Symbiotic Simulation System (S3) for Industry 4.0

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**Abstract**

This chapter discusses symbiotic simulation system, a simulation system that is designed to support online short-term operations management decision. The prevalence of real-time data and the advances in Industry 4.0 technologies have made the real-world implementation of the vision of using simulation to support real-time decision making a reality. The main contributions of this chapter are to provide a review of similar concepts in simulation, to provide the architecture of symbiotic simulation system at the conceptual level, to classify the types of symbiotic simulation applications, and to highlights research challenges in symbiotic simulation.

**Keywords**: symbiotic simulation, industry 4.0, system architecture, operations management

# 1. Introduction

Based on their planning horizons, management decisions can be grouped into three categories: strategic, tactical and operational. Strategic management decisions often have a long planning horizon (e.g. several years). A strategic management decision (or strategy) is then translated into one or more tactical management decisions. Each has a medium-term planning horizon (e.g. one year, six months). Finally, a tactical management decision is implemented in one or more operational management decisions. Each has a short-term planning horizon (e.g. monthly, weekly, daily). Given the shorter planning horizon, the time needed to make operational management decisions is limited. Hence, a tool to support short-term operational management decision-making is important, especially when dealing with complex operational problems. The symbiotic simulation system (S3) is a tool designed to support decision-making at the operational management level by making use of real-time or near-real-time data which are fed into the simulation at runtime.

## 1.1 Symbiotic Simulation System Definitions

The idea of using simulation as a real-time decision support tool is not new. For example, in 1991, Rogers and Flanagan used the term “online simulation” to describe their proposed real-time simulation-based decision-support tool for manufacturing systems (cited in Rogers and Gordon 1993). A few years later, Davis (1998) provided one of the earliest descriptions of the architecture of online simulation and generalised it as a simulation system that could be used to control a physical system (not just a manufacturing system).

A similar concept, called “co-simulation”, has also been used in electrical and computer engineering to describe an experiment in which a hardware simulator (e.g. integrated circuit simulator) communicates with a software component (e.g. firmware) with the objective of verifying that both hardware and firmware function correctly before the hardware is produced. There are several variations of this hardware/software co-simulation (see Rowson 1994). Later, some researchers also used it to describe a real-time simulation-based decision-support tool (e.g. Bohlmann et al. 2010).

Another related term is “real-time simulation”. A real-time simulation refers to a simulation that can run as fast as “wall-clock” time. Hence, a real-time simulation enables us to use it to test a hardware component (i.e. hardware-in-the-loop simulation). Since more digital devices contain both hardware and software components, real-time simulation has also been used to test software components, too (i.e. software-in-the-loop simulation). Real-time simulation has also been used to describe a simulation that interacts with a physical system in real time. IEEE and ACM have jointly run an international symposium on this topic since 1997 (see <http://ds-rt.com>).

With the introduction of Dynamic Data-Driven Application Systems (DDDAS) in 2000 (Darema 2004), the term Dynamic Data-Driven Simulation has also been used to describe similar applications of simulations. It puts emphasis on the ability of a simulation to (1) react to additional data from the physical system while the simulation is running and (2) control the physical system. At the 2002 Dagstuhl seminar on Grand Challenges for Modelling and Simulation, the term symbiotic simulation was coined (Fujimoto et al. 2002). The initial definition was heavily influenced by research in DDDAS, which put emphasis on the ability of a simulation to control a physical system. Aydt et al. (2008) propose a new definition of symbiotic simulation that is less restricted, i.e. “a close association between a simulation system and a physical system, which is beneficial to at least one of them”. A close association is less restrictive than the ability to directly control a physical system. This close association is enabled by communication channels between the simulation system and the physical system which allow them to interact in real or near-real time. This chapter adopts the term symbiotic simulation from Aydt et al. (2008) and refers to it as a *symbiotic simulation system* (S3). S3 is also referred to as a virtual system or digital twin. We will discuss the architecture of S3 in Section 2.

## 1.2 Symbiotic Simulation System and Industry 4.0

Historically, industrial revolutions were triggered by the introduction of new technologies. The first industrial revolution was triggered by the introduction of water- and steam-power engines. If the first industrial revolution is seen as Industry 1.0, then subsequent phases, Industry 2.0 and Industry 3.0, are associated with the introduction of electrically-powered mass-production technologies and automation using Information Technology (IT), respectively. The term Industry 4.0 was first announced at the “Hannover Messe” industrial trade fair in 2011. It was taken from the Germans’ strategic initiative to establish Germany as a leader in advanced manufacturing solutions. Since then, the term has spread and been adopted in various industries outside manufacturing.

Like many new terms, there have been several definitions proposed for Industry 4.0, as discussed in Chapter 1. However, these definitions agree that Industry 4.0 is a new paradigm that puts emphasis on real-time (or near-real-time) situational awareness to address the increasing complexity of products and processes in industry by making use of Cyber-Physical Systems (CPS). In addition to CPS, Industry 4.0 is also enabled by technologies across four groups (Szozda 2017): data and communication (e.g. Internet of Things (IoT), big data, cloud), advanced analytics (e.g. Artificial Intelligence (AI), data mining), advanced man-machine interface (e.g. augmented reality) and advanced actuators (e.g. robotics, 3D printers).

CPS has been perceived as the core foundation of Industry 4.0 (Yin et al. 2018, Xu et al. 2018). There are several definitions of CPS. If we look at the definition in Monostori (2014), CPS is a system of collaborating computational entities (i.e. virtual system), which have an intensive connection with the surrounding physical system and its ongoing processes. This is exactly what we have in symbiotic simulation, where a physical system and an S3 that represents the physical system form a symbiotic system. In both CPS and S3, the combined virtual-physical (or symbiotic) system provides benefits that would otherwise be unavailable if used separately. Hence, from the perspective of academia, S3 is closely linked to Industry 4.0 in at least two ways. First, S3 is a special form of CPS, which is the core foundation of Industry 4.0. Second, S3 uses the same technologies that support Industry 4.0. Hence, S3 and Industry 4.0 share the same design methodology and most of the challenges. These will be discussed in later sections.

From the perspective of industry, several simulation software vendors have marketed their products and services in the context of Industry 4.0. For example, the Simio homepage ([www.simio.com](http://www.simio.com)) has Industry 4.0 as one of its main menu items (see Fig. 1). Lanner has produced a briefing paper outlining how their product fits into Industry 4.0 and provided several case studies (Lanner 2017). Flexsim has written about their successful Industry 4.0 projects in Italy (Flexim 2018). AnyLogic has also written about their Industry 4.0 project at CNH Industrial, which was presented at the AnyLogic Company Conference in Baltimore (AnyLogic 2017). These are only a few examples of how simulation vendors have prepared themselves to provide simulation-based solutions to support Industry 4.0. The most commonly used term for S3 in industry is digital twin (Grieves 2014). Hence, both academia and industry believe that S3 will play an important role in Industry 4.0.



Figure 1. Industry 4.0 web page at Simio

## 1.3 Objective and Structure

The objectives of this chapter are to present the architecture of S3 (Section 2), introduce three types of S3 applications for Industry 4.0 (Section 3) and highlight the challenges that need to be addressed for the real-world adoption of S3 (Section 4). Finally, Section 5 summarises this chapter.

# 2. Symbiotic Simulation System Architecture

In this chapter, we use the following definitions: A *symbiotic system* is a system that is formed by a physical system and a *symbiotic simulation system* (S3) that represents the physical system. S3 is formed by a *symbiotic simulation* *model* (S2M) and other components, such as data acquisition, optimisation and machine-learning. The execution of S2M is referred to as *symbiotic simulation* (S2). A diagram showing the components of a symbiotic system and their relationship is shown in Figure 2.

As shown in Figure 2, an S3 extracts, transforms and loads real-time (or semi-real-time) data from a physical system using the data acquisition component. The loaded data are then analysed using appropriate analytics methods. The objective of analytics methods is to select the best way to use a combination of historic data when developing a model and new data that are only available when the model is running. The information extracted by analytics may be used to update the scenario manager, optimization model or S2M. Machine learning (ML) methods can be used to adapt the scenario manager, optimization model, S2M and analytics methods to make them perform better. Finally, the results from the scenario manager/optimization model are communicated to an actuator or a decision-maker, leading to changes being made to the physical system. These components work together to achieve a common system objective, e.g. maintain the stability of the physical system when facing external perturbations or make the physical system react in time in anticipation of a drop in its performance. The remainder of this section explains the main components of S3. A more detailed explanation and examples can be found in Onggo et al. (2018).

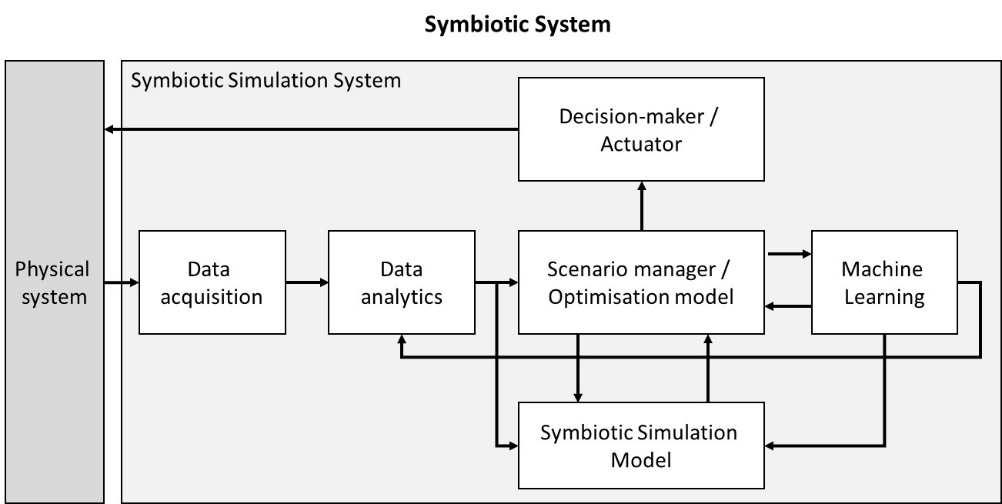


Figure 2. Symbiotic System formed by a Physical System and its Symbiotic Simulation System (Onggo et al. 2018)

## 2.1 Data Acquisition

The data-acquisition component is responsible for extracting, transforming and loading data (ETL) from the physical world to S3. The data can be read online (direct communication with the sensors) or off-line (the data from sensors are stored in a file, and the file is read by the data acquisition component) through a Web service, Web application or mobile application. The data can be real-time (always connected) or semi-real-time (connected at certain times or regular intervals).

## 2.2 Data Analytics

One of the characteristics that differentiates symbiotic simulation from non-symbiotic simulation is that symbiotic simulation is designed to respond to data when the simulation is running. The data may come in different volumes, velocities, varieties and veracities. Hence, there is a need for analytics methods to determine the best way of using various data sources to update the appropriate parts of S3. Typically, the data analytics methods used in S3 belong to time-series models or data-mining models.

## 2.3 Scenario manager

The role of a scenario manager is to implement various what-if analyses using a symbiotic simulation model. Typically, the scenario manager implements analyses such as sensitivity analysis and the design of experiment analyses.

## 2.4 Optimisation model

An optimisation model may be used instead of a scenario manager, especially when it is impractical to define a set of scenarios (e.g. too many possible solutions). In this case, the optimisation model explores the solution space and tries to find the best solution based on a predefined objective function (or functions, when there is more than one objective). The function is estimated by running the simulation model. This combination of simulation and optimisation models is referred to as simulation optimisation or optimisation-via-simulation (Fu 2015).

S3 is a tool designed for making short-term operational management decisions. Hence, the time to find a solution is relatively short. For this reason, the simulation model has to run fast. Many complex short-term operational decisions belong to a *combinatorial optimisation problem* (COP). A COP is a problem in which there are countable-but-vast possible solutions to choose from, e.g. staffing level to minimise waiting time, job scheduling to maximise throughput, inventory management to minimise stock-outs. Finding the best solution to a COP is known to take a long time and is impractical in practice. Hence, alternative methods are needed to find good enough solutions that can be achieved over a short planning horizon. The alternative methods include simheuristics (Juan et al. 2015), multi-fidelity modelling (Rhodes-Leader et al. 2018b) and parallel computing (Panadero et al. 2018).

## 2.5 Simulation model

The core model of S3 is the simulation model of the physical system (i.e. S2M). This S2M needs to be designed to communicate with the data-acquisition component at runtime and to make an appropriate response as specified by the modeller. The response can be in the form of:

* re-initializing the system states in the simulation using the latest data from the physical system
* adjusting the remaining service times for entities that are already in the system at the point of simulation re-initialization
* adjusting the parameters used in the simulation, such as input distribution functions and number resources
* updating the structure of the simulation model

Any simulation needs to maintain a set of system states (e.g. queue lengths and whether a server is busy in a discrete-event simulation, or the accumulated values of each stock in a system-dynamics simulation). In a non-symbiotic simulation, system states are initialised at the start of the simulation. In symbiotic simulation, the system states may be re-initialised a few times during a simulation run. Re-initialising system states is straightforward. Most simulation software has this functionality. The task of a modeller is to define the system states that need to be re-initialised and the mechanism that triggers the re-initialisation (e.g. periodically or when a value from the physical system is outside a certain range).

Re-initialisation means that the service time of an existing entity that is being served when the simulation is initialised should be sampled based on the time already spent in service. This requires the simulation software to support a conditional-distribution probability function. Most simulation software provides a capability for modellers to create user-defined functions which can be used to implement the required conditional-distribution probability functions.

Adjusting simulation parameters is also straightforward. Most simulation software provides this functionality. However, methodologically, this requires the model to be revalidated. When the adjustment happens regularly, a manual validation process becomes impractical. The simulation software needs to support an auto-validation mechanism. The validation suite in test-driven simulation modelling (Onggo and Karatas 2016) provides a promising approach for the auto-validation of a symbiotic simulation model. A modeller needs to define a condition that triggers parameter adjustment.

The ability to adapt the structure of a model at runtime in response to a structural change in the physical system is probably the most challenging, methodologically. Only a few simulation tools provide the functionality that allows us to change a simulation model at runtime. Nevertheless, it shows that, technically, such functionality can be implemented. Methodologically, however, the need for an auto-validation is even greater because the model structure can change during a simulation run. A modeller will also need to define a condition that triggers the change in the model structure.

## 2.6 Machine-learning model

The above components of symbiotic system provide an infrastructure that allows us to collect data about expected S3 outputs and the real output from a physical system over time. Hence, every time we run S3 we can collect data about the expected outcome of an operational management decision (from S3) and, after some delay, the real outcome from the physical system. These data, with an appropriate ML method, enable the simulation, optimization and analytics models to learn and make the necessary adjustments to make them perform better in the future (e.g. more accurate, faster).

# 3. Symbiotic Simulation System Applications in Industry 4.0

Moeuf et al. (2017) list four levels of managerial capacities that are aligned with the concept of Industry 4.0, namely: monitoring, control, optimisation and automation (see Fig. 3). The lower level provides components or data needed for the upper levels. Internet of Things (IoT) enables us to monitor the various parts of a physical system. IoT also provides the data needed for the upper levels. Based on monitoring data, we can define the standard behaviour of the physical system. This “standard” behaviour will be used to control the behaviour of the physical system. The optimisation level uses monitoring data and behavioural data to find the most optimal decision. Finally, ML can be used to create autonomy in which the system can learn from its behaviour and past performance. S3 can be used to support the top three levels of managerial capacities (i.e. control, optimisation and autonomy).

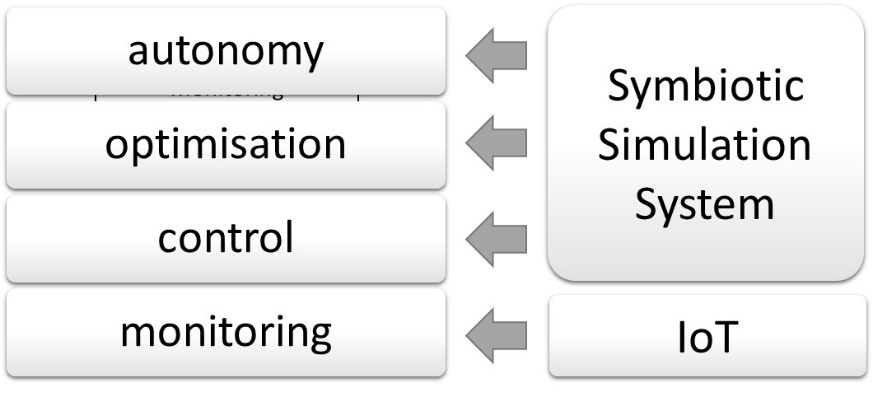


Figure 3. S3 supports the top three levels of managerial capacities

## 3.1 S3 for Control

When the term symbiotic simulation was introduced in 2002, there was a strong emphasis on its application as a control system. Hence, the idea of using S3 for control has been around since its inception. The way S3 is used to control a physical system can take several forms.

First, S3 can be used to create a reference model of a physical system (Aydt et al. (2008) refer to this type of application as an anomaly-detection system). When the behaviour of the physical system deviates from the model, a trigger is activated to investigate whether this is due to changes in the physical system or an inaccuracy in the model. The first case allows decision-makers to make a necessary plan to deal with the changes (indirect control via human decision-makers). The latter case enables the model to learn to improve its accuracy by comparing its outputs against outputs from the physical system. For example, Katz and Manivannan (1993) developed an S3 to detect discrepancies between what happens on a shop-floor and expected behaviour or performance (e.g. the number of operational machines and the length of a queue).

Second, S3 can be used to predict the behaviour of a system under the current settings (Aydt et al. 2008). One important application is to use S3 as an early-warning system if the expected (future) performance is outside an acceptable range. An example of S3 used as an early-warning system in a hospital to help hospital managers cope with potential overcrowding is given in Oakley et al. (2018). Hospital managers need to manage resources, such as beds and equipment, to be shared between emergency and elective patients. Emergency patients must be dealt with as they arrive, while elective patients require care scheduled in advance. Hence, some proportion of each resource must be set aside for emergency patients when planning for the number and type of elective patients to admit. S3 produces outputs that show the risk of overcrowding for a given elective patient schedule. To take another example, Patrikalakis et al. (2004) built a symbiotic simulation to predict the state of an ocean.

Third, S3 can be used to assist decision-makers in comparing different scenarios. This will include predicting the behaviour of the system under two or more scenarios. This is what the scenario manager in Figure 2 is for. In this case, decision-makers need to define the scenarios that will feed the simulation so that the scenarios’ expected performances can be compared. The final decision is made by decision-makers based on the simulation results. For example, Rhodes-Leaders et al. (2018a) developed an S3 that is used to compare decisions to recover airlines operations from disruption. The S3 uses data from FlightRadar24 of a small airlines company. The case they consider is that, one morning, one aircraft needs urgent maintenance at an airport. S3 is used to compare decisions, such as wait until the aircraft is available, replace the aircraft with another aircraft (may require further aircraft swaps) or cancel the flight. Oakley (2018) describes a case where hospital managers can compare three elective patient schedules using their S3. They show how hospital managers need to trade-off the risk of overcrowding and the risk of elective patient cancellation. Xu et al. (2018) demonstrate that dynamic data-driven fleet management strategies for emergency vehicles perform better than a static strategy.

## 3.2 S3 for Optimisation

When the number of possible decisions is too big to do a scenario comparison, an optimisation model can be used to replace the scenario manager in Figure 2. The optimisation model will search the decision space to find the optimal result. Since a model is subject to assumptions and simplifications, decision-makers will need to decide if the solution would work in the physical system. Hence, the final decision is still taken by decision-makers. For example, we can replace the scenario manager in Oakley et al. (2018) with an optimisation model that finds the optimal elective patient schedule. In their subsequent work, Rhodes-Leader et al. (2018b) replace the scenario manager in Rhodes-Leader et al. (2018a) with an optimisation model that finds a tentative optimal schedule so that the normal schedule can resume as soon as possible.

## 3.3 S3 for Autonomy

The S3 applications in sections 3.1 and 3.2 require a certain level of human involvement in the decision-making process. However, it is technically possible to use an S3 to automate a physical system. In this case, ML and advanced analytics methods are used to replace human decision-makers. This may be suitable for routine cases. When a case is too complex or unusual, S3 can alert human decision-makers to intervene. If this happens, the decisions made by human decision-makers can be used to train S3 so that it can handle similar cases in future. Although we have not seen any research papers on this topic, work on this has been reported. For example, Parashar et al. (2004) explain the infrastructure needed to achieve an autonomic self-optimising oil-production management process. Kotiadis (2016) explains her vision of self-adaptive discrete event simulation in which a simulation model can adapt with minimum human intervention to the changing physical system and its environment. Like symbiotic simulation, her vision is influenced by DDDAS.

# 4. Challenges

S3 combines several technologies, such as data acquisition, analytics and machine-learning. Hence, the first challenge is that S3 needs an integration framework. An integration framework is needed to make the S3 components interoperable (i.e. meaningful collaboration between S3 components to achieve common system-level objectives). Onggo et al. (2018) identify the challenge in integrating various analytics models (descriptive, predictive and prescriptive) and machine-learning methods in an S3. However, the integration challenge does not stop there because the virtual system needs to communicate with the physical system. Hence, the framework should cover integration between the virtual system and the physical system. The vision of Industry 4.0 includes end-to-end digital integration across organisations in a value chain including end-customers. Hence, integration should not stop at one symbiotic system, but all symbiotic systems across the entire value-chain.

Standardisation is important in an integration framework. Simulation standards related to distributed simulation (e.g. high-level architecture) and simulation interoperability (e.g. those managed by the Simulation Interoperability Standards Organisation) will play an important role in S3 implementation. Standards related to Industry 4.0, such as Industrial Internet Reference Architecture and Reference Architecture Model for Industry 4.0, will provide a good starting point for the development of standards for the real-world implementation of S3.

As computing and communication capabilities are embedded in more devices, they provide potential data sources for S3. However, as more devices feed data into S3, scalability issues may arise. Hence, there is a need for research into how S3 can effectively manage the amounts of data that arrive at high frequency in various forms (e.g. text, numbers, images etc.), which may contain noise. Furthermore, analytics methods suitable to analyse these data are needed so that S3 can make the best use of such data.

McKinsey interviewed more than 300 respondents working in production and service industries in Germany, Japan and the USA (McKinsey 2015). According to the respondents, security and data-privacy issues are amongst the main obstacles to the implementation of Industry 4.0. Given the close relation between Industry 4.0 and S3, we can see that security and data privacy issues may hinder the adoption of S3 in the real world. As virtual and physical systems become more integrated, the risk of physical systems being attacked or hacked is greater. In the case of end-to-end digital integration, data-privacy issues arise due the sensitive nature of the data and models used by organisations in a value-chain. Hence, research on the security and data-privacy aspect of S3 is important.

Finally, apart from the need for integration frameworks, there are other methodological challenges for S3 (Onggo et al. 2018), namely: how to deal with changes in a highly dynamic physical system, the need for algorithms suitable for short-term-operation management decision making, and how to make simulation models adaptive to reflect changes in physical systems.

# 5. Summary

This chapter has explained symbiotic simulation systems (S3) and highlighted their relevance to Industry 4.0. S3 is a special form of cyber-physical system that forms the core foundation of Industry 4.0. We have explained how S3 can be used in three Industry 4.0 application types, namely: control, optimisation and autonomy. The technological and methodological challenges that may hinder the adoption of S3 in industry have also been presented.

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