CREATING THE DIGITAL TWIN WITH GENERAL PURPOSE SIMULATION MODELLING TOOLS

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Abstract: *In this contribution we present several possibilities for the use of automated modelling and simulation methods within digitalization and automation projects implementing the Digital Twin as a part of the Industry 4.0 paradigm. First part of the contribution introduces the Industry 4.0 paradigm, current state of development and its influence on the development of the simulation modelling paradigm. In the second part of the contribution we examine a case where innovative approaches and methodologies were used to realize the Industry 4.0 paradigm concepts using general purpose simulation modelling tools, facilitating research and development projects for SMEs.*

Keywords: *Simulation modelling, Industry 4.0, Digital Twin, automated modelling, manufacturing automation*

1. INTRODUCTION

The aim of this contribution is to present the evolution of the simulation modelling paradigm in connection with the Industry 4.0 paradigm and two real-life cases of the application of the new simulation modelling paradigm using off-the-shelf simulation modelling tools. The presented cases introduce methodologies and solutions which enable the automation and integration of general purpose simulation modelling tools by using data exchange standards such as XML, and the development of automation solutions using the Digital Twin concept with widely available sensor technologies.

The »Industry 4.0« term was coined by the German federal government in the context of its High-tech strategy in 2011. It describes the integration of all value-adding business divisions and of the entire value added chain with the aid of digitalization. In the "factory of the future", information and communication technology (ICT) and automation technology are fully integrated. All subsystems – including non-producing ones such as R&D as well as sales partners, suppliers, original equipment manufacturers (OEMs) and customers – are networked and consolidated into one system, the cyber-physical production system (CPPS).

While the large industrial companies are concerned with the development of standardized methodologies and architectures that would allow integration within their R&D processes and existing ERP and MES solutions [1], and the purchase or development of automation technologies is not presented as problem, the SMEs have to consider using economical, off-the-shelf simulation modelling tools and commercially available sensors to build proprietary automation solutions, which would allow them to implement selected Industry 4.0 concepts, in order to remain a competitive supplier to their (larger) business partners.
Even though Industry 4.0 standards are still developed, the manufacturing and automation technology developers already market many technologies and solutions as "Industry 4.0". But

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even without specialized vendors there are many of the building blocks necessary for implementation of Industry 4.0 ideas already available – such as digital and networkable sensors and control elements (actuators), cloud computing, (industrial) communication networks, and general purpose simulation modelling tools as presented in this paper.

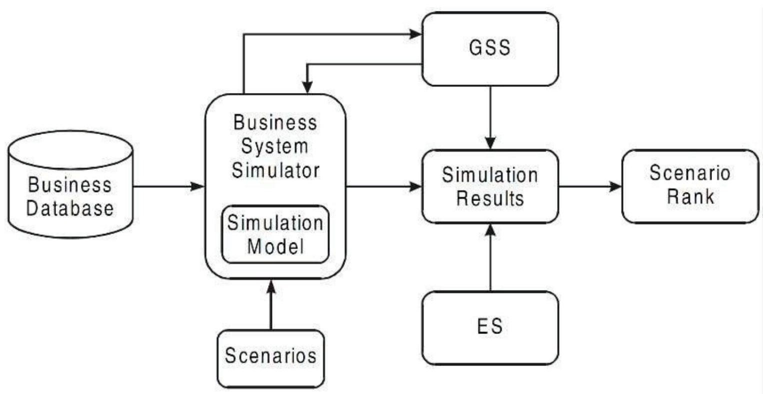
2. EVOLVING SIMULATION PARADIGM

Today, the use of simulation modelling in science and engineering is well established. In engineering, simulation modelling helps reduce costs, shorten development cycles, increase the quality of products and greatly facilitates knowledge management. A great body of scientific and professional body of literature on various aspects of simulation modelling, e.g. system dynamics, cybernetics and system theory, is available, such as [2] and [3].

Several methods have been developed for mathematical modelling of real systems. Each of them was motivated by the problem itself and the researcher in that field. Three most popular simulation methods today are System dynamics (SD) [2] [4], Discrete event simulation (DES) [5], and Agent based modelling (ABM) [6], [7]. The methods are selected depending on the complexity and abstraction level of the discussed system.

In the traditional simulation paradigm, the connectivity of a simulation model typically involves integration with a static database with business variables, a user friendly front-end and decision support tools such as online analytical processing (OLAP), or group decision support systems (GSS) [8]. The schematic of such a decision support system (DSS) is shown in Figure 1.

Figure 1: Schematic of a typical simulation modelling based DSS [8]



Increasing product variants and customizable products request more flexible production systems. The advent of the Industry 4.0 paradigm has brought changes to the simulation modelling paradigm as well. Part of the Industry 4.0 paradigm is modelling the manufacturing systems using the concept of a virtual factory or Digital Twin. Combining the real life data with the simulation models from design allows on the other side to give good predictions based on realistic data.
These three points summarize the main changes to the simulation and modelling paradigm in the change from stand-alone simulation-based decision support system to the Digital Twin:

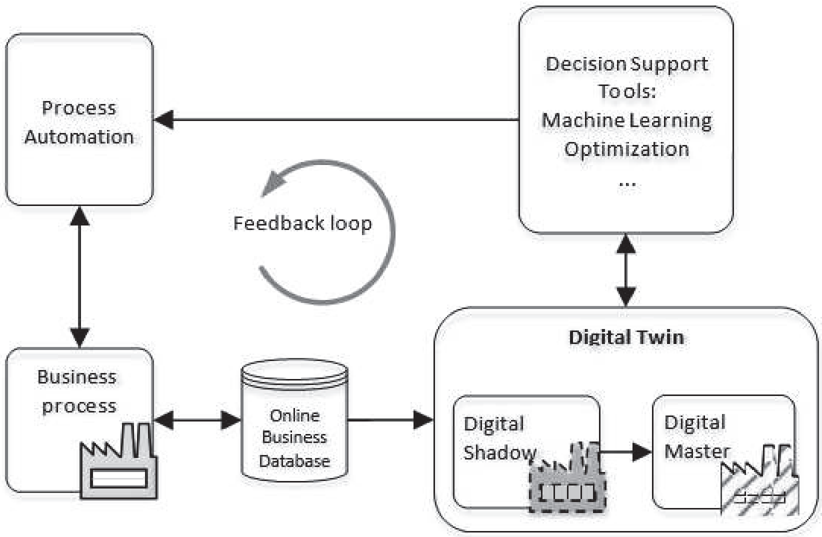
- Connectivity and integration in a wider IS (manufacturing or enterprise resource planning (MRP, ERP) is the norm,
- The system is modelled with a holistic, multi-level/resolution approach, which

includes physical modelling. Aspects of the simulation model require a high level of details and low level of abstraction,
- Modelling and modification of models is automated (data-based).

Within the Digital Twin concept every instance of an individual product or production system produces a “digital shadow”, which is the name for the structured collection of data generated by operation and condition data, process data, etc. Hence an instance of a Digital Twin consists of: a unique instance of the universal Digital Master model of an asset, its individual Digital Shadow and an intelligent linkage (algorithm, simulation model, correlation, etc.) of the two elements above [9].

Schematics of a decision support system (DSS) incorporating simulation modelling via Digital Twin is shown in Figure 2.

Figure 2: Schematic of a simulation modelling based DSS implementing the Digital Twin



In such systems, the Business System Simulator contains a Digital Twin model of the Business process. The Digital Twin is used to supply the array of decision support tools with a detailed, dynamically updated digital representation of the real-life business process (e.g. a manufacturing plant). The process data is gathered in real-time by the array of sensors and smart machines in the business process, stored in the business database and then transferred to the Digital Shadow. The Digital Master model’s operation is adjusted according to the data in the Digital Shadow, allowing on-line optimization and decision support, and control of the process automation, creating a controlling feedback loop, which is the basis of cybernetic systems [3].

3. IMPLEMENTING THE NEW PARADIGM

Implementing the new Industry 4.0 simulation modelling paradigm remains a serious challenge for researchers and companies. However, there are ways to improve the integration of models built in general purpose simulation modelling tools, automate their construction and modification, and implement such solutions without major financial investments, which is a very attractive prospect especially for the SMEs. A number of solutions have been developed for automated generation of DES simulation models corresponding to manufacturing systems, with a good overview of solutions presented in [10]. We will present a case of the implementation of the aspects of new simulation modelling paradigm, demonstrating datadriven automated simulation model construction for the development of a Digital Twin.

3.1. Automated model building using XML and Java

This case involves a novel automated DES model construction method, using the customer order data obtained with SQL queries to modify the XML (Extensible Markup Language) file containing the simulation model structure and data. The method was applied in a manufacturing process optimization project. Authors used discrete event simulation (DES) to build a model that reflects the current manufacturing processes and allows them to test optimization methods.

System optimization through modification of model structure can be performed by constructing several versions of the model and input data (i.e. scenarios) and comparing simulation results. To accelerate the development of model versions and scenarios one can construct algorithms that build or modify simulation models according to model input data. This is especially useful in cases of large simulation models and if the model variants are prepared by an algorithm, e.g. an optimization algorithm. Automated model building and modification however requires that the model structure can be modified with an algorithm, without manual interventions. [11]

Developing a static simulation model that would cover all possible (i.e. 30,000) products that may appear in client's orders is not realistic as it takes approximately 15 minutes to complete a model of a process for each product, and a model containing 30.000 processes also exceeds the memory limitations of the modelling tool used (Anylogic, http://www.anylogic.com/). Manual modifications of the simulation model can be time consuming, especially if a large set of variations of the model needs to be built. In Anylogic, simulation model is typically constructed by adding different blocks and connections to the canvas by "click and drag" technique.

Instead, a method for ad-hoc model construction for each set of open orders was developed using Java. The Java application builds the model from a model template, the database of technical procedures and the database of currently open orders. Based on the list of ordered products and technical procedures only the necessary machines are placed in the model. Anylogic stores the models as standard XML files, which allows easy manual or algorithmic modifications of the model. Anylogic XML simulation model file stores information on standard and user-defined blocks and agents, connectors between blocks, statistical monitors, input readers, output writers, etc. The data are stored as elements (nodes) and nested in a tree-like structure. An element can contain several attributes, describing type of the element and all the parameters describing element properties. The attributes can contain several lines of programming code describing how the block operates in different situations and states. [11]

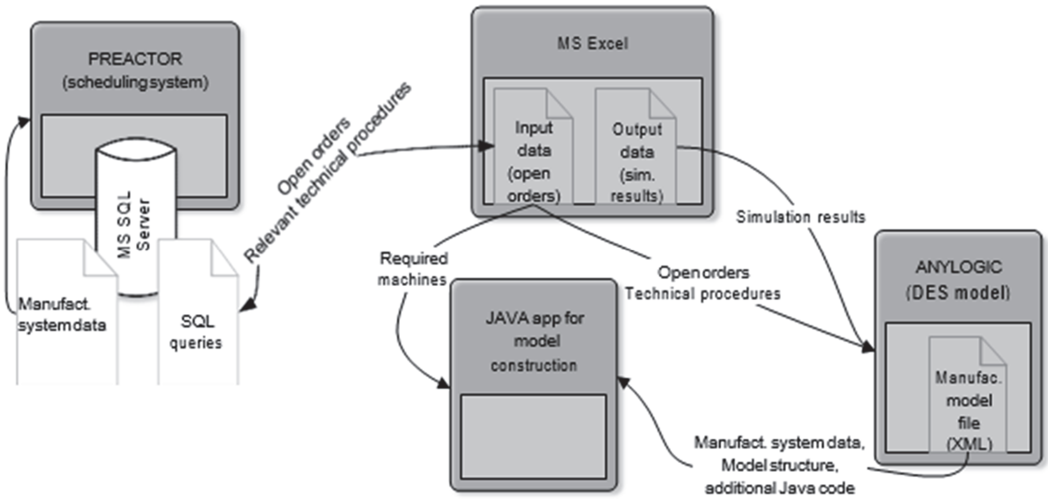
The developed Java application manipulates XML code to change data on machines and all other relevant abstract objects such as connectors, sources and sinks that are connected to the blocks of machines. Specifically, the Java application reads the blocks in the template file and copies them according to input data. A new element (block) is added to the model by the following procedure:

- find a node representing a template block in XML tree according to the searched attributes,
- copy the node and connect it to the parent of the original node,
- change the data of the copied block (name of the block, position on the canvas, properties of the block, part of the programming code, etc.).

The resulting XML structure is then saved to a new Anylogic file. Products and carts play a role of transactions in DES and are therefore constructed dynamically during simulation. The resulting modelling and simulation system, shown in Figure 3 is composed of four main elements [11]:

- Core manufacturing process simulation model in Anylogic environment.
- Java application that constructs XML Anylogic model from a template file.
- MS Excel as an intermediate input and output data storage, and analysis tool. MS SQL server database describing technical procedures and client's orders.

Figure 3. Automated DES model generation system schematic



4. CONCLUSION

The research presented in this paper includes a novel approach, that allows researchers and engineers to automate the model generation within simulation based decision support and engineering systems. The adoption of new simulation modelling paradigm in research environment requires closer cooperation with industry partners, and diversification of knowledge of researchers, in order to build integrated, multi-level models of systems. As shown by the presented case, lack of tools is not a problem, as the current generation of general purpose simulation modelling tools offers alternative integration options. As the CPPS concept involves the integration of diverse information systems and multi-level simulation models, the Industry 4.0 and Digital Twin concept present researchers with a new motivation for closer cooperation with industry and transfer of knowledge between research groups and institutes.

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