A Bigdata-inspired Chaotic Solution for Fuzzy Feedback Linearization Model in Cyber-Physical Systems

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Abstract

Cyber-Physical System (CPS) that integrated computational and physical capabilities has emerged as a promising topic. It interacts with physical world and humans through ad hoc communications. In contemporary, with the fast development of CPS theory and applications, CPS generates a large volume of data, which may lead its control into a chaotic status. Hence, it is an impressing demand to solve the chaotic status CPS control. To this end, chaotic time series prediction algorithm are employed to resolve the chaotic status featured by a fuzzy feedback linearization model. Modelling the CPS under big data without taking chaotic features into account may result in an unexpected results. This is because chaotic CPS is dramatically sensitive to small disturbances or minor changes of initiators. This paper developed a CPS model in light of fuzzy feedback linearization. Further, the chaotic time prediction algorithm is applied to solve the chaotic control problem in CPS. The developed algorithm takes both tracking control problem and synchronization control problem into account. The numerical results suggest that the developed method is feasible and efficient in tracking control problem and synchronize two chaotic CPS.

Keywords:

big data processing, cyber-physical system, fuzzy feedback linearization, chaotic time series prediction

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1. Introduction

Cyber-physical system (CPS) plays an important role in human's daily life. It rapidly expanding in all science and engineering domains, including distributed energy systems, transportation systems and healthcare monitoring systems [1]. Intelligent transportation systems, smart power grids, smart homes with network of appliances, are examples of CPS applications.

CPS is an integration of computation with physical system and physical process. It is recognized as a hybrid system that contains continuous dynamic physical process and discrete computing process. It includes physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by *control, computation and communication* (3C) [2]. In contemporary, it has attracted significant research effort. A number of logical mathematical models in the open literature have been proposed and developed since it emerged. A hybrid automata fuzzy control model based on automatic verification of real-time indicator of the finite state machine. Their work has been applied on the representation of the traditional CPS with the solution of the differential and difference equation [3]. However, their work may lead unexpected results when taking chaotic status into account. This is because the method is extremely sensitive to initial conditions [4]. Hence, it is not hard to see that chaotic CPS can not be effectively modeled by the hybrid automata model.

Chaos theory studies the behavior of dynamical systems that are highly sensitive to initial conditions, such as a famous effect that is referred to as the butterfly effect [5]. Small differences in initial conditions, such as those due to rounding errors in numerical computation, yield widely diverging outcomes, rendering long-term prediction impossible in general [6]. In chaos studies, tracking problem, which obtains reference signal by applying control signal, and synchronization problem, which two chaos systems with different initial conditions gradually reach one consistent trajectory, are two crucial issues [7]. In order to solve tracking and synchronization problems, a *chaotic time series prediction* (CTSP) algorithm based on numerical techniques has been proposed. This algorithm can convincingly distinguish low-dimensional chaos from randomness, and make statistical long-term predictions. For the aforementioned reasons, the CTSP theory can be ushered into the modeling of chaotic CPS. In addition, the development and evolution of CPS not only depend on the response of discrete transient events, but also relate to the response of the dynamic behavior represented by differential and difference

equation [8], [9]. It is ready to see that the process may lead to chaotic status. Thus, it is critical to solve the chaotic status in order to avoid deadlocks or unexpected results.

To the best of our knowledge, it is hardly to find an analytical model to feature the chaotic CPS by integrating the CTSP theory into a *fuzzy feedback linearization model* (FFLM). The developed model can be applied on the analysis of both traditional and chaotic CPS.

Apart from the aforementioned, chaotic systems are very sensitive to noises and their dynamic evolution possibly deviates far from the expected trajectory even though they are perturbed by a small noise [10], [11], and the traditional FFLM did not take into account that the differential and difference equation can be chaotic if it is extremely sensitive to initial conditions. Therefore, we have introduced the CTSP theory into the traditional FFLM to adapt new characteristics brought by chaos. In order to design experiments to verify the validity of the proposed model for chaotic CPS, the first leg of this work is to figure out the features which are able to characterize chaotic system.

Existing studies suggest strange attractor, which is a disorder stable motion modality with complicated stretch and twisty structure, can be a critical feature [12]. However, many different types of attractors co-exist in the phase space [13]. Hence, it is necessary to prove what kind of particular CPS can be chaotic. Unfortunately, there is seemingly total randomness in chaotic processes, even though the chaotic system is indeed deterministic. This fact makes it difficult to distinguish chaotic evolutions from stochastic processes [14]. It is not hard to see the most convenient method to verify the potential existence of chaotic CPS is to examine whether there exists stranger attractors in systems or not. Next, we verify the validity of the developed model for chaotic CPS by solving tracking and synchronization problems. These two problems are crucial issues with regard to the chaotic theory. Last but not least, we have compared the results with the traditional FFLM with the developed model in this paper to demonstrate the improvement in performance.

This work has examined the chaos under CPS and finds there exists strange attractors who control the movement of system's output, which indicates that it is chaotic. Furthermore, results have demonstrated that the proposed model can stabilize a fixed point of tracking control problem in 0.07s, and synchronize two chaotic CPS in 0.25s. Otherwise, the traditional FFLM is not feasible to solve these two problems. One plausible reason for

these observations is that the details are required for the traditional model, however, it is impossible when this is chaotic. As for the proposed model, after chaotic time sequence prediction method is introduced, it can benefit from both the closed loop stability and the chaos control ability, which makes this model suitable for chaotic CPS.

2. Related Work

CPS has been brought to us recently. It is a promising but immature theoretical system. In open literature, research works characterized CPS features by developing CPS models. Unfortunately, most of existing works on modeling CPS are based on conventional fuzzy control theories. For instance, in [15], it has proposed an event-driven monitoring framework for CPS based on the hybrid automata formalism using an FFLM . The framework combines model-based design and formal analysis, aiming at monitoring the status in the system development stage. It is worth noting that modelling the continuous behavior of a CPS using an ordinary differential equation is difficult. This is because it may include unknown or unpredictable variables. Zhang et al developed a hybrid neural network and fuzzy control for automatic generation control in power systems [16]. In their work, recurrent neural network is employed to forecast control and future output of the system based on the current *area control error* (ACE) and the predicted change-of-ACE. It is not hard to see the dynamic quality of a CPS can be improved by adapting control performance standard to the fuzzy controller design. Zhang’s work reveals that the system with hybrid fuzzy neural controller enhances a better stability than that of non hybrid fuzzy neural controller.

Apart from the popularity of CPS, a large volume of data generated by itself may throw the system into chaos. Recently, how to solve chaotic CPS has drawn much attention. For this reason, chaotic time sequence prediction theory has been widely applied to chaos control. Misir et al has studied a new methodology employing chaotic time series to model chemical sensor observations in embedded phase space[17]. This method adopted a long-term prediction of sensor baseline and drift based on *phase space reconstruction* (PSR) and *radial basis function* (RBF) neural network. PSR can record all of the properties of a chaotic attractor and clearly show the motion trace of a time series. Thus PSR becomes an enabler of the long-term drift prediction using RBF neural network. The numerical results demonstrate that the proposed model can make long-term and accurate prediction of chemical

sensor baseline and drift time series. Chen et al proposed a new multivariate radial basis functions neural network model to predict the complex chaotic time series[18]. The mutual information method and false nearest-neighbor method have been applied to obtain the time delay and embedding dimension, respectively. Then the method is expanded into the multivariate situation.

As aforementioned, researchers either developed analytical models of CPS or proposed methods of solving chaos itself. However, with the increment of data volume, CPS may fall into chaotic status. To the best of our knowledge, there is hardly an analytical model for solving chaotic CPS. In addition, traditional models of CPS are not able to capture the features when CPS are chaotic. To this end, a novel method of modeling chaotic CPS based on FFLM has been developed in this paper in order to fit the new characteristics of chaotic CPS. Moreover, the developed model is able to stabilize a fixed point in tracking control problem, and synchronize two chaotic CPS, due to the benefit from both the closed loop stability and the chaos control ability.

3. Modelling of the Chaotic CPS

3.1. Universal Abstract Model

Follow the standards of 3C, the term *entity* is employed to demonstrate data organization and encapsulation. Consequently, a basic CPS model can be abstracted with three primary entities: *cyber entity* (CE), *interactive entity* (IE), and *physical entity* (PE). CE represents the computation domain of CPS. It plays the role of a computational unit. A collection of CEs construct a computation platform, such as clouds. PE represents definition of sensors & control unit, the data stream of control, event, message, etc. This is because the physical worlds cannot be entirely modelled, however, their phenomena can be detected by tools and applications, e.g., sensors. Between CE and PE, IE carries communication protocols and capacities, interface definition & feature to CE and PE. There are *connections* between the different types of entities, which is shown in the Figure 1.

According to our model, connection is described with two modes: causal connection and non-causal connection. Causal connection presents data flow that has specific direction, while non-causal connection means data flow inside connection is bi-directional. Each entity is consisted of *input*, *output*, *data*, and *operations*. Thus, the definition of an entity can be readily given by:

Figure 1: The abstract model of CPS with entities.

Definition 1. $Entity = (Input, Output, Init, Type)$

$Input$ describes the set of input values, $Output$ describes the set of output values, $Init$ represents the initial state, and $Type$ represents a kind of entity type: CE, IE or PE.

Then, $Connection$ is defined as,

Definition 2. $Connection = (Input, Output, S, S_0, E, Act)$

Also, $Input$ and $Output$ represent the Input or Output values, S represents the state set, S_0 represents the initial state.

The term E represents the transition across two entities. It is consisted of three tuples $(S_i, Guard, S_{i+1})$, where $Guard$ represents a threshold value to guarantee the safety of a transition. The term Act maps on each state S with differential algebraic equations Fs , which represents the relationships of the system continuous state variable x , the state variable differential $\dot{x}$ and continuous variable w ,

$$F_s(x, \dot{x}, w) = 0 \quad (1)$$

The connection state is a binary pair $s = (q, x)$. $q \in Q$ is a discrete state to meet the position invariant $Inv(q)$, and x is a continuous variable value vector. Given two state $s1 = (q1, x1)$ and $s2 = (q2, x2)$, if there is a transition $e \in E : q1 \rightarrow q2$, then the values of $x1, x2$ must meet the Guard conditions

or reset conditions. Tuples $(s1, s2)$ is defined as a *jump* behavior to fulfill a transition, and state $s2$ is jump successor of the state $s1$. $\sigma = (s0, s1, s2...)$ is defined as the trajectory of the connection.

- Arbitrary $s1$ is legal state.
- Arbitrary tuple (s_i, s_{i+1}) is a jump.

Given two connections, $Con_1 = (I_1, O_1, Init_1, S_1, E_1, Act_1)$ and $Con_2 = (I_2, O_2, Init_2, S_2, E_2, Act_2)$, the composition of two connections is $Con = (I, O, Init, S, E, Act)$. The composition of $Con_1, Con_2, \dots, Con_m, (m > 2)$ is the synthesis of composite connections.

$$Con = Con_1 \parallel Con_2 \parallel \dots \parallel Con_m \quad (2)$$

3.2. Utilization of Fuzzy Feedback Linearization Models

Bogdan et al has proved that the FFLM is capable of modeling traditional CPS[16]. However, because chaotic systems are extremely sensitive to even tiny disturbance signals, hence the feedback signals in this model would possibly lead to an irredeemable disaster: the systems' dynamic evolutions deviate far from the expected trajectory, which means this traditional model is impossible to stable CPS when they are chaotic. Furthermore, the tracking and synchronization problems can be solved by a CTSP algorithm. Especially, chaos control has been used in power grid. For example, Sprott chaos synchronization-based voltage[19] relays for fault protection is used as a voltage detector to track the dynamic errors between the normal signal and disturbance signals in micro distribution systems.

The schematic diagram of the FFLM-CTSP is shown in Figure 2. There are both *cyber components signal* (CCS) and *physical components signal* (PCS) in the CPS. PCS belongs to analog signal. AD Converter is needed for transforming analog signal into digital signal. Hybrid Automata is used to combine this digital signal with CCS. At the Inner Level, a chaos examination module is applied to examine whether this system is chaotic. If it is, it can be controlled by a CTSP controller. At the Outer Level, a controller for FFLM is used to gradually reduce the steady-error until the difference between the obtained signal and the standard signal agrees with the configured tolerable-error. Following this procedure, we have designed an FFLM-CTSP algorithm as shown in the Algorithm 1.

Figure 2: The schematic diagram of the FFLM-CTSP algorithm.

Algorithm 1 Procedure of the developed model for chaotic CPS.

Input: C_{in} : Cyber Components Signal,

P_{in} : Physical Components Signal

Output: DS : Desired Output Signal

- 1: Initialize C_{in} and P_{in}
  - 2: **repeat**
  - 3: $P_{in} \xrightarrow{ADC} P'_{in}$
  - 4: $C_{in} + P'_{in} \xrightarrow{Hybrid\ Automata} \text{Mixed Signal (MS)}$
  - 5:   **if** MS is chaotic **then**
  - 6:   **repeat**
  - 7:   control chaos using Chaotic Time Series Prediction Controller
  - 8:   **until** chaos controlled
  - 9:   **end if**
  - 10:   **if** $MS \cong \text{Standard Signal}$ **then**
  - 11:   **return** MS
  - 12:   **else**
  - 13:   using Fuzzy Feedback Linearization Controller
  - 14:   **end if**
  - 15: **until** $MS \cong \text{Standard Signal}$
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4. Numerical Results

We have applied the developed model to smart grid as a typical CPS. Smart grid is primarily composed of central power plant, boosting transformer, high voltage transmission line, step-down transformer and industrial plants. In order to verify the performance of the developed FFLM-CTSP

algorithm, we have designed and implemented a simulation platform based on a field test of CPS. Hence, we configure a chaotic CPS with product inference engine, singleton fuzzifier, centers' average defuzzifier, and Gaussian membership function by Equation 3 :

$$f(x) = \frac{\sum_{i=1}^M \bar{y}^l \left[\prod_{i=1}^n \exp\left(-\left(\frac{x_i - \bar{x}_i^l}{\bar{\sigma}_i^l}\right)^2\right) \right]}{\sum_{i=1}^M \left[\prod_{i=1}^n \exp\left(-\left(\frac{x_i - \bar{x}_i^l}{\bar{\sigma}_i^l}\right)^2\right) \right]} \quad (3)$$

Where $\bar{y}^l, \bar{x}_i^l, \bar{\sigma}_i^l$ are free parameters that refer to the mean of output membership functions, mean of input membership function and variance of input membership functions. M is the number of rules that is a constant value during update. N is the number of inputs that should be determined in advance, which equals to our system dimension. Consequently, now designing the chaotic CPS is equivalent to determining the parameters $\bar{y}^l, \bar{x}_i^l, \bar{\sigma}_i^l$. Furthermore, the desired model for chaotic CPS can be obtained by choosing adequate membership functions for inputs and rules defined in the model. A system can be determined as chaotic if it meets two or more conditions:

- (1) sensitive dependence on initial condition and noise;
- (2) fractal dimension is larger than 1;
- (3) Lyapunov exponents is larger than 0;
- (4) having broadband spectrum;

In our work, the chaos in CPS is spotted by detecting fractal dimension and Lyapunov exponents, because fractal dimension can be obtained directly, and Lyapunov exponents is able to improve the accuracy of the diagnosis.

4.1. Tracking Control Problem

Tracking control problem forces one or more parameters of a chaotic system to follow the given reference target in light of asserting appropriate control. The ultimate goal of tracking control is chaos suppression. A sustained transient through tracking a system parameter is substantially varied. Thereby it allows sustained chaotic transients away from the crisis parameter values.

In this work, the goal is to target points near a chaotic transient once the iterates reach a neighborhood of an undesired attractor using the developed

FFLM-CTSP algorithm. Hence, the natural dynamics of the system would not engage again the iterations and chaotic motion.

As mentioned above, the details of chaos systems may not be available in some cases. We demonstrate with one experiment that the developed model is capable of tracking control problem, even not all of the details are provided. Consider $x_r = 0.15 + 2.5\sin(\alpha\pi t)$, where $\alpha \in (1.5, 2.5)$ for all states, note that α is the parameter unknown.

Figure 3: Comparison of fractional dimension between traditional hybrid automata model and the proposed FFLM for chaotic CPS

The status curves of CPS is shown in the Figure 3. It demonstrates that before the controller is applied, both models are chaotic because fractal dimension is larger than 1 and Lyapunov exponents is larger than 0. However, after the controller is applied, a substantial performance gap becomes apparent when the controller is applied: even though there is one parameter unknown in the given system, the proposed model is still able to depress chaotic response by tracking this unknown parameter using the FFLM. The developed model can control the chaotic CPS to implement chaos suppression, even though there is one unknown parameter α , and the steady state error coefficient falls within 0.73%. And the transient response time of this model is less than 50ms. These observations emphasize that FFLM-CTSP algorithm is capable of chaos compression, proved by the fact that fractal dimension is smaller than 1 and Lyapunov exponents is smaller than 0. Contrarily, the previous hybrid automata model is undesired in chaotic CPS cases. This result adds weight to the conclusion that the proposed model can suppress chaos within minor steady error coefficient, and the transient response time is commendable.

(a) $t = 10s + 0ms$.

(b) $t = 10s + 10ms$.

(c) $t = 10s + 20ms$.

(d) $t = 10s + 30ms$.

(e) $t = 10s + 40ms$.

(f) $t = 10s + 50ms$.

Figure 4: Time domain response, phase diagram and X-Z phase plane in tracking control problem.

In the Figure 4, it illustrates time domain response, phase diagram and X-Z phase plane in tracking control problem. From the Figure 4(a), we can readily observe that this CPS is chaotic. From the Figure 4(b) and the Figure 4(c), it is obvious that the chaos of this system is being gradually suppressed. In the Figure 4(f), it once again suggests that the efficiency of the developed FFLM-CTSP algorithm on chaos compression. It is worth noting that the transient response time of this model is less than 50ms.

4.2. Synchronization Control Problem

Synchronization of chaos is a phenomenon that may occur when two, or more dissipative chaotic systems are coupled. Because of the exponential divergence of the nearby trajectories of chaotic system, having two chaotic systems evolving in synchrony might appear surprising. However, synchronization of coupled or driven chaotic oscillators is a phenomenon well established experimentally and reasonable well understood theoretically. Synchronization control problem is controlling two or more chaotic systems to reach synchronization state where trajectories of these systems are consistent.

By using the idea of tracking we can extend that for synchronization of two chaotic systems. The states of master system are the desired trajectory for slave one. The drive system is $\dot{x}_m = f_m(x_m, t)$ and the response system is $\dot{x}_s = f_s(x_s, t) + u(t)$, by choosing $x_r = x_m$ and the same control $u(t)$ we can extend the method for synchronization between two chaotic systems. To show the feasibility of the method, the synchronization between two isomerism CPS is simulated. We choose a system with $\alpha = 0.3$ and initial values of $x_{1m}(0) = 3, x_{2m} = 2, x_{3m} = 3$ as a drive system, and a Lorenz system with $\alpha = 0.1$ and initial conditions $x_{1s} = 1, x_{2s} = 0, x_{3s} = 1$ as a response system.

In this part, the goal is to synchronize the drive system and the response system described before, using the developed FFLM-CTSP algorithm.

As aforementioned in tracking control problem, the controller is added to plant to synchronize the response system with master one. Synchronization of two chaotic CPS is shown in Figure 5. Simulation results demonstrate that: the developed FFLM-CTSP algorithm can control two chaotic systems to implementing chaos synchronization, and the absolute error falls within 2.5×10^{-4} . Simulation results emphasize that the developed method is also effective and feasible for the synchronization.

As demonstrated, the developed FFLM-CTSP algorithm is highly effective to solve both tracking control problem and synchronization control problem, and this model does not depend on the precise model of the chaotic CPS,

Figure 5: The Lyapunov Exponent and absolute error in synchronization control problem.

which makes it very useful for chaotic systems as they are too sensitive to model parameters and other disturbances. Simulation results emphasize the proposed model's validity and real-time performance. From all above we can conclude that presented model can be used for different purposes and different systems.

5. Conclusion

A novel FFLM-CTSP algorithm for modeling chaotic CPS has been proposed in this paper. The motivation of this generalization is the fact that chaotic CPS is very sensitive to change in plant model parameters and even initial values such as hardware instantaneity and external disturbance, etc. Previously, hybrid automata based on the FFLM has been widely used for modeling traditional CPS, however, it is undesired if one CPS is potentially chaotic. Based on the fact that chaos theories have never been applied to CPS modeling area, the key idea of this paper is introducing CTSP algorithm into the traditional CPS model. Two aspects of chaotic CPS, tracking control problem and synchronization control problem are modeled to emphasize the validity of this method. Also, mathematical equations and simulations results show that the proposed model is feasible to stabilize a fixed point

in tracking control problem and synchronize two chaotic CPS. The developed model can control the chaotic CPS to implement a chaos suppression in tracking control problem, even though there is one unknown parameter α , and the steady state error coefficient falls within 0.73%. While the transient response time of this model is less than 50ms. As for synchronization control problem, the absolute error of the developed model falls within 2.5×10^{-4} . However, only simulation trials have been considered in our study, but furthermore field trials are needed to gain additional insight into the chaotic CPS.

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Reference

- [1] K. Kyoung-Dae, P. R. Kumar, Cyber-physical systems: A perspective at the centennial, Proceedings of the IEEE 100 (Special Centennial Issue) (2012) 1287–1308.
- [2] R. Rajkumar, L. Insup, S. Lui, J. Stankovic, Cyber-physical systems: The next computing revolution, in: 2010 47th ACM/IEEE Design Automation Conference (DAC), pp. 731–736.
- [3] T. Paul, J. W. Kimball, M. Zawodniok, T. P. Roth, B. McMillin, S. Chellappan, Unified invariants for cyber-physical switched system stability, IEEE Transactions on Smart Grid 5 (1) (2014) 112–120.
- [4] P. Kumar, D. Goswami, S. Chakraborty, A. Annaswamy, K. Lampka, L. Thiele, A hybrid approach to cyber-physical systems verification, in: Proceedings of the 49th ACM/EDAC/IEEE Design Automation Conference (DAC), 2012, pp. 688–696.
- [5] M. Farajallah, S. El Assad, M. Chetto, Dynamic adjustment of the chaos-based security in real-time energy harvesting sensors, in: Proceedings of the 2013 IEEE International Conference on Green Computing and Communications (GreenCom), and IEEE International Conference on Internet of Things (iThings/CPSCoM), 2013, pp. 282–289.

- [6] L.-X. Wang, Design and analysis of fuzzy identifiers of nonlinear dynamic systems, *IEEE Transactions on Automatic Control* 40 (1) (1995) 11–23.
- [7] H.-C. Iu, D. S. Yu, A. Fitch, V. Sreeram, H. Chen, Controlling chaos in a memristor based circuit using a twin-t notch filter, *IEEE Transactions on Circuits and Systems I: Regular Papers* 58 (6) (2011) 1337–1344.
- [8] R. Alur, C. Courcoubetis, N. Halbwachs, T. Henzinger, P.-H. Ho, X. Nicollin, A. Olivero, J. Sifakis, S. Yovine, The algorithmic analysis of hybrid systems, *Theoretical Computer Science* 138 (1) (1995) 3 – 34, hybrid Systems.
- [9] J. Sztipanovits, X. Koutsoukos, G. Karsai, N. Kottenstette, P. Antsaklis, V. Gupta, B. Goodwine, J. Baras, W. Shige, Toward a science of cyber-physical system integration, *Proceedings of the IEEE* 100 (1) (2012) 29–44.
- [10] J. Zhou, C. Wen, Y. Zhang, Adaptive output control of nonlinear systems with uncertain dead-zone nonlinearity, *IEEE Transactions on Automatic Control* 51 (3) (2006) 504–511.
- [11] H.-T. Yau, Design of adaptive sliding mode controller for chaos synchronization with uncertainties, *Chaos, Solitons & Fractals* 22 (2) (2004) 341 – 347.
- [12] A. El-Gohary, Chaos and optimal control of cancer self-remission and tumor system steady states, *Chaos, Solitons & Fractals* 37 (5) (2008) 1305 – 1316.
- [13] A. El-Gohary, Chaos and optimal control of equilibrium states of tumor system with drug, *Chaos, Solitons & Fractals* 41 (1) (2009) 425 – 435.
- [14] M. Erol-Kantarci, S. Oktug, L. Vieira, M. Gerla, Performance evaluation of distributed localization techniques for mobile underwater acoustic sensor networks, *Ad Hoc Networks* 9 (1) (2011) 61 – 72.
- [15] Z. Zhang, E. Eyisi, X. Koutsoukos, J. Porter, G. Karsai, J. Sztipanovits, A co-simulation framework for design of time-triggered automotive cyber physical systems, *Simulation Modelling Practice and Theory* 43 (0) (2014) 16–33.

- [16] P. Bogdan, S. Jain, K. Goyal, R. Marculescu, Implantable pacemakers control and optimization via fractional calculus approaches: A cyber-physical systems perspective, in: Proceedings of the 2012 IEEE/ACM Third International Conference on Cyber-Physical Systems, IEEE Computer Society, 2012, pp. 23–32.
- [17] D. Misir, H. A. Malki, G. Chen, Design and analysis of a fuzzy proportional-integral-derivative controller, Fuzzy sets and systems 79 (3) (1996) 297–314.
- [18] D. Chen, W. Han, Prediction of multivariate chaotic time series via radial basis function neural network, Complexity 18 (4) (2013) 55–66.
- [19] C.-H. Lin, S.-J. Chen, J.-L. Chen, C.-L. Kuo, Using sprott chaos synchronization-based voltage relays for protection of microdistribution systems against faults, IEEE Transactions on Power Delivery 28 (4) (2013) 2093–2102.