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Executable Closed-loop Simulation Lifecycle Management Framework Incorporating Fault Detection Classification and Discrete Process Simulation

Heedong Hong[1] and Hyunsoo Lee[2*]

[1]Department of e-Commerce, Semyung University, Jecheorn, 390-711, South Korea
[2]School of Industrial Engineering, Kumoh National Institute of Technology, Gumi–730-701, South Korea; hsl@kumoh.ac.kr

Abstract

As contemporary manufacturing environments are getting more volatile and dynamic, many control frameworks and related information systems have been provided. Simulation Lifecycle Management is considered an advanced dynamic manufacturing framework with early warning control functionality among them. While other systems focus on fault detection and its classification, SLM reasons where the defects occur and how these are removed. This paper provides several executable control frameworks for achieving current manufacturing goals as well as for repairing defects. The suggested framework classifies the degree of defects and analyzes current production objectives with discrete process simulation techniques. Then, it generates the following-up schedule and modifies control parameters. The effectiveness of the provided control framework is proven with a numerical example.

Keywords: Closed-Loop Control, Early Warning Control, Fault Detection and Classification, Process Simulation, Simulation Lifecycle Management

1. Introduction

As one of main contemporary manufacturing technologies and innovations, big data and its analyses have been received considerable emphasis in several manufacturing areas. Traditional manufacturing data are comprised of various types of data such as processes' output, control parameters for manufacturing execution, resources' data and other historical data. While these data are used for improving several production performances including product quality or cycle time, their gathering mechanisms and analyzing techniques have been required and implemented into several systems. While Manufacturing Execution System (MES) is one of representing examples for achieving the goal[1], several issues including partial process coverage, the size of manageable data and dynamic configurations are considered as main barriers in MES. In order to overcome these limitations, a new system is required for controlling overall manufacturing processes and for managing process data – big data. As one of the alternative systems, Simulation Lifecycle Management (SLM) system is introduced. SLM system is an advanced information system for handling manufacturing big data and controlling overall production processes and related resources. The term – SLM is originated in a simulation software[2] of *Dassault Systems*. However, the concept is limited on integration between Computer Aided Design (CAD) tools and its related Engineering and Simulation software only. Lee and Banerjee[3] extend its concept and the coverage from the product development stages to overall enterprises processes including production and manufacturing stages. This paper uses the SLM term

**Author for correspondence*

which Lee and Banerjee[3] defines. One of key functionalities in SLM system is the extended Fault Detection and Classification (FDC) ability. Even though the existing MES has several FDC modules for a closed-loop quality control, SLM system predicts and simulates faults as well as detects them. The predicted faults is analyzed and reasoned for where those might occur and which resources and control parameters made them. Then, the diagnoses are executed using modification of control parameters or changes of resources. The successful execution of this early-warning module[4] is guaranteed with usages of the manufacturing big data and its analyzing techniques. While Process Mining (PM) techniques focus on methods using manufacturing big data in manufacturing domains, SLM system considered as an embodied information system with PM methods.

While many research studies propose new and efficient analyzing methods with relevant manufacturing big data, what they focus on is the reasoning mechanism mainly, where the relationship between performance variables and independent variables is modeled and learning processes are embedded. Even though these methods play a key role in improving manufacturing processes, the research on how to controls in current working facilities after reasoning and analyses is studied less.

As current manufacturing processes consist of several continuous flows such as semiconductor manufacturing or continuous casting processes, the fault correction and controls are executed based on a predefined schedule usually. It implies that related process simulation has to be considered with manufacturing big data and its mining techniques. This paper focuses on it and suggests a new and effective control framework incorporating manufacturing big data and discrete process simulation techniques.

The following chapter reviews the related literatures with the detailed backgrounds. Chapter 3 provides overall control framework in SLM and chapter 4 provides how discrete process simulation techniques are integrated with existing SLM modules. Then, a numerical study is provided in Section 5.

2. Background and Literature Reviews

Many blueprints for driving more advanced manufacturing techniques and systems have been suggested by a lot of industry companies and relevant research groups. Industry 4.0[5] is an example among them, which *Siemens* uses for describing the desired manufacturing environments. In similar, *Dassault*[6] named a concept of next generation manufacturing process with Digital Manufacturing, similarly. The common features in them are summarized into self-organizing abilities[7,8], closed-loop control[9], big data and its utilization and fast services for customers. While the first two terms have been related with the implantation of intelligent controls in manufacturing domains, the third and the last keywords are driven from the developments of big data technology and 3D printers. In order to integrate these features, existing systems are being evolved and new frameworks are being required. Among them, SLM system is considered one of effective systems equipped with the relevant functionalities such as overall processes coverage, collaboration, extension-ability, integration and interoperability. The early concept of SLM framework[3] focused on how the detected manufacturing problems can be resolved in processing. In order to achieve these goals, PLM module and BOM information are linked with process control modules using both DBs: Process DB and Engineering DB. Figure 1 shows the overall architecture of SLM framework. .

The detailed modules and their functions are summarized in Table 1.

Lee and Hong[4] intensify the early-warning detection functions in SLM system particularly. The module simulates predefined manufacturing indices (e.g. quantified quality score, defect pattern, cycle time or throughput) with current control parameters and environments. The simulation function has a key role for changing products/

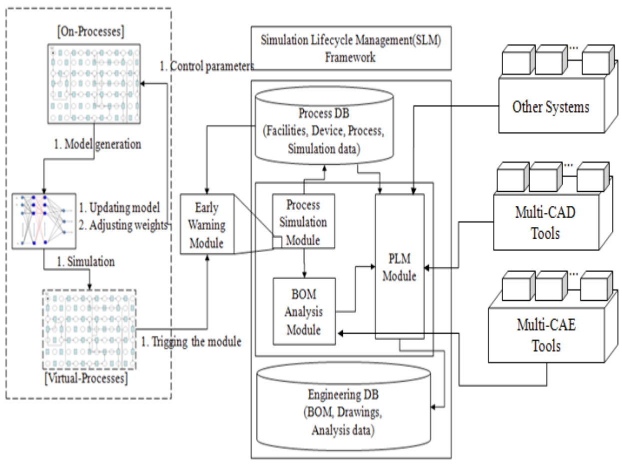


Figure 1. The architecture of SLM framework

Table 1. Main modules in SLM system

Configuration	Detailed Module	Functions
DB	Process DB	Data repository for facilities, process, resources, analyses and other simulation data
	Engineering DB	Data repository for BOM, drawings and other data in PLM
Interface	CAD interface	Multi-CADs interface module
	CAE Interface	Multi-CAE tools interface module
	System interface	Multi-systems Interface module (with PLM, MES, SCM and so on)
Simulation & Analyzing Module	Process Simulation Module	Discrete Event Simulation / Process Analyses
	BOM Analysis Module	Root-cause Analyses / Invoking PLM modules / BOM analyses
	Early Warning Module	Nonlinear Meta model Generation / FDC function / Control and Execution

parts designs and for checking a validation of process reconfigurations with minimizing delays of manufacturing operations. As a prior condition for the early warning module, the relationships between independent variables (e.g. manufacturing control parameters, BOM information and/or process information) and dependent variables (Types of defects, system performances and other KPIs) have to be constructed and utilized. Lee and Hong[4] use the latent-variable based neural net model (1) for formulating the relations.

$$Y_k = f_n\left(\cdots f_m\left(\sum_j w_j f_j\left(\sum_i w_i x_i + \sum_l w_l lv_l + b_k\right)\right.\right.$$
$$\left.\left. + \sum_o w_o lv_o + b_o\right)\right) \qquad (1)$$

Where, x_i is manufacturing control parameters,
Y_k is predictable variable,
w_i is the adjust weight,
b_i is a noise and bias vector,
$f(\cdot)$ is the ith layer's mapping function,
and lv_i is a latent variable reflecting manufacturing environment

While other research studies[3,4] focused on how the nonlinear mapping model (1) is generated in a target interesting process, this paper supposes that the relation is established and embedded in SLM system in advance. It means that the reasons causing defects are identified and controlled using parameters using the model. Then, the remaining issue is to correct the causes. However, the modification process requires the consideration of current manufacturing targets and progresses. After checking the severe degree and types of defects, the detailed modification schedule is fixed and the resources are assigned. As these situations occur irregularly, the controls in FDC have to be executed dynamically. This paper provides the new and effective scheduling methods for handling the issue.

3. Framework Considering Discrete Process Simulation

As discussed in the previous chapter, it is supposed that the FDC module is embedded on the SLM system in a manufacturing process. When several defects are detected in the processes, the following procedure is to determine the repairing schedule. The problematic sub-processes may be repaired at once or the fixing behaviors may be delayed for meeting current demands. This scheduling is related with the severe degree of the detected faults and remanufacturing availability of the Products-In-Process (PIP) with defects. Figure 2 shows a situation that the FDC module detects a problematic sub-process and there are several PIPs requiring remanufacturing processes.

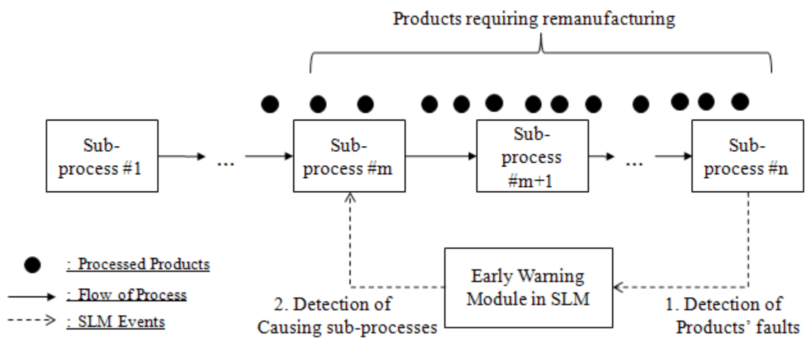


Figure 2. The architecture of SLM framework.

Table 2 describes the following-up measures considering several related cases. The products' defect degree is determined using the predefined quality indices and/or expert's knowledge.

As shown in Table 2, the remanufacturing process is ignored in the type 1 in general. However, the repairing procedure and schedule is established for preventing potential severe risks.

The type II and III are distinguishable with respect to the product's remanufacturing availability. When the products' defects are too severe to be repaired, the remanufacturing process is ignored (type II). In the case, the processes are stopped immediately, and then the correcting procedures are applied. Type III case indicates that a reasoned sub-process has to be repaired and PIPs passing the sub-process can be mended using a remanufacturing process. This paper considers these three types for increasing the efficiencies of overall process.

Table 3 shows strategies and related goals in each case.

The following chapter provides effective control mechanisms for applying the strategies to a detected problematic process in SLM.

4. Control Mechanism for Repairing and Remanufacturing Procedures

The control objective and related methods might be different. However, the strategies shown in Table 3 are considered as reasonable directions with respect to the decrease of cycle time and overall tardiness. The following sections suggest efficient control techniques for each case.

4.1 Type I: Detection of Tolerable Defects & Procedure Without Remanufacturing Process

When defects are considered as tolerable ones by FDC module in SLM system, the production processes are being progressed without any halt. However, the reasons causing the defects are analyzed for preventing potential several risks. Then, the maintenance schedule for the repairing sub-process is set up. Among many criteria, the idlest time in which the due date is not violated, is considered as the most suitable maintenance time.

Table 2. Scenario of following-up measures with default degrees

Severe degree of the detected Fault	Remanufacturing of product with defects	Following-up measures	Type No.
Tolerable	-	Progress the process & Setup the repairing schedule	I
Severe	X	Stop the process & Repair the sub-process	II
	O	Stop the process & Apply efficient schedule for repairing and remanufacturing procedures	III

Table 3. Strategies and related goals of each type

Type	Strategy	Objective
I	Determine the repairing schedule for minimizing Queue length	Min {Queue Length}
II	Fast Repair	Min {Repairing Time}
III	Rescheduling considering the due date	Min {Tardiness}

The idleness of a manufacturing process can be checked with various methods such as a bottleneck time period or Work-in Process (WIP) length over processes' predefined appropriate work capacity. If the production schedule is fixed, the idlest time can be driven easily. However, when the production scheduling is being changed by many volatile environments, it is difficult to find the maintenance schedule easily. This section focused on this situation. Then, it is considered that the most influencing parameter on the schedule's volatility is processes' throughput (λ). In a push-type manufacturing process[10], the high customer demand requires high throughput. In order to meet λ, the process is getting more busier, and it impacts on the WIP level of the process. For this reason, the existence of queue indicates the process's busy status. Similarly, the period with the highest queue length is considered the busiest processing time.

The cycle time in queue (CT_q) is calculated using (2) in a push-typed G/G/C system[11] with the service rate (μ) and the coefficient of variances ($C^2[A]$ and $C^2[S]$) in arrival process and service process, respectively.

$$CT_q = \left(\frac{U}{1-U}\right)\cdot E[S]\cdot\left(\frac{C^2[A]+C^2[S]}{2}\right)\cdot\left(\frac{U^{\sqrt{2c+2}-2}}{c}\right) \quad (2)$$

where $U = \lambda/(\mu\cdot c)$ and $E[S]=1/\mu$

Then, the queue length (W_q) is driven in (3) using (2) and Little's law[12].

$$W_q = \left(\frac{U^2}{1-U}\right)\cdot\left(\frac{C^2[A]+C^2[S]}{2}\right)\cdot\left(U^{\sqrt{2c+2}-2}\right) \quad (3)$$

Then, the idlest time in a process with several throughputs ($\lambda_i, i\in I$) is calculated using (4).

$$\lambda^* = \arg\min_{\lambda_i, i\in I}\left(\frac{\lambda_i^2}{\mu\cdot c}\right)\cdot\left(\frac{1}{\mu\cdot c-\lambda_i}\right)\cdot\left(\frac{C^2[A]+C^2[S]}{2}\right)\cdot\left(\frac{\lambda_i}{\mu\cdot c}\right)^{\sqrt{2c+2}-2} \quad (4)$$

As the λ^* guarantees the idlest process, the maintenance is executed during the period that the arrival rate λ^* is being kept. If a manufacturing process includes more composite links such as serial, merging and split links, the coefficient of variance (CoV) and arrival rate are calculated using equations in Table 4. Then, these equations are used for calculating λ^*.

4.2 Type II: Detection of Service Defects & Procedure without Remanufacturing Process

The second type handles the case of the products with severe defects which are detected by the SLM's FDC module. Even though there are products passing already by the causing sub-process (PIPs), the defects are too severe for the products to be reused. As the causing sub-process is stopped immediately after FDC's detection, the remaining control issue is to repair it as soon as possible.

The fast recovery means the recovery without any breaking of customers' due dates. In order to achieve this objective, the recovery rate (ν) is considered as a control variable. Figure 3 shows a transition diagram for describing a manufacturing process with the break-down case.

As shown in Figure 3, each circle represents the state with WIP level – the number in the circle. For instance, the state, 2 in the circle means that the situation where the WIP level is 2 and a manufacturing process is working. And, 2' in the circle means a state that the WIP level is 2 still, but the process is stopped for its maintenance. If overdue period is represented with DD, the cycle time (CT') preventing the delay is approximated in (5).

$$CT' \approx \frac{CT\cdot D - DD}{D} \quad (5)$$

where D is an order amount

As D is not an independent variable in real situation and DD is a dependent variable, the decrease of CT is pursed for achieving CT'. Due to the existence of the breaking down and recovering process, (2) is not applied to the calculation of CT. For this reason, CT is calculated from WIP (W) using Little's law indirectly. And, W is driven from the transition diagram (Figure 3) and (6).

$$W = \sum_{i=0}^{MW} i\cdot(P_i + P_{i'}) \quad (6)$$

where, MW is the maximum WIP level,

P_i = the probability of the state (i of the circle) and,

Table 4. Equations considering serial, merging and split links[13,1]

Links	Dependent Variable	Equations
Serial	Arrival rate	λ
	CoV	$C_a^2(n+1)=(1-U_n^2)C_a^2(n)+U_n^2\dfrac{C_s^2(n)+\sqrt{c_n}+1}{\sqrt{c_n}}$
Merg-ing	Arrival rate	$\sum_{i=1}^{n}\lambda_i$
	CoV	$\sum_{i=1}^{n}\dfrac{\lambda_i}{\lambda}C_d^2(i)$
Split	Arrival rate	$p\cdot\lambda_i$
	CoV	$C_a^2(n+1)=p\cdot C_d^2(i)+(1-p)$

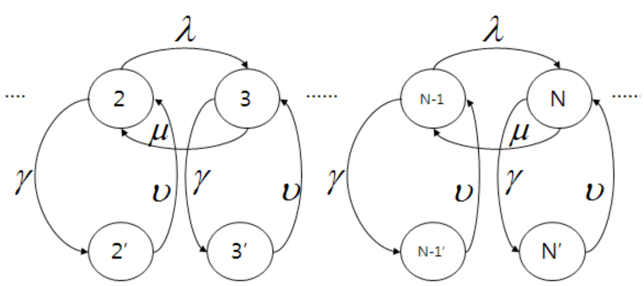


Figure 3. Transition diagram of the break-down process.

P_i = the probability of the state (I' of the circle)
The probabilities P_i and $P_{i'}$ are calculated using (7) and (8).

$$P_i=(\upsilon/\gamma)\cdot P_{i'} \tag{7}$$

$$(\lambda+\mu+\gamma)P_i=\lambda\cdot P_{i-1}+\upsilon\cdot P_{i'}+\mu\cdot P_{i+1} \tag{8}$$

Then, CT' and the control parameter value v^* are calculated. In order to meet the due date, the attempts for achieving v^* are executed.

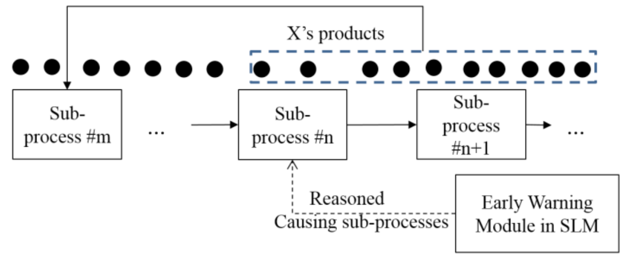
4.3 Type III: Detection of Severe Defects & pProcedure with Remanufacturing Process

This type is considered as a more general case in SLM system. The FDC detects severe defects and their causing sub-processes are identified. These sub-processes are halted for their corrections. However, several products passing by these sub-processes can be remanufactured using correcting processes. The correcting processes might be ones in existing sub-processes (Figure 4 (a)) or might be different from them (Figure 4 (b)).

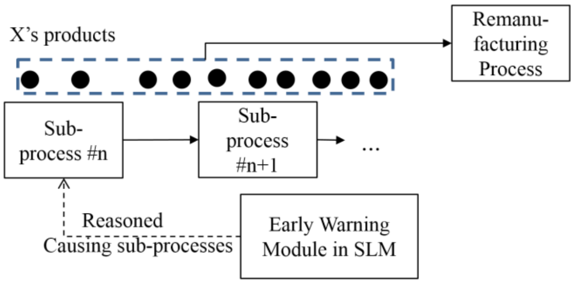
As shown in Figure 4 (a), the existing process (*#m*) has both roles as a production processes and a remanufacturing process. This fact implies that the schedule in *#m* has to consider multi-type products. The simplest heuristic rule is to compare both cycle times in the processing time in forward direction ($CT_{m,f}$) and backward direction ($CT_{m,b}$). If $CT_{m,f} > CT_{m,b}$, the remanufacturing activity has a higher priority in *#m*. Otherwise, the process handles products from the previous process. However, there might be the more complicate scenario such that each product has a different due date, compared to others. In this case, the suggested simple heuristic rule fails to meet the due dates. This case can be resolved using several heuristics such as various look-ahead controls[15].

The control and analysis of the second case (Figure 4 (b)) is much easier than the other cases. As there is an additional processor, it takes charge of remanufacturing process only. If the reassignment of resources from the existing processes to the remanufacturing process is ignored, the process is executed for remanufacturing the products with the normal recovery rate. If the reassignment of resources is allowed, the control policy follows the strategy in the type I.

The control and analysis of the second case (Figure 4 (b)) is much easier than the other cases. As there is an



(a) Existing process as a remanufacturing process.



(b) Additional remanufacturing process.

Figure 4. Different types of processes with remanufacturing process.

Table 5. Initial conditions of an exemplary process with type II case

Control Parameter	Objective
Number of Processe	1
Maximum WIP level	4
λ	4
μ	5
γ	3
υ	4

Table 6. System performances using SLM controls

System Performances	Value
Probability with WIP level 0	0.2975
Probability with WIP level 1	0.2380
Probability with WIP level 2	0.1904
Probability with WIP level 3	0.1253
Probability with WIP level 4	0.1218
Probability with break-down	0.4286
Total WIP	1.5631
WIP in working status	0.9628
Cycle time considering production time	0.2407

additional processor, it takes charge of remanufacturing process only. If the reassignment of resources from the existing processes to the remanufacturing process is ignored, the process is executed for remanufacturing the products with the normal recovery rate. If the reassignment of resources is allowed, the control policy follows the strategy in the type I.

The following chapter provides a numerical example supporting these control strategies.

5. Exemplary Study supporting SLM Controls

The previous chapter explains how a SLM's early warning module controls overall processes with FDC functionality. Three types of scenarios are considered and efficient control techniques are suggested.

This chapter provides a numerical example supporting the second case out of them, particularly.

As an exemplary process, a manufacturing process with a process is assumed. Table 5 shows an initial condition of the process.

As the due date is related with the cycle time (5), the cycle time is calculated using (7) and (8). Table 6 shows the analyzed process's performances using the initial conditions.

As shown in Table 6, the overall probability at repairing process is 0.4286, and the current cycle time considering the working status is 0.2407. When the cycle time has to be decreased to 0.1915 to meet the orders' due date using (5), ν^* is re-estimated from current value 4 to 2.5. Then, the attempts to keep the new ν^* are executed.

This numerical example shows how the SLM's early warning module integrates process simulation methods and controls overall manufacturing process achieving manufacturing objectives.

6. Conclusions and Further Studies

The SLM framework is considered as a new and efficient control framework with reinforced FDC functionalities. While other manufacturing information systems focused on the detection of product defects and faults, SLM's early warning module controls manufacturing processes dynamically for achieving several production goals.

This paper suggests several control heuristic algorithms in SLM system. These algorithms integrate existing stochastic approaches with the FDC module. When SLM detects defects and reasons the causing sub-processes, the repairing schedule and related following-up measures are executed using the provided control framework.

As further studies, more large-scale control framework is expected considering volatile environment. As contemporary manufacturing processes purse a large-scale scheduling including supply chain plans and attempt to achieve multi-objective goals, more dynamic and real-time based optimized control framework are expected in SLM system.

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