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Research Article

SVM-Based Dynamic Reconfiguration CPS for Manufacturing System in Industry 4.0

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CPS is potential application in various fields, such as medical, healthcare, energy, transportation, and defense, as well as Industry 4.0 in Germany. Although studies on the equipment aging and prediction of problem have been done by combining CPS with Industry 4.0, such studies were based on small numbers and majority of the papers focused primarily on CPS methodology. Therefore, it is necessary to study active self-protection to enable self-management functions, such as self-healing by applying CPS in shop-floor. In this paper, we have proposed modeling of shop-floor and a dynamic reconfigurable CPS scheme that can predict the occurrence of anomalies and self-protection in the model. For this purpose, SVM was used as a machine learning technology and it was possible to restrain overloading in manufacturing process. In addition, we design CPS framework based on machine learning for Industry 4.0, simulate it, and perform. Simulation results show the simulation model autonomously detects the abnormal situation and it is dynamically reconfigured through self-healing.

1. Introduction

The term Industry 4.0 refers to a strategy of German manufacturing industries in which strategy copes with a change such as social, technological, economic, ecological, and political using Information Communication Technology (ICT). The aim of Industry 4.0 is to primarily create a smart factory that will use ICT technologies actively, such as Internet of Things (IoT), enterprise software, location information, security, cloud, big data, and virtual reality. The Cyber-Physical System (CPS) plays a critical role in realizing Industry 4.0. CPS acts as a medium to link physical world, such as sensors, actuators, and mobile devices, with Internet service and also to mirror what happens in the real world to a cyber space to process preinspection, real-time management, and postmortem. Europe, Sweden, US, China, and South Korea use CPS in an attempt to realize Industry 4.0 [1, 2]. Recently, manufacturing countries in an industrially advanced nation are rapidly shrinking production populations, and the rate of elderly dependency is soaring. This decrease in production population is affecting the labor productivity, which is the foundation of a manufacturing industry. In this regard, Industry 4.0 emerged so that manufacturing evolution can complement future competitiveness.

The manufacturing facility is generally operated by a preset program under existing factory automation system. On the other hand, the manufacturing facility must decide how to operate autonomously in Industry 4.0. Smart manufacturing by a smart factory involves facilities and processing of an individual factory and shares and uses all production information by combining ICT with traditional manufacturing, thereby making it possible to achieve optimal production and operation. At the same time, it also connects related factories to establish a production system which will allow continued collaboration through extension of the smart manufacturing concept [3].

CPS refers to a computer-based component and system that closely connects various complicated processes and information of real space with the cyber space that provides data access and processing services through Internet. The smart factory CPS helps making optimal decision for the network connecting the manufacturing equipment as well as their design and operation through intelligent context awareness, decision making, and execution [4, 5]. In spite of being old itself, CPS can be used to develop a new technology by interfacing it with existing technologies, such as multiagent systems (MASs), service-oriented architectures (SOAs), wireless sensor networks (WSNs) [6], Internet of Things (IoT) [7, 8], cloud computing [9–14], augmented reality, big data [15], machine-to-machine (M2M), and mobile Internet [16]. Still, there are important tasks such as safety, security, and interoperability that need to be considered [17].

In the past decade, research on CPS concept, modeling method, and application method was broadly divided into studies on the integration of CPS technology with other ICT technologies or existing systems for application in manufacturing. The most commonly used keywords are cyber model, digital twin, real-time modeling, and analysis [18]. Studies on the application in manufacturing primarily involved problems such as aging of equipment and prediction of problems, and they were solved by using machine learning and artificial intelligence. Prior reports showed that a few actual manufacturing cases were solved, but such papers are a few in number and most of them focused on CPS methodology. In the early stage, the conceptual approach of the whole system or presentation of design methodology and partial application of elemental technology are mainstream, and more specifically, integrated and empirical research is needed.

In this paper, CPS was applied to shop-floor as a part of CPS research. The overall goal was to use machine learning to enable self-management functions, such as self-healing, and to prevent the system from further degradation, thereby, providing active self-protection and self-healing. To achieve this, we executed shop-floor modeling and applied self-healing in the modeling. For this purpose, 5C's CPS architecture model of Lee et al. was used. The 5C's CPS architecture model consists of Connection, Conversion, Cyber, Cognition, and Configuration. We have reconstructed the manufacturing process based on this. The manufacturing site modeled the conveyor belt manufacturing system using the M/D/1 queue, and the parameters used were μ, λ, and ρ. SVM, a machine learning method, was used to predict the occurrence of abnormal conditions, and an abnormal situation was detected through the change of ρ. These concepts and researches can serve as reference models for building CPS and can be useful in the design step before starting the application.

Section 2 will describe a related architecture research and basic research for implementing CPS. A framework for dynamically reconfiguring CPS-based shop-floor will be introduced in Section 3. Section 4 will explain the proposed system and its results. Finally, Section 5 will complete this with conclusions.

2. Related Research Work

In Section 2, we will describe three related studies for CPS implementation. Section 2.1 describes the architecture underlying the dynamic reconfiguration framework, Section 2.2 describes the Queuing Theory on which the simulation model is based, and Section 2.3 deals with related machine learning that is the basis for self-healing.

2.1. Cyber-Physical System. Figure 1 shows the results of Lee et al., who proposed CPS architecture of an Industry 4.0 based manufacturing system [19]. The architecture comprises 5 levels, which is "connection," "conversion," "cyber," "cognition," "configuration." It consists of methodologies and guidelines for CPS deployment for manufacturing from step-by-step design and data collection for analysis and final value creation. The paragraphs below explain the function of each level in detail.

2.1.1. Connection Level. Acquiring accurate and reliable data from machines and their components is the first step in developing a Cyber-Physical System application. The data might be directly measured by sensors or obtained from controller or enterprise manufacturing systems, such as ERP, MES, SCM, and CMM.

2.1.2. Conversion Level. Meaningful information needs to be inferred from the data. Currently, there are several tools and methodologies available to draw inference from the data in the information conversion level.

2.1.3. Cyber Level. The cyber level acts as central information hub in this architecture. Information is being pushed to it from every connected machine to form a machines network. Having massive information gathered, specific analytics have to be used to extract additional information that provides better insight on the status of individual machines among the fleet.

2.1.4. Cognition Level. Implementing CPS in this level generates a thorough knowledge of the monitored system. Proper presentation of the acquired knowledge to expert users supports leads to correct decision of the users. Since comparative information as well as individual machine status is available, decisions based on priority of tasks can be made taken to sustain optimal maintaining process.

2.1.5. Configuration Level. The configuration level is the feedback from cyber space to physical space and acts as a supervisory control to make machines self-configuring and self-adaptive. This stage acts as resilience control system (RCS) to apply the corrective and preventive decisions, which have been made in cognition level, to the monitored systems.

Lee et al. proposed a 5C's CPS architecture to achieve the goal of resilient, intelligent, and self-adaptable system. CPS in a manufacture and automation environments can be applied to diverse processes including simulation, design, control, and verification. In manufacturing, CPS can improve quality and productivity through smart presymptom and diagnosis using big data from different machines, network sensors, and systems. In addition to this, various related studies have been carried out, but the focus was primarily on the role of the CPS in methods for applications connected with technologies, such as manufacturing, application scenarios, conceptual or architectural design, and big data, analysis, IoT, and human-machine interface (HMI) [20, 21]. Additionally, the degree of CPS implementation in the enterprises is still low. These

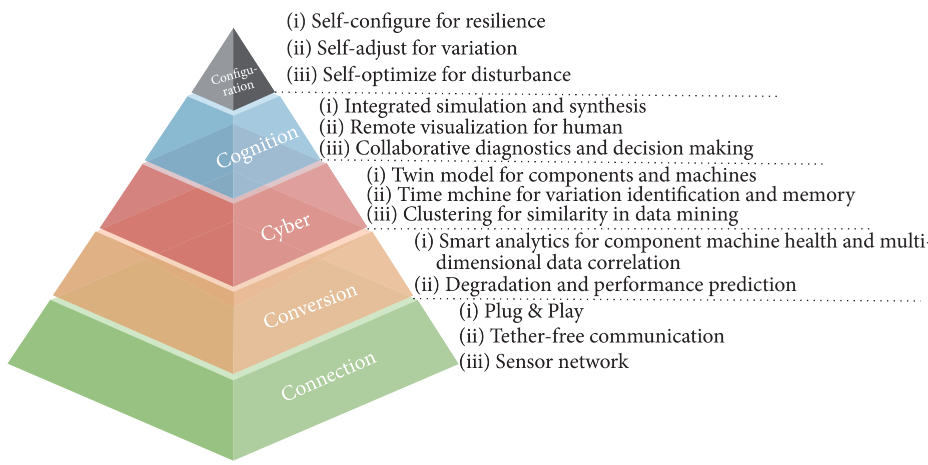


Figure 1: "5C" architecture of cyber-physical systems.

concepts and studies can act collectively as reference models for building CPS and can be useful in the design phase before starting an application. However, they dealt with issues such as cyber model which is essential for more practical implementation of CPS. In the present work, the production site of the manufacturing process was implemented through CPS. This can help to reduce the technology gap in the stage of technological innovation.

2.2. Queuing Theory. The Queuing Theory creates models (consequent insights) that are useful in predicting behavior of systems which provide services to randomly generate demand. It is also important to consider the statistical distribution of production operations (ex, process time, process cycle, and production mix) that allow for a description of the complex environment. When actually modeling a production system, the main benefits of Queuing Theory are the probability, average time of the system, average service time, average work time, work time, average number of customers in the system, and the probability of number of customers who will be in the system.

The use of Queuing Theory allows rapid modeling of a production system even when there are certain uncertainties in the environment. These uncertainties can be managed by statistical distribution of parameters, such as arrival and service rate of the queuing model.

Figure 2 shows a typical Queuing Theory, comprising input, output, queue, and service time of a production.

Table 1 shows the parameters associated with the adopted notation. The most commonly used parameters are λ, μ, and ρ. ρ is an important parameter that describes how busy a server is during a period of time.

This Queuing Theory is used in systems such as logistics service, AGV, Less Than Truckload (LTT), conveyor belt for assembling parts, airports with a queue for runway access, elevators of banks, and warehouses. The stochastic of transport routes, arrivals, and service times is mainly studied. However, there are a few studies on ρ of server. In this paper, we used a utilization of server to change the manufacturing process efficiently.

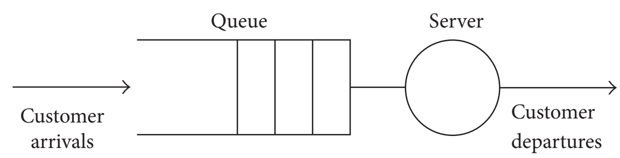


Figure 2: Queue of machine.

Table 1: Notation of the queuing models.

Symbol	Units	Description
λ	Job/h	Mean arrival rate of *jobs* at the system
μ	h	Mean service of *jobs* in the system
ρ	%	Utilization coefficient of the department

2.3. Machine Learning in CPS. Artificial intelligence techniques, such as artificial neural networks, inductive learning methods, case-based reasoning, and genetic algorithms, have been applied to the prediction field to recognize, predict, and reconstruct the present situation. Odom and Sharda were the first to apply artificial neural networks to predictions [22]. They compared prediction rates by applying discriminant analysis and artificial neural network model, between which the artificial neural network model showed better results than the discriminant analysis. Tam and Kiang applied artificial neural networks and compared the results with those of discriminant analysis, Logit, k-nearest neighbor, and inductive reasoning. As a result, the model based on artificial neural network showed better results in prediction and adaptability than other methods.

Despite the excellent predictive accuracy of the artificial neural networks, the main limitation is that it is difficult to explain the cause of the prediction results and the possibility of generalization is also reduced. Furthermore, another disadvantage is that a lot of time and effort are required to design an artificial neural network structure and excessive suitability problem in constructing an artificial neural network model.

In this paper, we have proposed a solution to the abovementioned problems by recognizing the present situation using support vector machine (SVM).

SVM proposed by Vapnik in 1995 is a learning algorithm that first divides input data into two groups and then analyzes them [23]. Figure 3 shows a typical SVM. To separate the data, the support vector which is the farthest away from the opposite group of data is found, the hyperplane, which is the criterion for dividing into two groups, is determined, and the margin is then calculated. There can be multiple hyperplanes, but there is one hyperplane that maximizes the margins and the distance between the support vector and the hyperplane. In our study, we found the hyperplanes and separated the data.

We give a brief mathematical summary of the classical SVM for binary-class classification. Assume there is a group of independent training samples, as shown in the following equation [24]:

$$\left\{x_i, y^i\right\}, \quad x_i \in R^n, \; y_i = \pm 1, \; i = 1, 2, \ldots, l. \tag{1}$$

Given that the adopted classification method of the samples is proposed as shown in the following equation:

$$f(x) = \operatorname{sng}(w \cdot x + b), \tag{2}$$

so, SVM line subclassification can convert a quadratic regression which can be recorded as

$$\begin{aligned} \min \quad & \left(\frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{l}\xi_i\right)^P\right), \\ \text{s.t.} \quad & y_i (w \cdot x + b) \geq 1 + \xi_i, \\ & \qquad \xi_i \geq 0, \; i = 1, 2, \ldots, l, \end{aligned} \tag{3}$$

where C stands for the penalty factor, the greater its experience error value is, the greater the penalty will be. By the application of Lagrange's multiplier method, (3) can be changed into a Wolfe Dual Planning shown as

$$\max \quad \left(\sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{i}\alpha_i\alpha_j x_i \cdot x_j\right). \tag{4}$$

α_i and α_j stand for Lagrange multipliers. In this way, after the adoption of dual planning, the research separates the SVM and the input sample dimensions, thus to avoid the appearance of so-called "Dimension Disasters." The final liner function for SVM can be shown as in the following equation:

$$f(x) = \operatorname{sng}(w \cdot x + b) = \operatorname{sng}\left(\sum_{i=1}^{l}\alpha_i\alpha_j y_i x_i + b\right). \tag{5}$$

For nonlinear problems, substituting the kernel function $k(x_i, x_j)$ into (6), one can obtain a final nonlinear function for SVM as shown in the following equation:

$$f(x) = \operatorname{sng}\left(\sum_{i=1}^{l}\alpha_i y_i k\left(x_i, x_j\right) + b\right). \tag{6}$$

The most important part of CPS is self-healing. There are various ways to solve problems when they occur, and self-healing using machine learning is becoming more popular these days [25, 26]. However, they are limited to real-time monitoring, as they do not only detect and diagnose machine failures, defective products, or training and test predefined dataset. Therefore, it is necessary to study the dynamic reconfiguration of manufacturing process based on CPS when an abnormal situation occurs.

3. Machine Learning Based Self-Aware Machines

Smart Factory is a manufacturing CPS that integrates physical objects, such as machines, conveyors, and products with information systems to enable flexible and agile production. In this section, a framework and shop-floor modeling for smart factory will be proposed. Discrete event simulation will be used to evaluate the proposed model.

3.1. Framework. The concept of smart manufacturing is actually based on the integration of IoT and CPS concepts. IoT's vision is to interconnect millions of devices and interconnect them with enterprise systems. The combination of IoT and CPS is essential to provide users with the data provided by the millions of devices in the shop-floor. Applying the general concept of CPS to the manufacturing system is called cyber-physical production system (CPPS). CPPS is the factor that enables IoT in the manufacturing process. Thus, the CPPS concept allows for high level integration and interoperability of manufacturing applications and systems by improving autonomy and flexibility in industrial environments. As the network communication technology developed, the virtual world that emerged as IoT and the real world have a vision to harmonize with each other. This indicates that it ensures a smooth data flow between real-time data on the shop-floor and information of the management system. Figure 4 shows the work type of shop-floor. In the manufacturing system, conveyor belt, AGV, warehouse, and machine exist. In order to obtain data of each equipment, data should be provided to users through wired/wireless communication networks based on smart object.

Figure 5 shows that a smart factory framework consists of physical layer and cyber layer. The physical layer transmits the actual data generated at the shop-floor to the cyber layer through an industrial network [27]. Shop-floor based real data is collected in real time on all elements in the factory layout, from automation facilities to equipment operated by the operator, work performed by the operator, warehouse,

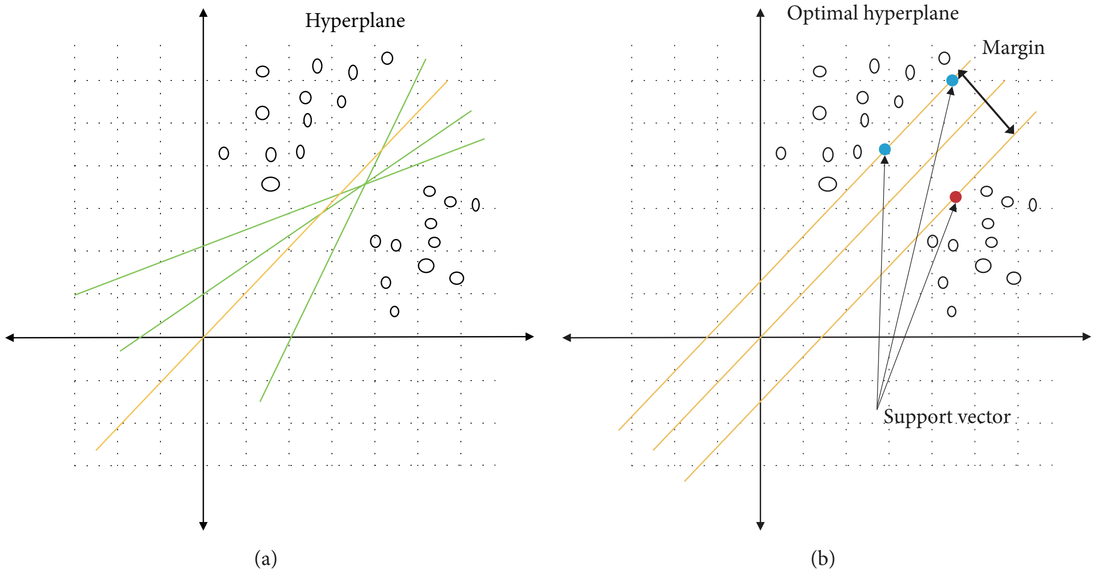


FIGURE 3: Compositions of support vector machine.

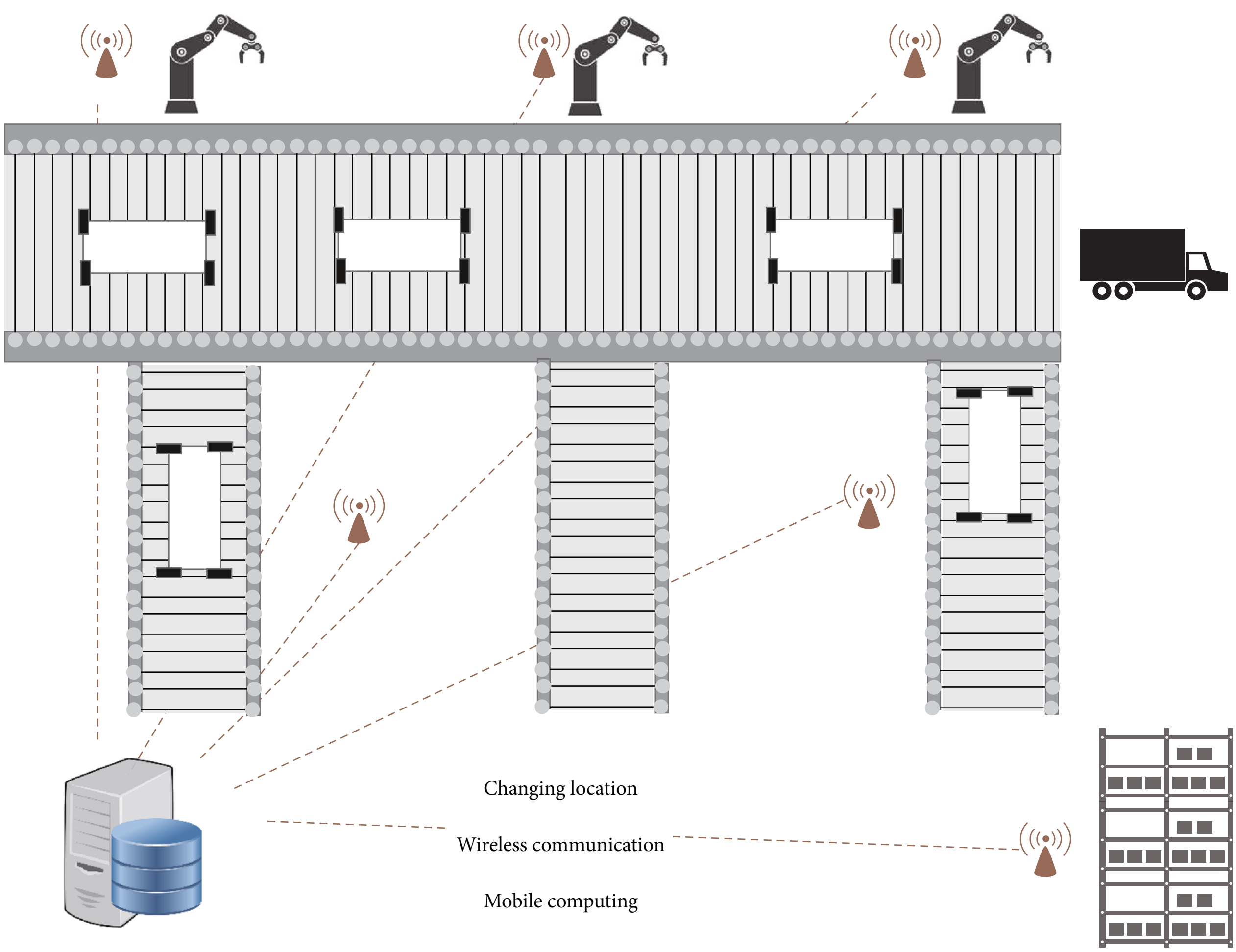


FIGURE 4: Manufacturing system case study.

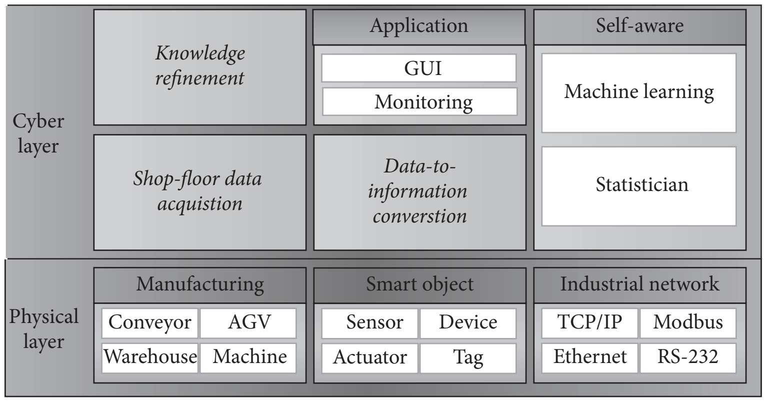


FIGURE 5: Framework of reconfiguration CPS.

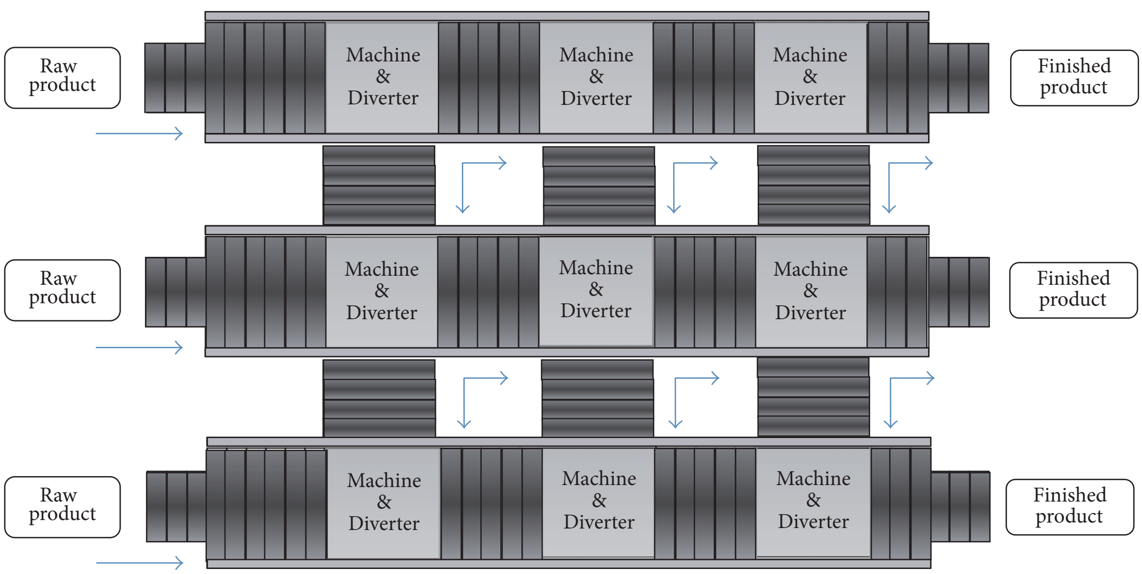


FIGURE 6: Shop-floor field modeling.

buffer, conveyor, and logistics facilities such as AGV. Data must be collected through smart objects such as sensors, devices, actuators, and tags. A smart object is an intelligent electronic device that has built-in Internet access control function which makes it easy to access online anytime and anywhere, thereby enabling data collection by equipment in the cyber layer. The cyber layer collects all the data from the industrial site and converts it into meaningful information [28]. Actually, the data generated in the physical layer is diverse and very large. Thus, it is necessary to reduce and convert the data to make it suitable for techniques such as machine learning and big data analysis [29]. The transformed information is trained through machine learning technology to generate a model and the generated model is then tested. The output data may be used for monitoring or GUI provided for user's service. The output data is also kept for future knowledge improvement.

3.2. Shop-Floor Modeling. Figure 6 shows a virtual model of the conveyor belt shop-floor. There are three products in the model, each product is manufactured and transported to the next line. If the process time of a particular device is long or short, there may be a change in the input quantity, which may indicate out of order of the machine. In such a case, it is necessary to stop the machine or change the order of operations with other equipment. The path of the model is changed through the diverter.

Figure 7 shows the open queuing network model. This shows the conveyor belt in Figure 6 as a queuing model. We will assume that a single server, and all nodes operate according to a FIFO queuing discipline. It is assumed that the data of all nodes are transmitted by wireless communication. The following assumptions are followed for modeling implementation and testing.

(1) Input product arrives at the system following a Poisson distribution.

(2) The machine's queue and server follow the M/D/1 standby queue.

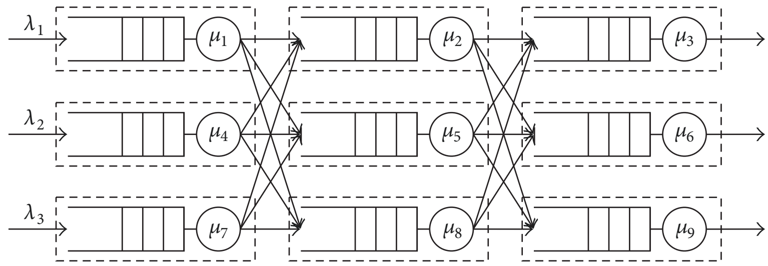


Figure 7: Queuing network model.

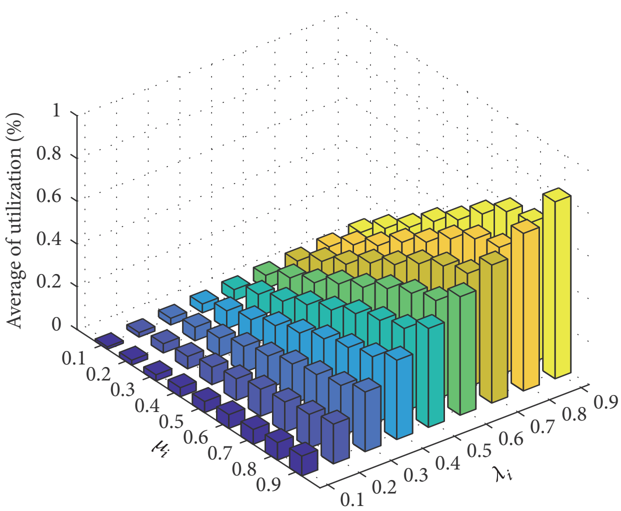


Figure 8: Parameter correlation.

The Poisson distribution is a discrete probability distribution that represents how many events occur within a unit of time. If the probability is sufficiently large or the probability is small enough, the Poisson distribution can approximate the problem. The M/D/1 queue is a model used when the service time is deterministic rather than random. It is a single server which sets the machine's working time constant in the production system and the number of machines as one.

Table 2 shows the average arrival rate (λ) and the average service rate (μ) as parameters of M/D/1 used in the model. The following relationship can be obtained in the M/D/1 queue [30].

$$\rho = \frac{\lambda}{\mu}. \tag{7}$$

If $\rho = 1$, it means that the server is operating 100 percentages, and if $\lambda > \mu$, the service of the equipment is blocked. In this paper, we do not consider the ratio of the server over 100 percentages and since μ is set to 1 at maximum, λ is specified as 0.1~0.9, according to (7).

Figure 8 shows the correlation of three parameters through (7). In order to verify the quality of the manufacturing process using SVM, a machine learning technology, the input data needs to be divided into two groups. The input parameter is required to divide into two groups, ρ, λ, where ρ is the percentage of time that the server works on all of the time. The results of ρ obtained according to the ratio of λ and the ρ obtained by changing μ during the manufacturing process are placed in two groups. Then, test is done through the newly modified μ.

Table 2: M/D/1 queue parameter.

Input parameter		
λ	μ	ρ
0.1~0.9	0.1~1	0~1

Figure 9 shows the SVM-based dynamic reconfiguration CPS flowchart. When the shop-floor shown in Figure 5 was initially constructed, the process proceeded to the M/D/1 queue and the data (λ, ρ, and μ) of the generated queues was input to the SVM training module. The SVM training module finds a support vector for the input data, divides the input vector into two groups, and calculates hyperplanes and margins. The data in the queue which will be processed in future is input to the SVM test module so that it belongs to one of the two groups "class 1" and "class 2" generated in the SVM training module. Then if the SVM test result belongs to "class 1," it decided that there is no abnormality in the equipment, whereas if it belongs to "class 2," it decided that the equipment is abnormal. If an abnormality is decided, it needs to be checked whether the average ρ of the equipment is out of the range of "λ ± threshold" and then change the path after confirming whether the state of the peripheral equipment is normal.

4. Simulation and Results

In this paper, we implemented the model through Matlab SimEvent of Mathworks, discrete event simulation software [31–34]. The remainder of this section describes the verification and validation of the simulation model and some preliminary results. In order to implement CPS-based environment, a network system capable of systematically managing collected data using smart objects, such as sensors and actuators and industrial networks, is needed. However, in this study, simulation software is used to collect data because there is no environment that can obtain data from factories through sensors [35, 36].

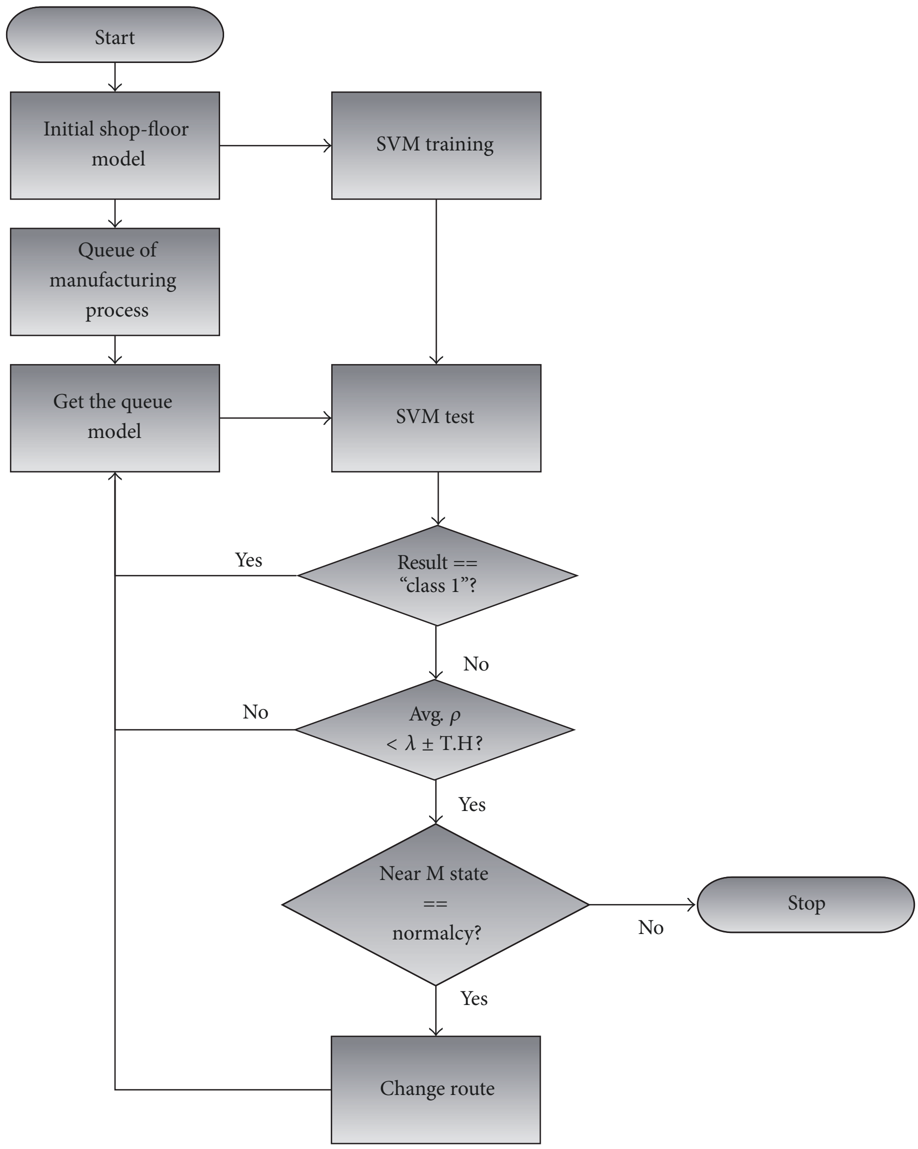


Figure 9: Flowchart of SVM-based dynamic reconfiguration CPS.

Figure 10 shows implementation of a conveyor belt at the shop-floor. The production time of the initial product and the process time of each equipment can be adjusted, and the number of production of the product can be confirmed. Exponential Arrival Time (EAT) can be generated with a Poisson distribution of 0.1 to 0.9, and Stamp Entity (SE) can cause an event to change μ during the manufacturing process.

Figure 11 shows the inside of each machine block. After fixing the machine service based on the M/D/1 system, μ is changed according to the event occurrence. If one needs to change the conveyor path by changing μ in the machine, the path can be changed through the entity output switch, which acts as a diverter. This signifies transportation of product to another line.

SVM is a machine learning algorithm that analyzes and classifies various input variables, as mentioned above. In this problem, λ and μ are used as input variables. As shown in Figure 7, training was performed through a predetermined λ and μ was changed in the manufacturing process.

Based on the input/output variables defined in Table 3, proceed according to the process represented in Figure 9. As mentioned above, if the machine shows no change in service time, it is assumed that it is under normal condition. On the other hand, if there is a change, it is assumed that it is an abnormal situation. Therefore, the output data is set as training and test output values before and after the change of μ.

Figure 12 shows the training results, where the x-axis represents λ and the y-axis represents the mean value of ρ from 0.1 to 0.9. The value of ρ was obtained by repeated experiment from 0.1 to 0.9 after fixing μ and λ. In this paper, "class 1" was used when there was no abnormal situation of the machine, and "class 2" referred to when the value of μ was changed. To note, the newly input data has been

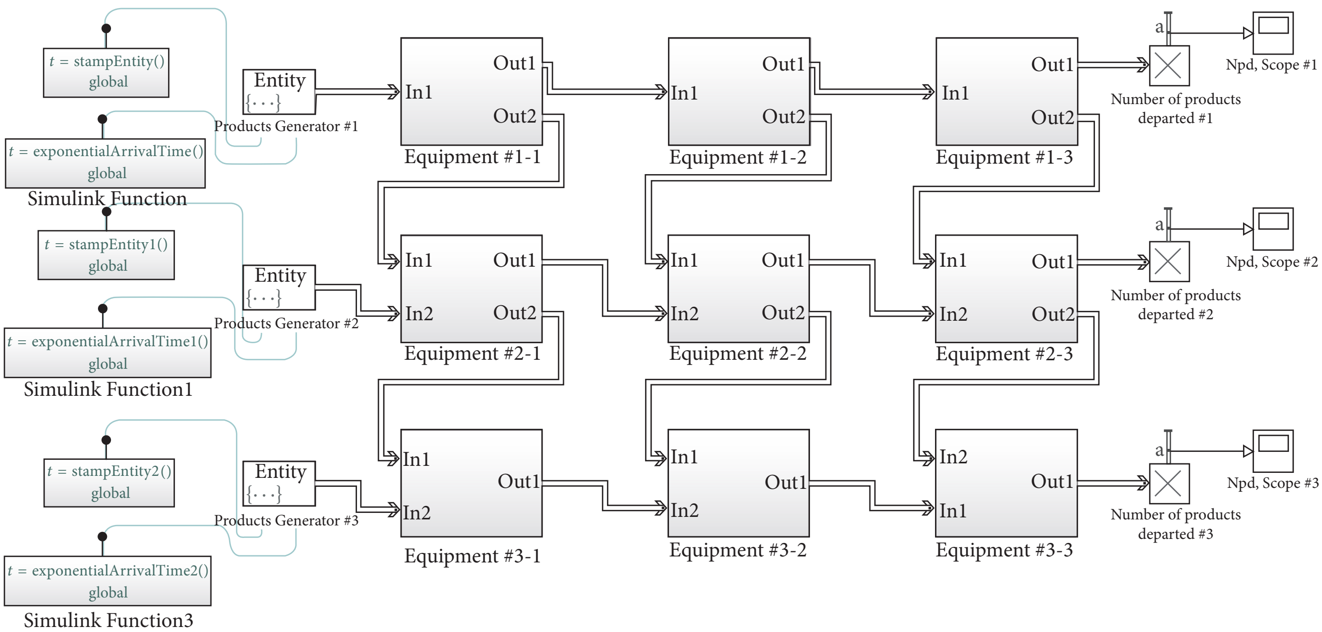


FIGURE 10: Matlab-based shop-floor field.

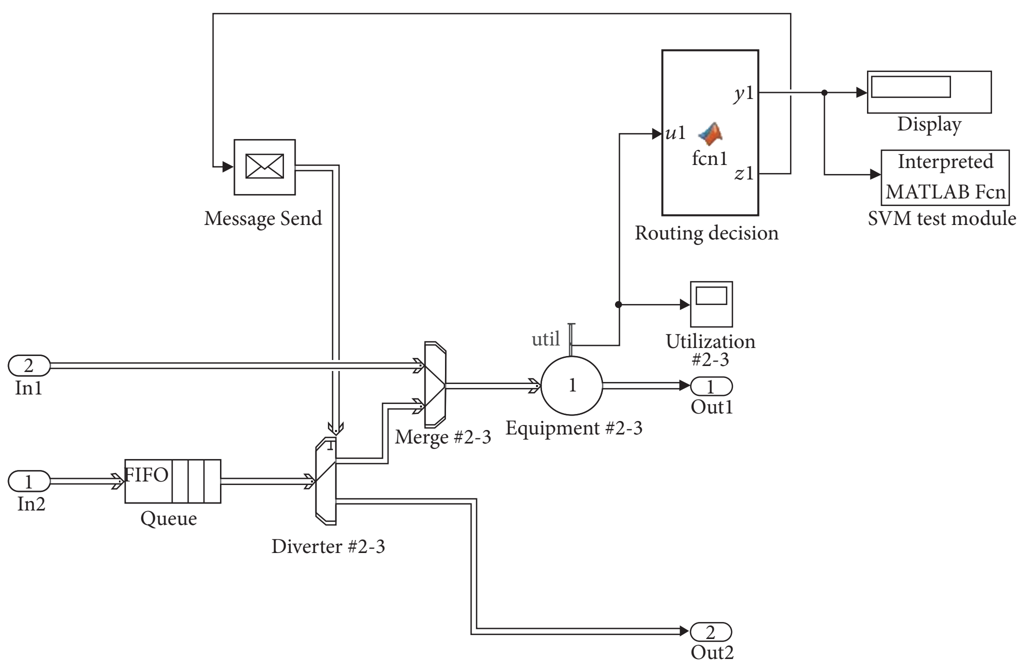


FIGURE 11: Machine process block.

TABLE 3: The variables of input and output data set.

	Input	Output
Before μ change (normal state)	λ_i ρ_i	SVM training results
After μ change (abnormal detection)	λ_i ρ_i	SVM test results

classified as "class 2" because the new data is located below the hyperplane.

In SVM modeling, property selection and parameter setting are important. These two have a decisive influence on the efficiency and accuracy of SVM classification. We used the Grid-search (GS) algorithm for parameter optimization. The Grid-search method is a method of finding optimal parameters by attempting a discrete value of a suitable interval within a predetermined range.

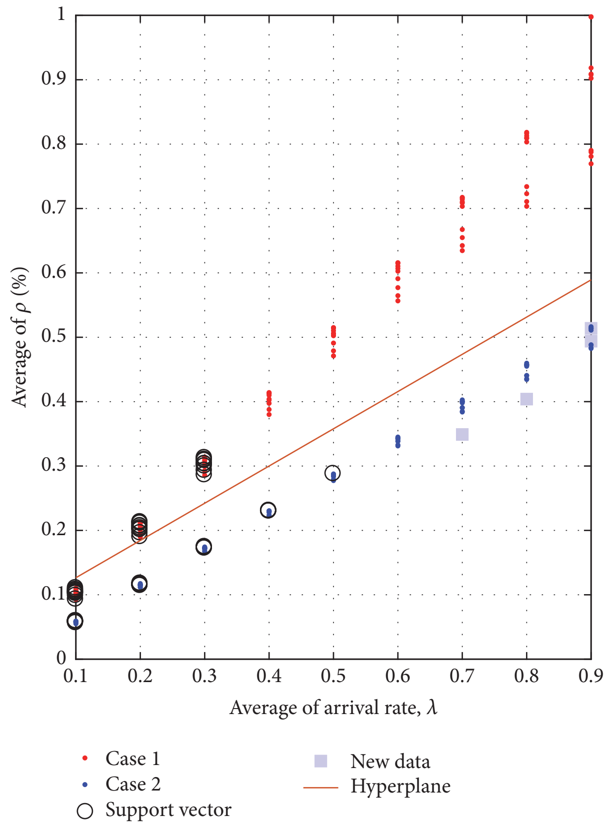


FIGURE 12: Detect abnormal situation using SVM.

```
*.*
optimization finished, #iter = 313
nu = 0.310837
obj = −312.668385, rho = 0.976663
nSV = 57, nBSV = 52
Total nSV = 57
```

BOX 1: Result of classification using LibSVM.

Two parameters (C, r) are required to execute the SVM using the Radial Basis Function (RBF) kernel. C is the penalty parameter of the SVM, and r is the kernel parameter. In the GS, basically, (C, r) pair with the highest cross-validation accuracy is chosen. Thus exponentially increasing (C, r) values finds the optimal parameter. In this paper, C and R were obtained using GS during training.

Box 1 shows the model result obtained after training. From the output, obj is optimal objective value of the dual SVM problem. The value ρ is $-b$ in the decision function. nSV and nBSV are number of support vectors and bounded support vectors, respectively.

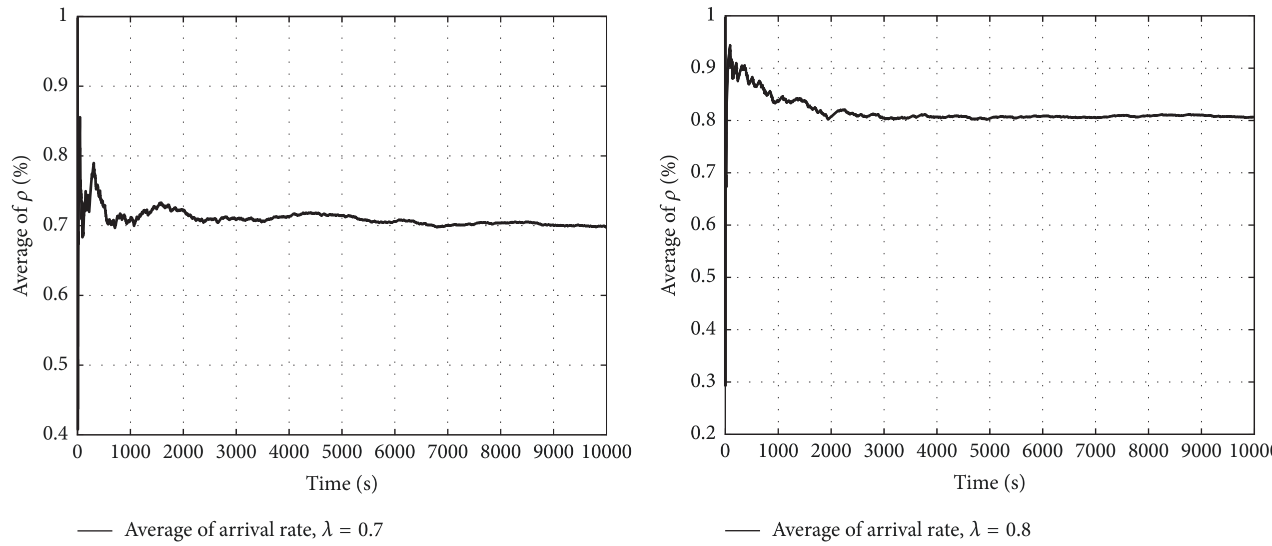
In order to verify the performance of the SVM-based dynamic reconfiguration production system proposed, we compared the server ρ before and after the abnormal situation occurred and then proceeded with the reconfiguration process of the production system. Abnormal situation means that the process rate of the machine is overloaded or the rate of service is changed due to decrease in speed. The processing time was 10,000 sec and the time and place of occurrence of the abnormal situation occurred randomly.

Figure 13 shows the server ρ of machines #1-3 and #2-3 when no abnormalities occur. The λ of each machine were 0.7 and 0.8. It was observed that ρ was similar to λ when no abnormal situation occurred. The average value of ρ were classified as "class 1" in Figure 12.

Figure 14 shows the variation of ρ after (a) and (b) occurred at $t = 3{,}000$ and 4,000. Abnormal situations indicate situations such as overloading or slowing down of the machine, which lowers ρ. The average value of this ρ has been classified as "class 2" in Figure 12.

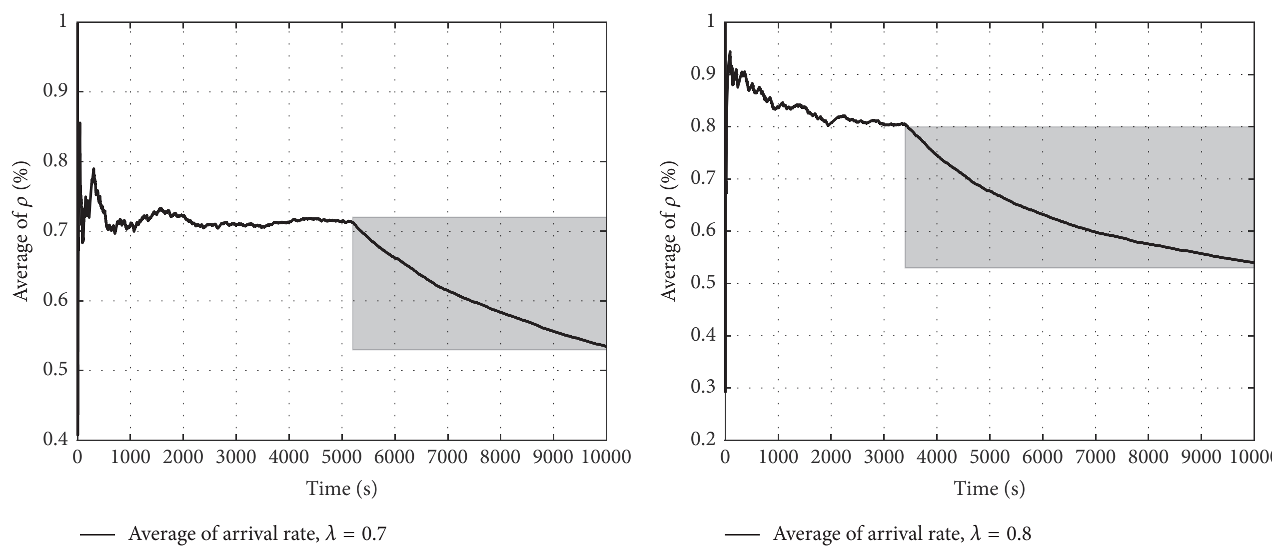
Figure 15 shows the ρ after the change of the production route after the abnormal situation occurs. After the abnormal situation occurred at $t = 3{,}000$ on machine #1-3, the average ρ was out of the range of $\lambda \pm$ threshold, and the production route was changed at $t = 8{,}000$ to the surrounding machine. On machine #2-3, the production route has not changed after the abnormal situation occurred at $t = 4{,}000$, because ρ has not exceeded threshold. The product of machine #1-3 flow into machine #2-3 and increased at $t = 8000$. This indicates that the simulation model has been reconstructed by recognizing machine #1-3 as an error in the model test.

Figure 16 shows a number of products produced after an abnormal situation has occurred and the production route



(a) (b)

Figure 13: Simulation results for server utilization when no event occurred (%): (a) server utilization in machine #1-3 ($\lambda = 0.7$); (b) server utilization in machine #2-3 ($\lambda = 0.8$).



(a) (b)

Figure 14: Simulation results for ρ during event occurrence: (a) event occurrence in machine #1-3 ($t = 5{,}200$); (b) event occurrence in machine #2-3 ($t = 3{,}400$).

has changed. (a) shows that machine #1-3 is stopped at $t = 8{,}000$, and (b) shows that the number of products increases because the products have flowed from machine #1-3 to machine #2-3. This indicates that the simulation model has been reconstructed.

5. Conclusions

In this paper, for development of CPS, we modeled and simulated conveyor belt manufacturing system based on M/D/1 queue and decided the occurrence of abnormal situation due to equipment overload at shop-floor using SVM. SVM is trained by using μ, λ, and ρ of M/D/1 queue as input parameters. As a result, it was possible to decide whether the condition was normal or abnormal. For any abnormality, the situation was solved by reconfiguring the manufacturing system. This enabled a flexible system even if an abnormal situation occurred in a CPS-based manufacturing system. Future research will explore ways to use multiple decisions by adding different types of decision making. It is expected that CPS will be useful for further research and development

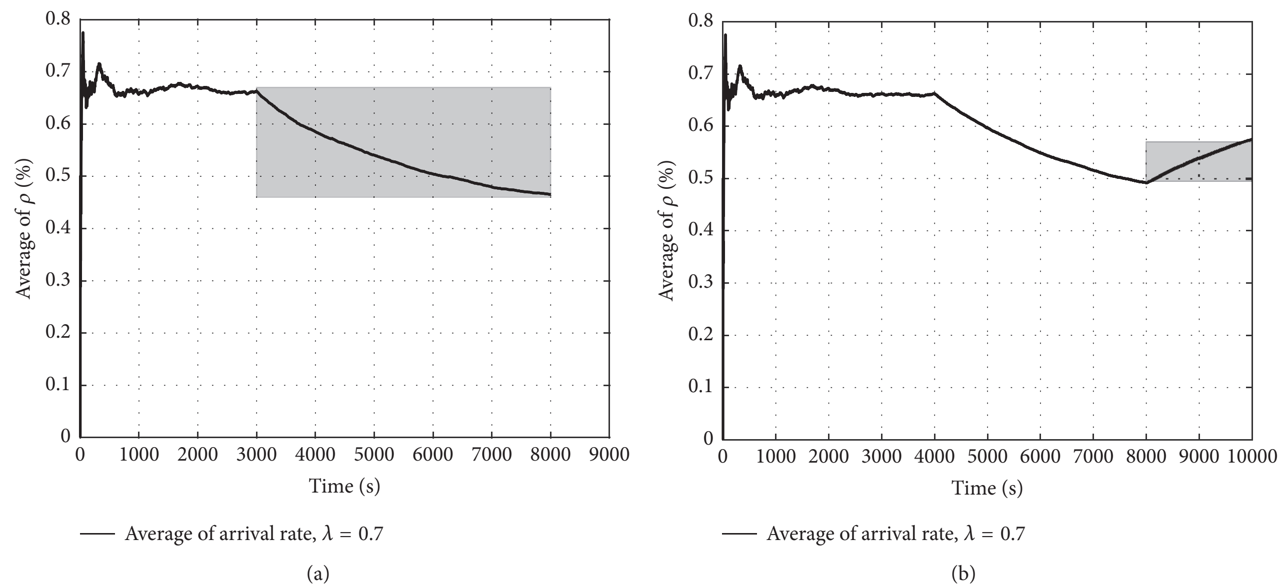


FIGURE 15: The utilization after the change of the production route in the abnormal situation occurs: (a) event occurrence in machine #1-3 (t = 3,000); (b) utilization changed due to abnormal situation recognition (t = 8,000).

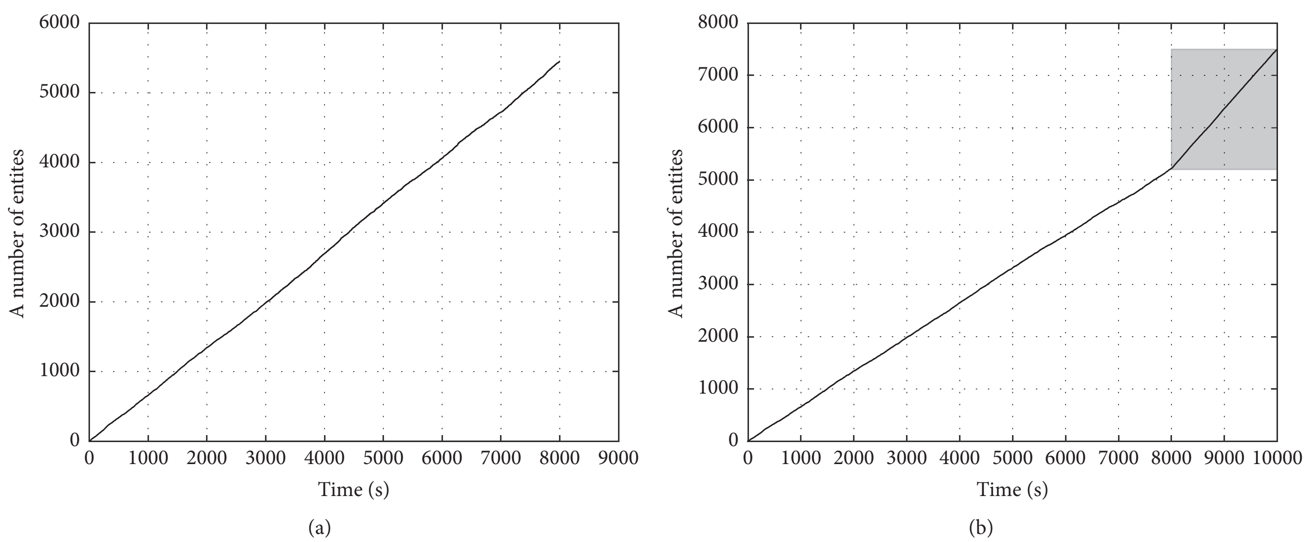


FIGURE 16: A number of entities after the change of the production route after the abnormal situation occurs: (a) event occurrence in machine #1-3; (b) a number of entities changed due to abnormal situation recognition (t = 8,000).

because it is a technology applicable to various fields as well as Industry 4.0 and is indispensable in fields requiring prediction and self-healing.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] M. Taisch, B. Stahl, and G. Tavola, “ICT in manufacturing: trends and challenges for 2020—an European view,” in *Industrial Informatics (INDIN), Proceedings of the IEEE International Conference on Industrial Informatics*, pp. 941–946, 2012.

[2] J. Park, “Technology and issue on embodiment of smart factory in small-medium manufacturing business,” *The Journal of Korean Institute of Communications and Information Sciences*, vol. 40, no. 12, pp. 2491–2502, 2015.

[3] H. Syed, P. Athul, K. Andreas, P. Apostolds, and J. S. Song, “Recent trends in standards related to the internet of things and machine-to-machine communications,” *Journal of Information*

and Communication Convergence Engineering, vol. 12, pp. 228–236, 2014.

[4] W. Guo, Y. Zhang, and L. Li, "The integration of CPS, CPSS, and ITS: a focus on data," *Tsinghua Science and Technology*, vol. 20, no. 4, pp. 327–335, 2015.

[5] X. Jin, B. A. Weiss, D. Siegel, J. Lee, and J. Ni, "Present status and future growth of advanced maintenance technology and strategy in US manufacturing," *International Journal of Prognostics and Health Management*, vol. 7, 2016.

[6] M. Qiu and E. H.-M. Sha, "Energy-aware online algorithm to satisfy sampling rates with guaranteed probability for sensor applications," in *Proceedings of the High Performance Computing and Communications*, pp. 156–167.

[7] F. Tao, Y. Zuo, L. D. Xu, and L. Zhang, "IoT-based intelligent perception and access of manufacturing resource toward cloud manufacturing," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 2, pp. 1547–1557, 2014.

[8] Q. Jing, A. V. Vasilakos, J. Wan, J. Lu, and D. Qiu, "Security of the internet of things: perspectives and challenges," *Wireless Networks*, vol. 20, no. 8, pp. 2481–2501, 2014.

[9] X. Xu, "From cloud computing to cloud manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 28, no. 1, pp. 75–86, 2012.

[10] Q. Liu, J. Wan, and K. Zhou, "Cloud manufacturing service system for industrial-cluster-oriented application," *Journal of Internet Technology*, vol. 15, no. 3, pp. 373–380, 2014.

[11] J. Wan, D. Zhang, Y. Sun, K. Lin, C. Zou, and H. Cai, "VCMIA: a novel architecture for integrating vehicular cyber-physical systems and mobile cloud computing," *Mobile Networks and Applications*, vol. 19, no. 2, pp. 153–160, 2014.

[12] Z. Zhang, H. Lim, and H. J. Lee, "The design of an efficient proxy-based framework for mobile cloud computing," *Journal of Information and Communication Convergence Engineering*, vol. 13, no. 1, pp. 15–20, 2015.

[13] Z. Yang, M. Awasthi, M. Ghosh, and N. Mi, "A fresh perspective on total cost of ownership models for flash storage in datacenters," in *Proceedings of the 8th IEEE International Conference on Cloud Computing Technology and Science*, pp. 245–252, December 2016.

[14] J. Bhimani, Z. Yang, M. Leeser, and N. Mi, "Accelerating big data applications using lightweight virtualization framework on enterprise cloud," in *Proceedings of the IEEE High-Performance Extreme Computing Conference*, pp. 1–7, September 2017.

[15] H. Gao, Z. Yang, J. Bhimani et al., "AutoPath: harnessing parallel execution paths for efficient resource allocation in multi-stage big data frameworks," in *Proceedings of the 26th International Conference on Computer Communication and Networks*, pp. 1–9, July 2017.

[16] F. Soliman and M. A. Youssef, "Internet-based E-commerce and its impact on manufacturing and business operations," *Industrial Management & Data Systems*, vol. 103, no. 8-9, pp. 546–552, 2003.

[17] Gartner's 2015 Hype Cycle for Emerging Technologies Identifies the Computing Innovations that Organizations Should Monitor, http://www.gartner.com/newsroom/id/3114217.

[18] H. S. Kang, J. Y. Lee, S. Choi et al., "Smart manufacturing: past research, present findings, and future directions," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 13, pp. 111–128, 2016.

[19] J. Lee, C. Jin, and B. Bagheri, "Cyber physical systems for predictive production systems," *Production Engineering Research and Development*, vol. 11, no. 2, pp. 155–165, 2017.

[20] B. Dworschak and H. Zaiser, "Competences for cyber-physical systems in manufacturing-first findings and scenarios," *Procedia CIRP*, vol. 25, pp. 345–350, 2014.

[21] L. Monostori, "Cyber-physical production systems: roots, expectations and R&D challenges," *Procedia CIRP*, vol. 17, pp. 9–13, 2014.

[22] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.

[23] M. D. Odom and R. Sharda, "A neural network model for bankruptcy prediction," in *Proceedings of the International Joint Conference on Neural Prediction Networks (IJCNN '90)*, pp. 163–168, 1990.

[24] J. C. Beard, C. Epstein, and R. D. Chamberlain, "Online automated reliability classification of queueing models for streaming processing using support vector machines," in *Proceedings of the International Conference on Parallel and Distributed Computing*, pp. 325–328, 2015.

[25] C. J. Lee, S. O. Song, and E. S. Yoon, "The monitoring of chemical process using the support vector machine," *Korean Chemical Engineering Research*, vol. 42, pp. 538–544, 2004.

[26] Y. Oh, H. S. Park, A. Yoo et al., "A product quality prediction model using real-time process monitoring in manufacturing supply chain," *Journal of Korean Institute of Industrial Engineers*, vol. 39, no. 4, pp. 271–277, 2013.

[27] S. Neumeyer, K. Exner, S. Kind, H. Hayka, and R. Stark, "Virtual prototyping and validation of cpps within a new software framework," *Computation*, vol. 5, no. 1, article 10, 2017.

[28] B. Bagheri, S. Yang, H.-A. Kao, and J. Lee, "Cyber-physical systems architecture for self-aware machines in Industry 4.0 environment," *International Federation of Automatic Control*, vol. 48, no. 3, pp. 1622–1627, 2015.

[29] M. Marques, C. Agostinho, R. Poler, G. Zacharewicz, and R. Jardim-Goncalves, "An architecture to support responsive production in manufacturing companies," in *Proceedings of the 8th IEEE International Conference on Intelligent Systems*, pp. 40–46, September 2016.

[30] U. N. Bhat, *An Introduction to Queueing Theory: Modeling and Analysis in Applications*, Springer, New York, NY, USA, 2008.

[31] MathWorks, SimEvents User's Guide, https://kr.mathworks.com/help/pdf_doc/simevents/simevents_ug.pdf.

[32] M. A. Gray, "Discrete event simulation: a review of SimEvents," *Computing in Science & Engineering*, vol. 9, pp. 62–66, 2007.

[33] A. A. Alsebae, M. S. Leeson, and R. J. Green, "SimEvents-based modeling and simulation study of stop-and-wait protocol," in *Proceedings of the 5th International Conference on Modelling, Identification and Control*, pp. 239–244, September 2013.

[34] N. Galaske, D. Strang, and R. Anderl, "Response behavior model for process deviations in cyber-physical production systems," in *Proceedings of the World Congress on Engineering and Computer Science*, pp. 443–455, 2015.

[35] S. C. Lee, T. G. Jeon, H. S. Hwang, and C. S. Kim, "Design and implementation of wireless sensor based-monitoring system for smart factory," in *Proceedings of the International Conference on Computational Science and Its Applications*, pp. 584–592, 2007.

[36] J. Jang and E. J. Kim, "Survey on industrial wireless network technologies for smart factory," *Journal of Platform Technology*, vol. 4, pp. 3–10, 2016.