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LINKING SYMBIOTIC SIMULATION TO ENTERPRISE SYSTEMS: FRAMEWORK AND APPLICATIONS

Benny Tjahjono
Xu Jiang

Supply Chain Research Centre
Cranfield University, Cranfield
Bedford, MK43 0AL, UK

ABSTRACT

Symbiotic simulation is a paradigm that emphasizes a close association between a simulation system and a physical system, which is usually beneficial to at least one of them and not necessarily detrimental to the others. Aimed at extending previous work in symbiotic simulation, this paper proposes a framework of symbiotic simulation that can be used to improve the performance of a production system controlled by an enterprise system. A tube manufacturing shop floor has been selected as an example to demonstrate how the framework of symbiotic simulation can be implemented in a commercial off-the-shelf simulation tool. Experimentation has been carried out to evaluate the extent to which the symbiotic simulation can deal with uncertainties and disturbances in manufacturing systems. Early trials of the framework have indicated that it is capable of extending the existing applications of symbiotic simulation beyond engineering domains, especially manufacturing and shop floor control systems.

1 INTRODUCTION

Symbiotic simulation is inspired by symbiosis in biology. The biological definition of symbiosis is, however, rather broad and includes several sub-categories, such as mutualism, commensalism and parasitism. For simulation related work, subcategories other than mutualism are often overlooked; and especially in symbiotic simulation, mutualism is thus often assumed to be the only form of symbiosis (Aydt et al. 2008). The notion of symbiotic simulation was first proposed at the 2002 Dagstuhl Seminar on Grand Challenges for Modelling and Simulation, indicating mutually beneficial interactions between a simulation model and a physical system (Fujimoto et al. 2002). Typically, a symbiotic simulation system comprises a simulation model and a physical system. In this setting, simulation models continuously acquire real-time data from the physical system using real-time sensors, and subsequently the physical system takes the benefits from the outcomes of the simulation experiments (Fujimoto et al. 2002).

Enterprise Systems are information systems applied to manage and integrate enterprise operations, such as human resources, manufacturing, project management and financial accounting (Davenport 1998). A recent survey carried out by Skoogh, Perera, and Johansson (2012) showed that in the context of simulation of manufacturing systems, the majority of operational data, e.g. cycle times, build sequence, parts routing etc., are stored in an Enterprise Resource Planning (ERP) system. Coupling the features of simulation to ERP systems seems to offer various benefits in supporting decision making, time compression and expansion, exploring scenarios, diagnosing problems, identifying constraints, visualization, etc. (Babulak and Wang 2008; Jovanoski et al. 2013). Work has already been carried out in improving the capability of ERP systems by linking it with simulation tools (e.g. Moon and Phatak 2005).

However, in the previous attempts, the techniques appear to accomplish only specific purposes and have some limitations, notably in terms of direct control of the system and feedback mechanism.

This paper therefore aims to investigate how ERP systems and symbiotic simulation can be linked together and can be used to improve the capability of simulation as a decision making tool. The notion of *symbiosis* allows the mutual benefits between the physical system managed by an ERP system (e.g. manufacturing shop floor) and the model of it.

2 LITERATURE REVIEW

The symbiotic simulation paradigm emphasizes a close association between a simulation system and a physical system, which is usually beneficial to at least one of them (Aydt et al. 2008) and not necessarily detrimental to the others. In practice the simulation model typically acquires real-time (or near real-time) data from the physical system using sensors, and then uses the data as input parameters to the model or as a trigger to run some pre-defined "what-if" scenarios. The results can be used to predict, optimize or control the performance of the physical systems. In this respect, symbiotic simulation can continuously execute simulation models and interact with physical systems in real-time (Fanchao et al. 2009).

Aydt et al. (2008) extended the definition of symbiotic simulation and designated five different types of symbiotic simulation systems: symbiotic simulation control system (SSCS), symbiotic simulation decision support system (SSDSS), symbiotic simulation forecasting system (SSFS), symbiotic simulation model validation system (SSMVS) and symbiotic simulation anomaly detection system (SSADS). Each type of symbiotic simulation system can either be individually implemented or integrated to model complex systems such as in semiconductor manufacturing. The integration of different symbiotic simulation systems is further referred to as the *hybrid* symbiotic simulation system (Aydt et al. 2008). Table 1 shows various purposes, loop types, what-if scenarios, and symbiosis types of the five symbiotic simulation systems.

Table 1: Different classes of symbiotic simulation systems (Aydt et al. 2009).

Class	Purpose	Loop	What-if scenarios	Symbiosis Type
SSCS	Control of a physical system	Closed	Control alternatives	Mutualism/Parasitism
SSDSS	Support of an external decision maker	Closed	Decision alternatives	Mutualism/Parasitism
SSFS	Forecasting of a physical system	Open	Different assumptions for environmental conditions	Commensalism
SSMVS	Validation of a simulation system	Open	Alternative models or different parameters	Commensalism
SSADS	Detection of anomalies either in the physical system or in the simulation model	Open	Reference model only	Commensalism

Applications of symbiotic simulation vary from industry to industry. A proof-of-concept symbiotic simulation system was developed by Low et al. (2005) to monitor, optimize and control the assembly and test operation of semiconductor backend with the purpose of improving the manufacturing process of semiconductor manufacturing. Experiments showed that the symbiotic simulation system has functionalities to effectively monitor, optimize and control various tasks. For a shorter simulation time, the symbiotic simulation system can respond rapidly to abrupt changes in the physical system.

Another application in semiconductor manufacturing was demonstrated by Aydt et al. (2008). The proposed symbiotic control system uses a reactive what-if analysis to obtain a stable configuration of a wet bench tool set in near real-time. Aydt et al. (2011) then developed a symbiotic simulation-based problem solver to automatically resolve decision making problems for various tools in an entire semiconductor manufacturing fab. The problem solver agent detects the physical system and executes what-if scenarios to identify and solve some manufacturing problems (Aydt et al. 2011).

In order to overcome the effects of new information or sensor observations of unmanned aerial vehicles (UAVs), a symbiotic simulation system was applied in the process of path planning to deal with these uncertainties (Kamrani and Ayani 2007). Another decision making and controlling application of symbiotic simulation was developed to improve the performance of inventory management in the lubricant industry (Fanchao et al. 2009).

Linking simulation to physical manufacturing systems controlled by an ERP system is relatively new. Efforts have been made mainly in the following two areas: (1) data exchange and (2) physical interaction between ERP Systems and simulation tools.

Input data management is a crucial and time-consuming process for both ERP systems and simulation tools (Skoogh, Johansson, and Stahre 2012). ERP systems typically host operational data, such as cycle times, set-up times, production routings and sequences. As ERP systems contain the information required by simulation models, ERP systems are often considered as main sources for simulation data. Better linkage between simulation tools and ERP systems is therefore needed in order to enable automatic data exchange between them (Robertson and Perera 2002).

Moon and Phatak (2005) claimed that ERP systems inherit some intrinsic drawbacks from their predecessors (i.e. MRP systems) due to the rigidity of the data inside the ERP database when dealing with uncertainty and the stochastic nature in manufacturing environments. They proposed a method to link simulation to an ERP system and connected a discrete-event simulation model to SAP R/3 using a pump manufacturing factory as a case to prove the concept. When SAP R/3 was triggered manually, the simulation model acquired relevant manufacturing data from it, ran some experiments on the model and sent the simulated lead times to a manufacturing manager. By comparing the simulated results with the actual due dates, the manufacturing manager could make an adjustment of the data in SAP R/3 and re-execute the simulation model. The process was repeated until the manufacturing manager was satisfied with the outcomes. Though working well, the proposed approach adopted the *off-line* (manual) simulation methods. The way this kind of system optimizes and influences the physical system also depends on the production manager as an intermediary.

3 RESEARCH GAP AND METHODOLOGY

Taking into account both various applications of symbiotic simulation and the ways simulation is currently linked to ERP systems, this paper attempts to propose a framework for the symbiotic simulation system that ultimately will be able to address the shortcomings of the aforementioned methods.

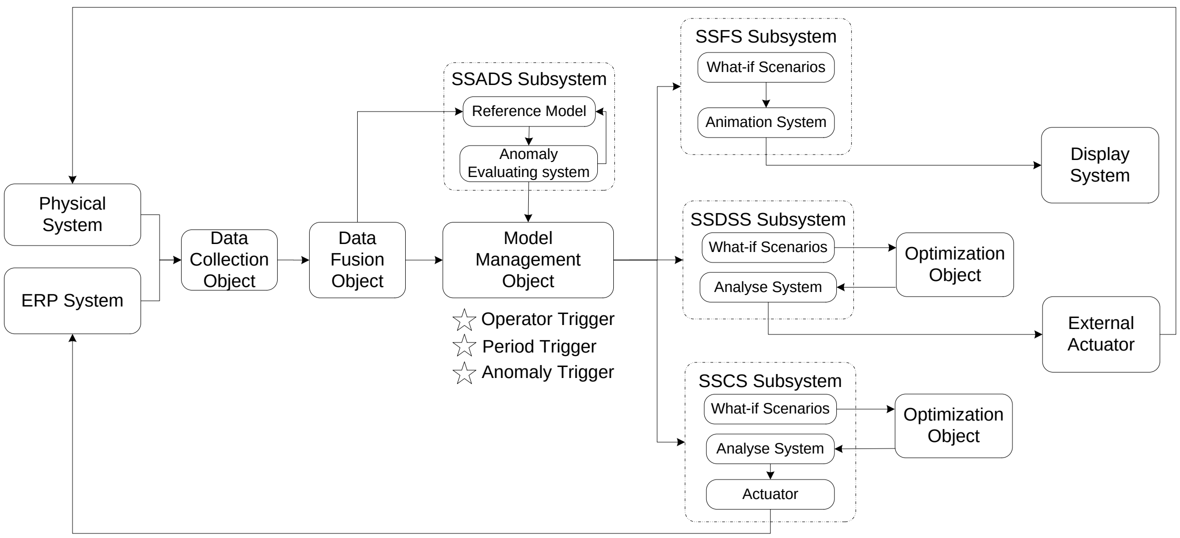
To achieve this goal, a three-stage research methodology was adopted. First, we tried to better understand the interactions between ERP systems and symbiotic simulation systems. The output from this stage was the symbiotic simulation framework. Second, we implemented the framework using a case example of an ERP-based symbiotic simulation. Third, we tested the framework, ran some experiments and analyzed the results. The subsequent sections describe the execution of the 3-stage methodology in more detail.

4 THE PROPOSED FRAMEWORK

This paper intends to address some forthcomings in the previous work by taking the advantage of, and building the extension to, previous research in symbiotic simulation research primarily that of Aydt et al. 2008 and Aydt et al. 2009, by proposing a new framework. The framework is illustrated in the form of block diagrams (see Figure 1). It is made up of four main subsystems: *Symbiotic Simulation Forecasting System (SSFS)*, *Symbiotic Simulation Anomaly Detection System (SSADS)*, *Symbiotic Simulation Decision Support System (SSDSS)* and *Symbiotic Simulation Control System (SSCS)*. The framework also incorporates *triggers* and *objects*. These subsystems, triggers and objects work collectively to exchange data to and from the ERP systems, evaluate trigger conditions, create and run what-if scenarios, optimize and analyze simulated results, visualize real-time states, forecast the future, recommend solutions and, if necessary, control the ERP systems directly.

The Data Collection Object (DCO) automatically extracts raw data from the ERP systems, transfers data to simulation models and presents them in an accessible format for the simulation models. The

Symbiotic Simulation Anomaly Detection Subsystem (SSADS) constantly monitors the information in the Data Fusion Object (DFO) and compares it with a reference model in order to detect anomalies. The Model Management Object (MMO) receives trigger notifications and uses the information in DFO to update the SSFS, SSDSS and SSCS what-if scenarios and invokes the three subsystems. The SSFS generates future prediction and visualization to the display systems. The SSCS and SSDSS request Optimization Object (OptO) to generate the optimum decision parameters, which are used to either control ERP systems directly or pass the decision parameters to an external actuator respectively.



SSFS = Symbiotic Simulation Forecasting System
SSDSS = Symbiotic Simulation Decision Support System
SSADS = Symbiotic Simulation Anomaly Detection System
SSCS = Symbiotic Simulation Control System

Figure 1: Block diagram of the symbiotic simulation.

The SSADS subsystem detects the anomalies from both physical systems and simulation models by comparing the simulation models with the actual behaviors from the data in DFO. For physical systems, anomalies can be an unexpected event or abnormal behavior, e.g. machine breakdown. When the discrepancy between the simulation model and the behavior is beyond a certain tolerance, it is considered as an anomaly.

The SSFS subsystem generates visualization and prediction data to a display system, e.g. a monitor. The essential part of the SSFS subsystem is the ‘what-if’ scenarios that can be used to forecast future events. It may contain animation systems to generate 2D/3D animations. MMO delivers static and dynamic data to the SSFS subsystem and invokes the what-if scenarios.

Both the SSCS and SSDSS subsystems are used to optimize, analyze and generate suggested decisions. SSCS incorporates an actuator, meaning that SSCS is capable of controlling and updating the ERP systems directly. Unlike SSCS, SSDSS intends to support external decision makers (e.g. managers) rather than directly applying the decisions on ERP systems (or physical systems), hence no actuators. The structure of SSDSS and SSCS are shown in Figures 2 and 3 respectively.

The what-if scenarios generated by either SSDSS or SSCS along with the Optimization Object are used to find the optimum decisions for certain problems. The Optimization Object (OptO) finds the parameter values that result in a *maximum* or *minimum* of the objective function while adhering to constraints.

Figure 4 shows the overall workflow of the symbiotic simulation.

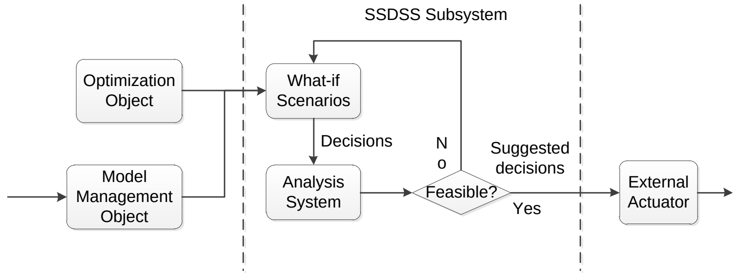


Figure 2: Structure of SSDSS.

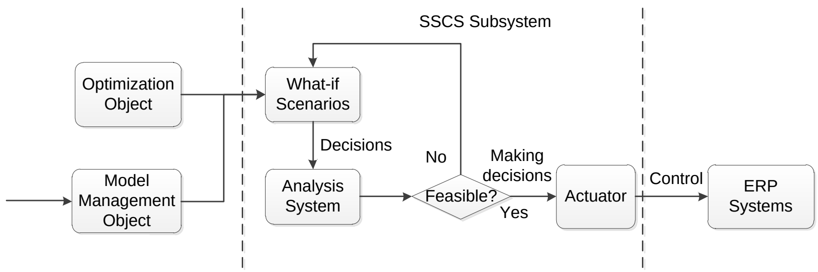


Figure 3: Structure of SSCS.

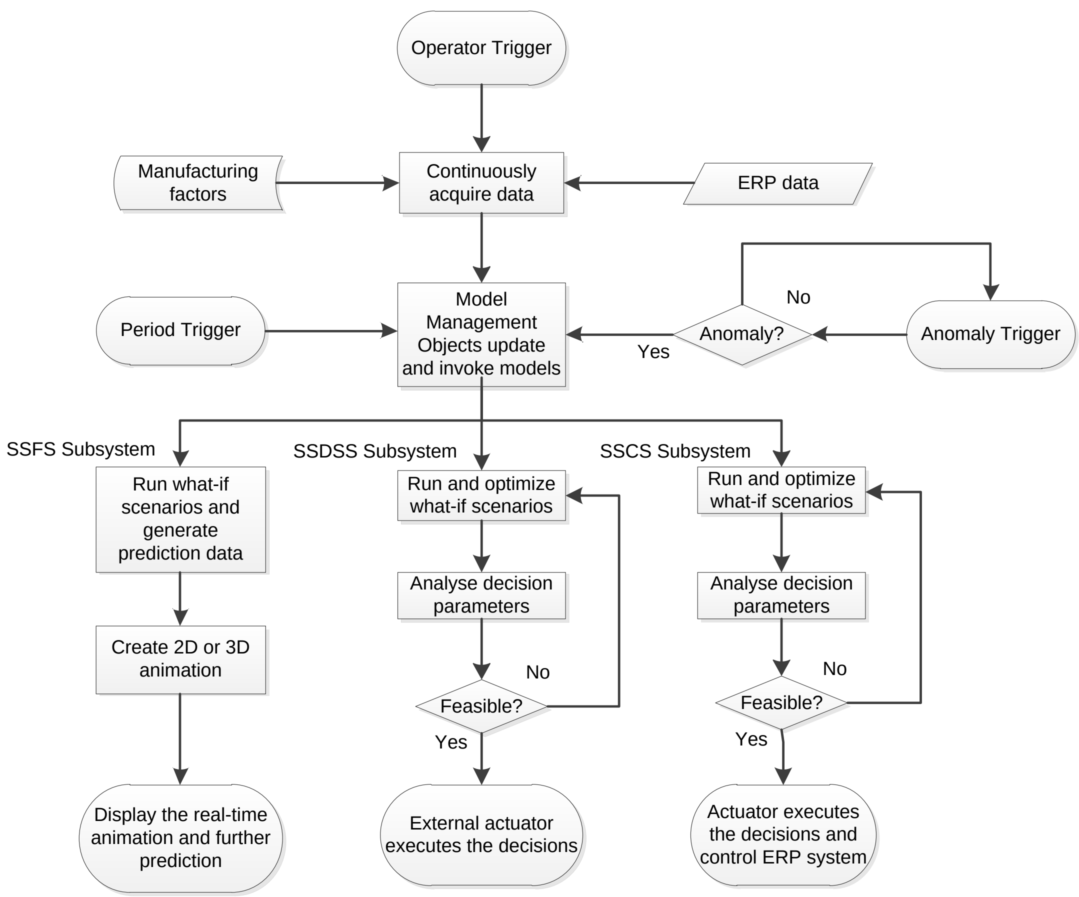


Figure 4: Workflow of the symbiotic simulation.

5 CASE EXAMPLE

In order to verify the functionality and practicality of the framework, an ERP-based symbiotic simulation system has been developed as a case example that is based on a tube manufacturing shop floor. All relevant manufacturing data from the shop floor are stored in mySAP ERP system. The tube manufacturing company is based in China. The company designs, tests and manufactures aircraft ducting systems which include fuel, anti-ice and environmental control systems. The shop floor produces nine different tube varieties from raw materials preparations to assembly. Three different raw materials are used: corrosion resistant steel (CRES), titanium (Ti) and aluminum (Al). CRES and Ti are used for high-temperature, high-pressure tubes and Al is used for lower temperature tubes.

The shop floor is split into the preparing area and assembly area. The main working content in the preparing area is to clean raw materials and to cut them to standard parts. Raw materials arrive in batches. After cleaning, raw materials are distributed to five different cutting machines by the distribution conveyors based on a set of probabilities. Each cutting machine operates at different reliability and efficiency levels. Having been cut, standard parts are stored in the storage rack. The assembly area contains a manufacturing line consisting of six work centers. Each work center has two or more machines and performs a certain working content. The shop floor is make-to-order, meaning that when customer orders are received, workers pick up standard parts in the storage rack and start producing in the assembly area. The tubes have distinct routings. Figure 5 shows the products and shop floor layout. Table 2 shows the main work contents of the six work centers and different types of tube and routes.

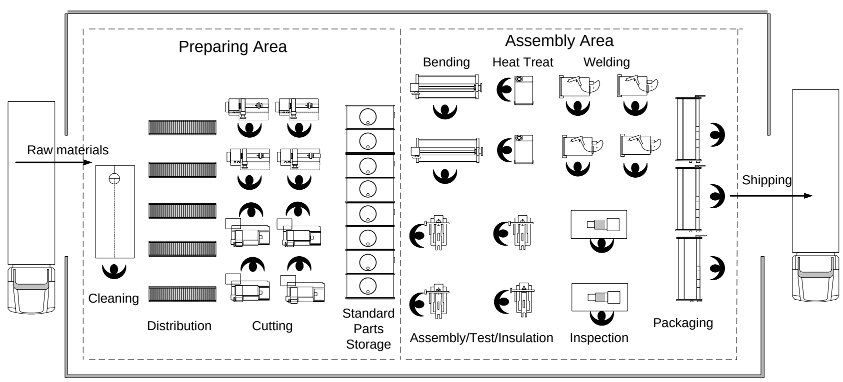


Figure 5: The products and the shop floor.

Table 2: Work content and routes.

Serial #	Work contents
WC 1310	Bending
WC 1410	Heat treat
WC 1420	Welding
WC 1510	Tube assy/test/ insulation
WC 1520	Inspection
WC 1610	Packaging/Shipping

Type	Description	Route
C100	CRES without fitting	1310 – 1410 – 1420 – 1510 – 1520 – 1610
C101	CRES with1 Swage fitting	1310 – 1410 – 1520 – 1420 – 1510 – 1610
C102	CRES with 2 Swage fittings	1310 – 1410 – 1520 – 1510 – 1610
A100	Al without fitting	1310 – 1410 – 1420 – 1510 – 1610
A101	Al with 1 Swage fitting	1310 – 1410 – 1420 – 1510 – 1610
A103	Al with 2 Swage fittings	1310 – 1410 – 1420 – 1510 – 1610
T100	Ti without fitting	1310 – 1410 – 1420 – 1510 – 1610
T101	Ti with 1 Swage fitting	1310 – 1410 – 1520 – 1510 – 1610
T102	Ti with 2 Swage fittings	1310 – 1410 – 1420 – 1510 – 1610

mySAP contains three types of data: raw material delivery information, probabilities of job distribution conveyors and customer orders. The raw material delivery information consists of raw material types, delivery times and quantities. At the delivery time, the corresponding quantities of certain raw materials are received. For the simulation model, raw material delivery information was loaded and at the specific delivery time, the simulation model injects the quantities of certain raw material entities. The jobs distribution conveyors transfer raw materials to different cutting stations based on their distribution probabilities.

Table 3 shows an example of raw material delivery information and an example of exit probability of the jobs distribution conveyors. In this case, the jobs distribution conveyor exports 34%, 18%, 22%, 14%, 12% of raw materials to the corresponding cutting stations.

Table 3: Delivery times and exit port probabilities.

Raw material	Delivery time	Quantity
CRES	9.00 AM 20/09/2014	80
Al	13.00 PM 25/09/2014	100
Ti	13.00 PM 26/09/2014	80
CRES	9.00 AM 28/09/2014	100
Ti	13.00 PM 28/09/2014	100

Exit port	Probability
1	0.34
2	0.18
3	0.22
4	0.14
5	0.12

A customer order indicates the types of tube and when the customer wants them (tube types, lead times and due dates). The lead times are collected based on time and motion studies or historical data. The ultimate goal is to fulfil the customer order before the due date or else a penalty might be imposed by the customer.

In this paper, the connection between mySAP and the simulation model is done via Microsoft Excel as an intermediary. The simulation model acquires key data from Excel which include parameters, variables and collections as input data needed to execute the simulation model. Upon completion of the simulation runs, the results are transferred to Excel and then to mySAP.

The simulation model is developed using Anylogic 6. Parameters, variables and collections of Anylogic are used to store the data from mySAP. Parameters are generally used to represent some characteristics of the modeled objects, such as cycle time of machines. Variables are used to store simulation results or object characteristics that are changing over time, e.g. lead times. Collections are a group of objects and are used to store, retrieve and manipulate aggregate data, such as a queue or sequence. Some java functions are created to remove data duplication, or carry out other calculations. Parameters, variables and collections, along with some Java functions, are used together as the Data Fusion objects. These are essentially a collection of functions that were built in Anylogic to carry out data loading and manipulations between the Excel spreadsheet and the simulation model.

Three triggers have been defined in the symbiotic simulation system as follows:

- *Operator trigger.* If an operator updates raw material delivery information or customer orders in mySAP, then certain fields in Excel will also be adjusted.
- *Anomaly trigger.* An example is machine breakdown. In practical cases, a real-time sensor can be applied to detect machine breakdown and to send notifications to the simulation model.
- *Period trigger.* A timeout triggered event sends a triggering notification to MMO periodically. The period of time of this event can be set by users.

The model acquires relevant real-time manufacturing data from mySAP and the tube manufacturing shop floor. After the simulation models have been executed, visualization and prediction animations, suggested decision parameters and direct controlling parameters are generated to improve the performance of the tube manufacturing shop floor. In this way, mySAP is physically linked to a symbiotic simulation system.

SSADS subsystem contains a reference model and aims to detect the anomaly. In this paper, machine breakdown is emulated using a 'button'. When the breakdown button is pressed, one of the cutting machines will break down randomly. An anomaly notification is then generated to trigger MMO to invoke other subsystems.

Future working states and lead times will be generated by SSFS by utilizing Anylogic's 2D/3D animations which can be used for visualization purposes.

What-if scenarios of the best sequence of jobs in a customer order are defined. After running the simulation, the best sequence can be generated to avoid job tardiness or reduce the impact of it. The manufacturing manager, as an external actuator, can then deploy the jobs. The job sequence parameter is set as the optimization parameter in the SSDSS subsystem. The objective function is defined to minimize *job tardiness*. 500 iterations of job sequences were executed in order to get the best sequence.

After running the what-if scenarios, optimized distribution probability parameters are generated by SSCS and transferred to mySAP directly. The probability distributions are set as optimization parameters. The objective function is designed to minimize *total lead time*. 200 iterations were set to get the best set of distribution probability parameters. Figure 6 shows the screenshot of the SSDSS and SSCS subsystems respectively.

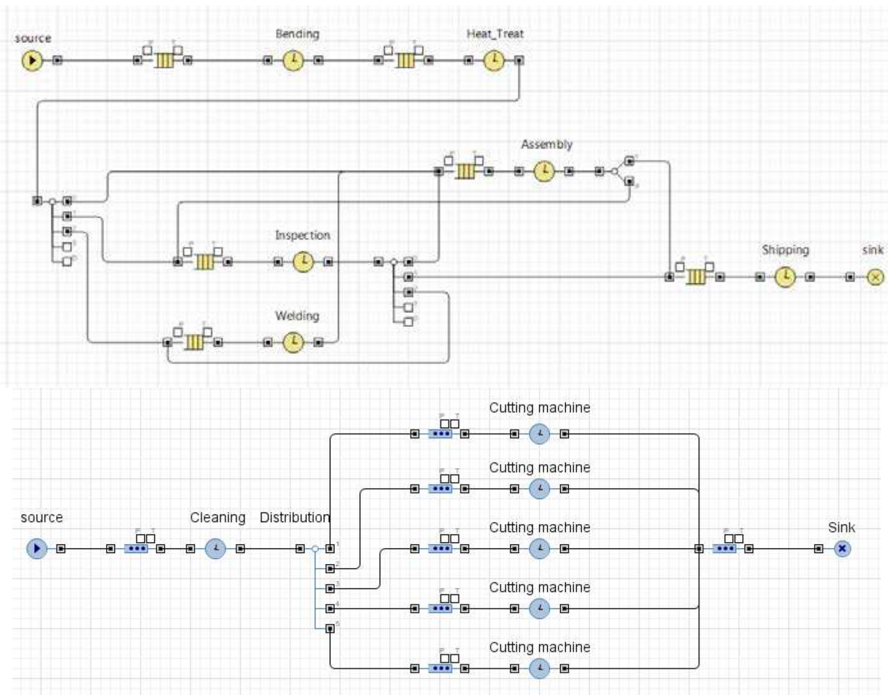


Figure 6: SSDSS and SSCS subsystems.

6 EXPERIMENTATION

A number of experiments have been carried out to verify the functionalities of the symbiotic simulation system. This is mainly carried out by comparing them with traditional, off-line simulation. The experimentation focuses on verifying that:

1. All the triggers and objects can work efficiently in a symbiotic simulation system.
2. The symbiotic simulation can demonstrate accurate prediction and visualization data (the functionalities of SSFS).
3. Suggested decision parameters can be generated for external actuators by the symbiotic simulation system (the functionalities of SSDSS).
4. The symbiotic simulation can directly update manufacturing data in mySAP (the functionalities of SSCS).

6.1 Experiments with Machine Breakdown

After cleaning the raw materials, the five conveyors distribute the raw materials to different cutting stations based on a set of probability rules. There are five cutting stations, each of which has cutting machines with different reliability data stored in mySAP. These experiments were designed to ascertain that the symbiotic simulation system can respond to real-time disturbances, e.g. machine breakdown, by generating a new sets of control functions and send them back to mySAP.

When one of the cutting machines is down, the MMO will invoke the simulation model and OptO to obtain the new sets of probabilities for the conveyor to distribute the jobs to the remaining machines. The objective function is to minimize total lead time as a result of the downtime. Since the predefined manufacturing parameters, e.g. cycle times of cutting machines, are stochastic, ten experiments are executed in order to get feasible results. In a specific time, 50 pieces of raw material are received. Having run the simulation model, the optimized parameters updates the data in mySAP.

Scenario 1: Traditional off-line simulation

With an offline simulation, the simulation model did not respond to the disturbance. The model run using the initial values of probability of the distribution conveyors. When the breakdown occurred the model continued to run, leaving the jobs queuing in front of the broken down machine until the machine was fixed.

Scenario 2: Symbiotic simulation

When the breakdown message is received, MMO receives the anomaly notification and invokes the subsystems. New optimized probability parameters are generated and sent to mySAP to redistribute the raw materials to the other four machines. The experiment result showed that the symbiotic simulation system could respond in real-time and had reduced the total lead time compared to Scenario 1. The average lead time of the ten experiments is reduced from 82.8 min to 58 min. Figure 7 shows the comparison between Scenario 1 and Scenario 2.

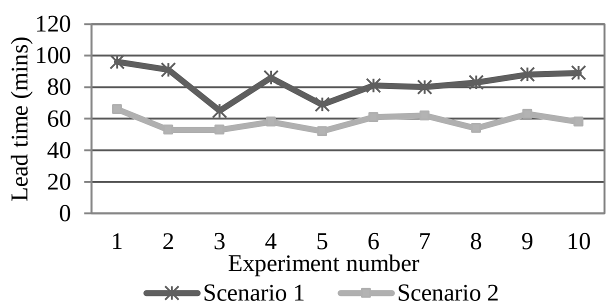


Figure 7: Lead times as a result from machine breakdown.

6.2 Experiments with Customer Orders

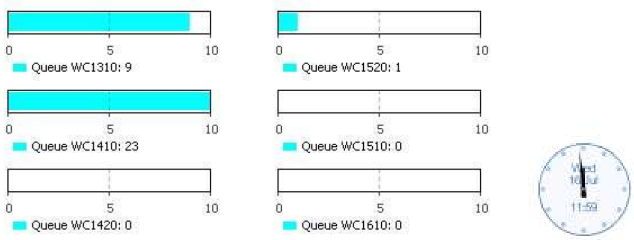
As soon as an operator uploads new orders in mySAP and enters the due dates requested by a customer, the line starts to manufacture the tubes. The shop floor must complete the orders before the due dates. Key experimental features are shown below:

- Source entity: Tubes
- Optimization objective: Minimize job tardiness
- Optimization parameters: Number of tardy jobs
- Number of optimization iterations: 500
- Simulation stop: Completion of order

The experiments were designed to verify that the symbiotic simulation system can generate prediction data (the SSFS subsystem's functionality) that can then be used to support the jobs of the manufacturing manager.

Scenario 1: Job tardiness

This scenario aims to provide the real-time states and future predictions as to whether or not a sequence of jobs will result in tardiness. A clock is used to show time and analysis tools are used to demonstrate statistical results. In this case, bar charts are used to show the number of entities in the queues in front of each work center. Figure 8 shows the prediction of this customer order that C102 and C101 cannot meet their due dates (indicated by *).



Type	ERP lead time (hours)	Due time (hours)	Running results (hours)
C100	48	72	48
A100	24	96	24
A101	48	72	56
A102	48	72	53
C102	72	72	88*
C101	48	48	61*

Figure 8: Predicted job tardiness.

The results were recorded in Excel automatically. The symbiotic simulation system continuously accesses data from spreadsheets and outputs the more accurate due date prediction and modifies mySAP. When late jobs are predicted, the symbiotic simulation reminds the manufacturing manager of the delay times.

Scenario 2: Optimal Sequence

The previous scenario has pointed out two tardy jobs. In this scenario, OptO was run to find the best sequence of jobs in order to reduce tardiness. The objective function, constraints and requirements were set to meet the objective. All the possible sequences are stored in a *collection*. Figure 9 shows the optimization results which recommends sequence number 589 that will result in all due dates being met.

Type	ERP lead time (hours)	Due time (hours)	Running results (hours)
C102	72	72	72
C101	48	48	48
C100	48	72	64
A102	48	72	56
A100	24	96	48
A101	48	72	72

Figure 9: Predicted job completion.

The symbiotic simulation system continuously monitors the states and produces an estimated lead time of each product. Output data are generated dynamically according to the simulation model. In this way, the symbiotic simulation system gives a suggested sequence of jobs to the manufacturing manager.

In summary, two sets of experiments have been carried out to validate the functionalities of the symbiotic simulation system. The experiments showed that the symbiotic simulation system can respond in near real time, periodically update the simulation results, tackle tardiness issues, suggest solutions and update mySAP. In addition, all the objects and subsystems of the symbiotic simulation system worked effectively to achieve the goals.

7 DISCUSSION AND CONCLUSIONS

This research focuses on investigating how to link symbiotic simulation to ERP systems. A framework which includes block diagrams and workflows has been developed to fulfil this aim. In this symbiotic simulation setting, the ERP system and simulation model can be mutually beneficial to each other. A case example has been presented to verify some functionalities of the symbiotic simulation and experiments have been carried out to demonstrate the concept.

In the past, the applications of symbiotic simulation systems were focused on engineering areas such as transportation systems, military communication networks, air traffic controllers and multi-agent systems (Fujimoto et al. 2002; Aydt et al. 2008; Aydt et al. 2011; Kamrani and Ayani 2007). The interface between simulation and physical systems is also known as *online* simulation (see e.g. Teixeira, Tjahjono, and Alfaro 2012).

This paper enables future applications of symbiotic simulation beyond engineering domains. Its primary contribution is the framework for linking symbiotic simulation to ERP systems. The framework enables symbiotic simulation systems to be employed in other shop floor control systems. The paper extends the existing methods of linking ERP systems and simulation tools, for instance, those that were proposed by Moon and Phatak (2005). The methods proposed in this paper also address the shortcomings in the previous work that did not take into account the automated optimization and feedback control between the simulation and the physical systems. With the framework, it is now possible to reduce human intervention in running the simulation experiments and optimization. As the system is now closed-loop, OptO, SSDSS and SSCS, for instance, can be added to automatically acquire the best overtime data and control the ERP system directly.

The paper also demonstrated a proof of concept of how a commercial off-the-shelf (COTS) simulation package was used to practically deploy the framework into a fully working symbiotic simulation system. The system includes a simulation model, a user interface, a real-time simulation engine, some what-if scenarios, an optimization engine and some control functions. The techniques and methods demonstrated in this paper can possibly be used as a reference for simulation modelers to convert existing simulation models into symbiotic simulation.

To a large extent, this paper focuses on dealing with manufacturing uncertainties. However, there are many other industry sectors that use both ERP systems and simulation tools. Future work might be focused on extending the framework to other IT systems and wider application areas. For instance, an ERP-based system in the retail sector may be linked to a symbiotic simulation system to appraise their investments by analyzing their ‘big data’ about market, products and customers.

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AUTHOR BIOGRAPHIES

BENNY TJAHJONO is a Senior Lecturer in Supply Chain Operations at the Supply Chain Research Centre, Cranfield University. He holds a first degree in Electrical Engineering, an MSc and a PhD both in Manufacturing Systems Engineering from Cranfield University. His research interests are in the area of contemporary simulation modeling applications. He has been working closely with global companies on a number of industrial research projects associated with the decision making process and analysis/design of manufacturing systems and supply chain operations. His email address is b.tjahjono@cranfield.ac.uk.

XU JIANG obtained a Master of Science degree from Cranfield University's Manufacturing department. His research interest is in the applications of simulation modelling in production systems, especially aircraft manufacturing. His e-mail address is xu.jiang@cranfield.ac.uk