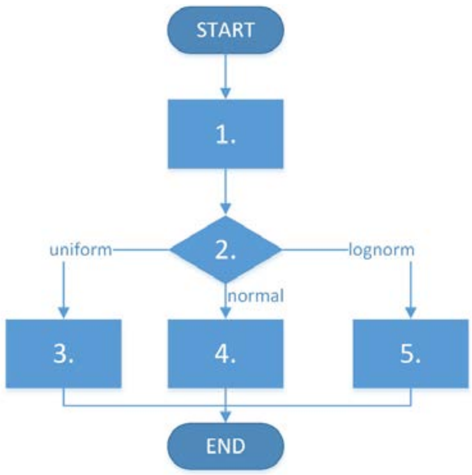

Fig. 4.: Flowchart of the program block of Fig. 3

In the example presented on Fig. 3 and Fig. 4 the number of predicates is 3 (π = 3), hence the cyclomatic complexity (v) of this program block is 4, based on the equation $v = \pi + 1$ (4).

The operation and control logics of a simulation model are realized in several program blocks as each of them covers a specific function. The overall algorithmic complexity of the model is calculated by summarizing the cyclomatic complexity of all the program blocks:

$$M_6 = \sum_{i=1}^{n} m_{6n} \tag{5}$$

where

n is the number of program blocks,

m_{6n} is the cyclomatic complexity of program block n.

A measure is defined to indicate the total number of lines in all the program blocks:

$$M_7 = \sum_{i=1}^{n} m_{7n} \tag{6}$$

n is the number of program blocks,

m_{7n} is the total number of lines of source code of program block n.

3.2.2. Computational complexity

In the domain of computational complexity M_8 was defined to determine the required time duration to fulfil a simulation run of a certain time period. In the case of the tests we fulfilled simulation runs with all the test models of 8 hours and measured the required time to calculate it by a computer with the following processors: Intel® Core™ i5-4210U CPU @ 1.70GHZ, 2394 MHz, 2 cores, 4 logical processors.

4. Use cases

7 different simulation model which are used to solve industrial problems were tested by the proposed complexity measuring approach. The models were classified by a few main features:

- type of modelled production system,
- size of the modelled area level of granularity,
- number of moving objects,
- level of visualization,
- complexity of control logic and
- average duration of processing times.

All the features of each model were categorized in a 3 class scale, where 1 is the lowest, 3 is the highest. Feature "type of modelled system" is an additional information of the use cases, see Table 1.

4.1. Assumptions of the results

4.1.1. Assumption 1

As it is highlighted in *Use case 1* software complexity is relatively high compared to *Use cases 2-4*, although the structural complexity measures are low. This is indicated by the high complexity of the control logic and the moderate level of granularity.

Table 1: Classification and results of the use cases

								Structural complexity					Software comp.		
	size of modelled area	type of modelled sytem	levelof granularity	number of moving objects	level of visualization	complexity of control logic	average duration of processing times	M_1 (number of objects)	M_2 (number of connections)	M_3 (number of attributes)	M_4 (number of changed attributes)	M_5 (number of not inherited attributes)	M_6 (total cyclomatic complexity)	M_7 (total length of programcodes)	M_8 (computational complexity)
Use case 1	1	continuous mat flow	2	1	1	3	1	40	17	7161	324	816	125	11018	0.333
Use case 2	2	flow shop	1	1	1	1	3	53	28	13531	397	1268	28	2241	0.096
Use case 3	2	flow shop	1	1	1	1	3	65	12	13343	199	1130	30	8612	0.095
Use case 4	1	continuous mat flow	1	2	2	1	1	68	48	17564	579	1904	24	2579	4.118
Use case 5	2	continuous mat flow	2	1	1	2	2	100	80	26456	824	2459	81	8734	0.204
Use case 6	2	continuous mat flow + logistics	3	2	3	3	1	838	227	145411	1335	8113	555	104283	6.722
Use case 7	1	producion line (automatic model generation)	3	2	2	2	1	3244	292	469283	3819	22181	43	9434	5.721

4.1.2. Assumption 2

In *Use case 4* the computational complexity is relatively high, although this case is not significantly different from *Use cases 1-3*. On one hand the relatively high computational complexity is indicated by the relatively high number of moving objects and high level of visualization. On the other hand in this case the duration of processing times, practically the number of events in the same time period is high.

4.1.3. Assumption 3

Use case 6 is a structurally complex model and covers 2 different area of the production system, which both have complex control logic. The effort to create this simulation model was relatively high compared to the other use cases. The total number of changed attributes and all of the software complexity measures highlight this type of models are possibly not reasonable to build in one model. It is recommended to define more areas with separate function and create more models regarding to the areas.

4.1.4. Assumption 4

In *Use case 7* the modelled area is relatively small, but the granularity of the model is extremely high and moreover the special application of the model required automatic model generation that means the modelled objects are generated automatically at the initial phase of every simulation run based on a table file. On one hand in the cases when automatic model generation is reasonable, the structural measures can be extremely high. On the other hand, high granularity and low duration of processing times indicates high computational complexity.

5. Conclusions

In the recent years manufacturing systems fulfil the requirements of the increasing production quality and flexibility demands. Analysis and evaluation of manufacturing systems' behavior and their performance became essential. Digital enterprise technologies support decision and in structure or performance analysis of manufacturing systems. One of most effective tools of these technologies is discrete event simulation (DES). Determining the complexity of a simulation model is indispensable. The paper introduced objective measures to estimate and compare several aspects of simulation model complexity. The novel approach of the calculation of the complexity apply measures of the state of the art and introduces new indicators as well. The potentials of the proposed approach is examined via several industrial cases. The tests revealed demonstrable correspondences between the nature of the manufacturing system and the complexity of the simulation model of it. They also discovered correlation between the problem investigated by the simulation model and the complexity of it. The size of the modelled area, the number of modelled events, the granularity of the model and the complexity of the control logic of the modelled system affect heavily the complexity measures of the simulation model.

The next reasonable step of the evolution of the complexity measures is to create a reference model to calculate general complexity measures of simulation models.

6. Acknowledgements

This research has been supported by the National Research, Development and Innovation Fund (NKFI), Hungary, Grant. No. VKSZ_12-1-2013-0038 and by the Hungarian Scientific Research Fund (OTKA), Grant No. 113038.

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