# Approaching Industry 4.0 Simulation Modelling Paradigm with General Purpose Tools

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***Abstract.*** *We aim to present the evolution of the simulation modelling paradigm as influenced by the Industry 4.0 paradigm and two real-life examples of the application of the new simulation modelling paradigm. Currently the development of a Digital Twin requires considerable resources and expertise, limiting the accessibility to SMEs. However, we demonstrate that data driven automated process modelling and integration of manufacturing information systems and simulation models is achievable without specialized tools or large budgets, and is thus within reach for research and development projects for SMEs.*

## 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 digitalisation. In the “factory of the future”, the machines, sensors and other automation technologies are integrated via information and communication technology (ICT) into one system, the cyber-physical production system (CPPS). The CPPS also integrates the non-producing subsystems such as R&D as well as sales partners, suppliers, original equipment manufacturers (OEMs) and customers’ information systems.

While the large industrial 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”. Currently the development of a Digital Twin requires considerable resources and expertise, limiting the accessibility of many solutions to bigger companies to the disadvantage of SMEs. [2] But 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. [1]

## 2 The evolution of the 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.

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. System dynamics (SD), which is based on cybernetics and system theory ( [3] and [4]) and discrete event simulation (DES) were developed several decades ago and are today well-established. Agent based modelling (ABM) [5], [6] is a more recent methodology, and has gained attention outside social sciences due to its flexible abstraction level and applicability to modelling of complex systems [7]. In a simulation modelling project the methods are selected depending on the complexity of the modelled system and required abstraction level.

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 additional decision support tools such as expert systems (ES) or group decision support systems (GSS) [8]. The schematic of such a system is shown in Figure 1.

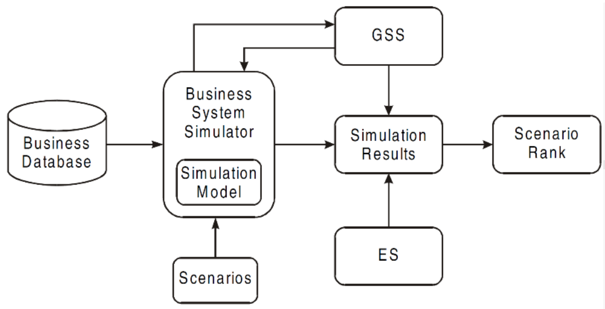


Figure 1: Schematic of a typical simulation modelling based decision support system [8]

### 2.1 New simulation modelling paradigm in Industry 4.0

Increasing product variants and products customized to order 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. 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 modelled 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).

The concepts themselves are not new, the novel aspect is the unifying paradigm of Industry 4.0, which promises standardization of methods and the new technologies that make their implementation easier. In Industry 4.0 paradigm 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 incorporating the concept of Digital Twin is shown in Figure 2. 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 update digital representation of the real-life business process (e.g. a manufacturing plant). The process data is gathered 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 [4].

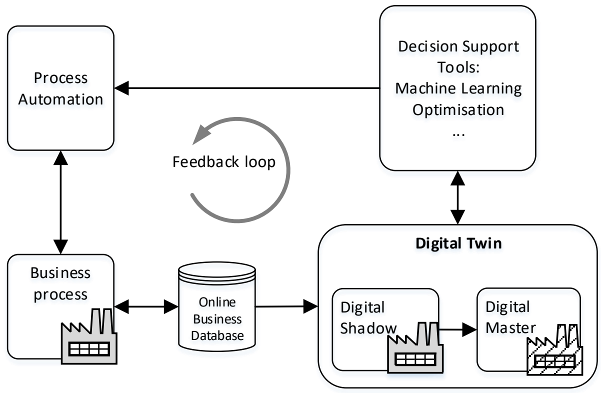


Figure 2: Schematic of a simulation modelling based decision support system implementing the Digital Twin

## 3 Implementing the simulation modelling paradigm

Implementing the new simulation modelling paradigm and the Industry 4.0 remains a serious challenge for researchers and companies. There are however novel 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 two cases of the implementation of the aspects of new simulation modelling paradigm, ranging from the development of new methods for data-driven automated simulation model construction to the development of a Digital Twin concept for SMEs.

### 3.1 Example 1: case of 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 optimisation project. Authors used discrete event simulation (DES) to build a model that reflects the current manufacturing processes and allows them to test optimisation methods.

Construction of a DES simulation model requires that the data that describe the manufacturing processes are obtained, analysed, extracted and prepared in a suitable format for the model. In order to maintain model accuracy despite changes in manufacturing processes, integration of simulation software, auxiliary applications and databases is necessary. System optimisation 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 optimisation 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 process also exceeds the memory limitations of the modelling tool used (Anylogic, http://www.anylogic.com/). While other DES tools would also serve the purpose, Anylogic was used as its licence is already owned by the faculty and the models are stored in XML files, allowing relatively easy modifications to model structure. 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 using a 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 models are 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.

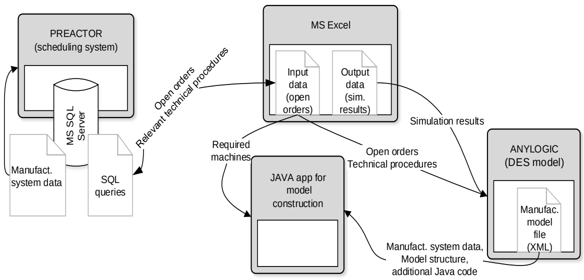


Figure 3. Automated DES model generation system schematic

### 3.2 Example 2: A Digital Twin for SMEs

Authors [12] present a concept for the realization of a Digital Twin of the production system within SMEs. Their concept is feasible by assuring sufficient data quality with minimized investment costs, and without compromising the advantages of the Digital Twin and of the CPPS. Their concept proposes a database structure and guidelines for the implementation of the Digital Twin in production systems in SMEs. The further concept of the Digital Twin for a production process enables a coupling of the production system with its digital equivalent as a base for an optimization with a minimized delay between the time of data acquisition and the creation of the Digital Twin. This allows the construction of a CPPS, opening up powerful applications. To ensure a maximum concordance of the cyber-physical process with its real-life model a multimodal data acquisition and evaluation has to be conducted.

Even though Industry 4.0 is one of the most prevalent subjects in production engineering, the methods of Industry 4.0 are still under-represented within manufacturing operations in SMEs. Authors furthermore describe the following main difficulties in the course of the realization of the Digital Twin in SMEs [12]:

- manual acquisition of motion data is widely used, but not with real-time availability, which limits the potential of simulation,

- in-house implementation of Industry 4.0 is frequently insufficient,
- slow standardization of data acquisition in productions systems hinders agile and adaptable system implementations,
- high costs for new IT and a centralised IS inhibit the application of vertical Industry 4.0,
- coupling of simulation and optimization is not sufficiently ensured to take full advantage of near real-time models, and
- data security concerns.

As the database of production data in SME is extremely heterogeneous, and its quality regularly insufficient for the realization of the Digital Twin, the authors [12] introduced sensor based tracking and machine vision for manufacturing process data acquisition. Sensor-based tracking provides information regarding routes and position of production employees and routes and position of large and highly mobile production devices, e.g. forklifts. The required technologies, i.e. sensor-based tracking systems and extensive program libraries for the machine vision implementation are commercially available, and therefore the implementation of the proposed concept is feasible.

In the last step, the data acquisition hardware is implemented into a real model process and linked with the data layer. This forms the final and major step within the realization of the CPPS in SME as part of the presented concept. The schematic of the proposed Digital Twin concept is shown in Figure 4.

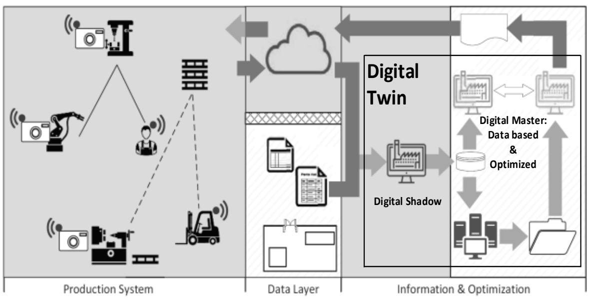


Figure 3. Concept of the implementation of a Digital Twin in SMEs (adapted from [12])

The described concept is novel in comparison to approaches prevalent in large enterprises, which focus on full automation. Automated gathering of machine data is not considered, as the low degree of digitalisation of manufacturing in SMEs data does not allow it. Furthermore, the collection of detailed machine data is not required with the presented concept. The innovative aspect of the concept is in the integration of well adopted and commercially available components, which are already available as isolated solutions [12].

# 4 Conclusion

The research presented in this paper includes novel solutions, that allow researchers and engineers to develop solutions that automate the model generation and solution seeking aspects of simulation based decision support and engineering systems. Presented methodologies and solution allow the development of Industry 4.0 automation solutions using the Digital Twin concept with widely available sensor technologies.

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 examples, lack of tools is not a problem, as the current generation of general purpose simulation modelling tools offer sufficient 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.

# Literature


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