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Modeling and Analysis of Early-warning Detection Module in Simulation Lifecycle Management Framework using Copula Function

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Abstract

The simulation lifecycle management framework is considered as an advanced manufacturing information system integrating product lifecycle management and manufacturing execution systems. While other manufacturing systems focus on the detections of current faults and the related controls, the framework has an early-warning detection module for predicting potential risks and for preventing them in advance. In order to design the module, the preliminary procedure is to construct the mapping model between manufacturing data and quality-based indicators. The mapping model is indicated as a nonlinear meta model. While neural network based models or response surface methods are applied for the meta model, it is limited in the fact that it is difficult to capture correlations among atypical manufacturing big data. In order to overcome the issue, a copula based nonlinear meta model is suggested with a numerical case study for clear understandings. The usage of copula theories helps to extract well-defined relationships among manufacturing data. The potential risks are predicted using the copular-based meta model and advanced controls are taken for preventing them effectively.

Keywords: Copula Theory, Early-Warning Detection Module, Fault Detection and Classification, Nonlinear Meta Model, Simulation Lifecycle Management

1. Introduction

As big data techniques and related software have been developing, manufacturing applications using big data have been received considerable emphases. The definition of big data can be classified into two types of definitions: the narrow definition and the broader definition. The narrow definition is that the big data is a data which is too large to be handled using current information processors. The latter definition of big data includes many techniques and algorithms for extracting meaningful implications and for analyzing the data. This paper uses the second definition for describing a big data.

One of main trends in contemporary manufacturing areas is to introduce the big data and to use it. The main reasons are in the facts that the big data can be used for increasing manufacturing efficiency and it is considered as a breakthrough technique for resolving current manufacturing issues which are impossible to be solved using current techniques and management skills. The big data in manufacturing area is called with many similar terms: Process Mining (PM) and Simulation Lifecycle Management (SLM). The PM implies a big data and its analyzing techniques applied in several productions and manufacturing processes. While PM covers manufacturing and productions stages only, SLM expands the coverage from the manufacturing processes to the Research and Development (R&D) stages in the overall New Product Development (NPD) processes[1]. In addition, The SLM includes many analyzing tools such as Design of Experiments (DOE)[2], Markov Chain Monte Carlo (MCMC)3 and many optimization techniques[4]. For this reason, a PM module can be a part in a SLM system.

The initial SLM is introduced by the software company, *Dassault Systems*[5] which is famous for the Computer Aided Design (CAD) tool- CATIA. The company focused

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on the issue that the information in R&D processes might be lost and it might hinder productive activities in an overall NPD lifecycle. This issue is originated from the case of Mir, the Russian space shuttle in 1995. After launching the shuttle, ground staffs found the strange object over the satellite's telecommunication rod. As it failed to explain the existences and usages of the object, the importance of R&D data and simulation results have been getting bigger. In order to prevent similar situations, the company attempted to store and manage overall R&D data over functionalities of Production Lifecycle Management (PLM) system. While *Dassault system*'s SLM concept is limited in the R&D process among overall NPD processes, Lee and Banerjee[6] extend its lifecycle coverage to production stages. Figure 1 shows the framework of the extended SLM.

As shown in Figure 1, SLM framework has both databases (DB): Process DB and Engineering DB. The former DB stores overall data generated in manufacturing processes and the latter manages the R&D data. With these data, the system integrates both processes: R&D processes and production processes.

Lee and Hong[7] focus on modeling and implementations of the early-warning detection module in SLM system. SLM's early-warning detection module is different from the general Fault Detection and Classification (FDC) modules in a general Manufacturing Execution System (MES). While a MES's FDC module plays a role of finding faults and classifying types of them, SLM's early-warning detection module controls the manufacturing processes' parameter for getting rid of the predicted faults. For this reason, FDC functionalities are considered as sufficient conditions for functionalities in SLM's module. This paper elaborates the modeling and analyses of the early-warning detection module in SLM. The key components in the module are the nonlinear meta model and the control logics. However, they are studied comparatively less. This paper suggests a new executable early-warning module using copula function.

The following chapter provides the related background knowledge and reviews relevant literatures. Chapter 3 explains the function and architecture of the early-warning detection module in SLM and the Chapter 4 examines the characteristics of copular theories as a basic model of

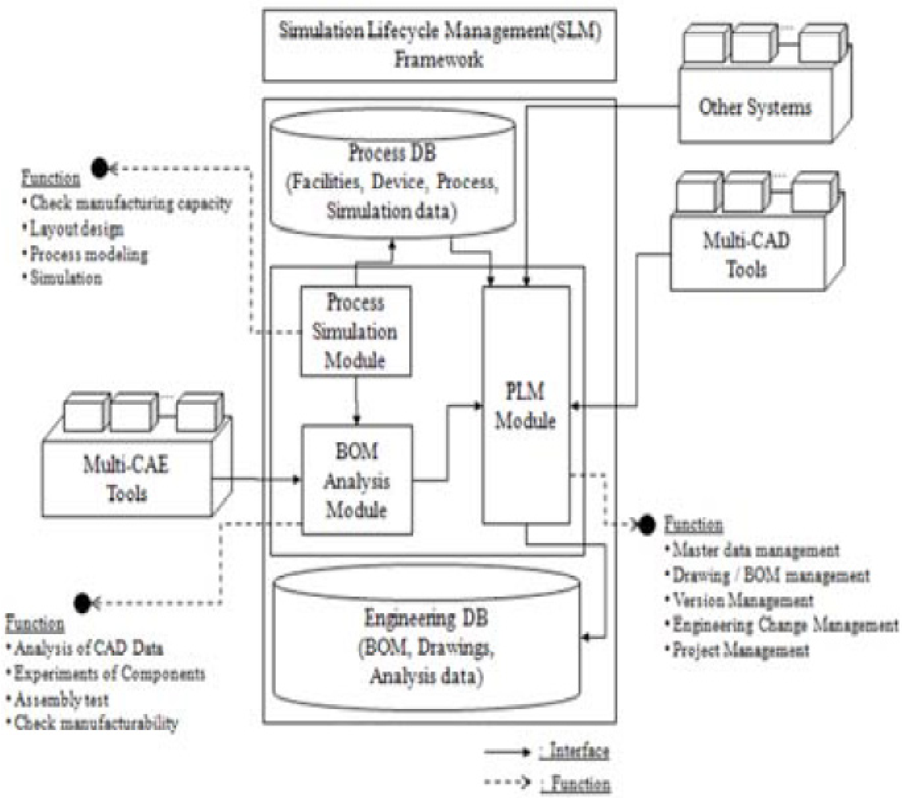


Figure 1. The extended architecture of SLM framework[6].

the nonlinear meta model. Then, a numerical case study provided in Chapter 5 for helping clear understandings.

2. Background and Literature Reviews

As introduced in the previous chapter, the initial SLM's coverage was limited in the R&D stage, in terms of NPD processes. Then, its coverage is extended to overall processes. In order to apply SLM concepts to manufacturing processes, Lee and Hong[7] focus on Manufacturing Execution System (MES) which is an essential information system in contemporary production processes. According to Manufacturing Execution Systems Associations (MESA)[7,8], the initial MES was introduced in the early 1990s by *Advanced Manufacturing Research (AMR) co.* and it has played roles of controlling information to optimize manufacturing resources and parameters in overall production processes. Table 1 shows sub-modules and related functions of a typical MES following MESA's definition.

Lee and Hong[7] apply the extend SLM concept[6] to MES's application areas and quality controls. One of main limitations in a current MES is that the system elaborates on detecting current faults and on managing related manufacturing environments. It implies that the current MES focuses on current manufacturing activities and might neglect to prevent potential risks. In order to take controls in advance, the essential activity is to predict potential faults and/or risks with current manufacturing data. As most of the data are stored in MES, SLM analyzes the historical and current manufacturing data. Then, it predicts potential manufacturing risks as well as detects current faults using FDC functionalities. As the data from R&D process (e.g. simulation data and E/M-BOM data) might be needed, a new system is required for integrating MES and PLM system - the extended SLM framework. In particular, Lee and Hong[7] focus on the functionalities which predict the potential risks and take a measure for preventing them. These activities are handled in the early-warning module in SLM framework. Figure 2 shows the early-warning module in SLM framework.

Table 1. MES's sub-modules

Classification	Functions
Scheduling	Operations Scheduling Detailed Scheduling Dispatching Production Units
Tracking & Genealogy	Product Tracking Product Genealogy
Resource Management	Labor Management Resource Allocation & Status Management
Process and Quality Control	Process Management Quality Management Maintenance Management Performance Analysis
Data Control	Data Collection Acquisition Document Control

The key function in the early-warning module is to predict the potential risk using a control logic or prediction formulas. These logics or formulas have two types of variables in general. The first variables are used as independent variables (Input variables, X) which are extracted using a lot of manufacturing data. The latter type of variables are dependent variables (Output variables, Y) describing risks or faults. Several quality-based indicators belong to the second type of variables. Lee and Hong[7] use a multi-layer perceptron model for reasoning the relation between both variables (Equation (1)).

$$Y_k = f_n\left(\cdots f_2\left(\sum_j w_j f_j\left(\sum_i w_i x_i + b_1\right) + b_2\right)\right) \tag{1}$$

where, x_i is a manufacturing control parameter,
Y_k is a predictable variable,
w_i is adjusted weight for control parameter,
b_i is a noise and bias vector,
and, $f_i(.)$ is the ith layer's mapping function

However, it is difficult to find the mapping relation with X and Y with several reasons. The main reason is resulted from the fact that the size of input variables is too huge - big data. It implies that it is difficult to find each weigh vector for overall X in Equation (1) accurately and the computation burden is big considerably.

$$Y_k = f_n\left(\cdots f_2\left(\sum_j w_j f_j\left(\sum_i w_i x_i + \sum_l w_l lv_l + b_1\right)\right.\right.$$
$$\left.\left. + \sum_o w_o lv_o + b_2\right)\right) \tag{2}$$

where, lv_i is a latent variable reflecting manufacturing environments

Even though the algorithm (Equation (2)) using latent variables[7,9] is suggested, the size of X data influences on the learning procedure and the classification performances,

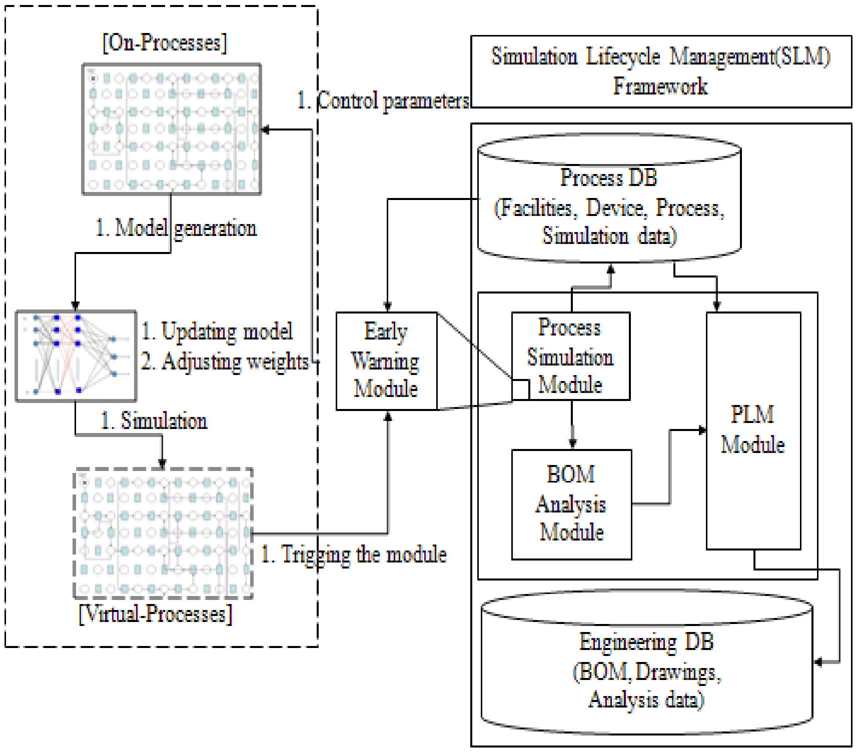


Figure 2. The early-warning module in the extended SLM framework[7].

still. For this reason, this paper suggests a more efficient method using copular theory. The detailed methodology using the characteristics of copular function is suggested in the following chapters.

3. Nonlinear Meta Model in Early-Warning Detection Module

This chapter elaborates on the nonlinear meta model in SLM's early-warning detection module. As explained in the previous chapter, the mapping relationship between X and Y is the crucial part for predicting potential risk in the early-warning detection module. The mapping relation can be a series of logics[10] or mathematical formulas. As general manufacturing processes include many nonlinear control rules, the relationship between both variables has nonlinear characteristics in general. For this reason, the formulated relation is called a nonlinear meta model in this paper. The term, "meta" indicates "after" or "beyond" in Greek language. As the model is to predict potential risk over current control logics, it has the term, "meta".

As the nonlinear meta model handles a large size of data, it is difficult to construct itself using general regression fitting methodologies. For the reason, many learning algorithms such as several types of neural networks[11] are more useful. However, several issues which provided in Chapter 2 make the performances of the nonlinear meta model be low. The following chapter resolves these issues using copular theory.

Figure 3 shows the conceptual image using the nonlinear meta model. As shown in Figure 3, the current control logics in MES focus on detections and classifications of faults or risks. Even though these activities are essential tasks for keeping acceptable quality levels, these are the limited in the fact that it helps to prevent near-future risks little.

The existence of the nonlinear meta model in SLM framework resolves this issue. It predicts potential faults using current manufacturing information, as shown in Figure 3. Then, the X are simulated and changed for acquiring desirable Y. After determining the X, the current X are modified and controlled with the findings.

In general, the early-warning detection is executed using three stages. Figure 4 shows the three-stage control mechanism using the nonlinear meta model.

As shown in Figure 4, an initial nonlinear meta model is generated in the first stage. As the generated model is updated with changes of manufacturing environment dynamically, the generated model is called an initial nonlinear model in Stage I. Then, dependent variables are predicted using the generated model in the second stage. The predicted output variables are used for controlling current manufacturing parameters for acquiring better manufacturing performances. The generated nonlinear meta model is updated reflecting dynamically changing input parameters and variables in the final stage. These stages are called as learning stage, prediction stage and reinforcement stage, respectively. The learning mechanism in the reinforcement stage might be the same algorithm in the learning stage. However, the usage of several reinforcement algorithms[12] is more effective for decreasing computation burdens and preventing over-fitting. Table 2 describes several activities in each stage.

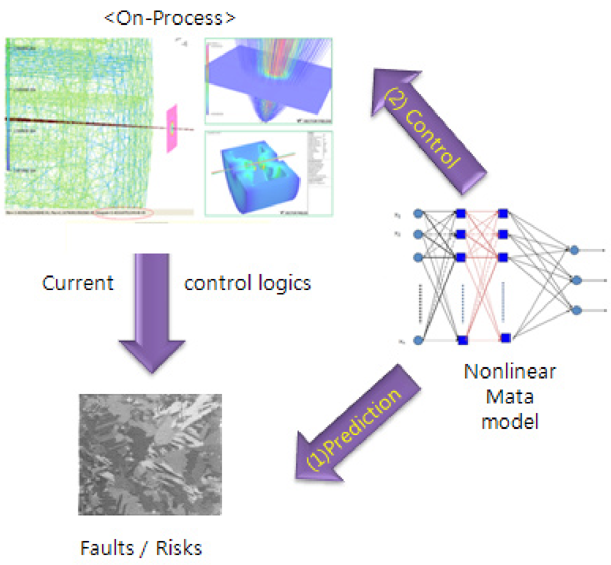


Figure 3. The control of manufacturing processes using the nonlinear meta model.

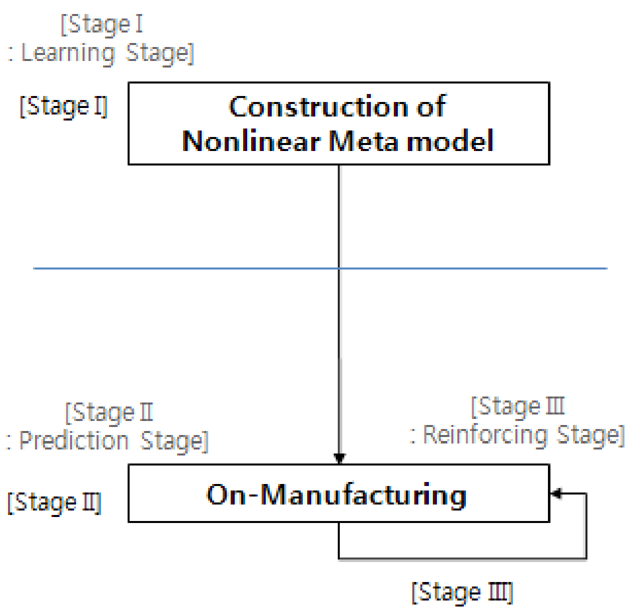


Figure 4. The three-stage control mechanism using the nonlinear meta model.

As suggested in this chapter, the nonlinear meta model is the essential module for determining overall performances of the early-warning detection module in SLM framework. However, it is difficult to select the suitable model covering overall manufacturing processes. The following chapter suggests a new and efficient methodology for modeling the nonlinear meta model using copula theory.

4. Copula Function as a Nonlinear Meta Mode

As described in Chapter 3, the nonlinear meta model is used for predicting potential manufacturing risks with dynamic changes of X. For this reason, the fixed regression formula is unsuitable for the model. In addition, the learning model with extracted variables using pro-processing might fail to capture relationships. In particular,

Table 2. The in 2011 K-NES

Stage	Following-up measures
Learning Stage	- Model type determination - Weight adjustment - Nonlinear mapping
Prediction Stage	- X measurement - Prediction of output variables - Control of manufacturing parameters
Reinforcing Stage	- Intentional Sampling - Applying reinforcement-based learning algorithm - Model updating

this issue occurs from the situation in which the relationship has a fluctuating form (Figure 5).

As shown in Figure 5, the exemplary relationship between X and Y has high valued derivations in several regions. It means that the relationship might be sensitive. Even though Equation (1) and (2) are useful for capturing relationships using repeated learning processes, these are limited in this particular situation. In addition, one of the contemporary trends in manufacturing control logics is to use big data with less preprocessing for preventing losses of information.

In order to represent the relationship with fewer distortions and minimized preprocessing, this paper applies the copular function. Copula function is introduced by Sklar[13] in 1973. The copular theory is considered as an effective modeling tool describing relationship among multi-variables using cumulative joint distributions. Copular function ($c(y_1, y_2, \cdots, y_d)$ in Equation (3)) is defined using Equations (4) – (5).

$$c(y_1, y_2, \cdots, y_d) = F(F(y_1)^{-1}, F(y_2)^{-1}, \cdots, F(y_d)^{-1}) \quad (3)$$

$$F(x) \geq y \quad (4)$$

where $F(x)$ is X's cumulative density function

$$f(F(y)^{-1} \leq x) = F(F(y)^{-1}) \quad (5)$$

where $f(x)$ is X's probability density function

The copula function is classified into both types of functions: parametric copula function and nonparametric function. Product typed, Student's t typed, Gaussian typed, Frank typed, Farlie-Gumbel-Morgenstern type

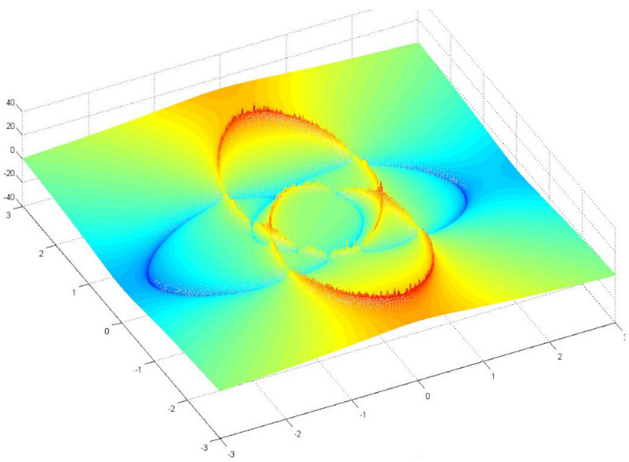


Figure 5. The nonlinear meta model with heavily fluctuating form.

and Ali-Mikhail-Haq typed copula functions belong to the former types of copular functions. The detailed definitions, related parameters and their applications[14,15] have been studied. The finance modeling is the main application area using copula theories. Kim and Lee[16] capture the relationship among multi-variables for forecasting fluctuated demands in a supply chain environment.

However, the usage of copula theories in SLM has been studied less. While Response Surface Methods (RSM) and Radial Basis Function (RBF) are considered as representing nonlinear meta models in SLM, these are unsuitable for capturing highly fluctuated relationships. The following chapter proves the effectiveness of the early-warning detection module with a copular function-embedded nonlinear meta model.

5. Numerical Example using Copula Function Embedded Early-Warning Detection Module in SLM

This chapter provides a numerical study using copular function based early-warning detection module for proving its effectiveness. Even though copular theories have many advantages in capturing correlations among multi-variables, the single independent variable (X) and a quality indicator (Y) are assumed for helping clear understandings.

Figure 6 shows the data plot of the measured manufacturing data indicating X and Y. These data are generated randomly from a nonlinear function with a highly fluctuated function. It is obvious that the function is unknown in SLM system. As Y is assumed as a quality indicator, the relationship between both variables is important for the prediction of a potential indicators in near-future.

Then, Figure 7(a) shows the scatter plot between X and Y in original space. While it shows the mapping with current data, the correlation and other predictable information are reasoned less. When copula approaches are applied for modeling the relationship, copula parameters are estimated and the relationship is formulated into a fitted copula function.

Figure 7 (b) shows a scatter plot between X and Y in the copula space. Student's t-copula is used as a copula model which is suitable for fitting heavy-tail typed data. Equation (6) represents a formula of the used Student's t-copula function.

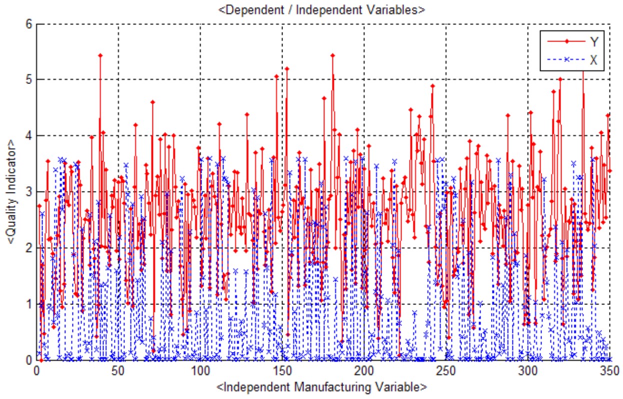
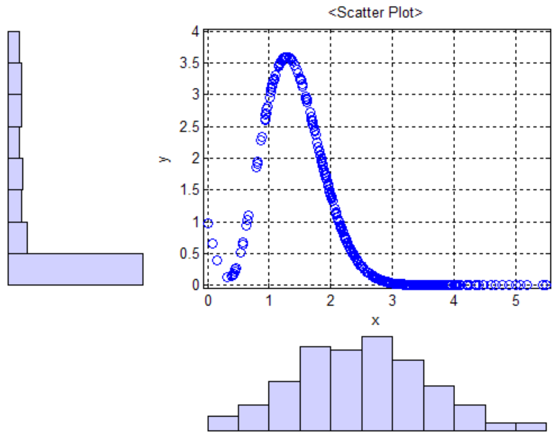
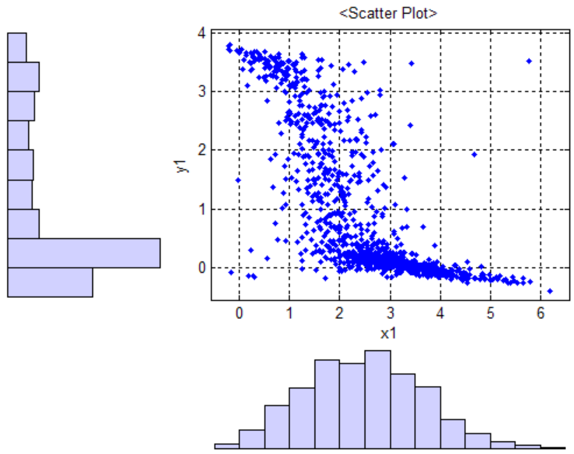


Figure 6. The manufacturing data indicating X and Y.



(a) Scatter Plot between Both Variables in the original space.



(b) Scatter Plot between Both Variables in the Copula space.

Figure 7. Scatter plot between both variables in the original space and in the copula space.

$$c(y_1, y_2; \theta_1, \theta_2) = \int_{-\infty}^{t_{\theta_1}^{-1}(y_1)} \int_{-\infty}^{t_{\theta_1}^{-1}(y_1)} \frac{1}{2\pi\sqrt{1-\theta_2^2}} \left(1 + \frac{s^2 - \theta_2 st + t^2}{\theta_1(1-\theta_2^2)}\right)^{-(\theta_1+2)/2} dsdt \qquad (6)$$

where θ_1 is the degree of freedom
and θ_2 is the estimated correlation coefficient

Both parameters are estimated using Weib's method[17]. Then, the copula probability density function (Figure 8) is generated. As shown in Figure 8, the scale in original space is normalized and the relationship is captured using the estimated Student's t-copula probability density function.

6. Conclusions and Further Studies

The simulation lifecycle management system is considered as one of contemporary manufacturing technologies for overcoming current production issues. While other manufacturing information systems focus on control activities against current production issues, SLM system has abilities to predict potential risks and to prevent them using the embedded early-warning detection module.

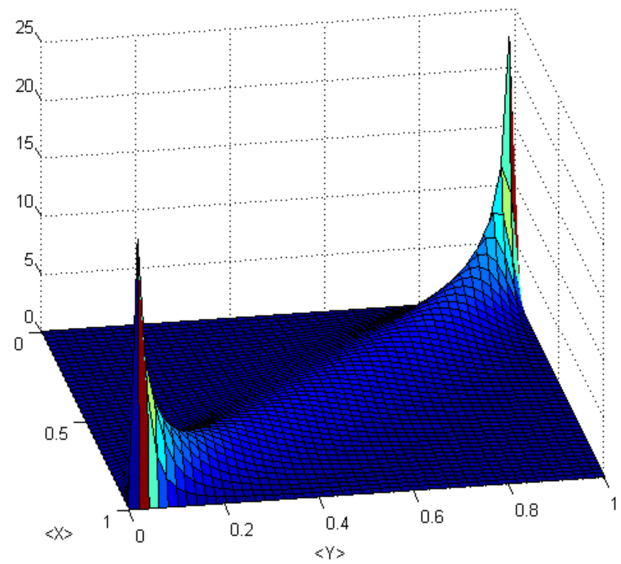


Figure 8. The student's t-copula probability density function describing the relationship between both variables.

The key algorithm of the early-warning detection module is supported by the nonlinear meta model.

This paper suggests a new and effective nonlinear meta model using copula theory. The copula function based nonlinear meta model has advantages in capturing highly fluctuating data relationships or in extracting correlations from atypical data such as heavy-tailed data. The nonlinear meta model with the highly reliable correlations is used for predicting potential faults and for indicating problematic independent variables or manufacturing parameters. Then, these are modified as advanced control strategies.

As further studies, it is considered that manufacturing big data are reasoned using the suggested method and the nonlinear meta model is generated using them. In addition, it is expected that the coverage of the early-warning detection model is expanded from manufacturing stage to overall NPD stages including R&D processes.

7. Acknowledgement

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