Simulation and the Fourth Industrial Revolution

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Abstract

Advancements in systems simulation over the past decade have propelled simulation into a new position as a decision-making tool in Industry 4.0 applications. This paper addresses the specific benefits of simulation which can be utilized to enable greater flexibility in decision making in the Industry 4.0 environment. It is stressed that both discrete event simulation (DES) and agent-based simulation (ABS) can be used to represent complex interactions in a fully integrated set of virtual and physical systems.

Keywords: System simulation, Industry 4.0, Operations management, Discrete-event simulation, Agent-based simulation.

1. Introduction

Over the past decades, simulation has played an important role in operations management as a means for evaluating systems, comparing alternatives, and optimizing configurations. Information technologies are extremely important for enhancing the performance of simulations to provide potential benefits to Industry 4.0 implementations. In this regard, advancements in system simulations have propelled simulation processes into a new position as decision-making tools in Industry 4.0 applications. In this paper, first, the digital industry technologies embraced by Industry 4.0 environments are described. Second, an example of a decision-making process using simulation in Industry 4.0 is proposed. The

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paper illustrates that based on variety of data utilization methods, symbiotic systems can be designed to represent physical systems that include various types of computing resources. Finally, a detailed introduction to symbiotic simulation factories is provided. Symbiotic simulation is one of the driving methodologies for rapidly assessing and predicting the impact of changes in complex manufacturing systems.

2. Industry 4.0 and Digital Industry Technologies

2.1. *Industry 4.0*

Simio describes the concept of Industry 4.0, the fourth industrial revolution, as shown in Figure 1. Here, “Industry 4.0” refers to industrial change based on the digital revolution. Widespread mobile internet services and powerful computing devices and sensors allow companies to gather, store, and manipulate data at an unprecedented level. The evolution of technologies has allowed greater integration of operations management with data collection because the collection and sharing of large volumes of data have been made easier using the Internet of Things (IoT). This has enabled the rapid dissemination of Industry 4.0 and its adoption in a wide range of industries outside manufacturing (Takakuwa et al. 2019).

IoT is a technology that enables the processing of real-time data through microcontrollers and servers. Industry 4.0 technologies based on the digital revolution lay emphasis on real-time (or near real-time) situational awareness of operations management. In operations management, varied IoT technologies are being developed to support efficient and effective decision making, which is required to survive and prosper in an Industry 4.0 environment. Yang and Takakuwa (2017) illustrated two types of integration in smart factories in the Industry 4.0 environment: vertical integration and horizontal integration. The former is an integration ranging from top management to the shop floor inside a factory, i.e., this integration occurs at the company, factory, and process level. The latter is the integration between suppliers, sales and distribution departments, and customers. Horizontal integration enables direct communication between suppliers and customers. Yoshida (2018) presented a new data collection system that demonstrated an intensive connection with the surrounding physical system and simulation models, as shown in Figure 2. An advanced man-machine interface was designed to collect real-time (or semi-real-time) data from a physical system. According to this study, the simulation model was used to query data from remote physical machines to update parameters and subsequently aid in optimizing later operations. Incorporating IoT devices such as data acquisition sensors with simulation enable the required processing of real-time data. The collected data are then used to adjust parameters and perform simulation models. Thus, the simulation model can represent the physical system and can be used to monitor the behavior and optimize the future behavior of the physical system.

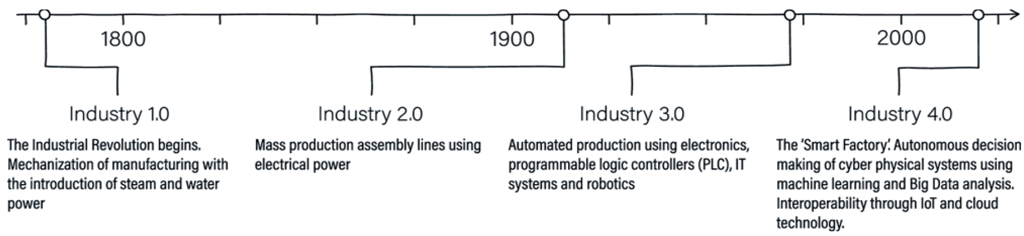
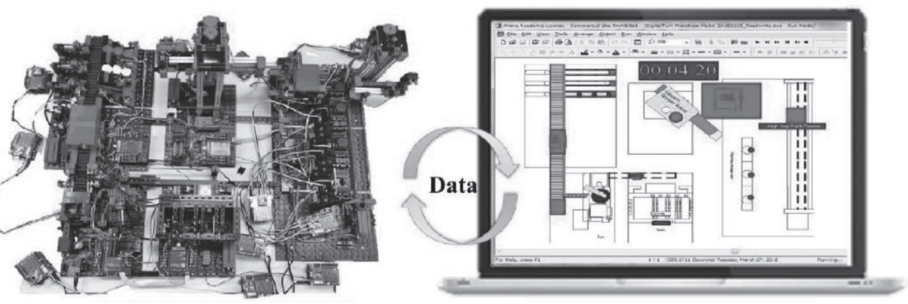


Fig.1. Schematic of the evolution of Industry 4.0 (Simio, 2019).



Physical production system Simulation model

Fig.2. Real-time data collection using sensors [5].

2.2. *Digital Industry Technologies Embraced by Industry 4.0*

The main purpose of the Industry 4.0 environment is to improve production flexibility, quality, safety, and customer response through use of digital industry technologies. In other words, digital industry technologies have in this regard transformed manufacturing from production automation to autonomous manufacturing. Additionally, the capability and sophistication of digital industry technologies have increased over time. With new technologies continuously emerging, digital industry technologies have been adopted by Industry 4.0 organizations in the following categories:

- Robotics and autonomous machines
- Advanced visualization, including augmented reality, virtual reality, and mixed reality
- Sensor technologies and industrial IoT (IIoT)
- Cybersecurity
- Cloud computing and software as a service
- Big data analytics
- Additive manufacturing

・Vertical and horizontal integration of systems
・Simulation

The digital industry technologies described above are being adopted by various industries within and outside of manufacturing (Gunal 2019). These technologies have improved organizational capabilities with respect to data collection. Integrated devices such as mechanical sensors are becoming more commonplace because varied business data can be collected and employed globally in real time (or semi-real time). Additionally, data combined with advanced analytics are used to derive insights from real-time data visualization and subsequently make predictions that can improve business value and automate critical business processes (Familiar and Barnes 2017). These technologies are used for increasing production quality and diversity, optimizing processes, and decreasing costs in manufacturing systems using smart systems. Data collected on supply chain management, customer behavior, marketing campaign performance, and workflow procedures among others are also widely available virtually. Therefore, these technologies have led to broad transformations that have in turn given rise to the Industry 4.0 environment.

Although digital industry technologies are prominent and contribute to the Industry 4.0, they remain a growing area of development. Continuing technology developments are inevitable, and operations management should embrace them in a bid to move forward in this environment.

3. Simulation in Industry 4.0 Environments

3.1. *Areas of Industry Using Simulation*

Computer simulations, referred to simply as “simulations,” were initially used for the analysis of military assignment problems in the 1950s. Later, many corporations employed simulation processes to resolve complicated operations issues. During the third industrial revolution, simulation was widely disseminated giving rise to material requirements planning for developing manufacturing planning, purchasing, and effectively managing factory activities. By the late 1980s, because computer graphics simulation animation became an important factor in decision making, simulation processes developed into a popular and powerful method for industry planning. Previously, the simulation process had been extensively applied in different areas; the following are examples of industries where simulation was applied:

・**Supply chain:** contingency planning, production allocation, inventory positioning, riskreduction, and transportation.

- **Manufacturing:** productivity improvement, personnel planning, product mix changes, and capital investment analysis.
- **Emergency response system:** response policy, routing, resource allocation, and personnel planning.

Advancements in simulation-related hardware and software over the past decade have rapidly upgraded. As large volumes of data can be continuously provided in real time or semi-real time through simulation modeling, operational logic can be described in detail at any level desired. This allows companies to animate and understand real system behaviors more easily. Thus, simulation was identified to support Industry 4.0 technologies combined with data warehouses, manufacturing execution systems (MESs), enterprise resource planning (ERP), and user-based systems among others. A general view of the different components working together in Industry 4.0 environments is shown in Figure 3. These components communicate with each other to achieve a common system objective, for example, in evaluating alternatives and predicting and improving the performance of a system in both long and short terms. Further, simulation models can be designed to solve complicated problems associated with Industry 4.0 environments. Gartner (2012) noted that a mobile client linked to cloud-based analytic engines and big data repositories can potentially enable the use of optimization and simulation anywhere and at any time. This new development provides simulation, prediction, and optimization alongside other analytics, thereby facilitating greater flexibility in decision making regardless of the time and place of a business process action.

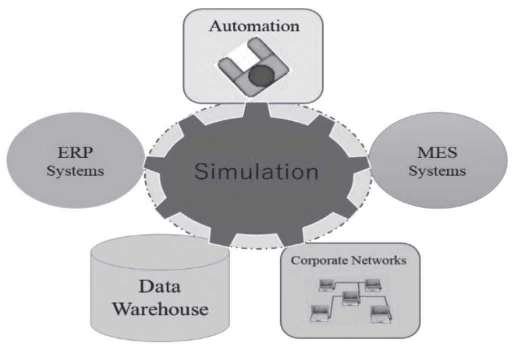


Fig.3. Schematic of different components working together in an Industry 4.0 environment.

3.2. *Decision-Making Processes Using Simulation*

An example of a decision-making process using simulation in an Industry 4.0 context is shown in Figure 4. The steps involved in decision-making processes using simulation are described below.

[Step1]: Data preparation involves requesting or extracting data from data warehouses, MESs, ERP, user-based systems, and/or other physical components. Data can include information regarding the historical demand for products, machine status data, and data linked to decision makers or actuators.

[Step2]: Data analysis is responsible for providing appropriate data to step 3. For example, demand forecasting results can provide ideas for efficient production planning. Because of the objectives of decision making and the characteristics of data, such as volume, velocity, variety, and veracity, advanced analytics are capable of performing data classification, such as grouping, sorting, filtering, and integrating.

[Step3]: Input data preparation is a basic step traditionally applied in system design applications.

[Step4]: A simulation model is created that represents real physical operation systems. In this step, a simulation model is required to successfully access data prepared from steps 1 to 3.

[Step5]: Simulation results are outputted to make short-term or long-term operational management decisions.

[Step6]: Simulation results using an appropriate machine learning method are further required to learn and make necessary data adjustments for the next step.

[Step7]: Evaluation of simulation results gathered from step 6.

The capabilities of simulation languages have also increased. Simulation techniques such as discrete event simulation (DES) and agent-based simulation (ABS) are major methods implemented in decision-making processes. The most basic form of simulation has been applied DES since its creation in the 1950s. In DES process orientation, “entity” is a generic term used to denote any person, object, or thing whose movement through the system causes changes in the state of the system (Pegden 1983; Pegden et al. 1990; Kelton, Sadowski and Swets 2010). In ABS, however, the use of “object” allows modelers to reduce large problems to smaller, more manageable issues. Objects represent machines, conveyors, forklift trucks, and aisles (Kelton, Smith, and Sturrock 2014). Objects are used to improve model reliability, robustness, reusability, extensibility, and maintainability. As a result, overall modeling flexibility and power are dramatically improved. ABS is now a major method used for constructing models.

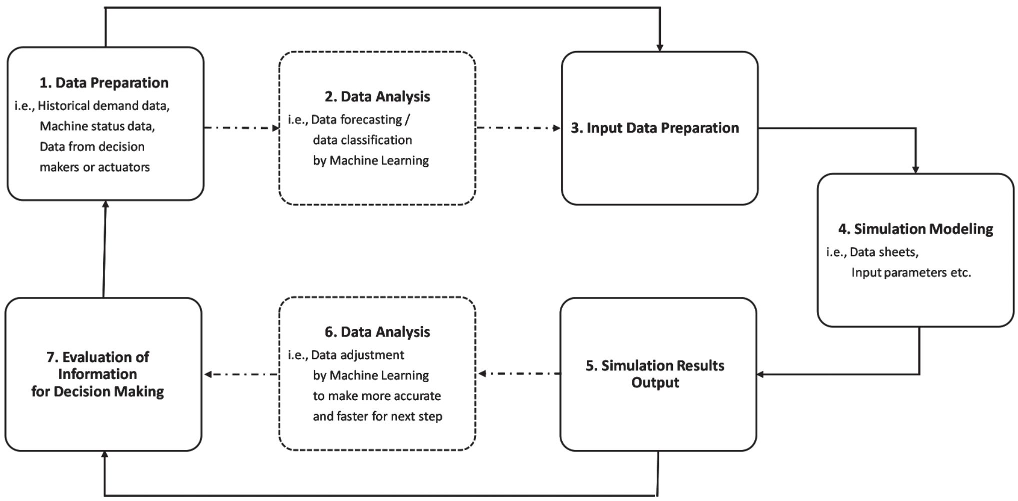


Fig.4. Decision-making processes using simulation in Industry 4.0 environments.

4. Benefits of Simulation in Industry 4.0 Environments

The significant benefits and role of simulation in an Industry 4.0 environment are detailed in sections 4.1 and 4.2. In an Industry 4.0 environment, planning and scheduling activities focus on how to generate an intermediate and precise plan or how to generate a schedule from computerized information, which include complete representations of operating constraints and custom rules (Smith et al. 2018).

4.1. *Integrating Various Data Sources with Symbiotic Simulation*

In the current age of Industry 4.0, a variety of data types related to customers, orders, and machine operations can be collected and shared more efficiently through powerful computing resources such as extensive sensor networks, wireless monitors, and embedded machine learning. An example of the selected resultant input data for the symbiotic simulation of an actual container terminal is shown in Table 1. A symbiotic simulation driven by real-time or near real-time data allows for cooperation between virtual and physical systems. Simulation with various data sources can enable better performance prediction of utilization areas and bottlenecks.

Effective data flow can be applied to the simulation modeling of an entire product life cycle and its value chain. The difference between simulation objectives in Industry 4.0 and 3.0 relate to the flexibility and accuracy of simulation results due to data requirements and their acquisition. Thus, the speed and flexibility of data collection and processing combined with other computing resources are critically important for symbiotic simulation modeling. In order words, although symbiotic systems present a useful system design for representing physical systems, including various types of computing resources, there is a need for data utilization methods to integrate different data sources before performing symbiotic simulation models.

Technological advancements have made the collecting and sharing of large volumes of data a great deal easier, in addition to facilitating its application to models and evaluating various possible scenarios to predict and drive outcomes (Smith, Sturrock, and Kelton 2018).

4.2. *Rapid Assessment and Prediction of the Impact of Complex System Processes*

Industry 4.0 includes terms such as “smart factory” and “smart manufacturing,” which redefined the concept of “factory” as a fully connected and automated manufacturing system. In smart factories, autonomous machines can exchange information electronically and continually. This communication enables symbiotic simulation models to collect more usable data, such as machine processing time, production speed, and maintenance status. Simulation is a powerful tool for evaluating the interactions between machines and optimizing manufacturing systems. Thus, the extensive range of applications presented by autonomous machines and robotics is a core aspect of simulation in Industry 4.0 environments.

Because of the level of automation and autonomy in smart factories, however, symbiotic simulation in Industry 4.0 environments faces more challenges than previously. The manufacturing processes in smart factories have become more dynamic and complicated. Complex system processes in smart factories present challenges for operations managers when unanticipated events such as material delays, machine breakdowns, and system failures occur. Therefore, different configurations and settings are needed to enable operational flexibility in smart factories. Operations managers must adapt to changes pertaining to machine status, priority orders, and various scheduling rules among others. For instance, an arriving entity should be immediately assigned to a machine regardless of other entities already in queue for processing by the same machine. Additionally, when failures or machine breakdowns occur, a substitute machine should be immediately assigned to the entity held in the work-in activity using symbiotic simulation models. Further, the assigned worker will need to cease his/her current processing task and a different on-shift worker should be assigned to continue processing the ceased work. It should be noted that symbiotic simulation factories are able to link physical and virtual environments. As a result, symbiotic simulation is one of the driving methodologies for rapidly assessing and predicting the impact of changes in complex systems. In summary, simulation is prominent in Industry 4.0 environments and aids in optimizing complex system processes, which is one of the advantages of using simulation.

Table 1: Selected resultant input data for the simulation of a real container terminal [6].

(a) Importing process (Operation types: UL and TU)

No.(Priority No.)	Container No.	Vessel No.	Berth crane No.	Real time of loading completion for a truck	Truck No.	Real time of handling instruction for a cargo-handling machinery
1	TRIU8380996	STNG	1	9.18	KR024	9.06
2	NSSU0072627	HTYO	4	10.71	TX170	10.69

Real Time of last job finished for a cargo-handling machinery	Cargo-handling machinery No.	Block No.	Bay No.	Row No.	Real time of job finished for a cargo-handling machinery
9.18	TC11	1F	15	4	9.29
10.62	TC11	2F	12	3	10.80

(b) Exporting process (Operation types: LD)

No.(Priority No.)	Container No.	Cargo-handling machinery No.	Block No.	Bay No.	Row No.	Real time of handling instruction for a cargo-handling machinery
1	PCSU2120915	TC18	2C	40	5	10.98
2	PCSU2108036	TC18	2C	40	6	11.01

Real Time of last job finished for a cargo-handling machinery	Real time of job finished for a cargo-handling machinery	Truck No.	Berth crane No.	Vessel No.
11.01	11.03	KP118	V4	HTYO
11.03	11.06	TK136	V4	HTYO

(c) Handling between the same bay in a block (Operation types: RS and IS)

No.(Priority No.)	Container No.	Cargo-handling machinery No.	Block No.	Bay No.	Row No.(from)	Row No.(to)
1	CRSU6022868	TC11	1F	17	2	3
2	YMLU7415614	TC11	1F	10	2	3

Real time of handling instruction for a cargo-handling machinery	Real Time of last job finished for a cargo-handling machinery	Real time of job finished for a cargo-handling machinery
8.80	8.80	8.87
9.36	9.34	9.43

(d) Handling between different bays in a block (Operation types: IB)

No.(Priority No.)	Container No.	Cargo-handling machinery No.	Block No.	Bay No.(from)	Row No.(from)	Bay No.(to)
1	CKLU4107919	TC30	3E	07	04	04
2	PCLU4050914	TC30	3E	07	05	04

Row No.(to)	Real time of handling instruction for a cargo-handling machinery	Real Time of last job finished for a cargo-handling machinery	Real time of job finished for a cargo-handling machinery
05	7.57	8.32	8.36
04	7.57	8.36	8.40

(e) Handling between yard station to outside tractor (Operation types: SO and D)

No.(Priority No.)	Container No.	Cargo-handling machinery No.	Block No.	Bay No.	Row No.	Real time of handling instruction for a cargo-handling machinery
1	KKTU7880852	TC15	1J15051	15	05	8.41
2	DFSU2085042	TC15	1J15022	15	02	8.41

Real Time of last job finished for a cargo-handling machinery	Real time of job finished for a cargo-handling machinery
8.63	8.67
8.67	8.69

(f) Handling between outside tractor to yard station (Operation types: SI and R)

No.(Priority No.)	Container No.	Cargo-handling machinery No.	Block No.	Bay No.	Row No.	Real time of handling instruction for a cargo-handling machinery
1	SNBU2114676	TC11	2F	33	02	8.50
2	TRIU8666969	TC26	2E	27	01	8.51

Real Time of last job finished for a cargo-handling machinery	Real time of job finished for a cargo-handling machinery
8.52	8.57
8.55	8.58

(g) Container attributes

Container No.	Size	Type	Height	FE(Full=1/Empty=0)	Weight	Vessel name
PCSU2120915	20	DC	86	1	15563	HTYO
CRXU6921757	40	RC	86	1	28900	JID

5. Conclusion

(1) Digital industry technologies, in particular, the IoT, which enables the processing of real-time data through microcontrollers and servers, in Industry 4.0 environments were described in this paper. The importance of Industry 4.0 based on the digital revolution was highlighted in terms of improving real-time (or near real-time) situational awareness of operations management.

(2) Digital industry technologies are prominent contributors to Industry 4.0 but are still developing. Technological developments will continue, and operations management should embrace them to progress in this new environment.

(3) An example of a decision-making process utilizing simulation in Industry 4.0 was provided. Using current data utilization methods, symbiotic systems can be designed to represent physical systems, including various types of computing resources.

(4) Symbiotic simulation factories can be linked to physical and virtual environments. Symbiotic simulation is one of the driving methodologies for rapidly assessing and predicting the impact of changes in complicated manufacturing systems.

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