Modeling and Simulation of Nonlinear Phenomena for Internet-Aided Manufacturing

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Abstract. Internet-Aided Manufacturing will soon face an era of Web 3.0/4.0 where the knowledge will be represented and shared using semantic web (or web of concept maps). To realize this, this article describes a methodology that helps model and simulate highly nonlinear manufacturing phenomena from the viewpoint of semantic web. The effectiveness of the methodology is demonstrated by performing a case study where the cutting force signals (a highly nonlinear phenomenon) of a material removal process is modeled and simulated. The extracted knowledge (the models and the respective simulation systems) is also presented using semantic web. The outcomes of this study provide some insights into knowledge representation for developing the artificially intelligent manufacturing systems for the next generation.

Keywords: Knowledge Management, Manufacturing, Semantic Web, Nonlinear Phenomena, Simulation

1. INTRODUCTION

Internet means a massive network among computing devices where the devices may be situated at different geographical locations. World-Wide Web (or, simply, web) makes the internet useful (Berners-Lee et al., 1994). This means that the web stores various types of contents (textural/graphical content, sound, motion picture, and program) in a way so that the contents can be exchanged through the internet. Web is now moving toward a new era called web 3.0/4.0 followed by its predecessors web 1.0/2.0 where the semantic web is the key concept (Berners-Lee et al., 2001; Fuchs et al., 2010). Semantic web puts the right emphasis on the meaning of the contents exchanged through the internet, and will play a key role in achieving the web-embedded intelligent devices in the years to come. The web-embedded intelligent devices is supposed to assist both humans and machines when they perform such intellectual tasks as think, plan, decide, judge, forecast, learn, analyze, memorize, estimate, and even create.

However, the advent of internet and web technologies has been playing a vital role in shaping the realities of numerous sectors including manufacturing. Manufacturing has also been evolving in a rapid speed where the usages of internet and web technologies have been contributing a lot (Ullah et al. 2013; Monostori, 2014). As a result, a new concept of manufacturing systems engineering called Industry 4.0 has emerged (Weyer et al., 2015). One of the main goals of Industry 4.0 is to bring all manufacturing enablers under the umbrella of the internet and web so that the enablers can exchange the necessary contents among each other. Here, the phrase "manufacturing enablers" means the physical infrastructures (e.g., machine tools), systems (e.g., process/production planning systems), and humans (operators, planner, and managers) that are needed to perform the manufacturing activities. Since the advent of internet and web is shaping the nature of Industry 4.0 (or internet-aided manufacturing), as mentioned above, it (Industry 4.0) will soon face a stage where the semantic web-embedded systems will become its valuable constituents.

Now, when a manufacturing enabler performs an intellectual task (e.g., plan, decide, forecast, learn, analyze, memorize, or estimate), the enabler needs a great deal of knowledge. In order to learn the required knowledge, the enabler must understand the underlying manufacturing phenomena. Since a manufacturing phenomenon is highly nonlinear and stochastic in nature, understanding it by employing a purely analytical approach is somewhat difficult. Alternatively, a manufacturing phenomenon can be understood from a set of experimental results. One can even model a manufacturing phenomenon based on the understanding gained from a set of experimental results. In addition, one can develop a simulation system that faithfully simulates the modeled phenomenon. Since the next generation manufacturing systems (Industry 4.0) will require semantic-web-based systems, as mentioned above, the modeling and simulation of manufacturing phenomena must be semantic-web-friendly. Accordingly, this study addresses certain issues of modeling and simulation of nonlinear and stochastic (manufacturing) phenomena for the sake of next generation internet-aided manufacturing. In particular, this study considers a manufacturing system development scenario, as schematically illustrated in Fig. 1. As seen from Fig. 1, first, one studies a manufacturing phenomenon by conducting experiments. Afterwards, s/he models the phenomenon understanding the results they way s/he prefers. In the subsequent step, s/he develops simulation systems to implement the model. While doing so (modeling and simulation), one must not forget the aspects of semantic web. This means that not only the syntax of the models but also its meaning must be systemized using the semantic web technology. In other words, a semantic-web-embedded high-level description of the model (and simulation system) is needed. Finally, the (modeling and simulation) outcomes must be integrated into a manufacturing system intended for the Industry 4.0. The aim is to achieve personal intelligent devices that operation using the knowledge stored in the semantic-web-embedded models and simulation systems. Here, the phrase "operate" means performing such intellectual tasks as think, plan, decide, judge, forecast, learn, analyze, memorize, estimate, and even create.

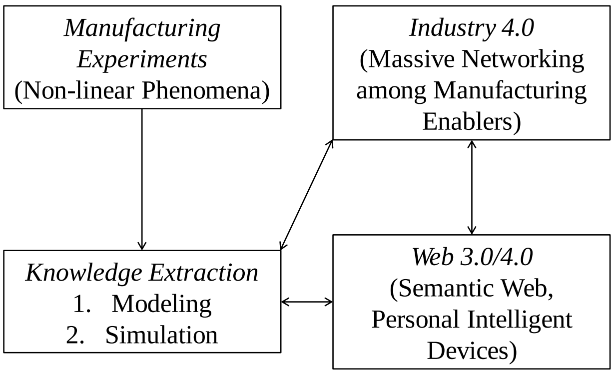


Figure 1: The main facets of this study.

For the sake of better understanding, the remainder of this article is organized as follows. Section 2 describes some of the manufacturing systems development issues centering semantic web. Section 3 describes a modeling and simulation techniques. Section 4 describes results obtained by implementing the modeling and simulation techniques described in Section 3. Section 5 provides the concluding remarks of this study.

2. SYSTEMS DEVELOPMENT

This section describes some of the general manufacturing systems development issues centering the concept of semantic web. Before introducing the core idea, the current manufacturing systems development scenario is described.

2.1 Current Practice

Currently, internet/intranet integrates some standalone manufacturing systems, namely, CAD, CAM, CNC, robotic, CAPP, ERP, and SCM systems, to perform numerous manufacturing activities. A family of standards denoted as ISO 103030 (popularly known as STEP [Standard for the Exchange of Product model data]) dictates the integration process (Matsuda et al., 2008), as schematically illustrated in Fig. 2. Different types of models (e.g., models of machine tools, cutting tools, products, manufacturing processes, collection detection, and maintenance procedures) are created using the standard ontology prescribed by STEP (Matuda et al., 2008). These models become the contents that are exchanged from one system to another. Therefore, a rigid data structure accompanies the systems that are being used (Fig. 2).

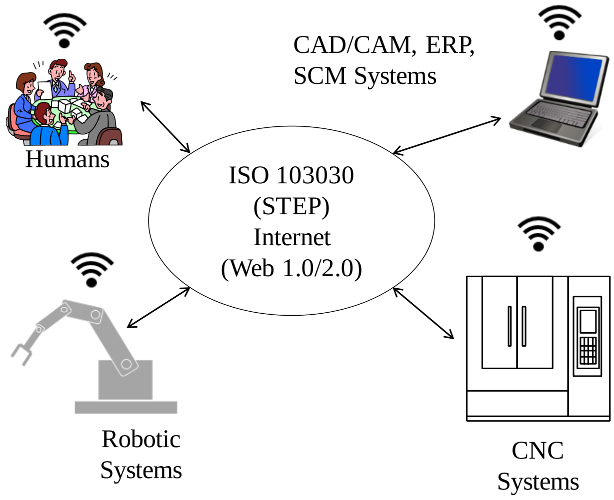


Figure 2: Current practice.

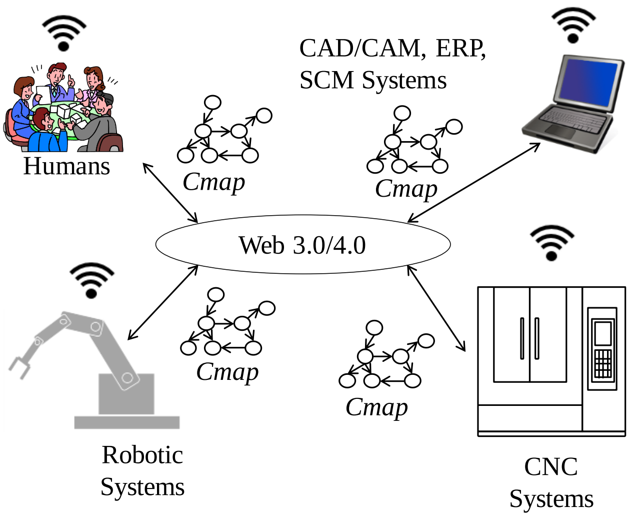
2.2 Futuristic Practice

One the other hand, in the case of semantic-web-based integration, one can imagine a flexible and customized structure of the contents (models). A network of concepts called Concept map (Cmap) (Ullah et al., 2013; Sharif Ullah, 2016), as schematically illustrated in Fig. 3 becomes the models or contents to be exchanged.

Here, a concept means a perceived regularity or pattern in events, objects, or records of events or objects designated by a label (Ullah et al., 2013; Sharif Ullah, 2016). The Cmaps are the units of contents that contain necessary data, information, and knowledge. Sharif Ullah (2016) has described how to build Cmap from the context of manufacturing knowledge representation. Figure 4 shows one of the examples of Cmap taken from Sharif Ullah (2016). As seen from Fig. 4, one needs to introduce a set of concepts centering a focus question. Afterwards, the concepts introduced are integrated by a network, as if the concepts are the parts of few sentences. For example, consider the concepts shown in Fig. 4, namely, turning, surface roughness, environmental burden, tool life, machining time, evaluation, and performance. The focus question is the performance evaluation of turning. Therefore, the following sentence can be constructed:

Performance of turning can be evaluated by machining time, environmental burden, tool life, and surface roughness.

This sentence manifests the Cmap as shown in Fig. 4.



Cmap = Concept map

Figure 3: Futuristic manufacturing systems.

Now, a Cmap can be integrated with other Cmaps. For example, all concepts in Fig. 4 need to be explained further so that they make sense to an individual how is not familiar with the focus question. In this case, Cmaps A,...,E, can be integrated with the concepts called turning, surface roughness, environmental burden, tool life, and machining time, as shown in Fig. 5. All these Cmaps are ultimately linked to some general Cmaps called material universe, shape universe, process universe, precision universe, control universe, and sustainability universe. These universes are explained in Sharif Ullah (2016). However, the process universe consists of some Cmaps that represents the knowledge of different manufacturing processes based on addition (e.g., powder deposition and laser curing), subtraction (e.g., machining and grinding), formation (e.g., casting, drawing, forging, forming, and other bulk deformation), joining (e.g., welding and soldering), and surface treatment (e.g., chemical/physical vapor deposition, plating, and deburring). The Cmaps in process universe also include the phenomena that underlie the manufacturing processes.

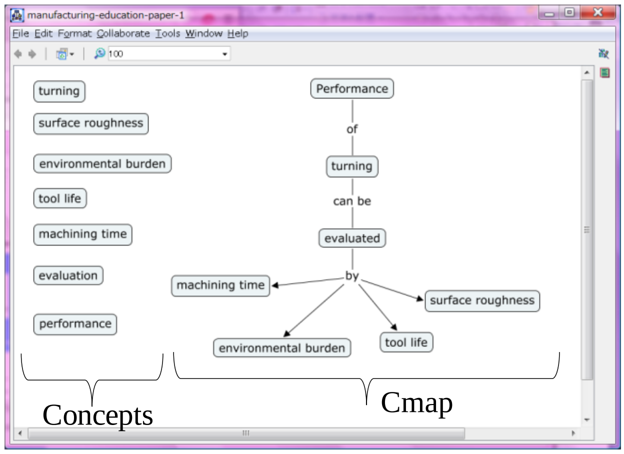


Figure 4: Example of building a Cmap.

Nevertheless, when one models a highly nonlinear and stochastic phenomenon associated with a subtractive manufacturing process (turning, milling, drilling, or grinding), the model consists of some stochastic features. In particular, when the cases of cutting force and surface finish are considered, the model consists of some cycles. In each cycle, there are some segments. Each segment consists of some other stochastic features called trends, irregularities (or noise), and bursts. See Ullah and Harib (2010) and Ullah et al. (2010) for the detail. Therefore, one can model the nonlinear phenomena associated with the subtractive manufacturing processes using the stochastic features called trend, irregularities, burst, and alike. The features must form some segments that repeat in a periodic manner. At the same time, simulation systems can be developed to implement the models. The models and the underlying simulation systems can be integrated within the framework of a semantic web, as shown in Fig. 6 (Ullah et al., 2013). The contents can be exchanged among the manufacturing enables as schematically illustrated in Fig. 3. Now the question is how to build such models and simulation systems? The next section describes the modeling and simulation of a nonlinear phenomenon using an example. Based on the ideas outlined in the example (Section 3), one can use them to construct the models and simulation systems for other cases (see Section 4).

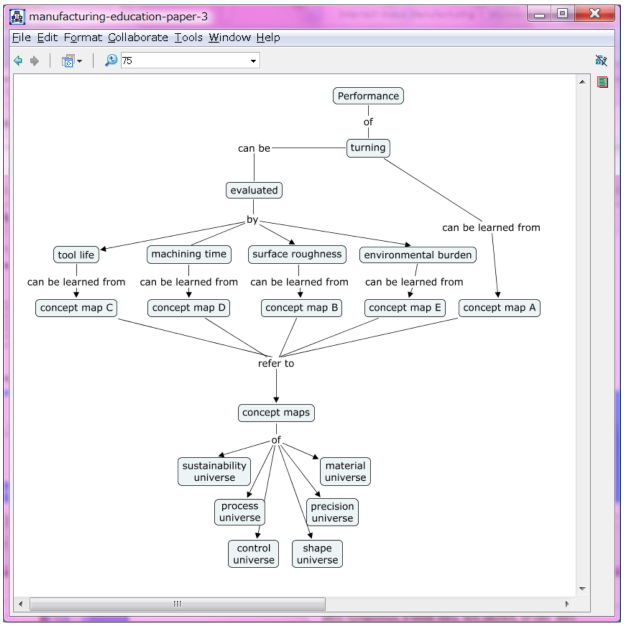


Figure 5: Integrating manufacturing Cmaps.

3. MODELING AND SIMUALTION

The previous section provides an abstract outline of how to model the nonlinear and stochastic phenomena (e.g., cutting force and surface finish) associated with the subtractive manufacturing processes from the context of semantic web. This section uses an example and describes the key ideas of modeling and simulation of a nonlinear phenomenon of manufacturing, particularly the subtractive manufacturing (e.g., turning, milling, and grinding).

Consider the time series plot $((i,z(i)),\ i = 0,1,\ldots)$ of the surface heights of a ground surface as reported in Ullah et al. (2010). The time series plot is shown in Fig. 7.

As seen in Fig. 7, the surface finish data consists of some cycles. In addition, each cycle consists of a segment. Moreover, each segment consists of three stochastic features, namely, trend, irregularities, and burst. It is possible to model these features using some mathematical functions. Needless to say, the functions must incorporate certain stochastic processes.

First, consider the modeling and simulation of a trend. As seen in Fig. 7, a trend here is simply a straight-line having a negative slope. The magnitude of the slope slightly varies from cycle to cycle. The heights of the first and last points of a trend vary from cycle to cycle. Therefore, the following formulation for creating a time series $x(i)$, $i = 1,2,\ldots,n$, can be used to model a trend. In equation (1), $N(\mu,\sigma)$ denotes a normally distributed variable with mean μ and standard deviation σ. The subscripts f and l denote the first and last points, respectively. To ensure a negative slope, $x(1) > x(n)$ must be maintained. Therefore, the time series $x(i)$, $i = 1,\ldots,n$, models the trend. A Monte Carlo simulation system is developed to implement the model. The simulation result is shown by the first time series plot (from the top) in Fig. 8.

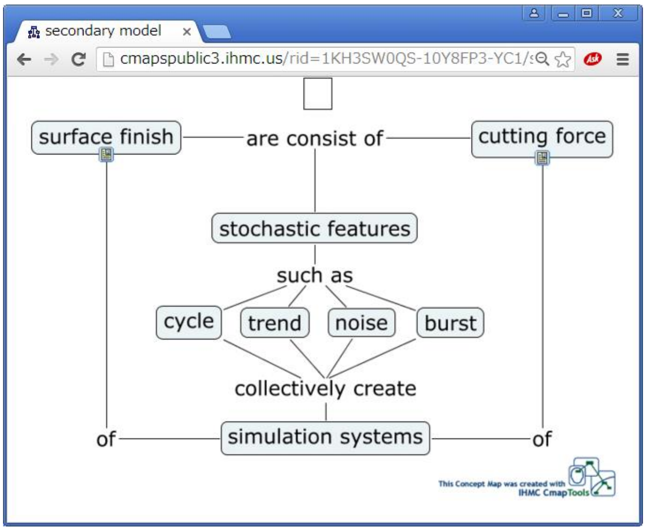


Figure 6: Semantic web for non-linear phenomena.

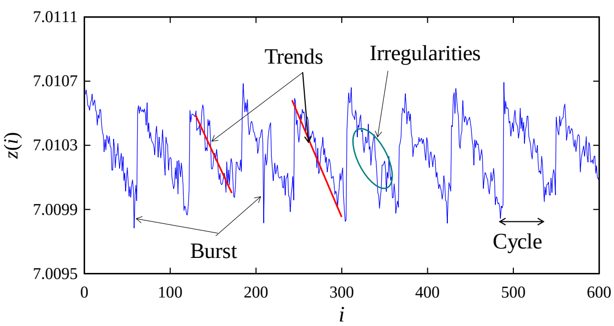


Figure 7: A time series plot of surface finish heights.

$$\begin{aligned} & x(1)=x_f \leftarrow N(\mu_f,\sigma_f) \quad x(n)=x_l \leftarrow N(\mu_l,\sigma_l) \\ & for \quad i=2\ldots n-1 \\ & \quad do \quad x(i)=x(i-1)+\frac{x_f-x_l}{n-1} \end{aligned} \tag{1}$$

Consider the modeling and simulation of irregularities. The time series plot shown in Fig. 7 exhibits that a cyclic noise accompanies the trends where both the amplitude and periodicity of the noise are highly stochastic. Therefore, a cyclic function (e.g., a trigonometric function) with a stochastic period and frequency can be used to model the irregularities. This yields a model of irregularities as defined by equation (2).

$$\begin{aligned} &a = [a_L, a_H] \quad b = [b_L, b_H] \quad A = [A_L, A_H] \quad B = [B_L, B_H] \\ &for \quad i = 1 \ldots n \quad do \quad y(i) = a \sin\left(\frac{2\pi}{A} i\right) \pm b \cos\left(\frac{2\pi}{B} i\right) \end{aligned} \tag{2}$$

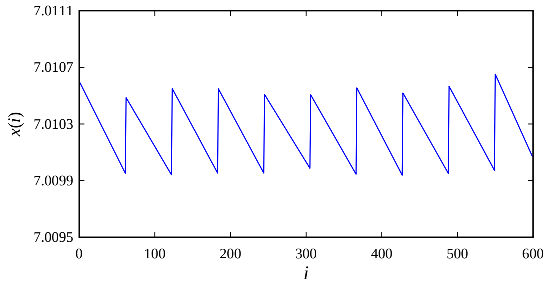
According to equation (2), two trigonometric functions (sine and cosine functions) having stochastic amplitudes (a = [a_L,a_H] and b = [b_L,b_H]) and frequencies (A = [A_L,A_H] and B = [B_L,B_H])) are used to model the irregularities. Here, the subscripts L and H means "low" and "high", respectively. Therefore, the time series $y(i)$, i = 1,2,..., models the irregularities for each cycle, wherein ± (i.e., + or −) are determined at random. A Monte Carlo simulation system is developed to implement the model defined by equation (2). The simulation result is shown by the second time series plot (from the top) in Fig. 8.

Consider the modeling and simulation of a burst. As seen from Fig. 7, a burst is a localized irregularity causing a large deviation in the trend. Therefore, one can insert a signal that causes a large deviation at a particular location in the trend. The location and magnitude of the deviation can be selected stochastically. This means that it is important to set the tentative location of burst P_B = [n_1,n_2], n_1, n_2 ∈ [1,n], stochastic magnitude M_B = [x_L,x_H], and likelihood L_B ∈ [0,1] for modeling a bust. At the same time, the model must choose the exact location of the bust stochastically from P_B. This yields a model denoted as $xx(i)$ that modifies $x(i)$, ($i \in P_B$) by M_B for the chosen location. Thus, modifying a trend $x(i)$ by inserting a point burst refers to the following formulation. In equation (3), r_i is a random number in the interval 0 to 1. A Monte Carlo simulation system is developed to implement the model defined by equation (3). The simulation result is shown by the third time series plot (from the top) in Fig. 8.

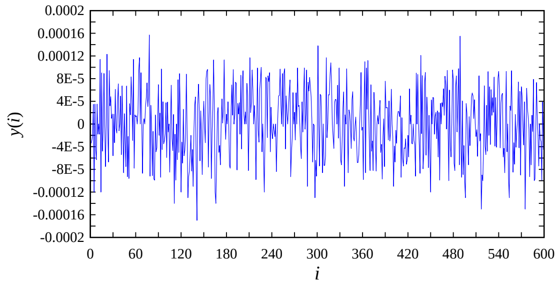
The output of the formulation defined by (4), i.e., $z(i)$, i = 1,...,n, is the time series that models the time series shown in Fig. 7. A Monte Carlo simulation system is developed to implement the formulation defined by (4). The simulation result is shown by the fourth time series plot (from the top) in Fig. 8. The concept called "simulation system" as shown in Fig. 6 contains a system that implements the mathematical procedures defined by equations (1)–(3).

$$\begin{aligned} &P_B \leftarrow [n_1, n_2], L_B \leftarrow [0,1], M_B \leftarrow [x_L, x_H] \\ &for \quad i = 1 \ldots n \quad if\,(i = P_B) \wedge (r_i < L_B) \quad do \quad xx(i) = M_B \\ &\qquad\qquad otherwise \quad xx(i) = x(i) \end{aligned} \tag{3}$$

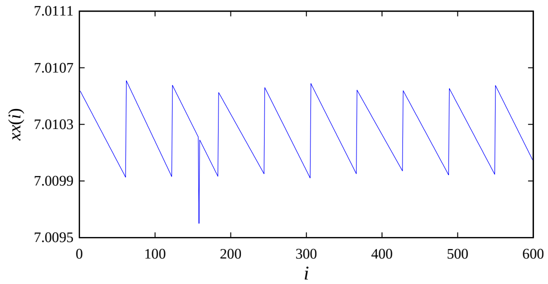
The models defined by equations (1)–(3) can be added to create another model, as follows.



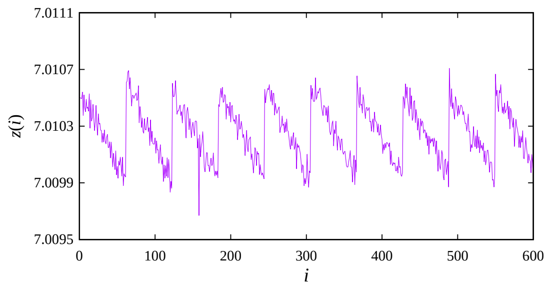
(Trends)



(Irregularities)



(Trend + Burst)



(Simulated Time Series)

Figure 8: Modeling and simulation of surface finish heights.

$$for \quad i = 1 \ldots n \quad do \quad z(i) = xx(i) + y(i) \tag{4}$$

4. RESULTS

The previous two sections outline the key concepts associated with the semantic-web-based modeling and simulation of highly nonlinear (manufacturing) phenomena. In this section, we apply those key concepts to developing a semantic-web-based system for modeling and simulation of cutting force while turning a bimetallic workpiece.

Bimetallic components are significant from the point of view of sustainability (Sharif Ullah et al., 2014). To gain the knowledge of how to manufacture a bimetallic component experiments have been conducted. The experimental results provide an insight into the machining phenomena (e.g., nature of surface finish and cutting forces for different cutting conditions) (Sharif Ullah et al., 2015; Matusi et al., 2015; Wu et al., 2015). In particular, consider the cutting force signal shown in Fig. 9 when the cutting tool passes the mild steel segment of a bimetallic specimen made of mild steel (S15C) and stainless steel (SUS304). See Matsui et al. (2015) for the description of the experiments. As seen in Fig. 9, the cutting force signal is highly nonlinear and stochastic in nature. To model this signal, one can use the concept of trend, irregularities, and burst as defined by the equations (1)–(4). This does not mean that one cannot model it by other means. Nevertheless, in our study, we have found that a least four features are needed to model the cutting force signal shown in Fig. 9, as follows: shift, trend, noise, and burst. All these features are similar to the respective ones described in the previous sections, except shift. Shift is introduced here for this particular case. Figure 10 shows the semantic web constructed to represent the model of cutting force signal shown in Fig. 9.

If one adds the simulation systems denoted as S, T, I, and B (Fig. 10) for the features called shift, trend, noise, and burst, respectively, the semantic web becomes a complete one. Otherwise, it may not be useful for other systems of Industry 4.0. It is worth mentioning that the concepts shown in the Cmap (Fig. 10) need explanation. This can be done by using the methodology described in Fig. 5, i.e., by integrating Cmaps of sustainability, process, and other universes.

However, what are the mathematical functions of S, T, I, and B? This question is answered as follows.

First, consider the case of S. It is a means to shift the signal to specific location, i.e., it is a constant value (say, $C \in \Re$). This yields the following expression.

$$for \quad i = 1 \ldots n \quad S(i) = C \qquad (5)$$

Consider the case of T. For this particular case, it is a cyclic trend or a periodic function. The amplitude of the function must vary stochastically. Since the cutting force is a non-stationary Gaussian process (Ullah and Harib, 2010), the amplitude can be varied by a normally distributed variable. As a result, equation (6) holds. In equation (6), the amplitude $a(i)$, $i = 1,...,n$, of the sine function takes values at random from a normally distributed variable $N(\mu_a,\sigma_a)$. The period $b(i)$ of the function is a nonzero integer assigned randomly from the set $\{b_w \mid w = 1,2,...,\}$, $\forall b_w \in \aleph - \{0\}$.

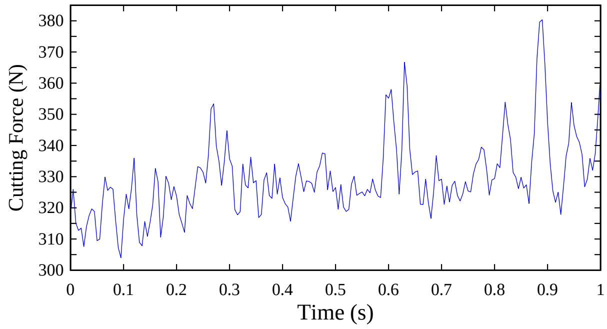


Figure 9: A segment of cutting force signal.

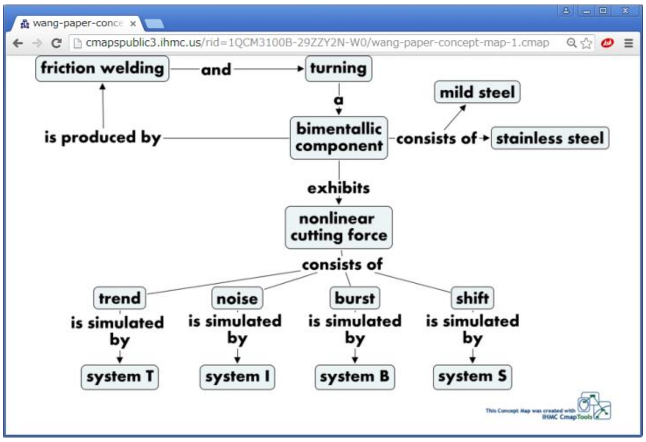


Figure 10: Semantic web of cutting force.

$$for \quad i = 1,\ldots,n \quad a(i) \leftarrow N(\mu_a, \sigma_a) \quad b(i) \leftarrow \{b_w \mid w = 1,2,...\}$$
$$T(i) = a(i)\sin\left(\frac{2\pi}{b(i)} i\right) \qquad (6)$$

Consider the case of I. It can also be considered a Gaussian process, since the cutting force is a non-stationary Gaussian process. Therefore, the following formulation holds.

$$for \quad i = 1 \ldots n \quad I(i) \leftarrow N(\mu_I, \sigma_I) \qquad (7)$$

Consider the case of B. The equation (3) defines a point burst. One can consider other formulations of burst creation. For example, one can consider cyclic burst acting on a segment of a signal. In addition, one can consider multiple cyclic bursts each having its own magnitude. However, a cyclic burst can be represented by a function where the magnitude of burst gradually increases, i.e., $B(j) < B(j+1)$ for $j = i + k$, $k = 0,...,P-1$, and gradually decreases, i.e., $B(m) > B(m+1)$, $m = i + P + l$ for all $l = 0,...,Q-1$. To ensure $B(j) < B(j+1)$ for $j = i + k$, $k = 0,...,P-1$, one can use any function as preferred. For cutting force, the default choice is a normally distributed variable. Thus, $B(j)$ is a normally distributed variable $N(\mu_j,\sigma_j)$ so that $\mu_j < \mu_{j+1}$ for all $j = i + k$, $k = 0,...,P-1$. Similarly, $B(m)$ is a normally distributed variable $N(\mu_m,\sigma_m)$ so that $\mu_m > \mu_{m+1}$ for all $m = i + P + l$, $l = 0,...,Q-1$. The point (i) from where the $B(j)$ starts can be controlled by a stochastic process as defined by equation (3). As such, the following expression holds.

$$
\begin{array}{l}
P_B \leftarrow [n_1, n_2],\ L_B \leftarrow [0,1],\quad P,Q \in \aleph \\
for \quad i = 1 \ldots n \quad r_i \leftarrow [0,1] \\
\quad if\,(i = P_B) \wedge (r_i < L_B) \quad for \quad k = 0 \ldots P-1 \\
\qquad\qquad j = i + k \\
\qquad\qquad B(i) = B(j) \leftarrow N(\mu_j, \sigma_j) \quad \mu_j < \mu_{j+1} \\
\quad\quad for \quad l = 0 \ldots Q-1 \quad m = i + P + l \\
\qquad\qquad B(i) = B(m) \leftarrow N(\mu_m, \sigma_m) \quad \mu_m > \mu_{m+1} \\
\quad otherwise \quad B(i) = 0
\end{array}
\tag{8}
$$

Needless to say, in equation (8), $n_1, n_2 \in \{1,...,n\}$.

The simulation system of cutting force F is as follows.

$$for \quad i = 1 \ldots n \quad F(i) = S(i) + T(i) + I(i) + B(i) \tag{9}$$

Figure 11 shows an instance of the $S(i) + T(i) + I(i)$ component of $F(i)$ where $C = 325$, $\mu_a = 8$, $\sigma_a = 2$, and $b(i) \in \{14, 15\}$, $\mu_I = 0$, $\sigma_I = 3$. These values are suitable for simulating the signals similar to the cutting force (Fig. 9). On the other hand, two types of burst have been considered for this particular case. The values of the burst segment are the same: $P = 5$, $Q = 3$. For the first burst, the magnitude functions are as follows:

$N(\mu_j,\sigma_j) = N(9,2)$, $j = i + k(=1)$, $N(\mu_j,\sigma_j) = N(13,2)$, $j = i + k(=2)$, $N(\mu_j,\sigma_j) = N(22,2)$, $j = i + k(=3)$, $N(\mu_j,\sigma_j) = N(31,2)$, $j = i + k(=4)$, $N(\mu_m,\sigma_m) = N(22,2)$, $m = i + P + l(=0)$, $N(\mu_m,\sigma_m) = N(13,2)$, $m = i + P + l(=1)$, $N(\mu_m,\sigma_m) = N(9,2)$, $m = i + P + l(=2)$. Whereas, for the other type of burst, the magnitude is as follows:

$N(\mu_j,\sigma_j) = N(14,2)$, $j = i + k(=1)$, $N(\mu_j,\sigma_j) = N(21,2)$, $j = i + k(=2)$, $N(\mu_j,\sigma_j) = N(42,2)$, $j = i + k(=3)$, $N(\mu_j,\sigma_j) = N(56,2)$, $j = i + k(=4)$, $N(\mu_m,\sigma_m) = N(42,2)$, $m = i + P + l(=0)$, $N(\mu_m,\sigma_m) = N(21,2)$, $m = i + P + l(=1)$, $N(\mu_m,\sigma_m) = N(14,2)$, ,$m = i + P + l(=2)$.

The likelihood of the first burst is about 0.15 and the likelihood of the other burst is about 0.05. One of the results of burst formation is shown in Fig. 12 where four bursts of type 1 and one burst of type 2 is seen.

Figure 13 shows the simulated cutting force, i.e., summation of the results shown in Figs. 11 and 12. Figure 14 shows the return maps of the real and simulation cutting force signals. It is worth mentioning that the time series plots shown in Figs. 11-13 do not represent the same simulation instance. For this reason, the positions of bursts in Figs. 12-13 are not the same. Similarly, the trends and the degree of noise in Figs. 11 and 13 are not the same.

From the visual inspection, it is understood that both return maps resemble each other but they are not exactly the same. This is desirable because the cutting force will not exactly be the same at every instances of cutting. The simulation system ensures that.

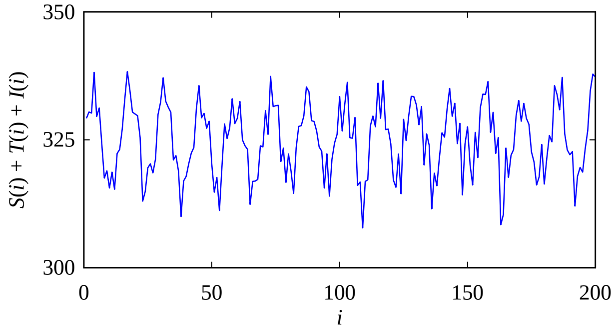


Figure 11: Adding shift, trend, and noise.

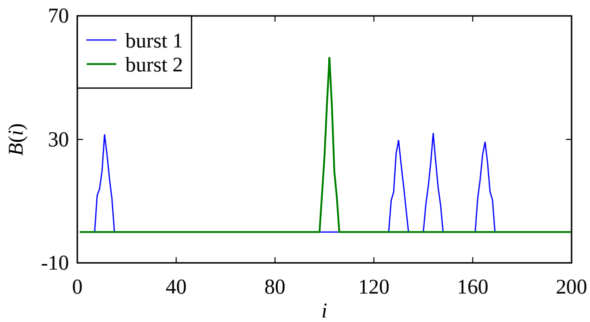


Figure 12: Simulating two types of bursts.

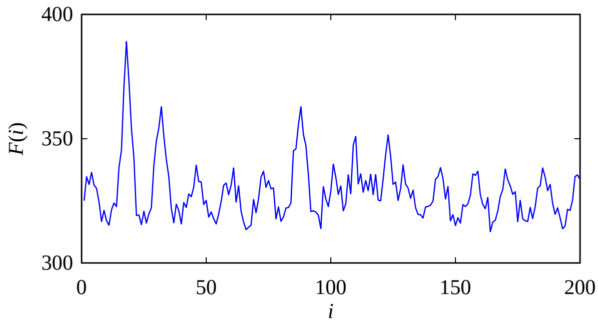
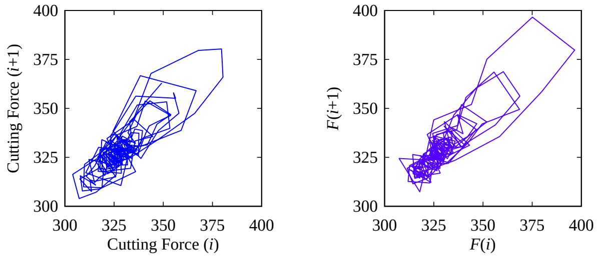


Figure 13: Simulated cutting force signal.



Real cutting force Simulated cutting force

Figure 14: return maps of real and simulation cutting force signals.

5. CONCLUDING REMARKS

The previous section shows how to model and simulate the nonlinear cutting force when cutting a single material. In the next phase, we will develop a system that captures the dynamics in the cutting force for the bimetallic joint area. At the same time, simulation systems will be incorporated with the semantic web shown in Fig. 10.

To see the degree of similarity of real and simulated signals, some formal procedures, i.e., cumulative probability curve (Khozaimy et al., 2011) and possibility distribution (Sharif Ullah and Shamsuzzaman, 2013), will be considered in the next phase of this study.

Since the cutting force will not exactly be the same at every instance of cutting, the simulation result must produce different but similar cutting force signal. This objective has been achieved in this study.

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