ABSTRACT The increasing complexity of product calls for manufacturing integration, while in turn high integration brings the problems of system level complexity. This paper proposes that complex product system (CoPS) should be managed as a dynamical system. The dynamical characteristics of CoPS are discussed from the perspective of emergence. A conceptual model is established to analyze the cause, process and result of the CoPS emergence. The mechanism of inner state emergence in CoPS is interpreted by formal languages to provide a point view of state space. It is concluded that the behavior of CoPS, especially the complexity, exhibits the 'entity is greater than the sum of the parts' phenomena when satisfying given necessary conditions. A novel methodology is then established to evaluate this emergence-based complexity. The feasibility and application of the novel complexity measurement is verified by an example of turbine housing production process. Further discussions are made on how to manage the potential emerging complexity based on the proposed measurement.

INDEX TERMS Integrated manufacturing, adaptive CoPS, emergence, complexity evaluation.

I. INTRODUCTION
In the background of mass customization production, increasing product complexity is becoming one of the biggest problems facing manufacturing industry [1], [2]. Focusing on the manufacturing problem, modern complex product system (CoPS) embraces a kind of system engineering in which the product shape is complex, the product composition is complex, the production operation is complex and the production environment is complex, etc [3]. Product complexity calls for manufacturing integration. Manufacturing architects have keenly realized the importance of the hierarchical optimization [4]–[6]. For example, manufacturing systems have been reengineered to achieve complex product integrated manufacturing, while varied manufacturing frameworks have been established to serve for the prediction and control of their extended complexity in manufacturing system [7]–[9].

However, integration simultaneously greatly increases the number of uncertain relationships within the system, and system-level complexity can be attributed to this kind of inevitable unpredictability [10], [11]. Many integrated manufacturing systems, which are designed to be effective, are actually constrained by the system complexity to be ineffective [12], [13]. Many researchers have realized that the evaluation and management of manufacturing complexity is essential for realizing full potential of manufacturing capabilities. In 1992, Cooper et al. [14] conceptualized operational complexity in the form of indexes. The motivation of Cooper’s research is to interpret intuitively what happens to the operations of a high-tech plant. The operational complexity is further tied in with information theory in the research made by Frizelle and Woodcock [15], who try to measure the contribution each operational source makes to the total complexity. The key idea is to calculate the entropy based on the approximate ratio of the total observed occupancy time of the states (programmable states and the non-programmable states), to the total time. Under this kind of thoughts, Deshmukh et al. [16] proposed the concept of static complexity that refers to the measure of decision information needed to describe the system and components.
Calinescu [17] adjusted Deshmukh’s method and proposed an entropy-based measurement called scheduling-related decision-making complexity index. The core of the Calinescu measurement is to introduce a contributing factor to quantify cause-effect relationships between operations. Considering that abnormal state (breakdown and awaiting resources) may occur in actual process, Zhang [18] evaluated the probabilities corresponding to the entropy based on practice. Abad et al. [19] focused on the linkage of input/output relationship and assessed a divergence between what is demanded and what is produced by the quality rate of product. Modrak and Soltysova [20] stressed on the layout complexity and took into account the probability of parts being processed on individual machine according to scheduling order.

The essence of the above classic complexity measurement is the same that complexity is evaluated by a linear entropy function of probabilities of states. With the logarithmic form remaining, ElMaraghy and Urbanic [21] attempted to use a complexity coefficient in place of the probability, aiming at measuring manufacturing complexity from three levels including product complexity, process complexity and operational complexity. Isik [22] modified the classic complexity measures and claimed that each state can have different complexity levels of its own. The main contribution of Isik is adding a ratio to evaluate the deviation of outcomes from the expected outcome value for the state. Samy and ElMaraghy [23] further proposed a complexity code for manufacturing system. Varied characteristics are analyzed by a code equilateral polygon, of which a complexity index is defined as the ratio between evaluated area and the total area. The limitation of this method is the ignorance of spatial, weighted and sequential relationship between these characteristics. To study the interaction within the system, Wang et al. [24] proposed a possible way to evaluate the complexity contribution within two nodes in a supply chain. Hu et al. [25] proposed that the upstream/downstream stations could influence each other and use a linear superposition method to evaluate the propagation of complexity. However, the linear sum of the parts is contradictory to the nonlinear nature of complex manufacturing system. Taking advantages of ideas pertaining to nonlinearity, Papakostas et al. [26] proposed execution complexity index to quantify the intrinsic structure and uncertainty. Mattson et al. [27] had a different point of view that complexity should be studied through visualizing system trends rather than studying system parts. A questionnaire method is then presented using Likert scales (on a scale between 1 and 5). The precision of this ranking questionnaire should be argued.

The export of existing quantitative results fails to reflect the nonlinear dynamical characteristics of the actual complex manufacturing system. The dynamic nature of integration manufacturing can make manufacturing system exhibit additional manufacturing capabilities [28]. To study the dynamical essence of manufacturing integration, Forrester [29] adapted structure dynamics to industry and proposed industrial dynamics theory in the 1950s, in which the stand point is that the structure determines the functionality of the industrial system. The inner interaction of operation is highlighted and is termed by the concept of flows. Teece et al. [30] established a dynamic capabilities framework to analyze the sources of wealth creation by private enterprise firms operating in environments of rapid technological change. Sterman [31] and Swanson [32] made research on innovation diffusion and the growth of new products. Warren [33] proposed the concept of strategy dynamics of resource management. Tian et al. [34] studied the influence of manufacturing dynamics on the performance of enterprise. Fetene Adane et al. [35] applied the theory of system dynamics for analysis of manufacturing performance. What’s more, it has been assumed that manufacturing system could show dynamical chaos [36], [37]. Based on discrete-event simulation, Schmitz et al. [38] showed that a two-machine production system has apparently chaotic behavior. Wilding [39] verified that the supply chain complexity chaos results from supply chain control systems.

From the perspective of studying the complex manufacturing system as a whole, Complex Adaptive System (CAS) theory is an essential approach. CAS theory, proposed by John Holland in 1994, is a methodology to investigate this ‘entity is greater than the sum of the parts’ phenomena [40], defined as emergence, which integrated manufacturing system also exhibits. CAS can provide theoretical background to cope with the inner complexity of integrated manufacturing systems [41]. Contributions have been made on the application of CAS to manufacturing system. Choi et al. [42] argued that supply networks should be recognized as a complex adaptive system (CAS). Monostori and Csaji [43] proposed that CAS can be probably used to model production systems. ElMaraghy et al. [44] mentioned that the enterprise networks may emerge. Frei et al. [45] made an attempt to show the self organization and emergence of evolvable production system. van Lier [46] tried to interpret the autonomous phenomenon existing in based on complexity science, and [47] further investigated whether complexity science can support the development and elaboration of an industrial info sphere. Intepe and Koc [48] focused on the technologies that related to the behavior of subsystems.

To better understand the dynamical behavior of complex integrated manufacturing system, our works highlight the emergence existing inside CoPS, especially oriented production process. In Section 2, we analyze the emergence mechanism of CoPS based on CAS theory. A conceptual model is presented to interpret the generation process and condition of emergence. In section 3, the emergence of each composition is studied by formal languages for semantic representation. This paper also presents a methodology to evaluate the dynamical propagation of complexity in section 4.

II. THE EMERGENCE OF COMPLEX PRODUCT SYSTEM

In the original sense, CoPS is merely a deterministic system, a production system constructed for a specific
complex product. However, minor changes in one place of CoPS may cause vibrations everywhere else. For instance, a slight change in the part parameters could lead to changes in the overall upstream manufacturing scheme (layout and configuration). To explain how the dynamic complexity in CoPS arises, we propose that CoPS is a CAS and should be established as such. The focus of this section is to demonstrate how to interpret the emergence of CoPS dynamics under the perspective of CAS, as well as the emergence process and result of CoPS.

As shown in Figure 1, whether a system is CAS can be distinguished from three effects concluded from the Paul Cilliers’ point of view [49] as: the environment effect, the component effect and the structure effect. Composition effect refers to the state change of internal compositions. Structure effect stresses on the added novel input into the original system structure. The environment effect embraces the concept of external flow and focuses on the influence of the environment. Each effect has some detailed perspectives offered by CAS. We seek to extend this application stream to issues in the analysis of CoPS.

**A. COMPLEX ADAPTIVE ANALYSIS**

The emergence of CoPS highlights the unexpected behavior existing in a complex integrated production process. It generally refers to that the production system could generate new functionalities and benefits beyond expected in certain patterns, which can be explored by the CAS’s concept of aggregation, diversity, tag mechanism, flows, nonlinearity, constraints, self organization and feedback. Figure 2 illustrates that how a CoPS could be framed as CAS. The left part presents that when a manufacturing system oriented complex product wants to be constructed as an efficient CoPS, the production system of the whole entity should be decomposed into several components’ and parts’ production subsystem layer by layer. The production of a car is presented here as an example. The characteristics of CAS can be reflected in the construction process and are summarized as the right part. The emergence mechanism can be further interpreted as follows:

The aggregation of production units refers to the fact that CoPS is composed of several independent production units /members /models. All the production units /members /models are supposed to be created for serving the whole manufacturing system and are tightly coupling to aggregate into one single manufacturing entity. What the aggregation wants to transmit is the collaboration of CoPS’s units and the breakthrough of the information island within CoPS, which is best exemplified by the popularity of the collaborative manufacturing.

The essence of constraint in CoPS is to control the degrees of freedom that production units have to enact behavior in a relatively autonomous way. New manufacturing members/models added to the entity must be adaptive to the typical rules, while the basic rule is that the expected performance should be consistent with the goal of the manufacturing entity. This performance-based constraint forces the manufacturing system to respond the deviation of system behavior and evolve towards a new steady state. It must be noticed that the formation of effective constraints should not limit the emergence of production units’ behavior, but prompt the manufacturing capabilities to emerge.

The concept of diversity in CoPS contains the variety of the units, the variety of the layout and the variety of the system configuration. The diversity of CoPS is the existent basis of CoPS’s emergence. A CoPS that has higher level of diversity is more likely to emerge and survive than the ones are not. For instance, if the downstream machining layer could offer varies of processing schemes, and then the upstream links of manufacturing entity would have more space to operate when facing the disturbance from the manufacturing environment.

The tag is the basic mechanism in relation to the multilayer organization of CoPS. Tag mechanism can help classify the diversity based on units’ functionality. The production process of complex product is always a interdisciplinary cooperation. The entire production process can be tagged with layers named whole vehicle production, components production and parts production. If further analysis needs to be made on each layer, each layer could be further decomposed and tagged with more detailed categories (the mechanical production could be tagged with mechanical subsystem. The electrical control production could be tagged with control subsystem. The power equipment production could be tagged with power subsystem). The application of the RFID (Radio Frequency Identification) in production process is a kind of engineering realization of tag mechanism.

The external perturbations result in the deviation of the steady state, which can be explained by flows stimulus mechanism. This kind of energy flows in CoPS could be in form of flow of order, flow of cost, flow of equipment, flow of material, flow of information, etc. The flow-based stimulus mechanism could make the CoPS entity work as a dynamical system. The dynamical flow characteristic is shown in two
aspects. One is the dynamical interaction between the manufacturing entity and the production environment. In presence of perturbations, the entity is capable of adjusting its organization while maintaining its manufacturing functionality. The influence of the flow can be treated as energy pouring through every unit of manufacturing entity renewing each one’s state. Another is the inner mapping relationships within the compositions. Any variation of each unit’s response to the external flow will affect the others. For example, if the design unit spends more time than expected, the other units must be adapted to maintain the expected efficiency, while a good performance on the design unit could decrease the time cost and financial cost of the test unit and machine unit.

The CoPS should have this adaptive capacity which can be described as self organization and feedback. In CoPS, the self organization and feedback is the fashion of state evolvement (which will be further analyzed in the next section). Self organization has two interpretations. One is that manufacturing units can make self-selection from the diversity. The other is the alternation of interaction networks. If we understand the core idea of self organization and feedback, one can easily understand the thirst for digital production and intelligent manufacturing.

The external perturbations from production environment are nonlinear, and this kind of nonlinearity exists simultaneously in the inner mapping relationship of the manufacturing entity. The external and the inner nonlinearity are the basic reason of unexpected behavior of the manufacturing entity. In other words, the nonlinearity is the key power source of CoPS emergence. The CoPS obviously cannot be a deterministic and static system that is constructed as a linear combination of production units. The nonlinearity determines the dynamic behavior of the CoPS that could be reflected in different expression, such as the fluctuating profit (far beyond the initial investment), the exponential growth of system efficiency (far beyond the increase of communication speed), the rich content of cloud manufacturing (far beyond the content of cloud computing) etc.

CoPS entity aggregates, self organizes, responds dynamically to the flows and evolves. If the entity fails to adapt to the change, then system collapse happens. If the entity succeeds to evolve towards another manufacturing steady state, unexpected functionalities are then generated and surprising manufacturing capability emerge. If CoPS is constructed following the conditions of CAS, this kind of CoPS will be a nonlinear dynamical system that has clear production objectives (corresponding to constraint), collaborative manufacturing mode (corresponding to aggregate), varied production units and schemes (corresponding to diversity), multilayer structure (corresponding to tag), updated subsytems (corresponding to self organization), fast response speed (corresponding to flow and feedback).

This phenomenon can be described by the emergence of CoPS and the proposition is given as follows:

Emergence of integrated CoPS refers to the response ability to emerge extraordinary performance which is not possessed by the simple superposition of its components. Once the manufacturing entity is restored to a single subsystem, this response ability no longer exists.

The existence of emergence phenomenon points out that what the production system possess is not equal to the linear sum of what the compositions possesses. A deduction can be made that the complexity of an entity should not be equal to the linear sum of the complexity of its parts. In other words, the dynamical complexity of CoPS could emerge.

**B. STATE EMERGENCE MECHANISMS**

Based on the above analysis, it has been verified that the CoPS have the requisite conditions to emerge. The interaction process and state emerging process is needed to be further...
explained. Figure 3 is a model simplification of how the manufacturing units interact with each other. Model explanation is as follows: manufacturing unit A is tagged based on the basic manufacturing functionality and selectively percept the manufacturing environment oriented a manufacturing objective. When A percept the flow from the environment, A must make contribution to respond it. What A possess is limited, which will result in A’ state variation and the delivery of the processing information to Manufacturing cell B. Model B carries different attributes and will work under the same procedure. Inspirations generated by B will be organized and feed back to A. This kind of state propagation process can be further interpreted by formal languages for semantic representation proposed by Aumann [50].

Let the complete space of the manufacturing system be $\Omega$ whose members represent all states of the manufacturing performance. Then function $k_i$ and $\tilde{k}_i$ on $\Omega$ could be defined as the performance reserve function. $k_i(\omega)$ represents manufacturing capability possessed by participating individual (the manufacturing cell) i when a manufacturing event is $\omega$. A reasonable way to explain $k_i(\omega)$ is as a signal on that $i$ can perceive the manufacturing environment when manufacturing events start. $\tilde{k}_i(\omega)$ represents manufacturing capability not possessed by $i$ and is as a signal on that $i$ cannot perceive the manufacturing environment when manufacturing events start.

The manufacturing capability function $I$ is defined in $\Omega$ as

$$I(\omega) := \{ \omega' \in \Omega : k(\omega') = k(\omega) \}$$

$I(\omega)$ is the set of all those states that $i$ cannot distinguish from $\omega$. $I(\omega)$ shows that in a real manufacturing event, the manufacturing performance reserve function only contains the capability that can serve part of the demands of $\omega$. In other words, what each manufacturing cell can describe is just one state (or some states) of $\omega$ belonging to $k_i(\omega)$. $I(\omega)$ is a cut set of performance on $\omega$ and consists of those capabilities that $i$ consider possible.

Corresponding to the hierarchy of the manufacturing system, the manufacturing capability model also has a multilayer structure. As the degree of unit interaction continues to increase, the level of capability continues to advance. As shown in Figure 4, each cells’ capability can be divided into three parts, $k_i(\omega), \tilde{k}_i(\omega)$ and $I(\omega)$. $k_i(\omega)$ is the set of capability that $i$ knows that it possesses. $\tilde{k}_i(\omega)$ is the set of capability that $i$ knows that $i$ does not possess. $I(\omega)$ is the set of capability that $i$ need to be mined, and can be divided into a multilayer structure, where $h^m_i$ represent the $m$ layer of $I(\omega)$ in $i$.

Considering a manufacturing event $\omega$ consisting of two production cells, $i$ and $j$. As shown in Figure 5, at the initial state, there are three partitions of $\omega$’s capability area, including Low capability area (LCA), potential capability area (PCA), high capability area (HCA). Capability area refers to the range covered by the capability of members in $\omega$. $i$’s LCA refers to the demand that $i$ fail to cover, while HCA refers to the demand that $i$ is expected to satisfy and PCA refers to the area $i$ need to be stimulated. The potential capability needs to be mined by interacting with $j$. In the interaction relationship, the multilayer capability is supposed to be established in the multilayer state space $\varphi^1 \times \varphi^2 \times \cdots$, where $\varphi^m$ is the state space of the layer $h^m_i$. $h^{m-1}_i$ is the mapping of $h^m_i$ in $\varphi^{m-1}$. That is, the capability of $i$ in one layer depends upon the capability in the previous layer. Once the interaction starts, in the layer $k_i(\omega)$, $i$ can enrich its own capability through the HCA of $j$, renewing and evolving its PCA to $h^1_j$. $j$ evolves to $h^1_j$ in the same procedure. This mutual stimuli process happens at each layer at $h^2$, then $h^3$, then $h^4$...
Finally, based on the existing capability hierarchy \((h^1, h^2, \ldots, h^n)\), a new layer \(h^{n+1}\) will emerge in the LCA. In the case of interaction, a network of interactive manufacturing capability flow is formed, as shown in the schematic diagram Figure 6. Each square represents manufacturing units at different levels of practice and operation of different fields. The horizontal axis represents the same operational layer and the units will have similar views, information and specific technologies. There will be channels of capability generation and dissemination between them, which lead to the growing of PCA and the decreasing of LCA. The vertical axis refers to the units in the same field. They share same operating goals and similar practical manufacturing experience with tacit understanding. There also exist channels of capability which lead to the growing of both PCA and HCA. The LCA is reducing while the HCA and PCA is expanding. This kind of manufacturing expansion goes beyond the linear sum of units’ manufacturing capabilities, which is the essence of the emergence of manufacturing system.

III. EMERGENCE-BASED EVALUATION OF MANUFACTURING COMPLEXITY

We now know that: (i) The manufacturing system can emerge if satisfying the necessary conditions of the complex adaptive system. (ii) If there exists channels of capability within the system, then the complexity of CoPS should emerge. (iii) The emergence could be interpreted by the concept of state space. (iv) Existing measurement of complexity cannot reflect the dynamical nature of manufacturing system. A novel method to quantify this emergence-based complexity of manufacturing system will be shown in this section.

A. EMERGENCE-BASED MODEL OF COMPLEXITY

The complex integrated manufacturing entity can be regarded as a kind of basic units connected by various physical and logical processes. As shown in Figure 7, if an integrated CoPS is divided into several independent subsystems \(S_1, S_2, S_3, \ldots\), then the interaction between these basic units actually constitutes a interaction network structure. The meaning of each unit can represent both physical nature and concept nature, which depends on in what aspects a framework designer want to describe the manufacturing system.

Under the influence of constraint, each unit’s state starts to change over time. The deviation of the system’s complexity can be interpreted as the inner respond to the external environment.

Considering one unit, take \(S_m\) as an example, the original state of complexity at time point \(k\) and the emergence state of complexity at time point \(k+1\) can be written as \(S_m(k)\) and \(S_m(k+1)\) respectively. Here, we assume that within two stable states, the changing speed remains approximately \(\lambda\) that is equivalent to the level of the unit’s complexity. The state change of a continuous production system can be further expressed by the differential equation.

\[
\dot{x} = \lambda_m x_m
\]  
(2)

The emerging state of integrated manufacturing system can then be described with Eq. 3

\[
\dot{X} = f(X, \Lambda, P, u, t)^T
\]  
(3)

or

\[
\dot{X} = \Theta(\Lambda, P)X + u
\]  
(4)

where \(X = (x_1, x_2, x_3, \ldots, x_n)\) is the state of \(S_1, S_2, S_3, \ldots, S_n\), \(\Lambda = (\lambda_1, \ldots, \lambda_n)\) is complexity coefficient representing the unit’s level of complexity, \(P = (p_{12}, \ldots, p_{ij}, \ldots, p_{mn})\) is the interaction probability within the interval \((0,1)\), representing the level of interaction between two units if there exists interaction channel between them. \(u\) is the input representing the input of flow. \((x_1, x_2, x_3, \ldots, x_n)\) satisfies the following conditions mathematically:

1) Minimality. \(n\) is the minimum value that can completely explain the capability of the manufacturing system. Reducing
the number of $S$ and $x$ will compromise the integrity of the manufacturing system, while adding the number of $S$ and $x$ will not endow more meaning on the target system.

2) Non-uniqueness. $(x_1, x_2, x_3, \cdots, x_n)$ is not the only expression of the response capability. One manufacturing system can be interpreted in different ways and the meaning of $(S_1, S_2, S_3, \cdots, S_n)$ is changing at the same time.

3) Dynamics. For a definite moment, $(x_1, x_2, x_3, \cdots, x_n)$ is a point in $n$-dimensional space. For the evolved process, $(x_1, x_2, x_3, \cdots, x_n)$ is a trajectory. Dynamics is the basis that differential equation can be used to model the emerging state.

$\Theta$ is defined as the interaction complexity matrix. Each column of $\Theta$ contains all the correlated influence factors corresponding to the complexity of each component. The geometric mean of all non-zero elements in each column is defined as the component complexity, given as

$$C_{inj} = f(\Theta(\ast, j)) = \sqrt[n]{\prod_{i=1}^{n} \Theta(i, j) \Theta(i, j) \neq 0} \quad (5)$$

where $k$ is the number of non-zero elements. The interaction based complexity index $C_{inb}$ is introduced to capture the interacted relationship of system’s inner complexity, shown as

$$C_{inb} = \sum_{j=1}^{n} C_{inj} \log_2 (C_{inj} + 1) \quad (6)$$

Each independent unit has the perception of interaction expressed by Eq.5. $\lambda_j$ can show different manifestations of complexity in each unit. These influence factors form a multi-dimensional space that is shown as the radar chart (take six factors as an example) in Figure 8.

The center of the space is the origin denoting to the lowest complexity while the end of the space is one hundred percent denoting to the highest complexity. In general, $\lambda_j$ is treated as the spatial distance of the space can be calculated by

$$\lambda_j = \sqrt{\sum m_i^2} \quad (7)$$

where $m_i$ is the complexity level of each influence factors.

The interaction probability is used to describe the probability of which the current complexity can map to the next level. In general, the interaction probability $p$ could be evaluated by a multi-tier ranking method where low to high correspond to the level of the correlation coefficient variation 0 to 1.

The methodology to calculate the $C_{inb}$ is as follows:

1) Decompose the target manufacturing system into several independent units.
2) Judge the relationship between two units and establish the interacted structure model.
3) Evaluate the interaction probability $p$.
4) Determine the complexity level $m_i$ for each member.
5) Calculate each complexity coefficient $\lambda$ based on Eq. 7.
6) Establish interaction differential equations and get the interaction complexity matrix $\Theta$.

7) Determine the component complexity $C_{inj}$ based on Eq. 5.
8) Calculate the emergence-based complexity $C_{inb}$ based on Eq. 6.

The layout of manufacturing units is diversiform. Without loss of generality, three different structures of classic CoPS are taken as example in order to illustrate the calculation method of interaction based complexity, shown in Figure 9.

Structure a is a classic assembly manufacturing system and as shown in Figure 10(a), the emerging state can be represented by Eq. 8.

$$\dot{x} = \Theta p x + u = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 & 0 \\ p_1 \lambda_2 & \lambda_2 & \cdots & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_{n-1} & 0 \\ 0 & 0 & \cdots & p_{n-1,n} \lambda_n & \lambda_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{bmatrix} + u$$

(8)
Structure b is a cellular manufacturing system and there is no interaction between the units. As shown in Figure 10(b), the emerging state can be represented by Eq. 9.

\[
\dot{x} = \Theta u x + u = \begin{bmatrix}
\lambda_1 & 0 & \cdots & 0 & 0 \\
0 & \lambda_2 & \cdots & 0 & 0 \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
0 & \cdots & \lambda_{n-1} & 0 & \lambda_n \\
0 & \cdots & 0 & \lambda_n & \lambda_n
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
\vdots \\
x_{n-1} \\
x_n
\end{bmatrix} + u
\] (9)

Structure c is a hybrid system and as shown in Figure 10(c), the emerging state can be represented by Eq. 10, as shown at the bottom of this page.

Suppose \( n = 4, k = 2 \). The calculated result is shown as (11), as shown at the bottom of the next page.

**B. APPLICATION OF THE PROPOSED METHOD**

Considering the turbine housing production process, the turbine housing, shown in Figure 11 and Figure 12, is made of heat-resistant steel. The turbine shell has a complicated tapering spiral structure integrating the intake and exhaust shell and nozzle ring. For production complexity, the main factors includes Threaded hole, Mating hole, Through hole, Flow surface, Outer contour surface, Mounting surface. The machining process is divided into phases as follows: blank machining performs in advance for flow surface. Once the blank machining operations are finished, rough milling and milling for mounting surface take place. Then, the work piece is sent to be drilled for both mating hole and through hole. Then the tapping machining performs for thread hole. Deburring and polishing process is the last operation for outer contour surface. The complexity relationship is shown in Figure 13.

The complexity level of each influence factors is evaluated as shown in Table 1, then complexity coefficient matrix \( \Theta \) could be gotten as Eq. 12. \( \lambda_1 \) is 1.5588 for flow surface, \( \lambda_2 \) is 1.3379 for Mounting surface, \( \lambda_3 \) is 1.6583 for Mating hole, \( \lambda_4 \) is 0.8521 for through hole, \( \lambda_5 \) is 1.1491 for threaded hole, \( \lambda_6 \) is 0.7228 for outer contour surface. In this case, the interaction probability \( p \) for each is set to 1.

\[
\Theta = \begin{bmatrix}
\lambda_1 & 0 & 0 & 0 & 0 \\
\lambda_2 & \lambda_2 & 0 & 0 & 0 \\
0 & \lambda_3 & \lambda_3 & 0 & 0 \\
0 & \lambda_4 & 0 & \lambda_4 & 0 \\
0 & 0 & \lambda_5 & \lambda_5 & \lambda_5 \\
0 & 0 & 0 & \lambda_6 & \lambda_6
\end{bmatrix}
\] (12)

Then the component complexity \( C_{un} \) can be calculated as follows: \( C_{un_1} = \sqrt{\lambda_1 \lambda_2} = 1.4441, C_{un_2} = \sqrt{\lambda_2 \lambda_3 \lambda_4} = \)
In another case, the factories want to upgrade the design of turbine housing to satisfy the demand of new turbine equipment. There are two processing schemes: (1) Milling twenty thread hole with higher requirement of accuracy (increase the complexity $C_{inb}$).

Finally, the emergence-based complexity $C_{inb}$ in this case is 7.4259.

$$C_{inb} = \begin{cases} 
\lambda_1 \log(\lambda_1 + 1) + \lambda_2 \log(\lambda_2 + 1) + \lambda_3 \log(\lambda_3 + 1) + \lambda_4 \log(\lambda_4 + 1) \\
\sqrt{p_{12} \lambda_1 \lambda_2 \log(\sqrt{p_{12}} \lambda_1 \lambda_2 + 1)} + \sqrt{p_{23} \lambda_2 \lambda_3 \lambda_4 \log(\sqrt{p_{23}} \lambda_2 \lambda_3 \lambda_4 + 1)} + \lambda_3 \log(\lambda_3 + 1) + \lambda_4 \log(\lambda_4 + 1) \\
\sqrt{p_{12} \lambda_1 \lambda_2 \log(\sqrt{p_{12}} \lambda_1 \lambda_2 + 1)} + \sqrt{p_{23} \lambda_2 \lambda_3 \lambda_4 \log(\sqrt{p_{23}} \lambda_2 \lambda_3 \lambda_4 + 1)} + \lambda_3 \log(\lambda_3 + 1) + \lambda_4 \log(\lambda_4 + 1) 
\end{cases}$$

(11)
complexity coefficients of geometric tolerance and surface roughness to one). (2) Improve the processing quality of flow surface and mounting surface (increase the complexity coefficients of nominal dimensions, dimensional tolerance and geometric tolerance to one). As shown in Table 2, we could get that $C_{inb}$ is 8.8991 for the first scheme and the complexity increases by 19.84%, while $C_{inb}$ is 9.2973 for the second scheme and the complexity increases by 25.20%. In order to get the lowest production complexity, the scheme one is better.

IV. DISCUSSIONS

In this section, the influence of individual complexity on the system entity will be further discussed by the proposed method.
In a general case, a CoPS consists of four units in three different structures (structure a, b, c mentioned in section 4.1). Each unit possesses nine factors and interacts with other units in probability $p$. In structure b, $p_{12}$ is set to 0.2, $p_{23}$ is set to 0.5, $p_{34}$ is set to 1. In structure c, $p_{12}$ is set to 1, $p_{23}$ is set to 0.5, $p_{34}$ is set to 1. The range of $\lambda$ is $[1/4, 3]$. In order to show the effect of different units on system complexity, let one unit’s $\lambda$ vary while the others remain 1. Figure 14 shows the variation of system complexity. A conclusion can be made as follows: if a production process is in the form of structure a, the complexity variation of the operation in each step has the same influence on the system level complexity. If the production is in the form of structure b, the sequence of operation is directly related to the variation of system complexity, the state change of low priority steps could has much more influence on the system complexity that of higher priority. The interaction level contributes to the degree of complexity variation too. If the production is in the form of structure c, the variation can be treated as a coupled effect of structure a and b, and it is noticed that the influence of $p_{23}$ and $p_{34}$ could be considered as one coefficient.

V. CONCLUSION

Integration make the contemporary manufacturing system emerge. This paper provides a better understanding on the inherent dynamics of CoPS. CAS theory is used to analyze the emergence mechanism. An emergence-based method is proposed to measure the potential emerging complexity. The main contributions can be summarized as follows:

(i) The emergence mechanism of complex product system is analyzed based on CAS theory. A conceptual model is presented to interpret the generation process and condition of emergence. Three generation effects are obtained as the basic conditions of CoPS emergence, including environment effect, structure effect and composition effect. The inner interaction process is studied based on representative factors including aggregation, diversity, tag mechanism, flows, nonlinearity, constraints, self organization and feedback.

(ii) The mechanism of inner state emergence in CoPS is interpreted by formal languages for semantic representation to introduce the concept of state space. A multi-layer manufacturing capability model is established to show the mechanism of state emergence.

(iii) A emergence-based complexity measurement is presented to evaluate the dynamical propagation of complexity. The feasibility and application of the novel complexity measurement is verified by an example of turbine housing production process.

(iv) Three different structures of CoPS is studied based on the proposed method. Further discussion is made on how to manage the potential emerging complexity.

This paper has sketched an outline for clarifying the emergence essence of an integrated manufacturing system. Our contributions could provide novel perspectives and solid theoretical background for managers to treat manufacturing system as complex and dynamical system. Further theoretical work is needed to tighten the framework. The ultimate goal is to minimize the manufacturing complexity, decrease the associated cost and increase production autonomy.

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