Time-efficient Pulse-Coupled Oscillators Based Synchronous Sensing for Demand Side Fault Source Localization in Cyber Physical Energy System

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***Abstract*—Synchronous measurement is very important in distributed power quality detection in cyber physical energy system applications, such as electrical power metering in building area network. On account of energy and communication capability limitation, the power safety supervision is challenging in large scale metering network while fault diagnosis demands high measurement and temporal synchronous accuracy. In addition, dynamic network management has been a general scenario in power information sensing networks, which introduces interruptions into network synchronization state. These require synchronization method to be time-efficient, accurate and scalable. There has been a wide variety of researches in synchronization methods for dynamic wireless networks, and pulse-coupled oscillators (PCO) has been a leading point for its fast synchronize rate and outstanding scalability. This paper depicts a cyber-physical energy system architecture for electrical power metering and, in order to raise the measuring reliability, proposes a time-efficient PCO synchronization method. We theoretically analysis the factors that have effect on PCO performance, then optimized the PCO dynamic model to improve the synchronize rate and verified it with simulation. Experiment results showed that the proposed model effectively reduces the time to reach synchronization without increase energy cost and complexity. And through applying the method in voltage sag fault localization, the effectiveness of PCO was certificated.**

Keywords*—*cyber physical energy system; time-efficient; pulse-coupled oscillators; dynamic sensing networks; demand side network safety

I. INTRODUCTION

ELECTRICAL information metering is widely employed in smart building management in demand side management for energy efficiency. With the increase of the scale and complexity of power supply network, traditional electrical metering systems no longer satisfy the real-time and accuracy requirements of online electrical analysis. The cyber-physical energy system (CPES) systematically synthesis the sensing, communication, computation and control processes and has been widely adopted in smart grid. Employing numbers of smart meters and intelligent sensors, CPES architecture effectively integrates and manages the energy, computing resources on demand [1]. Distributed sensing networks [2] offer a differential solution for the growing electrical metering.

As the scale and complexity of the electrical metering network increases, the supervisory of the electric safety has become more significant. Measuring reliability of power quality characters such as harmonics, voltage sags, flickers, etc. greatly interferes the fault diagnosis of electrical power network. As to improve the measuring reliability, synchronous metering is a matter of considerable importance in distributed dynamic sensing networks, and real-time requirements have been the most urgent and focused problems. In order to reach a higher fault diagnosis accuracy, electrical data is claimed to be measurement in the same temporal section. This requires measuring actions to be synchronized in time, otherwise, the data reliability will decrease thoroughly. Researches of the influence of synchronism on power network safety supervision has been carrying on [4], however, the growing measuring network has claimed more requirements and restrictions on synchronization method.

Numerous synchronization methods within distributed wireless sensing networks have been studied. Traditional solutions, such as TPSN (Timing-sync Protocol for Sensor Networks), RBS (Reference Broadcast time Synchronization), FTSP (Flooding Time Synchronization Protocol), Glossy, etc. [10]–[12] have been widely applied in wireless sensing networks. Nevertheless, conventional synchronization methods have limited scalability because they either divide the network into connected single-hop clusters or organize the whole network into a spanning tree, which is computationally challenging to construct for distributed large-scale networks.

In order to improve the time efficiency and scalability, Pulse-coupled Oscillators (PCO) method utilizes simple identical pulses to couple the sensing nodes within the communication range and to reach synchronization. PCO-based strategies have many advantages over conventional synchronization methods: they are implemented at the physical layer or MAC layer, which eliminates the high-layer intervention; their message exchanging is independent of the origin of the signals, which saves the memory to store the time information of other nodes. PCO has draw the focus of worldwide researchers. Anna Scaligone [13], [14] analyzed its scalability and synchronization characters and presented differential schemes to improve synchronous performance in multi-hop networks. Francis J. Doyle [15], [16] made an analogy between PCO method and

This paper is supported by National Natural Science Foundation of China under Grant #61272428, by PhD Programs Foundation of Ministry of Education of China under Grant #20120002110067, and by a grant from the National High Technology Research and Development Program of China under Grant #2012AA121500.

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neural cell, then theoretically developed the phase response model. Xiaowei Li [17] studied the influence of nonidentical network environment on PCO synchronization rate. Since PCO method simply interact each sensing node with pulse signals, the intrinsic response model plays an important role in network synchronization performance. The state of art approach for pulse-coupled oscillators derives from the phase models in neural science [18], which however have not completely taken sensing network characters into account. The distributed, disperse computing mechanics with hardware and software delay was not considered. This paper optimized the response model to improve the time efficiency.

This paper represents the electrical power metering architecture under cyber-physical energy system. In order to reach whole network synchronization faster, a new PCO model is proposed to increase synchronization convergence rate. Theoretical analysis of the synchronization rate is presented and critical indicators of PCO method with various models are depicted. Finally, experiments based on general platform are set to prove the validness of the new PCO method.

The rest of the paper is organized as follows. Section II introduces the requirements of fault localization and relevant synchronization methods. Section III introduces the CPES architecture for the grid metering on the demand side and fault localization requirements for network synchronization. Section IV describes the dynamics of pulse-coupled oscillators method and proves its convergence criterion. According to the criterion, an optimized PCO model is proposed in Section V and its properties are discussed. In Section VI, the PCO method performance and its effect on fault localization are testified in simulation experiments. Finally Section VII provides conclusive remarks and future work.

II. Related Works

Synchronization requirements has long been a fundamental problem in grid measurement system. Especially within distributed metering architecture in cyber-physical energy system, all the power sources and utilities need to be synchronous measured for accurate online fault diagnosis and power grid safety [3].

There has been a lot of research on fault diagnosis and localization in smart grid [4], [9], [19]–[22], [32]. As a fundamental service, fault diagnosis methods make requirements on the synchronization accuracy. IEC Standard 61588 [24] and implementation of GPS has provide precise time stamping of the measuring data. Nevertheless, on the demand side the expense of PMU and GPS is high. Smart meters at the utilization side do not afford complicated communication wires. Sufficient synchronous accuracy for distributed wireless network is urgent [9].

Synchronization works Studies have been proposed to solve the synchronization problem in large decentralized wireless networks. [5] Ever since NTP (Network Time Protocol) was proposed in 1988, the time synchronization has become a research focus. Within distributed wireless sensing networks Numerous synchronization methods have been proposed. Traditional solutions, such as TPSN, RBS, FTSP, Glossy, etc [10]–[12]. have been widely applied in wireless sensing networks. Yet conventional synchronization methods were mostly designed for energy limit sensing networks. As to reach a high synchronization accuracy, these methods sacrifice the communication bandwidth under specific network topology, which limits scalability because they either divide the network into connected single-hop clusters or organize the whole network into a spanning tree, which is computationally challenging to construct for distributed large-scale networks.

In order to improve the time efficiency and scalability, Pulse-coupled oscillators method utilizes simple identical pulses to couple the sensing nodes within the communication range and to reach synchronization. PCO-based strategies have many advantages over conventional synchronization methods: they are implemented at the physical layer or MAC layer, which eliminates the high-layer intervention; their message exchanging is independent of the origin of the signals, which saves the memory to store the time information of other nodes. PCO has draw the focus of worldwide researchers. Anna Scaligone [13], [14] analyzed its scalability and synchronization characters and presented differential schemes to improve synchronous performance in multi-hop networks. Francis J. Doyle [15], [16] made an analogy between PCO method and neural cell, then theoretically developed the phase response model. Xiaowei Li [17] studied the influence of nonidentical network environment on PCO synchronization rate. Since PCO method simply interact each sensing node with pulse signals, the intrinsic response model plays an important role in network synchronization performance. The state of art approach for pulse-coupled oscillators derives from the phase models in neural science [18]. The dynamics of the synchronization mechanism have not completely taken sensing network characters into account. The distributed, disperse computing mechanics with hardware and software delay was not considered. This paper study the dynamics of PCO performance in sensing networks. Through theoretical inference, optimized aspects are analyzed. Several dynamic PCO models' performance have been compared and modified to reach time-efficient and stable synchronization. Thus better temporal measuring reliability can be achieved and fault localization at demand side be improved under distributed cyber physical architecture.

III. Electrical power active sensing networks

Large scale electrical sensing network has attracted sufficient researchers focus and electric metering system has been evolving ever since. Traditional Automated Metering Reading (AMR) System which behaves only one-way manual centralized detection is at last gasp, while Advanced Metering Infrastructure (AMI) with a distributed architecture and integrated electrical analysis service has gradually taking the place [23]. In the prospect of electrical metering system, smart grid is the promising solution for a less centralized and more consumer-interactive network. [3] Cyber-physical system offers a distributed, dynamic-configuration, demand require response solution. [1] With dynamic sensing networks, the cyber system will be able to collect real-time electrical power quality parameters and deploy distributed data analysis and computation for the energy saving. The basic architecture is shown in Fig.1.

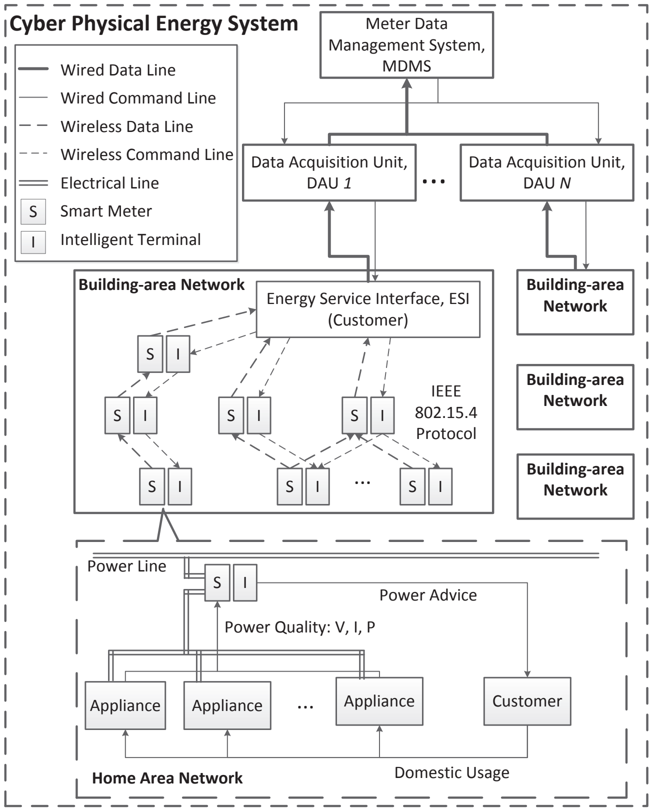

Fig. 1. Cyber-physical energy system distributed measuring architecture

Under the distributed measuring architecture, safety supervision of power network faces new challenges. Continuous online monitoring will be unavailable in such large scale with energy and communication constraints, and the transient power accidents are hard to capture. For example, voltage sag, which is the cause of nearly 80% power quality faults [4], persists for only 10ms-1min, and the signal will spread in the power network. The fault localization requires high voltage measurement accuracy, especially temporal synchronization of the monitoring nodes. With time sequence disorder, it is difficult to identify the fault source.

In addition, to enhance fault diagnosis performance Within the dynamic sensing networks, real-time electrical power metering faces a lot of problems. Sensing networks operates under energy and communication limits which are the main obstacles to meet the real-time and large scale measuring requirements. Thus, dynamic energy and communication management becomes important. Sleeping and waking up of electrical sensing nodes will certainly break the transient stability of topology and synchronization state of the networks. Under SCADA (Supervisory Control And Data Acquisition system) measuring theory, the power quality metering requires the measuring data to be in the same temporal section, otherwise, the time error will be introduced in data analysis and mining process. The temporal measuring error is [25]:

$$Err_{temporal} = diag\{D_i \rho_i^2\}, i = 1, 2, ..., N \tag{1}$$

While D_i represents the square variance of the time offset of the ith sensing node. ρ_i represents the changing rate of measured power quality character by the ith node. It is manifest that decreasing time offset is the only way to reduce temporal measuring error, which is the reason why synchronization methods are adopted.

These requirements claim a synchronization method fulfilling the requirements of high flexibility and scalability. As mentioned in section I, pulse-coupled oscillators behaves better in these perspectives than traditional wireless synchronization methods. PCO method is decentralized, scalable, and can be adopted into various network types. Its simplicity, time- and energy-efficiency has drawn remarkable attention. The Algorithm scheme and validation is analyzed below.

IV. Synchronous Measurement Algorithm

A. Pulse-Coupled Oscillator Algorithm

To solve the dynamic synchronous metering problem mentioned above, Anna Scaglione [13] introduced PCO synchronous method in 2005. Pulse-coupled oscillators method was first proposed to explain the oscillation dynamics in neural science [18] and physics [29]. However its simplicity, scalability and flexibility to network topology has gained itself great attention all over the world recently, and has been widely studied in wireless sensor networks and smart grid [10]. The basic algorithm is introduced as follows.

Consider a decentralized network of N nodes, and each performs as a pulse-coupled oscillator. Each node has a intrinsic state variable x, which increases monotonically from 0 to 1. All oscillator nodes can receive and trigger pulses from the neighbourhood, and once received the pulse the state variable x gains a step transition. The dynamic function of the oscillator network is denoted as follow [15]

$$\dot{x}_i = f_i(x_i) + \varepsilon \sum_{\substack{j \neq i \\ 1 \leq j \leq N}} a_{i,j} \delta(t - t_j) \tag{2}$$

for $i = 1, 2, ..., N$, where $x_i \in [0, 1]$ denote the states of the oscillator nodes. f_i describe the dynamics of oscillators and determines how x changes. $a_{i,j} \in [0, 1]$ denote the effect of oscillator j 's firing on oscillator i: when x_j reaches 1 (at time instant t_j), the node fires an pulse and reset to 0, and simultaneously pulls oscillator i up by an amount $\varepsilon a_{i,j}$. The increased amount is produced by dirac function $\delta(t)$, which is zero for all t except $t = 0$ and satisfies $\int_{-\infty}^{\infty} \delta(t)\, dt = 1$.

Remark 1: If $a_{i,j}$ is 0, then oscillator node i is not affected by oscillator node j.

Then, within wireless sensor network environment, we have following 2 assumptions:

Assumption 1: We assume $a_{i,j} = a_{j,i}$, which means the firing pulses' effects between 2 oscillator nodes are equal.

Assumption 2: We assume weak coupling, that is $\varepsilon \ll 1$.

Assumption 2 follows from the fact that the amplitudes of postsynaptic potentials measured in the soma of neurons are far below the amplitude of the mean EPSP (Excitatory Post-Synaptic Potential) necessary to discharge a quiescent cell [26], and weak coupling also improves robustness of synchronization in PCO-based wireless network [13].

Based on Assumption 2, the dynamic function in (2) can be described by the following phase model using the classical phase reduction technique and phase averaging technique [18]:

$$\dot{\theta}_i = \omega_i + \varepsilon \sum_{\substack{j \neq i \\ 1 \leq j \leq N}} a_{i,j} Q\left(\theta_j - \theta_i\right) \tag{3}$$

for $i = 1, 2, ..., N$, where $\theta_i \in [0, 2\pi)$ denote the phases of the oscillator i. Each phase θ_i corresponds with a state variable x_i. The relation between $Q(\theta)$ and $f(x)$ is [18]:

$$Q(\theta_j - \theta_i) = \frac{1}{T} \int_0^T f_i(x_i(t)) \delta(t - t_j + \theta_j - \theta_i) dt \tag{4}$$

T represents the period of the synchronization process. f_i denotes the dynamics of the ith oscillator node.

The transformation from (2) to (3) is a standard practice in the study of weakly connected pulse-coupled oscillator system and it is applicable to any limit-cycle oscillation function f_i . The detailed procedure has been well documented in [18].

Assumption 3: Assume that $Q(\theta)$ satisfy the following conditions:

$$\begin{aligned} &Q\left(0\right) = 0; \forall \theta \in \left(-\pi, \pi\right), \frac{Q\left(\theta\right)}{\theta} > 0 \\ &Q\left(-\theta\right) = -Q\left(\theta\right) \end{aligned} \tag{5}$$

This limit gives an advance-delay phase response function, which is common in biological oscillators. However, in wireless sensing networks, the phase response function can be designed and modified for an optimized synchronization behavior. Assumption 3 can simplify the analysis and design process of the synchronization method.

In order to study the synchronization performance of this method, we inspect the phase dynamics' behavior under network environment:

$$\dot{\vartheta} = \Omega - \varepsilon \boldsymbol{B} Q\left(\boldsymbol{B}^T \vartheta\right) \tag{6}$$

while $\vartheta = [\theta_1, \theta_2, ..., \theta_N]^T$, $\Omega = [\omega_1, \omega_2, ..., \omega_N]^T$. $\boldsymbol{B}$ is a $M \times N$ matrix which indicates the connect state of the oscillator nodes in the network: when node j's pulse enters node i, $\boldsymbol{B}(i, j) = -1$ and $\boldsymbol{B}(i, j)$ changes to -1 if node j leaves node i, otherwise, $\boldsymbol{B}(i, j) = 0$. M is the nonzero number of $a_{i,j}$,denoting the number of the interaction between nodes.

From (6) it can be seen that the node phases are affected by the intrinsic frequency Ω, network communication state $\boldsymbol{B}$ and phase response function $Q(\theta)$.

Assumption 4: Without loss of generality, the frequency fluctuations of oscillator nodes can be neglected under unstrict synchronization condition, e.g. $\omega_1 = \omega_2 = ... = \omega_N = \omega$. Under Assumption 4, define $\phi_i = \theta_i - \omega t, \forall i = 1, 2, ..., N$. Thus, the dynamics of the oscillators' phase deviation can be expressed as follow:

$$\dot{\varphi} = -\varepsilon \boldsymbol{B} Q\left(\boldsymbol{B}^T \varphi\right) \tag{7}$$

$\varphi = [\phi_1, \phi_2, ..., \phi_N]^T$. Therefore, if all the nodes in the network are to be synchronized, the oscillator nodes should perform as follows:

1) All the node phases will asymptotically convergence, e.g. $\theta_1 = \theta_2 = \cdots = \theta_N$ as time goes to infinity, and ϕ_i convergence to 0.

2) According to the dynamic system theory [28], the synchronization rate can be verified by exponential bound $\alpha(\alpha > 0)$, namely φ fulfills the convergence condition under some constant C:

$$\left\|\varphi\left(t\right)\right\| \leq C e^{-\alpha t} \left\|\varphi\left(0\right)\right\|, \varphi = \begin{bmatrix} \varphi_1 & \varphi_2 & \cdots & \varphi_N \end{bmatrix}^T \tag{8}$$

where $\|\bullet\|$ is the Euclidean norm. Faster synchronization claims larger α.

B. Synchronization of Pulse-Coupled Oscillators in Networks

From (7), the synchronization of weakly coupled network is a nonlinear dynamic system. The convergence behavior is discussed in the following.

Theorem 1: The weakly coupled oscillator network described in (7) will either synchronizes or convergence to stable phase locking state.

Proof: Construct Lyapunov function $V = (\varphi^T \varphi)/2$. V is non-negative and will be zero only if all the $\phi_i = 0$, which indicates all the node in the network synchronized. Thus, differentiating V yields:

$$\begin{aligned} \dot{V} &= \varphi^T \dot{\varphi} \\ &= -\varepsilon \varphi^T \boldsymbol{B} Q\left(\boldsymbol{B}^T \varphi\right) \\ &= -\varepsilon \varphi^T \boldsymbol{B} \Sigma \boldsymbol{B}^T \varphi \end{aligned} \tag{9}$$

where Σ is defined as

$$\Sigma = diag\left\{ \frac{Q\left(\boldsymbol{B}^T\phi\right)_1}{\left(\boldsymbol{B}^T\phi\right)_1}, \frac{Q\left(\boldsymbol{B}^T\phi\right)_2}{\left(\boldsymbol{B}^T\phi\right)_2}, ..., \frac{Q\left(\boldsymbol{B}^T\phi\right)_M}{\left(\boldsymbol{B}^T\phi\right)_M} \right\}$$

and $\left(\boldsymbol{B}^T\phi\right)_i, i = 1, 2, ..., M$ denoting the ith element of the vector $\boldsymbol{B}^T\phi$. In dynamic systems, if Σ is positive definite matrix, $(\dot{V})$ will be negative unless $\varphi = 0$ and V will monotonically decrease.

According Assumption 3,$\forall \phi_i \in (-\pi, \pi)$, we have $Q\left(\theta\right)/\theta > 0$. For diagonal matrix, eigenvalues follows:

$$\begin{aligned} \lambda_0 &= \min_{1 \leq i \leq N} \left(\boldsymbol{B}^T\phi\right)_i > 0 \\ \lambda_N &= \max_{1 \leq i \leq N} \left(\boldsymbol{B}^T\phi\right)_i > 0 \end{aligned} \tag{10}$$

then the (9) leads to:

$$\dot{V} = -\varepsilon \varphi^T \boldsymbol{B} \Sigma \boldsymbol{B}^T \varphi \leq -\varepsilon \lambda_0 \varphi^T \boldsymbol{B} \boldsymbol{B}^T \varphi \leq 0 \tag{11}$$

the equality submitted only when every element in $\boldsymbol{B}^T\varphi$ is 0 or $\lambda_0 = 0$. The former equals $\theta_1 = \theta_2 = ... = \theta_N$, which states that the oscillator nodes within interaction already synchronized. The latter condition means nonzero solution exits for $Q(x) = 0$, and at a specific time point, $\boldsymbol{B}^T\varphi(t)$ exactly equals the nonzero solution. Nonzero solution indicates that the oscillator phases reaches stability while the phases are not equal with each other.

Without reaching stability, we have $V > 0$ and $\dot{V} < 0$, thus the monotone decreasing series $V(t)$ have a non negative lower limit V_l. Different value of the limit denotes various network state:

1) $V_l = 0$: the Lyapunov function equals (8) and the oscillator nodes in networks will synchronize.

2) $V_l > 0$: the phase deviation vector φ has non zero element, the oscillator nodes will not synchronize, e.g. the phase locking stable state.

Under either condition, the lower limit of convergence rate can be described as:

$$\begin{aligned} \dot{V} &\leq 2\alpha\frac{\varphi^T\varphi}{2} = -2\alpha V \\ \alpha &= \min_{\varphi} \varepsilon\boldsymbol{B}\Sigma\boldsymbol{B}^T \end{aligned} \tag{12}$$

α denotes the worst case synchronize rate, which is defined in (8). Since Σ is a diagonal matrix, the formula equals:

$$\alpha = \lambda_{min}\varepsilon\boldsymbol{B}\boldsymbol{B}^T = \lambda_0\varepsilon\boldsymbol{B}\boldsymbol{B}^T \tag{13}$$

Therefore, the network described (7) will convergence to either synchronized or phase locking state. ■

Through (13), in a given oscillator sensing network, the nodes interaction state matrix $\boldsymbol{B}$ and coupling strength ε are specified constants, the convergence rate α is affected by λ_0 which is defined in (10). To improve the time-efficiency of network synchronization, one way to optimize the PCO network is to enhance the $Q(\theta)/\theta$, thus a larger λ_0 promising a larger α.

The strict mathematical justification of the weakly coupled oscillator networks is also discussed in [15], [16], [26]. The convergence rate limitation depends on the specific formula $Q(\theta)$. Designing and selecting appropriate $Q(\theta)$ is the crucial point to determine the final convergence rate and stable state. According to former analysis, it can be seen that the optimizing phase response model is the key step of acquiring for higher convergence rate.

V. Time-efficient Pulse-Coupled Oscillators Model

Given that the PCO model makes an impact on the synchronization rate, the model should be well designed for the computation and energy limitations. Researchers have proposed various models and design methods to satisfy the time-efficiency, which are to be introduced in the following.

A. Pulse-Coupled Oscillators Model

1) Kuramoto Model: Kuramoto Model was first proposed by Yoshiki Kuramoto [29] to explain the oscillators phenomenon in chemistry and neuroscience. F.J. Doyle III introduced and validated this model in wireless network. The model is defined:

$$\frac{d\theta_i}{dt} = \omega_i + \frac{K}{N}\sum_{j=1}^{N}\sin(\theta_i - \theta_i), i = 1, ..., N \tag{14}$$

The $Q(\theta)$ can transform as:

$$Q(\theta) = \sin(\theta) \tag{15}$$

2) Advanced Delay Tanh Model: Advanced Delay Tanh Model was proposed by Francis J. Doyle III in 2013. [16]. The design idea drived from the advance-delay function in biology community, such as Hodgkin-Huxley model [30]. The advanced delay model has the following form:

$$Q(\theta) = \frac{\tanh(\theta/\epsilon)}{\tanh(\pi/\epsilon)} - \frac{\theta}{\pi}, \theta \in [-\pi, \pi] \tag{16}$$

while the parameter ϵ can be designed for a better synchronization performance. By experience, $\epsilon = 0.1$.

3) Quadratic Polygon Model: Since the convergence rate is influenced by $Q(\theta)/\theta$, the

$$\frac{d\theta_i}{dt} = \omega_i + \varepsilon\sum_{j=1}^{N} Q(\theta_i - \theta_i), i = 1, ..., N \tag{17}$$

$$Q(\theta) = \begin{cases} \sum\limits_{i=1}^{N} a_i\theta^i & \theta \in [0, \pi) \\ \sum\limits_{i=1}^{N} a_i(-\theta)^i & \theta \in [-\pi, 0) \end{cases} \tag{18}$$

Considering the phase θ is limited in $(-\pi, \pi)$, the smooth function $Q(\theta)$ should satisfy the limitation:

$$\begin{aligned} Q(-\theta) &= -Q(\theta) \\ Q(-\pi) &= Q(\pi) = 0 \end{aligned} \tag{19}$$

As discussed in section IV, to maximize the $Q(\theta)/\theta$, take quadratic polygon function for example, the phase function should have the following form:

$$Q(\theta) = \begin{cases} k\theta(\pi - \theta) & \theta \in [0, \pi) \\ k\theta(\pi + \theta) & \theta \in [-\pi, 0) \end{cases} \tag{20}$$

Thus $Q(\theta)/\theta = k(\pi - \theta)$, which increases with the parameter k.

These 3 models' phase response function are shown in Fig. 2. All these models are odd function and continuous at $\theta = \pm\pi$, which avoid step changes in the dynamic system and gain stability of the network synchronization. However, in this way, it brings in nonzero solutions for $Q(\theta)$, which may lead to phase locking and influence local convergence of the dynamic system.

B. Model Analysis and Optimization

In section IV, it can been explained from (13) that the $Q(\theta)/\theta$ may influence the convergence rate, however, the criterion only explicitly defines the lower-limit of the convergence rate. Simulations are presented to evaluate the novel phase model. The convergence criterion $Q(\theta)/\theta$ of 3 Phase models are shown in Fig. 3.

As shown in Fig. 3, the Advanced Delay Tanh model reaches the highest on $Q(\theta)/\theta$ at phase 0, however, the polygon

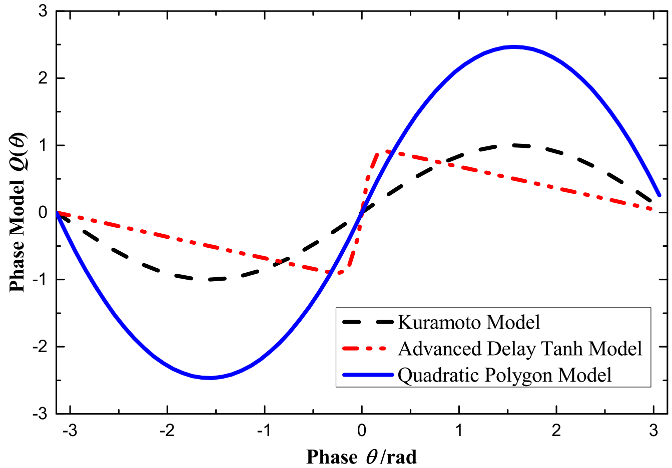

Fig. 2. Shapes of 3 phase response models for pulse-coupled oscillators.

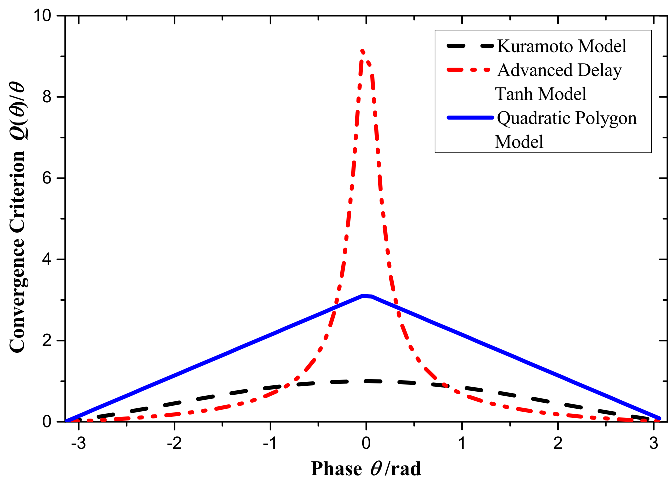

Fig. 3. The convergence rate criterion $Q(\theta)/\theta$ of 3 phase response models for pulse-coupled oscillators

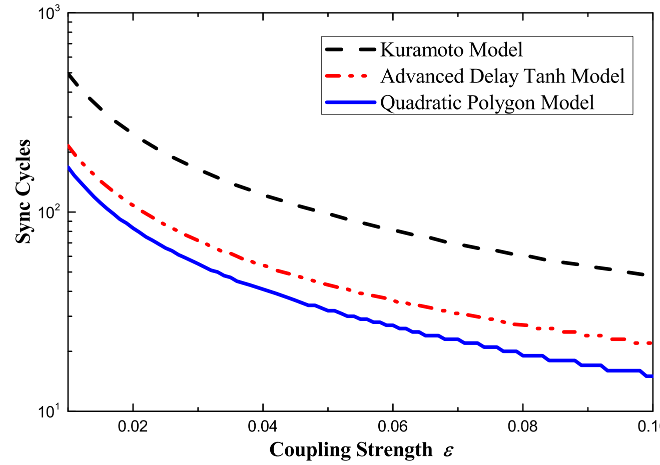

Fig. 4. Synchronization consumption of 3 models under 100-node scale and coupling strength varying from 0.01 to 0.1

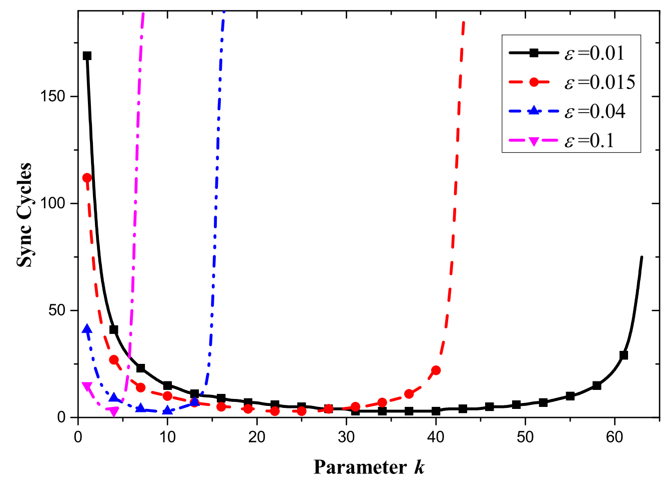

Fig. 5. Synchronization cycles required under various parameter k and coupling strength ε

model with second order overcomes the other two models in most phase section. Thus, the synchronization rates of these 3 models are not simply decided by the $Q(\theta)/\theta$. Simulations are carried out to evaluate their synchronization features.

Synchronization performance of the 3 models is tested with simulation. Network scale set as 100 nodes and coupling strength varies among $[0.01, 0.1]$, which is generally adopted in weak coupled networks. Synchronization error threshold is set as 0.01 rad. Simulation result is shown in Fig. 4. From the result, it can be figured out that computing cycles needed to realize synchronization decrease as the coupling strength grows, and the decreasing speed is higher than exponential. This is helpful in designing dynamic sensing networks, since as the coupling strength ε reduced, network scalability and flexibility reinforced, the energy consumption grows as a result of growth of synchronization cycles. In addition, pulse-coupled oscillators method with the Quadratic Polygon Model reaches synchronization state faster than the other 2 models under coupling strength in the section.

Detailed modification of the Quadratic Polygon Model was realized under the same simulation condition. In the form in (20), the parameter k may have effect on synchronization performance. Synchronization cycles required under different parameter k and coupling strength ε is verified and results are shown in Fig. 5.

The simulation result indicates that with different coupling strength ε, the synchronization rate can reach a rather optimal level through modifying parameter k. The optimized synchronization cycle numbers are the same. In Quadratic Polygon Model $Q(\theta)/\theta = k(\pi - \theta)$, which will increases while k increase. This means that if k grows, the lower limit of convergence rate will rise, and synchronization cycles upper limit number will fall. The simulation results show affirm the deduction to certain extent, yet if k is too large, the synchronization rate will decrease, and lead to phase locking of

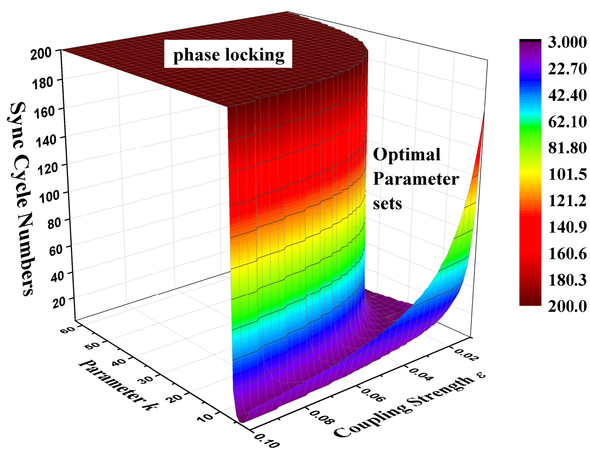

Fig. 6. Various parameter k under different coupling strength ε

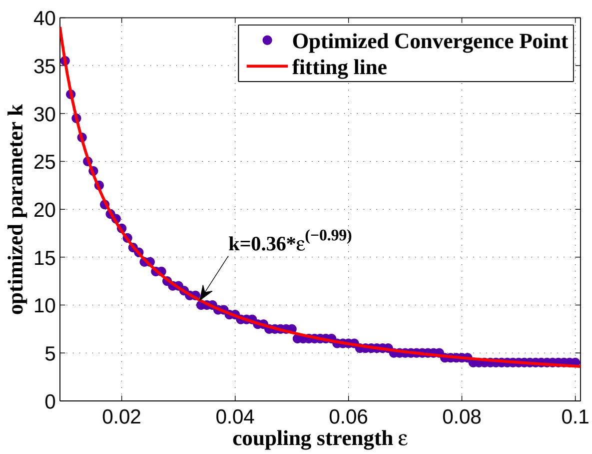

Fig. 7. Optimized parameter k under different coupling strength ε

the whole network. Thus through optimizing k can reach a high synchronize rate despite the coupling strength. The optimized k and the corresponding ε are shown in Fig. 7.

Substitute $Q(\theta)$ in (20) to (13), the convergence rate would be:

$$\alpha = \left(\lambda_{min}\varepsilon\mathbf{B}\mathbf{B}^T\right) = k\varepsilon\left(\pi - \theta\right)\mathbf{B}\mathbf{B}^T \tag{21}$$

Considering the decentralized network, with φ at certain time point, the factor $k\varepsilon$ will influence the convergence rate. Simulation results also present that the optimized k follow reciprocal of ε. Yet it is not exactly proved theoretically the validation of quadratic polygon model modification, the result can be a reference in designing coupled networks.

So through theoretical analysis and stimulation, the proposed quadratic polygon model offers a better time-efficient synchronization performance over traditional models. The performance can also be optimized by modifying parameter k in the model. Employing the experiential relation between optimized k and

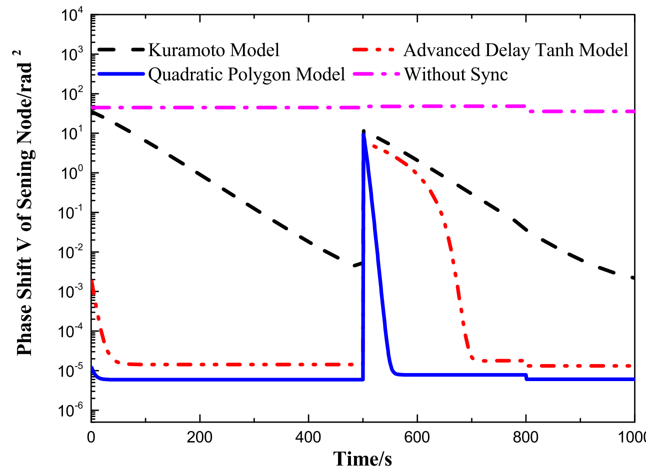

Fig. 8. Dynamic interruptions on PCO synchronization performance

network coupling strength ε, sensing network design will be able to cover both time-efficiency and energy consumption.

VI. Experiments and Analysis

To evaluate the proposed PCO model in electrical metering system, experiments are introduced in this section. Electrical information metering based on cyber-physical energy system mentioned in Section III was settled as the testing environment.

A. Experiment Setup

The simulation testing system is realized on OMNET++, which is widely used simulation platform for network communication test. A Sensing network based on IEEE 802.15.4 protocol was settled. Under cyber-physical energy system architecture, the networks contains 3 layers of sensing nodes and forms a whole cluster, while the end sensing node simulate the electrical information metering process. The communication rate is limited in 250 kbps. According to the multi-function meter communication protocol standard DL/T 645-2007 [31], the standard answering message from the smart meter end device is 19 byte. Electrical information transformation event is triggered every minute. In order to avoid channel preemption, the metering process is triggered sequentially. Sensing network complied with 50 end sensing nodes and 1 cluster head.

Synchronous metering process is controlled by the global coordinator, e.g. the cluster head node. Synchronization period is 30s, and once synchronized the end sensing nodes execute simulative electrical information transmission.

B. PCO Model Optimization

C. Synchronous Sensing of PCO Models in Dynamic Sensing Networks

Dynamic sensing network management implies sensing nodes dynamically leave and join the network, and the interruption brought to the network transient stability depends on the dynamic node scale. The time required to synchronize network under various dynamic node scale is presented in Fig. 7. 2 types of dynamic interrupts were introduced at t=50s and t=80s, former is 10 nodes joining in, latter is 5 nodes leaving. Apparently, the nodes leaving event do not interfere present synchronization state of the network, yet nodes joining will bring step change. 3 PCO models were adopted separately to synchronize the sensing network.

Results show that under non-ideal environment the synchronization accuracy varies according to different models. Quadratic Polygon model reached the lowest phase shift error of the 3 models. Phase shifts brought by the node joint took different time to regain synchronization. Quadratic Polygon model took 5s, Advanced Delay Tanh Model took 24s and Kuramoto Model took over 30s. This means that Quadratic Polygon model performs a better synchronization accuracy and speed, even under non-identical frequency and time delays.

Synchronization error will be introduced into electrical quality measurement as described in section III. The measurement error is influenced by changing rate of the measured characters and time disorder. Take harmonic detection for example. Simulation data was measured in residential standard electrical environment 220V/50Hz, and the power quality characters measuring accuracy is important for information mining. The synchronization methods will bring various measuring error according to the time accuracy. Residential power characters data samples were collected, and the power consumption is shown in Fig. 8(to be modified). To get a typical result, high-power electrical appliances were turned on and off to introduce interruptions. The time synchronizations influence on temporal measuring error is shown in table I.

It can be figured out from the result that time synchronization accuracy has effect on temporal measuring error. Although the errors magnitude is not that large when compared with the measured data, yet in large scale analysis and data mining, the error is not ignorable. Since the Quadratic Polygon Model reaches the highest accuracy in Part B, it also brought in the least temporal error in the 3 models.

D. Fault Localization with Synchronized Measurement

To validate the synchronization in electrical fault diagnosis, voltage sag source localization is an appropriate test. The simulation sample of electrical network set is shown in Fig. 9. The Source supplies 110kV before the transformer and 3 different types of loads are organized, which are composed of nonlinear resistance load, linear resistance load and an asynchronous motor. These 3 types of loads represent the most electrical appliances. A simulation is carried out within simulation environment Simulink.

Set 3 false sources at different time points, M1, M2, M3, as shown in Fig. 8. M1, M2, M3 are short-circuit fault, while M1 is set at bus line, and M2, M3 are set in local lines at user side. Locate the voltage sag source 100 times using system trajectory slope method [32] which is a widely authenticated way in voltage sag source location. With synchronization, the voltage sag source localization accuracy result is shown in table II.

From the result, it can be figured out that the 3 types of faults can be detected from the 3 different meters. However,

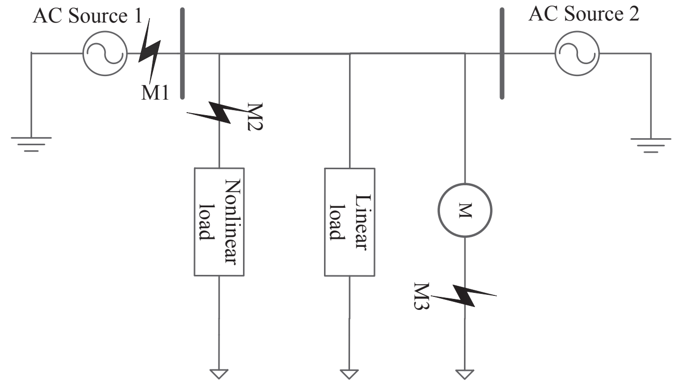

Fig. 9. Voltage sag source localization verification electrical model

TABLE I. TEMPORAL MEASURING ERROR FOR POWER QUALITY CHARACTERS (FIRST ELEMENT: AVERAGE ERR; SECOND ELEMENT: MAX ERR)

Power Quality	PCO Model		
	Kuramoto Model	Advanced Delay Tanh Model	Quadratic Polygon Model
Power/kW	(0.063, 1.521)	(6.2*e-4, 0.012)	(2.3*e-4, 0.003)
3th Harmonic[1]	(0.182, 4.104)	(18.0*e-4, 0.041)	(7.0*e-4, 0.015)
5th Harmonic*	(0.073, 1.622)	(7.2*e-4, 0.016)	(2.7*e-4, 0.006)
7th Harmonic*	(0.027, 0.584)	(2.7*e-4, 0.005)	(1.0*e-4, 0.002)

TABLE II. VOLTAGE SAG SOURCE LOCALIZATION ERROR

Fault Event	Kuramoto Model	Advanced Delay Tanh Model	Quadratic Polygon Model
M1	13.22%	2.71%	0.82%
M2	6.13%	1.64%	0.65%
M3	6.91%	1.82%	0.71%

for the sake of various synchronization accuracy, the localizing precision differs thoroughly. Detection with Kuramoto model synchronization reaches the lowest precision of the 3 models while the new quadratic polygon model almost catches the fault every time. This experiment confirms that the amendment of the pulse coupled oscillator model, through increasing synchronization accuracy of the measuring device, will reduce the fault localization error, and improve the whole safety of the cyber-physical energy system described in Section III.

VII. Conclusion

Synchronous sensing is very important in power safety supervision in cyber-physical energy system. Synchronization method is required to be time-efficient, accurate and scalable in dynamic sensing networks. This paper proposed a new dynamic model for pulse-coupled oscillators synchronization method, to improve synchronization time efficiency and accuracy. By both theoretical and simulative analysis, models influence on PCO method performance is inquired and the coefficient of model parameters and coupling strength ε is examined. In

[1]The harmonics are calculated with the power and voltage data. Voltage fluctuates slightly around 220V, and is not listed in the paper.

application of power network safety supervision on voltage sag localization under cyber-physical energy system, simulation experiments were carried out to evaluation PCO method. Result indicated that the new Quadratic Polygon Model fulfilled the time-efficiency and data measuring reliability requirements in dynamic sensing networks, and the fault localization exactitude was improved.

To further enhance the safety supervision in cyber physical energy system through raising synchronization accuracy, the non-identical frequencies and transmission delay of the sensing network should be considered in the design of pulse-coupled oscillators method. Specific theoretical analysis of discrete metering and synchronization process is to be carried out.

REFERENCES

[1] C.A. Macana, N. Quijano, E. Mojica-Nava, "A survey on cyber physical energy systems and their applications on smart grids", in *Innovative Smart Grid Technologies (ISGT Latin Ame*.2011, pp. 1-7.

[2] X. Wang, S. Wang, "Collaborative signal processing for target tracking in distributed wireless sensor networks," *Journal of Parallel and Distributed Computing*, vol.67, no.5: pp. 501-515, Feb. 2007.

[3] X. Yu, C. Cecati, T. Dillon and M. Simoes. "The new frontier of smart grids," *IEEE Trans. Ind Electron.*, vol.5, no.3, pp.49-63, Sept. 2011.

[4] T. Brennan, "Market failures in real-time metering," *Journal Regulatory Economics*, vol.26, no.2, pp.119-139, Sept. 2004.

[5] E. Serpedin, Q. Chaudhari, "Synchronization in wireless sensor Nnetworks: parameter estimation, performance benchmarks and protocols", *Cambridge University Press*,2009, Aug. 31.

[6] D. Ingram, P. Schaub, D. Campbell, and R. Taylor "Evaluation of precision time synchronisation methods for substation applications" *IEEE Symposium on Precision Clock Synchronization for Measurement, Control and Communication*, 2012:1-6

[7] S. Ganeriwal, R Kumar, M B. Srivastava. "Timing-sync protocol for sensor networks," *ACM Proceedings of the 1st international conference on. Los Angeles, California, USA*, 2003: 138-149.

[8] S. Karnouskos, "Cyber-physical systems in the smart grid," *in IEEE Conf. 9th Industrial Informatics (INDIN)*, 2011, 20-23.

[9] V. Gungor, B. Lu, G. Hancke, "Opportunities and challenges of wireless sensor networks in smart grid," *IEEE Trans. Ind Electron.*, vol.57, no.10, pp. 3557-3564, 2010.

[10] Y. C. Wu, Q. Chaudhari, and E. Serpedin, "Clock synchronization of wireless sensor networks, " *IEEE Signal Process. Mag.*, vol.28, no.1, pp.124-138, Jan. 2011.

[11] M Marti, B Kusy, G Simon, et al. "The flooding time synchronization protocol," *in Proceedings of the 2nd international conference on Embedded networked sensor systems-SenSys*, 2004, pp. 39-49.

[12] F. Ferrari, M. Zimmerling, L. Thiele, et al. "Efficient network flooding and time synchronization with glossy," *Information Processing in Sensor Networks (IPSN), 2011 10th International Conference on*, 2011: 73-84.

[13] Yao-win H., A. Scaglione. "A scalable synchronization protocol for large scale sensor networks and its applications," *IEEE Journal on, Selected Areas in Communications* vol.23 no.5, pp.1085-1099, May, 2005.

[14] R. Pagliari, A. Scaglione, "Scalable network synchronization with pulse-coupled oscillators," *IEEE Trans. on, Mobile Comput.* vol.10, no.3, pp.392-405, Mar., 2011.

[15] Y.Q. Wang, F.J. Doyle, "Optimal phase response functions for fast pulse-coupled synchronization in wireless sensor networks," *IEEE Trans. on, Signal Process.*, vol.60, no.10, pp5583-5588, Oct., 2012.

[16] Y.Q. Wang, F. Nunez, F.J. Doyle. "Increasing sync rate of pulse-coupled oscillators via phase response function design: theory and application to wireless networks," *IEEE Trans. on, Control Systems Technology*, vol.21, no.4, pp.1455-1462, 2013.

[17] Z. L. An, H. S. Zhu, X. R. Li, et al. "Nonidentical linear pulse-coupled oscillators model with application to time synchronization in wireless sensor networks. "*IEEE Trans. on Ind. Electron.*, vol.58, no.6, pp.2205-2215, Jun., 2011.

[18] E. M. Izhikevich, Dynamical systems in neuroscience: the geometry of excitability and bursting. London, U.K. MIT Press, 2007.

[19] Z. Galijasevic and A. Abur, "Fault localization using voltage measurements", *IEEE Trans. on, Power Deliv.* vol.17, no.2, pp.441-445, 2002.

[20] Y. Sillapawicharn and Y. Kumsuwan, "An improvement of synchronously rotating reference frame based voltage sag detection for voltage sag compensation applications under distorted grid voltages", *IEEE PEDS*, 2011

[21] Y. Dong, C. Zheng and M. Kezunovic, "Enhancing accuracy while reducing comutation complexity for voltage-sag-based distribution fault location",*IEEE Trans. on, Power Deliv.*, vol.28, no.2, pp.1202-1212, 2013.

[22] McGranaghanM F, RMuellerD. Voltage sags in industrial systems. *IEEE Trans. on Ind. Appl.*, vol.29, no.2, pp.397-403, Feb., 1993.

[23] Smart meters and smart meter systems: a metering industry perspective, A Joint Project of the EEI and AEIC Meter Committees, 2011.

[24] "Precision clock synchronization protocol for networked measurement and control systems",2004

[25] R. C. Leou, C. N. Lu. Adjustment of the extemal networks measurements and its effect on the power mismatch analysis, *Proeeedings of IEEE Industry Application Society Annual Meeting*, Vol.3, pp.2072-2076, 1999.

[26] F.C. Hoppensteadt and E.M. Izhikevich, *Weakly Connected Neural Networks*, Springer, 1997.

[27] Mirollo R.E., Strogatz S.H.. "Synchronization of pulse-coupled biological oscillators," *SIAM Journal on Applied Mathematics*, vol.50, no.6, pp.1645-1662, Dec., 1990.

[28] H. K. Khalil, *Nonlinear Systems*, Englewood Cliffs, NJ: Prentice-Hall, 2002, pp. 1-42.

[29] Kuramoto, Yoshiki, *Chemical Oscillations, Waves, and Turbulence*, Springer-Verlag, New York, 1984, pp. 164.

[30] B. Ermentrout, Type I membrances, phase resetting curves, and synchrony, *Neural Comput.*, vol.8, no.5, pp. 979-1001, Apr. 1996

[31] DL/T 645-2007, "Multi-function watt-hour meter communication protocol", 2007

[32] C. Li, T. Tayjasanant, W. Xu, et al. Method for voltage-sag-source detection by investigating slope of the system trajectory. *in IEE Pro, Generation, Transmission and Distribution,* , vol.150, no.3, pp.367-372, Mar. 2003.

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