Advanced Engineering Informatics 39 (2019) 1–13

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Full length article

Modeling and simulation of complex manufacturing phenomena using sensor signals from the perspective of Industry 4.0

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ARTICLE INFO

Keywords:
Industry 4.0
Semantic web
Cyber-physical systems
Meta-models
Webized phenomenon twin

ABSTRACT

This article presents a methodology defined as semantic modeling to create computable virtual abstractions of complex manufacturing phenomena denoted as phenomena twins from the perspective of the fourth industrial revolution (also known as Smart Manufacturing, Connected Factory, Industry 4.0, and so forth). The twins are created such that they become friendly to both sensor signals and new-generation web technology (i.e., the semantic web). The efficacy of the proposed modeling approach is demonstrated by creating a phenomenon twin of cutting force (a highly complex and stochastic phenomenon associated with all material removal processes) and also by representing it using the semantic web. The relevant epistemological and systemological issues (e.g., those of meta-models, ontology, classification/trustworthiness/provenance of knowledge associated with the webized phenomenon twin) are also discussed. This article will help developers of embedded (e.g., cyber-physical) systems needed for functionalizing Industry 4.0.

1. Introduction

The advent of information and communication technology has been shaping new realities for many fields, including manufacturing. Consequently, a concept of manufacturing called the fourth industrial revolution (popularly known as Industry 4.0, Smart Manufacturing, and Connected Factory) has emerged [1–3]. This article denotes this concept as Industry 4.0. Accordingly, Industry 4.0 requires the best that the advanced information and communication technology can offer. This does not mean achieving mere automation among product realization enablers (e.g., machine tools, robots, assembly lines, CAD/CAM/CAE systems, ERP systems, and SCM systems), as was the case for its predecessor [1]. Instead, it means achieving such high-level intellectual tasks as understanding (i.e., why is it happening), prediction (what will happen), and adaptation (what decisions should be taken and implemented to choose the right course of action) [1–3]. For this reason, Industry 4.0 needs embedded systems, namely, Cyber-Physical Systems (CPS) [3–9], Human Cyber-Physical Systems (HCPS) [3], Internet of Things (IoT) [10–12], and Internet of Content and Knowledge (IoCK) [3]. These systems operate on contents called digital twins [13], which are computable virtual abstractions of objects, processes, and phenomena underlying manufacturing [14–23], while achieving the abovementioned high-level tasks [1]. In particular, object twins capture information pertaining to product geometry and topology, machine tools, cutting tools, and so forth. Process twins capture information regarding scheduling, production line balancing, and so forth. The phenomena twins, which are the focus of this article, capture the information of different manufacturing phenomena, for example, chatter vibration, machining forces and temperature, thermal deformation, and so forth. A considerable amount of research has been conducted on the object and process twins [14–22], which is not the case for the phenomena twins [23], because creating computable virtual abstractions of manufacturing phenomena is a cumbersome task due to the inherent complexity [24,25]. However, as far as the material removal processes (machining, grinding, and so on) are concerned, modeling and simulation systems of the mechanisms of chip formation, cutting force, tool wear, surface finish, and so on constitute the phenomena twins [23]. This article addresses the aspect of phenomena twins from the viewpoints of sensor signals and the semantic web. These viewpoints are described as follows.

First, consider the viewpoint of sensor signals. Nowadays, different kinds of sensors (e.g., position, speed, force, torque, acoustic emission, surface roughness, temperature, and thermal deformation sensors) accompany manufacturing devices (e.g., machine tools, cutting tools, actuators, and programmable logic controllers, and material handling devices). The signals collected from the respective sensors are used to understand the underlying phenomena (why is it happening), predict (what will happen), and, thereby, decide the right course of action [3,6,7]. In addition, when a manufacturing phenomenon is studied in laboratory settings, the signals collected from various sensors are used

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https://doi.org/10.1016/j.aei.2018.11.003
Received 10 July 2018; Received in revised form 26 October 2018; Accepted 18 November 2018
Available online 26 November 2018

to elucidate the underlying aspects [24,25]. Therefore, sensor signals are relevant from the perspectives of both real-life manufacturing operations and laboratory-based manufacturing experimentations.

Consider the other issue, that is, the semantic web. The contents made available on the Internet are accessed and used by web technology [26]. A new web technology called the semantic web (or Web 3.0/4.0) has gradually been replacing its predecessors (Web 1.0/2.0) [27–29]. The primary goal of the semantic web is to pull down walls among information silos (e.g., seamless integration between social networks like Facebook and Twitter) [27]. For achieving this goal, the concept of provenance has been introduced to the semantic web, which consists of the layers called ontology, unified logic, rules, proof, trust, and user interface [29]. Thus, both the contents (textual/graphical/audio contents, motion pictures, and applications) and their provenance populate the semantic web [29–32]. Therefore, when the sensor signals available on the Internet is used to construct a phenomenon twin, or a phenomenon twin already available on the Internet is used to decide the correct course of action, the provenance module of the twin makes the contents transparent, human-machine comprehensible, and trustworthy to its shareholders.

In synopsis, while populating the systems underlying Industry 4.0 using the phenomena twins, the viewpoints of sensor signals and the semantic web, as described above, must be considered simultaneously. This article is based on this notion. Accordingly, the objective of this article is to construct a phenomenon twin so that it becomes friendly to both sensor signals and the semantic web. For achieving this objective, a modeling approach, defined as the semantic modeling, is introduced, as illustrated in Fig. 1. The remainder of this article describes this modeling approach as well as other relevant issues (mathematical formulations, examples, a case study, and semantic webized phenomena twin construction).

The remainder of this article is structured as follows. Section 2 describes the semantic modeling process and shows its interplay with concept mapping (an outcome of human learning activity, which is an essential content of the semantic web). Section 3 provides a general description of how to implement the semantic modeling described in Section 2, to construct a sensor-signal-based phenomenon twin. Section 4 describes a case study where the phenomenon twin of cutting force (a complex phenomenon associated with all material removal processes such as turning, milling, drilling, and so forth) is constructed using the procedure described in Section 3. Section 5 discusses the implications of this study. Section 6 concludes this study.

2. Semantic modeling and concept mapping

This section defines semantic modeling and explains its interplay with concept mapping. Both mathematical formulations and examples are used for the sake of better understanding.

Let P and C be a phenomenon and a set of conditions, respectively. Let $E(P,C)$ be the set of expected states of P for C. Let $M(P,C)$ be a model (i.e., the virtual abstraction) of P for C. Thus, using $M(P,C)$, the expected states can be produced whenever needed, that is, $M(P,C) \to E(P,C)$. In reality, both $M(P,C)$ and $E(P,C)$ may not be known beforehand due to the lack of knowledge or any other reasons. Alternatively, the following modeling scenario can be considered. Let $Ex(P,C)$ be the states of P for C obtained either by conducting experiments or by analyzing the situations with reasonable precision and accuracy. A model defined as $Mx(P,C)$ can be reverse-engineered using $Ex(P,C)$, that is, $Ex(P,C) \vdash Mx(P,C)$. The formulations of $Mx(P,C)$ and $Ex(P,C)$ take the following form for the case of sensor signals. Let $Sl(P,C)$ be the states of P for C observed by using an appropriate sensor during laboratory experimentations. One can reverse-engineer a model of P for C, defined as $Es(P,C)$, using $Sl(P,C)$, that is, $Sl(P,C) \vdash Ms(P,C)$. Let $Sx(P,C)$ be the set of signals produced by executing $Ms(P,C)$, $Ms(P,C) \to Sx(P,C)$. Let $Sr(P,C)$ be the set of signals obtained by monitoring the same phenomenon P for C in a real-life setting. If $Sx(P,C)$ and $Sr(P,C)$ are reasonably close to each other (i.e., $Sx(P,C) \cong Sr(P,C)$), then the model that has been reverse-engineered using $Sl(P,C)$, that is, $Ms(P,C)$, becomes the virtual abstraction of P for C. Therefore, $Ms(P,C)$ can be used to create the phenomenon twin of P for C and applied to systems related to Industry 4.0. From the viewpoint of the semantic web, the meaning–base or human comprehension of the modeling process "$Sl(P,C) \vdash Ms(P,C)$" must be constructed. Creating a meaning–base of an issue entails creating a concept map [33,34]. Representing the outcomes of the modeling process "$Sl(P,C) \vdash Ms(P,C)$" with a concept map (or a set of concept maps) is defined as semantic modeling. The explanation is as follows. Consider the term "concept map." It refers to the learning theory called meaningful learning [32–34]. The salient points are as follows. Humans, by nature, associate some linguistically expressed labels (or concepts) while communicating their understanding of a

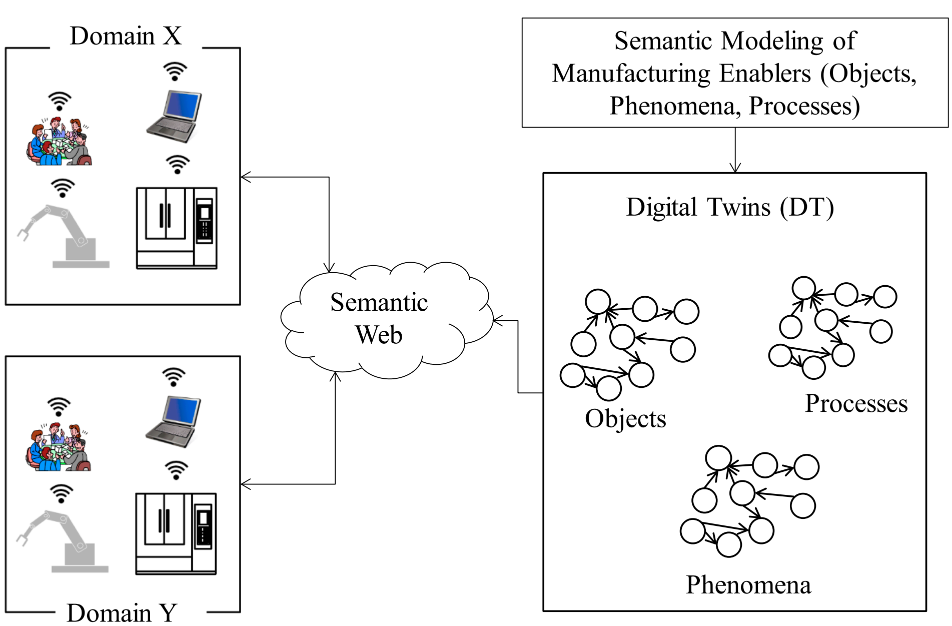


Fig. 1. The context of digital twins.

given issue [33,34]. As a result, a network of concepts, called concept map, forms [33]. A concept map usually corresponds to an issue known as the focus question [33,34]. Thus, it conveys the understanding of an individual regarding a given issue (focus question), that is, it is the meaning–base or the outcome of semantic modeling regarding that issue. It is possible to add relevant contents to the respective concepts that act as the provenance (i.e., ontology, rules, unified logic, and trust) of the digital twin of an object, process, or phenomenon. Thus, the terms "semantic modeling" and "concept mapping" can be used interchangeably, as done for the remainder of this article.

However, more specifically, the constituents of a concept map are defined as follows. A concept map denoted as *CM* consists of (at least) a Focus Question (*FQ*), a set of concepts $CP = \{CP_i \mid i = 1,2,\ldots\}$, a set of relationships or propositions $RE = \{RE_j \mid j = 1,2,\ldots\}$ showing the linguistic or mathematical relationships among the members of *C*, a set of syntactic phrases $SP = \{SP_k \mid k = 1,2,\ldots\}$ that are needed to create a set of propositions using the members of *CP*, and a set of documents added to concepts denoted as $DC = \{DC_{il} \mid l = 1,2,\ldots,\ i = 1,2,\ldots\}$ consisting of text, mathematical and logical derivations, videos, sounds, pictures, illustrations, computer programs, and/or the links to other concept maps. Thus, a concept map is given as follows: $CM = (FQ, CP, RE, SP, DC)$. The sets of syntactic phrases and documents can be empty, but the same is not true for the sets of concepts and their relationships. Thus, the manifestation of semantic modeling "$Sl(P,C) \vdash Ms(P,C)$" is a set of concept maps denoted as CM_1, CM_2,…. This yields the following formulation of the semantic modeling.

$$(Sl(P,\ C) \vdash \mathrm{Ms}(P,\ C)) \rightarrow (CM_1,\ CM_2 \ldots) \quad (1)$$

For the sake of better understanding, consider the concepts and *CM* shown in Fig. 2 [35]. As seen in Fig. 2, the constituents of *CM* are as follows: *FQ* = "Evaluate the performance of turning," *CP* = {performance, turning, surface roughness, environmental burden, tool life, machining time, evaluation}, *RE* = {Performance of turning can be evaluated by machining time, surface roughness, environmental burden, and tool life}, *SP* = {of, can be, by,…}, and $DC = \{DC_{21}, DC_{41}, DC_{51}, DC_{61}, DC_{71}\}$ (DC_{21}, DC_{41},…,DC_{71} are the links to other concept maps from the respective concepts).

Note that a given concept can be modified from the linguistic viewpoint while incorporating it into the map. For example, the concept called evaluation is modified to "evaluated" before using it in the *CM* (Fig. 2) to make it linguistically meaningful. Other semantic phrases can be used (e.g., "of," "can be," and "by," as used in the concept map shown in Fig. 2) for the same reason. Depending on the *FQ*, a concept can be used in syntactic phrases, without making it a concept or vice versa. For example, consider the syntactic phrase "can be" in Fig. 2. This phrase can be rephrased as "can be evaluated by." In this case, the concept "evaluated" is no longer a concept. Since *FQ* = "Evaluate the

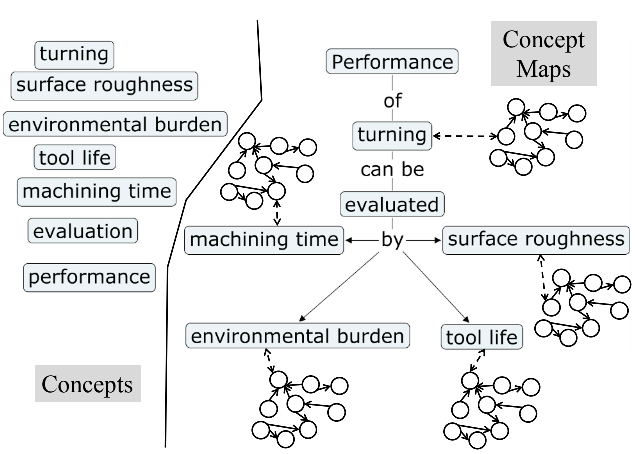


Fig. 2. An example of concept map relevant to manufacturing [35].

performance of turning," "evaluated" it is considered as a concept of the *CM*. An individual not familiar with the manufacturing process called turning cannot make sense of it using the *CM* alone. This means that some of the members of *CP* can be connected to other *CM*s, as schematically illustrated in Fig. 2, to make the content meaningful to the users. As far as the manufacturing engineering is concerned, all arbitrary *CM*s (e.g., the *CM* in Fig. 2) must be connected to large concept maps such as those of the material universe, shape universe, process universe, precision universe, control universe, and sustainability universe. (See [35,36] for more details on concept mapping for manufacturing knowledge representation.) Thus, for this particular case, DC_{21}, DC_{41},…,DC_{71} are the links to the large concept maps denoted as the material universe, shape universe, process universe, precision universe, control universe, and sustainability universe.

3. Phenomena twin construction using semantic modeling

This section provides a general description of how to implement the semantic modeling defined in Eq. (1) to construct a sensor signals-based phenomenon twin, denoted as *PT*.

Since the outcomes of the semantic modeling are some concept maps (CM_1, CM_2,…) underlying "$Sl(P,C) \vdash Ms(P,C)$," *PT* is also a collection of *CM*s. The schematic illustration of *PT* is shown in Fig. 3.

As seen in Fig. 3, four interconnected concept maps (CM_1, CM_2, CM_3, CM_4) form the *PT*. Among these *CM*s, CM_1 consists of the information of $Sl(P,C)$, that is, $Sl(P,C) \rightarrow CM_1$. CM_2 consists of the information of $Ms(P,C)$, that is, $Ms(P,C) \rightarrow CM_2$. CM_3 consists of the information of the simulation tool evolved from $Ms(P,C)$ that produces $Sx(P,C)$ whenever necessary, that is, $Sx(P,C) \rightarrow CM_3$. The last concept map (i.e., CM_4), consists of the verification process so that the results offered by the simulation tool are reasonably close to the real ones, that is, $Sx(P,C) \cong Sl(P,C) \rightarrow CM_4$. Thus, the formulation of *PT* is as follows:

$$PT = ((Sl(P,\ C) \rightarrow CM_1),\ (Ms(P,\ C) \rightarrow CM_2),\ (Sx(P,\ C) \rightarrow CM_3),\ (Sx(P,\ C) \cong Sl(P,\ C) \rightarrow CM_4)) \quad (2)$$

Regarding the member of *DC*, the following remarks can be made. There exists at least one link, denoted as DC_{1ij} ($\exists i,j \in \{1,2,\ldots\}$), attached to a concept CP_{1i} that helps connect at least one of the concepts of CM_2 with CP_{1i}. The vice versa is also true, that is, there exists at least one link denoted as DC_{2kl} ($\exists k,l \in \{1,2,\ldots\}$), attached to a concept CP_{2k}, which connects at least one of the concepts of CM_1 with CP_{2k}. The other concept maps, that is, CM_2, CM_3, and CM_4, are also connected similarly. Note that both concept CP_{1i} (to which a link denoted as DC_{1ij} is attached) and concept CP_{2k} (to which a link denoted as DC_{2kl} is attached) can be the same concept. In this case, the concept maps (CM_1, CM_2, CM_3, CM_4) in *PT* result in a single concept map, that is, in some circumstances, *PT* can be expressed by a single concept map consisting of the information of $Sl(P,C)$, $Ms(P,C)$, $Sx(P,C)$, and $Sx(P,C) \cong Sl(P,C)$. For example, see the *CM* in the case study.

Recall the *CM*s of *PT*. As mentioned, the formation of CM_1 deals with the information of $Sl(P,C)$, that is, sensor signals, their origin, and other relevant aspects. This refers to a general form of CM_1, as shown in Fig. 4. As seen in Fig. 4, there are nine concepts, seven semantic phrases, and five propositions (relationships). In particular, the five propositions are as follows: (1) A manufacturing process called MP was performed under conditions to obtain sensor signals regarding *P*. (2) Conditions are denoted as *C*. (3) The conditions *C* are described in Documents. (4) Sensor signals are denoted as $Sl(P,C)$. (5) Sensor signals are recorded in "Signal Database." Here, MP denotes a specific manufacturing process (e.g., turning, milling, or drilling). The concept "Documents" must link some documents that provide the details of *C* (the conditions based on which the signals regarding *P* are collected). The concept "Signal Database" must direct the users to a source from where one can access and reuse the signals $Sl(P,C)$. Therefore, the concepts "Documents" and "Signal Database" possess the entities

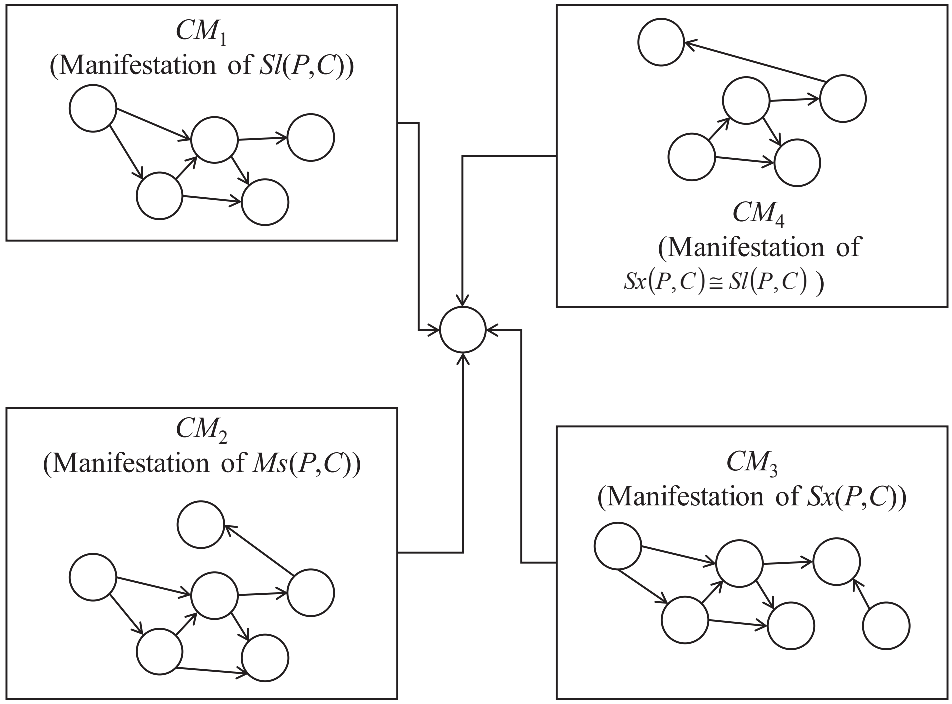


Fig. 3. The structure of *PT*.

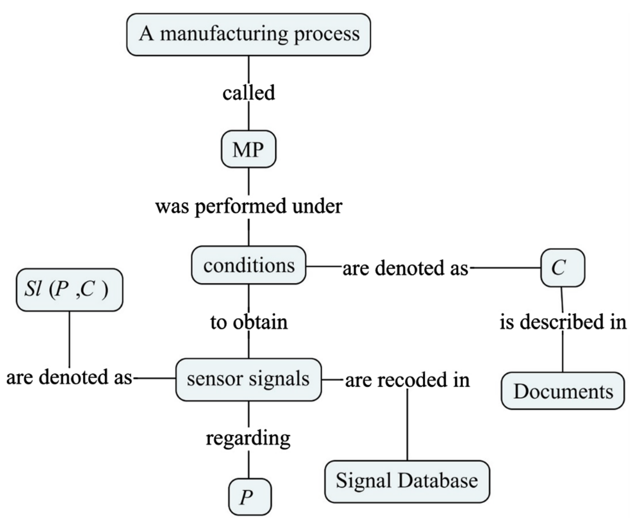


Fig. 4. CM_1 of the proposed *PT*.

denoted as $DC_{1(.)}$, directing the users to the required contents, as mentioned above. Other concepts can also possess $DC_{1(.)}$ for linking CM_1 to CM_2.

The formation of CM_2 deals with the information of *Ms*(*P*,*C*), that is, the semantic model that mimics the dynamics of *Sl*(*P*,*C*) and other relevant aspects, which, in turn, serve as the ontology or meaning–base for the user's understanding of signal dynamics. As such, CM_2 is not as straightforward as CM_1. It is highly subjective. One of the recommended formations of CM_2 is described as follows. The sensor signals *Sl*(*P*,*C*) associated with a material removal process often exhibit four stochastic features, namely, cycle, trend, irregularity (noise), and burst [23,24]. A cycle refers to the periodic regularity associated with *Sl* (*P*,*C*). A trend refers to a monotonic shift (or a set of monotonic shifts) associated with *Sl*(*P*,*C*). An irregularity refers to a small-magnitude noise associated with *Sl*(*P*,*C*). A burst refers to a large short-period deviation of *Sl*(*P*,*C*). Thus, the formulation of CM_2 takes the general form shown in Fig. 5.

As seen in Fig. 5, there are nine concepts, five semantic phrases, and three relationships (propositions). The propositions are as follows: (1) Sensor signals recorded in "Signal Database" underlie a "Model." (2) "Model" is denoted as *Ms*(*P*,*C*). (3) "Model" consists of four stochastic features, namely, trends, cycles, irregularities, and bursts. In CM_2, two of the concepts ("Sensor Signals" and "Signal Database") also belong to CM_1. This means that these two concepts integrate CM_1 and CM_2. Whether the model consisting of the four stochastic features is effective can be verified from CM_3 and CM_4.

Since CM_3 consists of the information of the simulation tool evolved from *Ms*(*P*,*C*), which produces *Sx*(*P*,*C*) whenever necessary, it can be expressed by the concept maps shown in Fig. 6. As seen in Fig. 6, it consists of twelve concepts, where the first four concepts are taken from CM_2. In CM_3, the most significant relationships are as follows: (1) Four stochastic features, namely, "Trends," "Cycles," "Irregularities," and "Burst," can be defined by four mathematical entities. (2) Four mathematical entities, namely, *Tr*, *Cy*, *Ir*, and *Br*, are added to produce "Simulated Signals." (3) "Simulated Signals" are denoted as *Sx*(*P*,*C*). (4) "Simulated Signals" are generated by the "System." Therefore, a simulation tool that generates *Sx*(*P*,*C*) following the formulation of *Tr*, *Cy*, *Ir*, and *Br* must be linked to the concept "System" so that the users can download it if needed.

Since CM_4 consists of the verification process showing the results created by the simulation process are reasonably close to the real ones, *Sx*(*P*,*C*) ≅ *Sl*(*P*,*C*), it can be given by the concept map shown in Fig. 7. As seen in Fig. 7, some of the concepts of CM_4 are taken from the previous concept maps. The new concepts are "Characteristics," "Method," and "Same," resulting in the following two relationships: (1) "Simulated Signals," denoted as *Sx*(*P*,*C*), and "Sensor Signals" stored in "Signal Database," denoted as *Sl*(*P*,*C*), resemble each other because their "Characteristics" are the same. (2) "Characteristics" are confirmed by a "Method." As such, the concept "Method" must direct the users to a method by which they can quantify the characteristics of the simulated and given signals. The next section describes one of the effective methods.

While constructing a *PT* for a specific application, the concept maps shown in Figs. 4–7 can be integrated into a single concept map. The following section shows an example of such an integrated concept map.

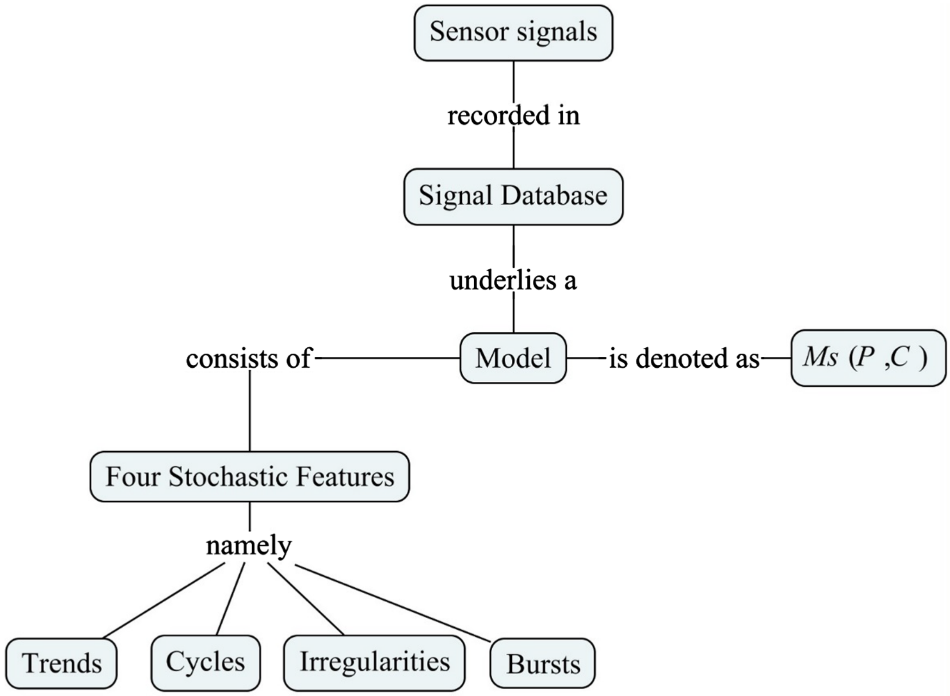


Fig. 5. CM_2 of the proposed *PT*.

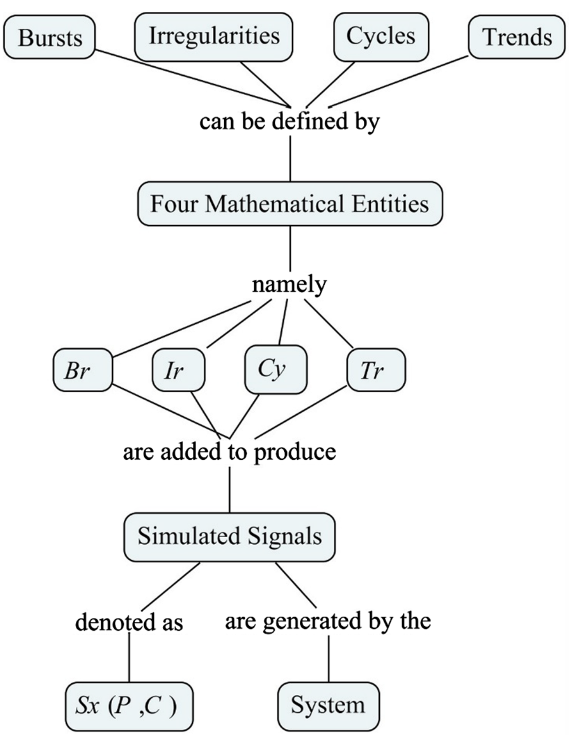


Fig. 6. CM_3 of the proposed *PT*.

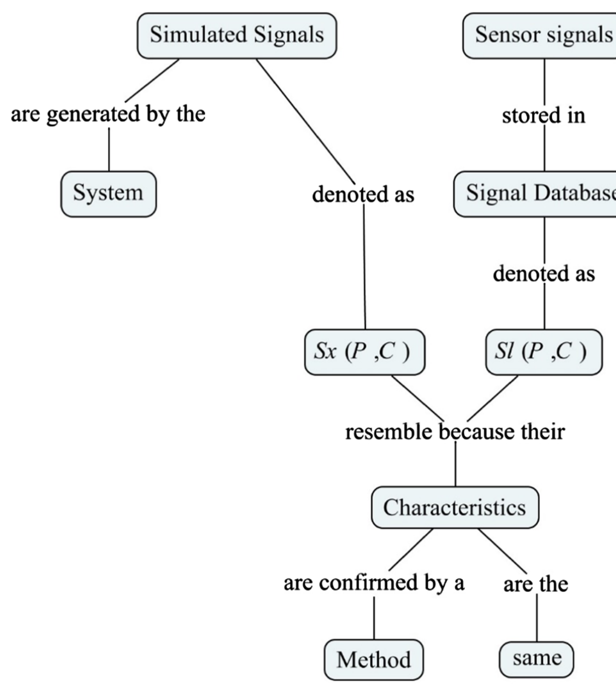


Fig. 7. CM_4 of the proposed *PT*.

4. Phenomenon twin of cutting force: a case study

This section shows how to construct a *PT* of cutting force. Cutting force is a complex phenomenon associated with all material removal processes (turning, milling, drilling, and so forth). The signals of cutting force obtained by using an appropriate sensor are used to visualize, optimize, and/or monitor a material removal process in either a laboratory or real-life setting.

For example, consider the cutting force signals shown in Fig. 8. The signals are obtained while turning a bimetallic specimen made of mild steel (denoted as S15CK) and stainless steel (denoted as SUS304). The details of the experiments can be obtained from [25]. However, as seen in Fig. 8, when the cutting tool moves to the side of the stainless steel from that of the mild steel, the cutting force gradually decreases. In the other direction, the cutting force gradually increases. The nature of the increment or decrement is not the same.

From the viewpoint of CM_1 of the *PT* (Fig. 4), *P* is the cutting force, and the information of the cutting conditions, cutting tool, machine tool, specifications of the bimetallic specimens, and so forth, constitute *C*. The signals shown in Fig. 8 are $Sl(P,C)$, that is, the sets of time series of the cutting forces denoted as $F(t)$, t = 0,0.005,…, (the units of cutting

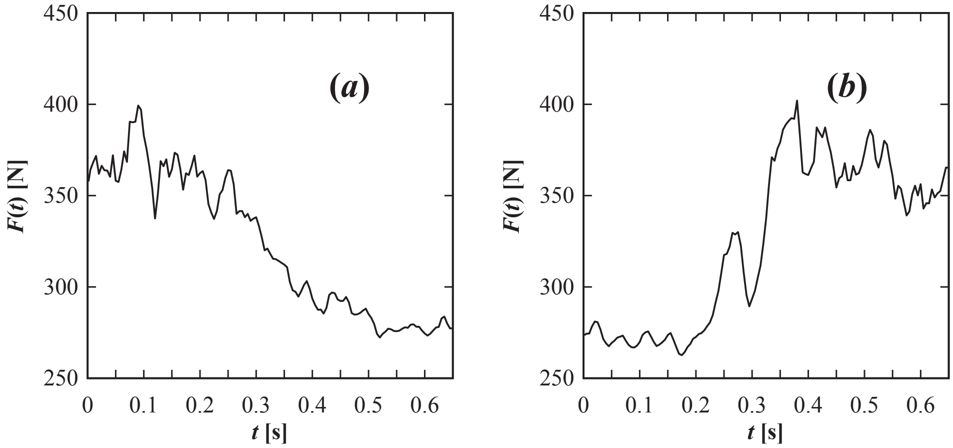


Fig. 8. Cutting force signals while turning a bimetallic specimen made of mild steel (S15CK) and stainless steel (SUS304) under a certain condition [25].

force and time are newton (N) and second (s), respectively), $Sl_i(P,C) = F(t)$, $i = t/0.005$. Using the abovementioned information, *P*, *C*, and *Sl* (*P*,*C*), the first concept map of *PT*, denoted as CM_1, can be constructed.

For constructing the second concept map of *PT*, that is, CM_2, the cutting force signals shown in Fig. 8 must be modeled using the following four stochastic features: "Trend," "Cycle," "Irregularity," and "Burst." As such, for constructing the third concept map of *PT*, that is, CM_3, the mathematical expressions of "Trend," "Cycle," "Irregularity," and "Burst" (denoted as *Tr*, *Cy*, *Ir*, and *Br*) must be defined. *Tr*, *Cy*, *Ir*, and *Br* can be defined in many different ways. One of the most straightforward ways is described as follows.

Since *Tr* creates a monotonic trend for a given period, its simplest form is as follows:

$$Tr(i) = a(i) + b(i)\cdot i \tag{3}$$

In Eq. (3), $a(i)$, $b(i) \in \Re$ are two constants, and $i = 0,1,\ldots$. These constants remain the same for a given period and may vary in a systematic manner. Note that for the cases shown in Fig. 8, $i = t/0.005$, where *t* is the time interval of cutting force sampling.

Since *Cy* creates a cyclic behavior, its simplest form is as follows:

$$Cy(i) = c(i)\sin\left(\frac{i}{d(i)}\right) \tag{4}$$

In Eq. (4), $c(i)$, $d(i) \in \Re$ are two constants. In particular, $c(i)$ is the amplitude constant and $d(i)$ is the frequency constant. These constants can be varied randomly with iterations $i = 0,1,\ldots$, if needed.

Since *Ir* contributes an amount of noise to the simulated signal, its simplest form is as follows:

$$Ir(i) = rn(i) \tag{5}$$

In Eq. (5), $rn(i) \in \Re$ is a normally distributed random variable with mean μ and standard deviation σ. (Alternatively, one can use a pure random number for adding an amount of noise to a signal.) See [24] for more details on how to create $rn(i)$.

Since *Br* introduces a sudden shift in the signal, its mathematical setting is somewhat complex, requiring at least six parameters, namely, position (P_B), likelihood (L_B), span of ascending shift (*p*), span of descending shift (*q*), magnitude of ascending shift (B_A), and magnitude of descending shift (B_D). As such, the following formulation holds:

$$Br(i) = f(P_B, L_B, p, q, B_A, B_D) \tag{6}$$

The nature of the function $f(.)$ defined in Eq. (6) depends on the given signal. For the cases shown in Fig. 8, the following algorithm can be used to create $Br(i)$.

Burst Algorithm (*Br*):
$L_B \leftarrow [0,1]$
$p,\ q,\ n_1,\ n_2,\ n \in \aleph,\ n_1,\ n_2 < n$
$P_B \leftarrow [n_1, n_2]$
For $i = 0,\ldots,n$
  $Br(i) = 0$, $r_i \leftarrow [0,1]$
    If $(i = P_B)$ and $(r_i < L_B)$
      For $k = 0,\ldots,p-1$
        $j = i + k$, $\mu_j < \mu_{j+1}$
        $Br(i) = Br(j) \leftarrow N(\mu_j,\sigma_j)$
      End For
      For $l = 0,\ldots,q$
        $m = i + p + l$, $\mu_m > \mu_{m+1}$
        $Br(i) = Br(m) \leftarrow N(\mu_m,\sigma_m)$
      End For
End For

Here, r_i is a random number in the interval [0,1], $N(\mu_{(.)},\sigma_{(.)})$ is a normally distributed variable where $\mu_{(.)}$ and $\sigma_{(.)}$ are the mean and standard deviation, respectively.

Therefore, adding $Tr(i)$, $Cy(i)$, $Ir(i)$, and $Br(i)$ creates the simulated signal $Sx(P,C)$. As a result, the following relationship holds.

$$Sx_i(P,C) = Tr(i) + Cy(i) + Ir(i) + Br(i) i = 0, 1, \cdots \tag{7}$$

Thus, if a simulation tool is developed based on the formations defined in Eqs. (3)–(7) and uploaded to the concept "System" of CM_3, then the users can download it for reuse.

Since the last *CM* of *PT*, that is, CM_4, consists of the information of the verification process of the results produced in CM_3, the constituents of CM_4 are described as follows. The parameters associated with the expressions of $Tr(i)$, $Cy(i)$, $Ir(i)$, and $Br(i)$, as defined in Eqs. (3)–(7), for both sets of cutting force signals shown in Fig. 8 are tuned in such a way so that the simulated signals $Sx_i(P,C)$, $i = 0,1,\ldots$, become very close to the real ones, $Sl_i(P,C)$. For the sake of better understanding, consider the signals reported in Figs. 9 and 10. The signals shown in Fig. 9 correspond to the turning direction S15CK to SUS304 [25]. The signals shown in Fig. 10 correspond to the other direction (i.e., SUS304 to S15CK). For the sake of better understanding, the results of $Tr(i)$, $Cy(i)$, $Ir(i)$, $Br(i)$, and $Sx_i(P,C)$ for the respective signals are also shown in Figs. 9 and 10. A visual inspection reveals that there is a good match between the simulated and real signals (Figs. 10(f) and 11(f)).

The simulation process was repeated many times to ensure the consistency of the results. The results of three consecutive trials are reported in Figs. 11 and 12 for both turning directions, respectively. This time, along with the time series plots shown on the left-hand sides in Figs. 11 and 12, return (or delay) maps are plotted as shown on the right-hand sides of the respective time series plots. This means that Fig. 12(a), (c), and (e) are the time series plots, and Fig. 12(b), (d), and (f) are the corresponding return maps. The same argument holds for the

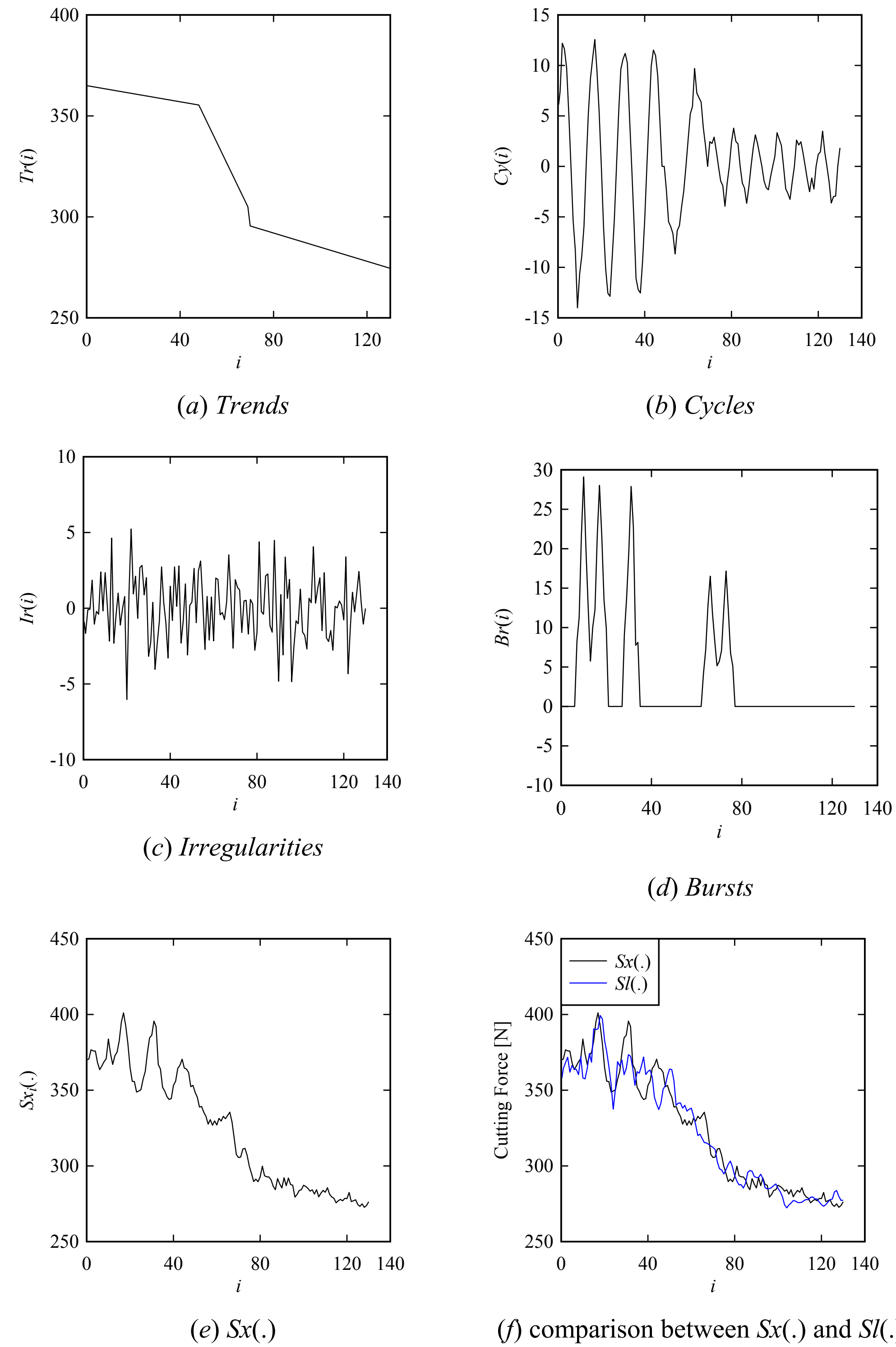


Fig. 9. Simulated cutting force singals and its comparison with real cutting force force signals (cutting direction S15CK to SUS304).

time series and return maps shown in Fig. 12.

It is worth mentioning that a return map is more informative than the time series plot because it is a visual representation of the underlying complexity of the phenomenon. See [37] for more detail regarding the role of the return maps in signal processing.

In addition to the abovementioned visual inspections, $Sx_i(P,C)$ can be compared with $Sl_i(P,C)$, $i = 0,1,\ldots$, in a more rigorous way. In this case, the concepts of possibility distributions [38] and correlation dimension [24,37] can be applied since these are useful for quantifying the complexity of a time series. In this article, the concept of possibility distribution is used to compare $Sx_i(P,C)$ with $Sl_i(P,C)$. (A possibility distribution (or a fuzzy number) is the probability distribution neutral representation of the uncertainty associated with a quantity.) The procedure to induce a possibility distribution from a time series can be obtained from [38]. Fig. 13 shows the possibility distributions of the real and simulated cutting force signals. Here, the degree of possibility is denoted as Poss $\in [0,1]$. As seen in Fig. 13, for both cases (cutting forces obtained while cutting from the direction of S15CK to SUS304 and vice versa) the possibility distributions of the simulated cutting force signals ($Sx(.)$), denoted as $Sx(.)-1$, $Sx(.)-2$, and $Sx(.)-3$,

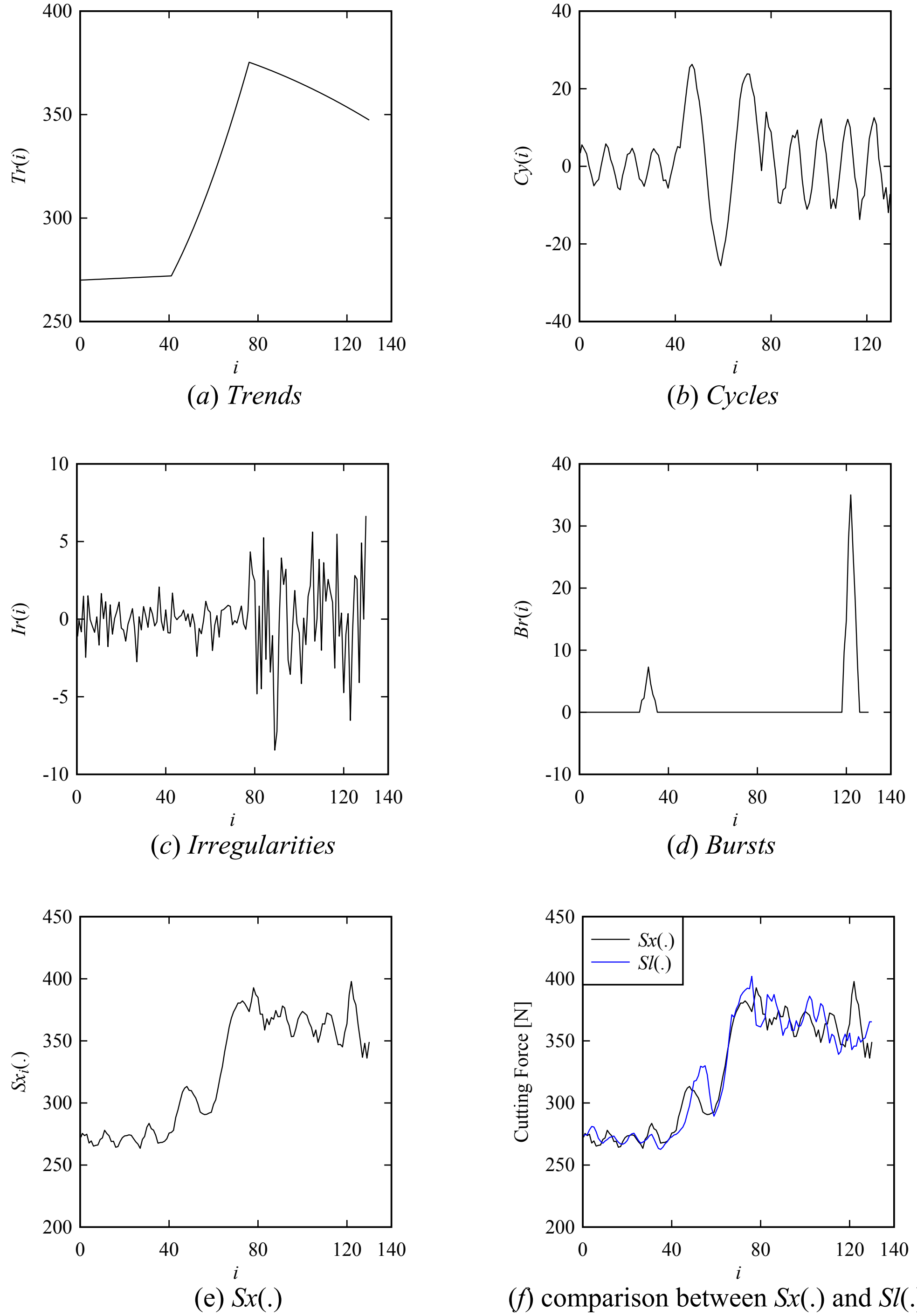


Fig. 10. Simulated cutting force singals and its comparison with real cutting force force signals (cutting direction SUS304 to S15CK).

resemble that of the real cutting force signal (*Sl*(.)).

In synopsis, the simulated cutting forces, *Sx*(*P*,*C*), are similar to the real ones, *Sl*(*P*,*C*), from the quantitative and qualitative viewpoints.

Based on the above descriptions on $CM_1,\ldots,CM_4$, a *PT* of the cutting force is constructed, as shown in Fig. 14. The upper-left segment of the *PT* shown in Fig. 14 is its CM_1. The upper-right segment of the *PT* shown in Fig. 14 is its CM_2. The lower-right segment of the *PT* shown in Fig. 14 is its CM_3. The lower-left segment of the *PT* shown in Fig. 14 is its CM_4. All relevant contents needed to justify the propositions (i.e., the relationships among the concepts) underlying the *PT* are linked to the respective concepts (i.e., the concepts with some icons, as seen in Fig. 14). The *PT* can be accessed for reuse from the following URL: http://cmapspublic3.ihmc.us/rid=1SY7KW5M5-15XP5HV-1GB5/bimetal-cutting-force-phenomena%20twin.cmap. The XML data of the *PT* can be exported to other systems using AutomationML [16] and/or MT Connect [17] while utilizing them from the context of Industry 4.0.

5. Discussions

The implication and significance of the digital twin construction process presented in the previous three sections can be discussed from numerous points of view. One of the points of view is with regard to the systems architecture [39], which lays out the hardware and software systems for formal integration or disintegration. Vogel-Heuser et al. [40] consider that the system architecture of systems involved in Industry 4.0 is not layered or hierarchical; rather, it takes the form of a

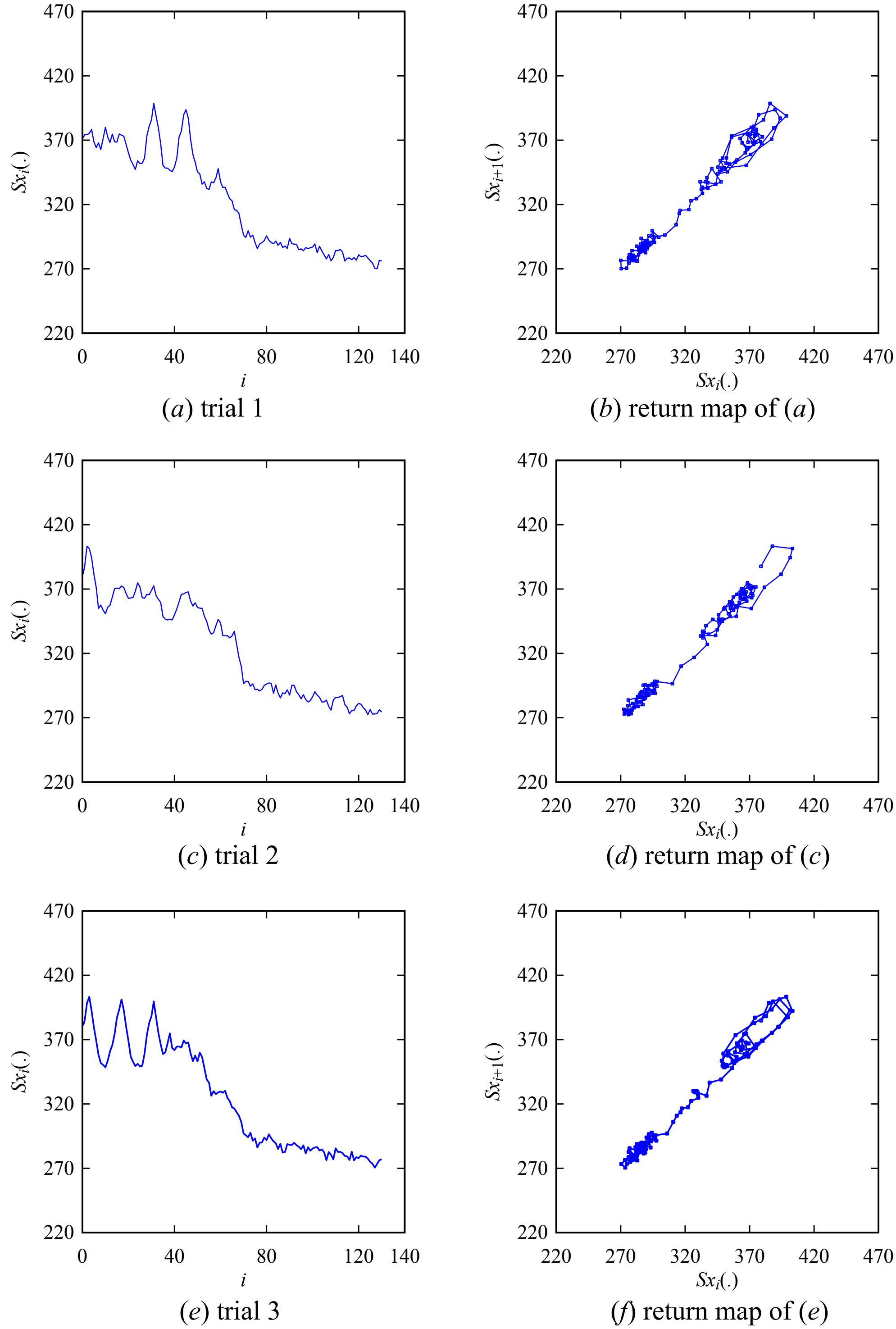


Fig. 11. Consistency of the simulated cutting force (S15C to SUS304).

network. However, Lee et al. [6] consider that it must follow a layered or hierarchical structure to coordinate among different levels of functionalities (sense, understand, analyze, decide, and adopt). On the other hand, systems engineering analyses find that no ideal system architecture (out of network, tree-hierarchy, and layered) exists to fit all circumstances; the performance depends on the environments to which the systems are exposed [41]. However, to solve the problems arising from system complexity (high-impact low-probability events), system architecture must incorporate abstraction (meaning of the system) along with decomposition (structure of the system) [42]. The meaning of the term "abstractions" is also debatable when enterprise integration is considered. It is denoted as a semantic annotation (meta-model or meta-meta-model) in enterprise integration [43–45]. In the semantic web, the abovementioned meaning of abstractions or semantic annotation takes a more formal structure called provenance (as mentioned in Section 1), where the layers (ontology, unified logic, rules, proof, trust, and user interface) are added to make the contents more trustworthy, autonomous, and human–machine comprehensible [27,29–32,46,47].

To achieve the systems engineering requirements set by abstraction of systems rather than its structure, semantic annotation, and provenance, the concept map-embedded information (i.e., the outcomes of semantic modeling), as presented in the previous section, can be used

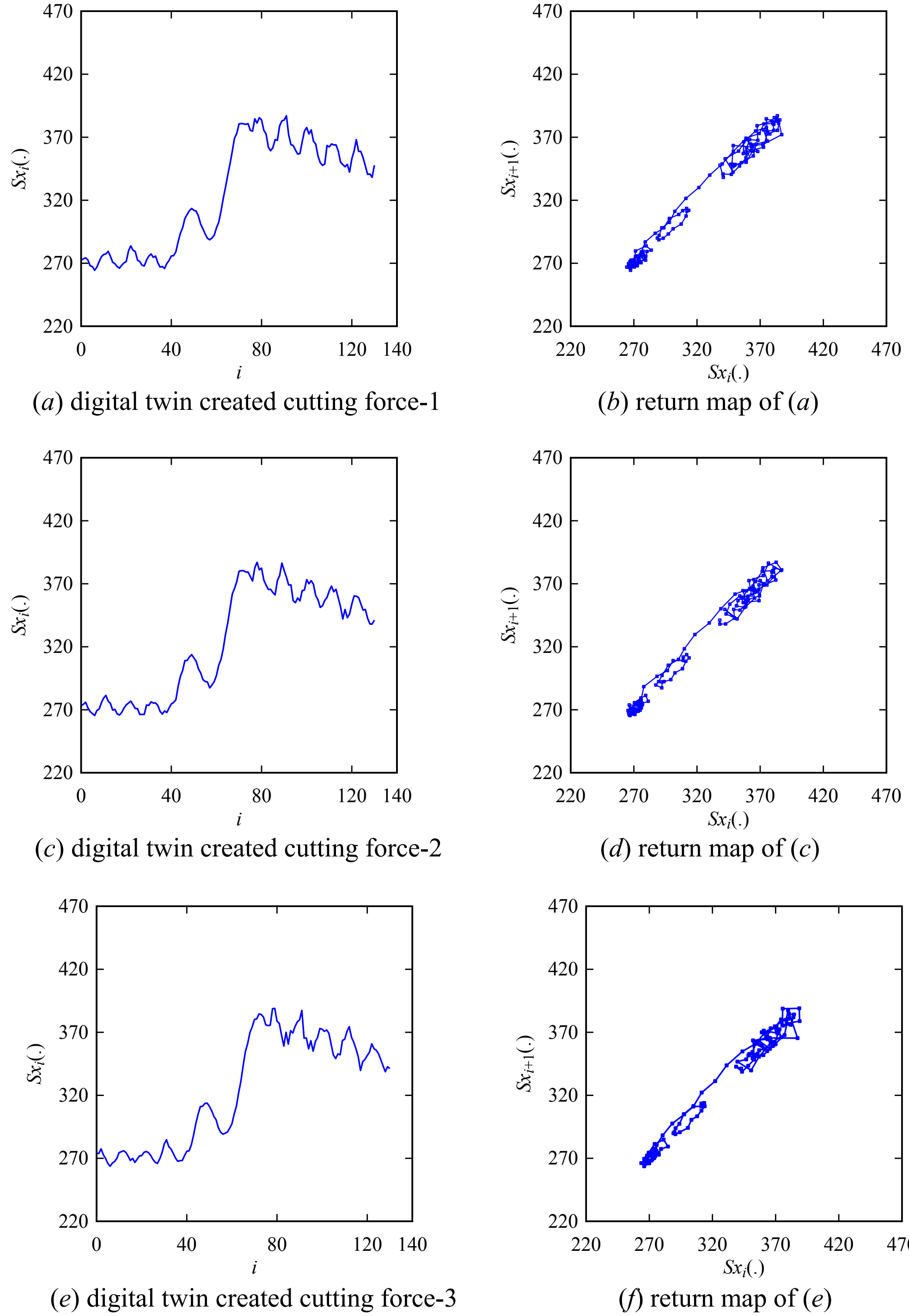
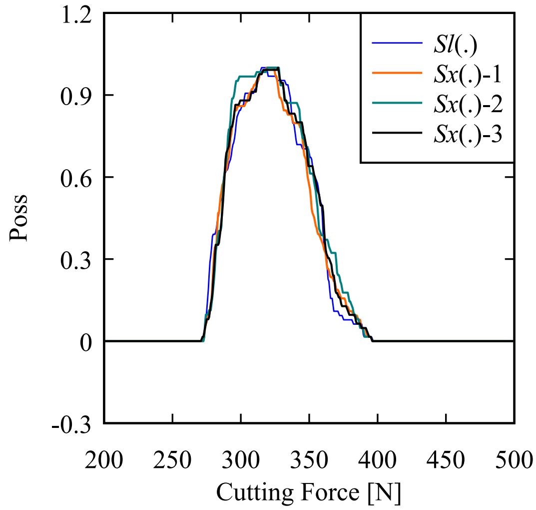


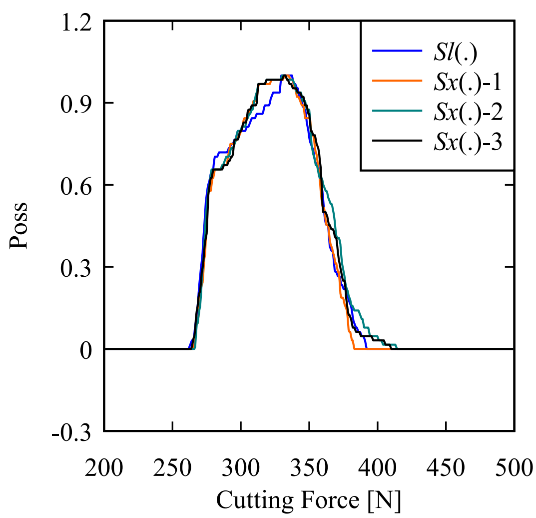
Fig. 12. Consistency of the simulated cutting force (SUS304 to S15C).

because it is the abstraction of the relevant contents, it semantically denotes the data and systems attached to it, and it provides the provenance-related information (e.g., the source of data, how the data are manipulated to come to a conclusion, whether or not the results should be trusted, and so on).

However, the *PT* shown in the previous section can be rearranged to form a meta-model of sensor signals of machining processes as a whole, as shown in Fig. 15. The meta-model consists of the following relationships: (1) Sensor signals collected from a material removal process (e.g., turning, milling, drilling, and grinding) consist "Cycles," "Trends," "Irregularities," and "Bursts." (2) "Cycles," "Trends," "Irregularities," and "Bursts" are defined by the mathematical settings *Cy*, *Tr*, *Ir*, and *Br*, respectively. (3) *Cy*, *Tr*, *Ir*, and *Br* are added to form *Sx*(.). (4) *Sx*(.) recreates sensor signals. (5) *Sx*(.) is available from here. The meta-model carries different types of knowledge: explicit-tacit knowledge [48], knowledge gained by cognitive processes [49], and knowledge gained by machine learning processes [50]. However, from the sense of theory of knowledge (i.e., epistemology), the knowledge underlying the meta-model can be categorized into five distinct categories, namely, (1) analytic a priori knowledge, (2) synthetic a priori knowledge, and (3) synthetic a posteriori knowledge, (4) creative knowledge, and (5) decisive knowledge. The first three categories of



(*a*) Cutting force for SC15 to SUS304



(*b*) Cutting force for SUS304 to SC15

Fig. 13. Comparison between simulated and real cutting forces.

knowledge refer to Kantian epistemology [51]. The other two refer to pragmatism. The descriptions are as follows.

Analytic a priori knowledge refers to the knowledge gained by defining things (e.g., feed rate is the velocity at which a cutting tool is advanced against the workpiece). Thus, analytic a priori knowledge is always true (i.e., tautology). On the other hand, synthetic a priori knowledge is gained by using mathematical derivation and logical deduction. An example of synthetic a priori knowledge is as follows: (p =) the summation of the internal angles of a triangle is equal to 180°. Synthetic a priori knowledge is true within the relevant context. For example, p is true when the triangle is drawn on a plane surface, not on a curved surface. The other category of knowledge is called synthetic a posteriori knowledge, which evolves from real-world experiences due to a logical process called induction (e.g., the feed force is less than the cutting force). As a result, synthetic a posteriori knowledge can be proven true, partially true, partially false, or even false, that is, it is true for one stakeholder but may not necessarily be true for other stakeholders (i.e., it is a matter of fact). Creative knowledge comes into being due to the pragmatic preferences of an individual, where new concepts are introduced (i.e., concepts that are neither true nor false [52]). For example, the following proposition is a piece of creative knowledge: a signal consists of four features, namely, cycle, trend, irregularities, and burst. The above propositions cannot be proven true or false until a piece of synthetic a priori or a posteriori knowledge becomes available to support or reject the propositions. On the other hand, decisive knowledge refers to knowledge that can be used to decide an action (e.g., planning, monitoring, deciding, and optimizing) and implement it accordingly. For example, the following proposition can be considered as decisive knowledge: use the *PT* (Fig. 14) to develop a monitoring system using cutting force signals. The execution of decisive knowledge determines its truth value.

Besides the epistemic nature of the meta-model shown in Fig. 15, there are other important issues associated with it. Particularly, the meta-model can be used to solve one of the following problems: Class I, II, and III problems [53]. A Class I problem considers that both the goal and environment are certain. A Class II problem considers that the goal is certain, but the environment is uncertain. Lastly, a Class III problem considers that both the goal and environment are uncertain. Therefore, the combinations of the five categories of knowledge and three classes of problems collectively characterize the systemological nature of the meta-model of the phenomena (and even the other) twins. Studies focusing on the systemological nature will lead to a better formulation of ever-growing knowledge bases of embedded systems (e.g., cyber-physical systems) [3].

6. Concluding remarks

Numerous studies have been conducted to constantly improve the offerings of Industry 4.0, wherein a merger between the virtual and real worlds is emphasized, resulting in a new content creation approach called digital twin. Semantic modeling of sensor signals provides a convenient way to construct the digital twins for complex manufacturing phenomena, as demonstrated in this article. The construction process shows the existence of a meta-model of sensor signals, which inevitably integrates five categories of knowledge, namely, analytic a priori knowledge, synthetic a priori knowledge, synthetic a posteriori knowledge, creative knowledge, and decisive knowledge. These pieces of knowledge can be represented using concept maps such that the semantic web can apply them within the realm of Industry 4.0, as described in this article.

The main focus of current research on Industry 4.0 is to design and implement manufacturing systems from the perspective of machine-to-machine communication. This might confine the progress of manufacturing systems engineering to the realm of mere automation and connectivity (akin to the predecessor of Industry 4.0). The concept of semantic modeling must be manifested in the form of webized concept mapping to achieve the high-level requirements prescribed in the maturity index of Industry 4.0. The ever-expanding embedded systems involved in Industry 4.0 create an atmosphere where the whole system acts as an open system, and the reuse of contents (preferably available on the semantic web) might be subject to Class III problems (i.e., both the goal and environment are uncertain). In this sense, there is still no definite set of systemological guidelines that help system engineering to develop the required embedded systems. As such, this article will help those who want to develop certain embedded systems (e.g., cyber-physical systems). Having said that, the author does not mean that all relevant aspects have been described elaborately in this article. Instead, the author wishes to point out that the content preparation for Industry 4.0 (e.g., digital twin construction and its representation using the semantic web, as shown in this article) is likely to be in its infancy. Thus, there is considerable scope for additional research in this area.

Acknowledgments

The initial short version of the work was presented in the Asia Pacific Industrial Engineering & Management Systems Conference,

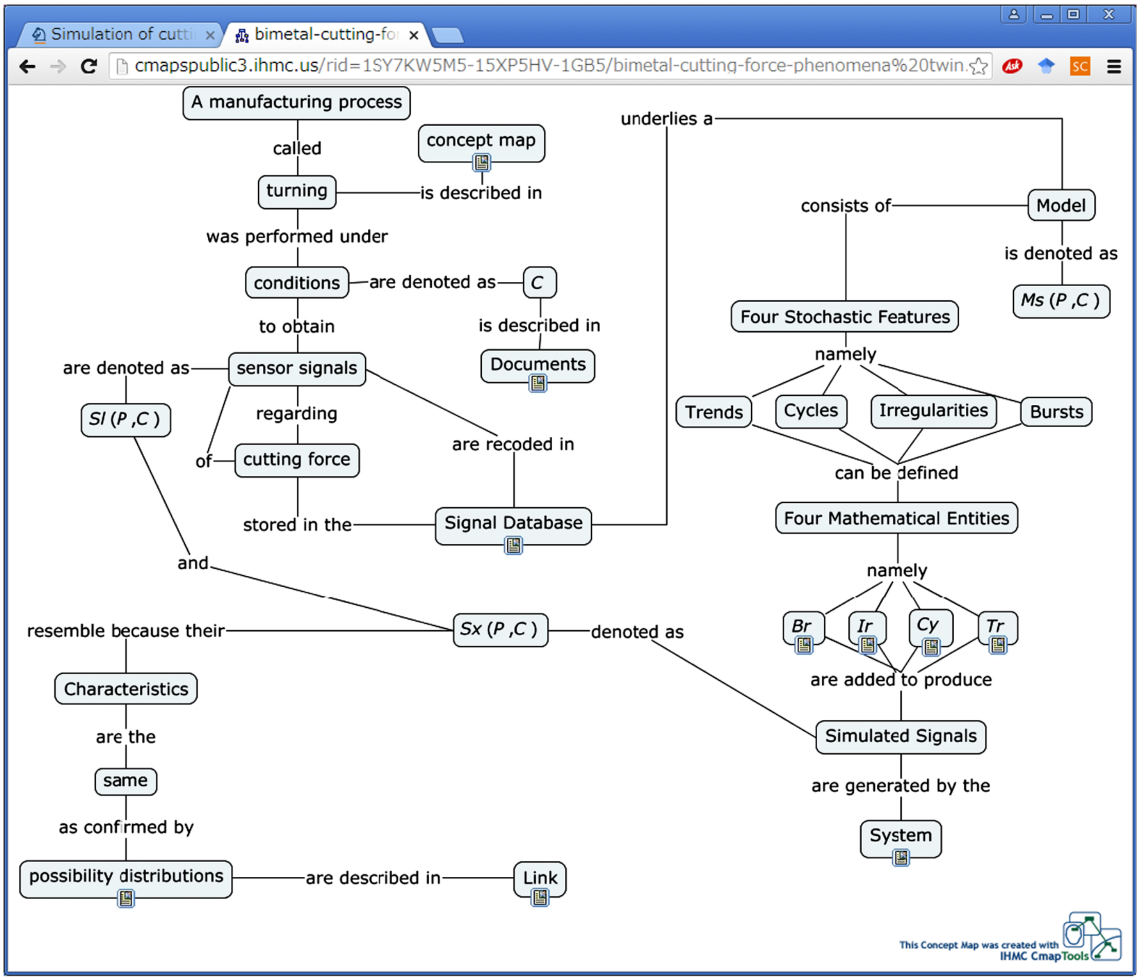


Fig. 14. A *PT* of cutting force.

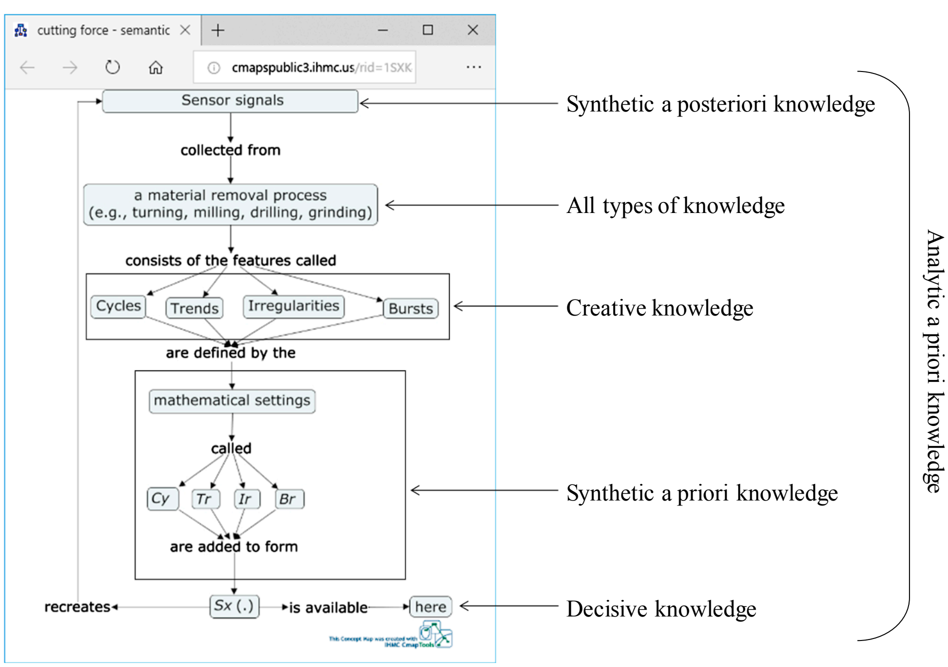


Fig. 15. Meta-model of cutting force and its epistemic nature.

7–10 December, 2016, Taipei, Taiwan. The author acknowledges three of his former graduate students (Shin Matsui, Wu Dong Yuan, and Xinhai Wang) for helping him with this project. The work receives financial and material supports from Kitami Institute of Technology.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.3390/jmmp2040068.

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