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Kuramoto-Desync: Distributed and Fair Resource Allocation in a Wireless Network

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ABSTRACT With recent rapid increases in the number of devices connected to wireless networks, the importance of scalable radio resource management operating in a distributed manner and the role of fairness among nodes are critical aspects in ensuring reliable services to numerous nodes in such network environments. In this paper, we consider the Kuramoto model for achieving fair and distributed radio resource allocation in a wireless network. Because, the conventional Kuramoto model is designed for synchronization only and is thus not suitable for fair resource allocation, we propose a modified Kuramoto-Desync model, whose purpose is to achieve fair resource allocation among nodes in a distributed manner. The proposed Kuramoto-Desync model evenly spaces the phases of all the nodes in the network. By mapping the evenly spaced phase interval of each node to the time-division multiple access or TDMA-based data time slot, we achieve fair resource allocation among contending nodes in a distributed way. The necessary condition for the convergence of the Kuramoto-Desync model is analyzed. The simulation results show that the proposed model successfully performs fair resource allocation even in dynamic network topology and that the convergence speed of the proposed model is quite stable compared to that of the comparison model.

INDEX TERMS Kuramoto model, fair resource allocation, de-synchronization.

I. INTRODUCTION

With the advent of 5G and Internet of Things (IoT) eras, the number of wireless devices are increasing rapidly in number. The number of nodes in a network varies very dynamically depending on network conditions, node mobility, and service attributes. In this network environment, scalable resource management is required for the stability of systems with varying numbers of nodes; also, distributed resource management is needed to control many nodes with low overhead and complexity. Moreover, in the upcoming IoT service environment, terminals desire to be always connected and want to periodically transmit or receive a certain amount of data traffic. Therefore, fair resource allocation is necessary in terms of quality of service (QoS). In this context, scalability, decentralization, and fairness are important design factors in a wireless network [1], [2].

A biologically inspired (bio-inspired) algorithm models a number of natural life-forms, such as fireflies, flocks of birds, and schools of fish, which show synchronized phenomena with the purpose of achieving their certain goals in an efficient and distributed manner in dynamic and complex natural environments [3], [4]. Bio-inspired algorithms have three inherent features: 1) scalability, so as to adapt quickly to dynamic environment changes, 2) distributed operation by independent entities without a centralized coordinator, and 3) converged performance achieved by equalizing a target metric for all nodes. Among several bio-inspired models, the Kuramoto model explains the synchronization phenomenon mathematically [5], [6]. It models for the behavior of a large set of coupled oscillators and proves that synchronization is achieved by interactions sinusoidally depending on the phase difference between each pair of objects.

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The Kuramoto model has been used to solve various problems in engineering fields, such as spectral clustering [7], pattern recognition [8], robotic control [9], and load balancing [10].

As mentioned above, an important factor for ensuring QoS for a large number of nodes in a wireless network is fairness [11], [12]. Basically, fairness means providing an unbiased working environment for distribution, sharing, allocation, and supply of resources among the networked devices. The concept of fairness in terms of resource allocation involves guaranteeing the allocation of equal bandwidth to all contending users. A centralized network can easily guarantee fairness via the elected coordinator among the nodes. In a distributed network where no centralized coordinator exists, however, it is difficult to ensure perfect fairness because the nodes are allocated resources opportunistically [13].

In this paper, we apply the bio-inspired Kuramoto model to the task of providing fair distributed allocation of resources in a wireless network. Since the conventional Kuramoto model is designed for synchronization only and is thus unsuitable for resource allocation, we propose a modified Kuramoto-Desync model for desynchronization[1]. This proposed model ensures that the phases of all network nodes are evenly spaced, thus achieving desynchronization over phases of all network components. We note that fair resource allocation among users based on the proposed algorithm is different from the conventional round-robin scheme because the proposed algorithm is not a centralized resource allocation scheme with a specific scheduler, but a distributed self-scheduling scheme in which each wireless node autonomously performs a resource allocation algorithm.

This paper is organized as follows. Section II summarizes some related research. In Section III, we explain the operational principle of the Kuramoto model, propose our Kuramoto-Desync model, and prove the stability of this model. In Section IV, we apply the proposed Kuramoto-Desync model to the problem of obtaining a TDMA-based self-scheduling resource allocation in a wireless network. In Section V, we evaluate the performance of the proposed resource allocation scheme via simulation and we summarize our findings in Section VI.

II. RELATED WORKS

With the recent rapid increase in the number of devices connected within wireless networks, research has been focused on allocating limited radio resources efficiently at the MAC (medium access control) layer. In this section, we classify resource allocation algorithms into three categories: contention-based, scheduling-based, and bio-inspired algorithms.

Contention-based algorithms allocate resource opportunistically through contention among nodes, so packet collision is inevitable and is an important limiting factor in performance. As the number of nodes increases, more collisions occur and performance degrades due to retransmission overhead. The Sensor-MAC (S-MAC) protocol is a representative contention-based resource allocation algorithm that reduces energy consumption through duty-cycle functionality, which forces a node to repeatedly operate cycles between sleep and wake-up segments of the terminal [15], [16]. However, as the number of devices increases, the lack of countermeasures for collision avoidance causes user QoS to deteriorate and increases nodal energy consumption. X-MAC, another contention-based resource allocation algorithm, is specialized for low-power communication in IoT networks [17], [18]. To reduce the energy consumption due to overhearing of long, useless preamble, X-MAC employs a strobed preamble which inserts pauses between consecutive short preamble packets. Each device receiving short preamble messages during duty-cycling operations recognizes the key-ID and decides whether to enter sleep mode or active mode. Correlation-based collaborative MAC (CC-MAC) is a contention-based resource allocation algorithm for high density network environments [19], [20]. It exploits spatial correlation of data at the MAC layer to regulate and prevent redundant transmissions. The CC-MAC protocol comprises event MAC (E-MAC) and network MAC (N-MAC) algorithms. E-MAC filters out the correlated data packets to prevent redundant transmissions, while N-MAC prioritizes the routing packets to provide a collision-avoidance functionality. By combining these two MAC components, CC-MAC decreases energy consumption and overhead effectively.

In scheduling-based algorithms, a central coordinator allocates resources for each node and this resource allocation information is shared among nodes. Scheduling-based resource allocation avoids packet collision and can provide nodes with stable QoS. However, it requires signaling overhead for information sharing in proportion to the number of nodes. Time division multiple access (TDMA), the best-known type of scheduling-based resource allocation algorithm, allocates a dedicated time slot to each user for contention-free transmission and reception. In recent years, TDMA-based protocols have been extended and combined with the simultaneous use of multiple frequencies, for instance in multi-frequency TDMA (MF-TDMA) which controls both frequency and time slot [21], [22]. In MF-TDMA, each user is allocated a particular set of sub-bandwidths at a particular set of times. Generally, different users can be assigned different sub-bandwidth sizes for different time durations. The various user allocations must then be packed into the limited bandwidth available to the system. Mobility-adaptive, collision-free MAC (MMAC) is a scheduling-based protocol that schedules nodes depending on traffic information and the mobility pattern of the nodes [23], [24]. It is assumed in MMAC that each node is aware of its location. This information is used to predict the mobility pattern of nodes and to adjust frame length, transmission slot, and random-access slots accordingly, which

[1]De-synchronization is the logical opposite of synchronization. While synchronization occurs when nodes perform periodic tasks at the same time, the de-synchronization occurs when each node performs its task as far away as possible from all other nodes [14].

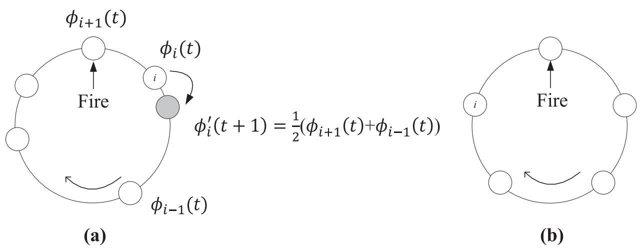


FIGURE 1. Convergence in the De-synchronization model.

enables the protocol to adapt dynamically to mobility constraints.

To solve the collision problem for contention-based algorithms and thus achieve the efficiency of a scheduling-based algorithm, bio-inspired resource allocation algorithms have recently received much attention because they hold the promise of efficient decentralized communication and networking [13]. Among these, De-synchronization model was proposed to achieve the logical opposite of firefly synchronization, which is inspired by the synchronized flashing of thousands of fireflies [25]. The authors of [14] presented the first de-synchronization-based TDMA protocol in a fully-connected network. Suppose there are N nodes where each node performs a task periodically with period of T. Let $\phi_i(t) \in [0, 1]$ denote the phase of node i for $0 \leq i \leq N-1$ at time t, where phases 0 and 1 are regarded as being identical. Upon reaching $\phi_i(t) = 1$, node i "fires" to indicate the termination of its cycle to the other nodes. Upon firing, the node resets its phase to $\phi_i(t^+) = 0$. Node i records the times of the following two firing events: the one that precedes its own firing (previous firing $\phi_{i+1}(t)$), and the one that occurs just afterward (next firing $\phi_{i-1}(t)$), as shown in Fig. 1(a). These firing events are called the reference phases for node i. Node i calculates the midpoint of its two reference phases as $\phi_{mid}(t) = \frac{1}{2}(\phi_{i+1}(t) + \phi_{i-1}(t))$ and jumps toward it as follows:

$$\phi_i'(t) = (1-\alpha)\phi_i(t) + \alpha\phi_{mid}(t), \tag{1}$$

where $\phi_{mid}(t) = \frac{1}{2}(\phi_{i+1}(t) + \phi_{i-1}(t))$ and $\alpha \in [0, 1]$ is a parameter that scales how far node i moves from its current phase toward the desired midpoint. Each node observes its neighbors firing phase, and then uses this information to jump its phase forward or backward in the phase according to (1). Thus, all of the oscillators are evenly spaced around the phase ring, as shown in Fig. 1(b). Node i occupies TDMA slots beginning at the previously computed midpoint between node i and its previous-phase neighbor $i+1$ and ending at the previously computed midpoint between node i and its next-phase neighbor $i-1$. In this way, all of the nodes occupy non-overlapping time-slots that cover T evenly.

The De-synchronization model shares some important characteristics with our proposed Kuramoto-Desync model. First, both adopt distributed resource allocation, in which each node determines the quantity of resources to be allocated to itself in an autonomous way. Second, the purpose of the both models is to provide fair allocation of resources to all users. In this study, we will therefore compare the performance of our proposed model with that of the De-synchronization model.

III. PROPOSED ALGORITHM

A. KURAMOTO MODEL

The Kuramoto model proposed by Kuramoto Yoshiki in 1975 describes synchronization phenomena. Suppose that there are N objects. The phase at time t and natural frequency of the i-th oscillator at time t are denoted as $\theta_i(t)$ and w_i, respectively. The phase of each node increases linearly from 0 to 2π in a cycle. Upon reaching $\theta_i(t) = 2\pi$, node i fires and reset its phase back to 0. All nodes listening to firing of node i updates its phase by using the following equation,

$$\frac{d\theta_i}{dt} = w_i - \frac{K}{N}\sum_{j=1}^{N}\sin(\theta_j - \theta_i), \quad i = 1, \ldots, N, \tag{2}$$

where K is the coupling strength among oscillators. Each oscillator tries to operate according to their natural frequency, and the coupling tends to synchronize all the oscillators. It is showed that while the coupling is increasing above a certain threshold, the oscillator naturally generates collective synchronization [26].

B. DISCRETE-TIME KURAMOTO MODEL

In this subsection, a discrete-time Kuramoto model is suggested to apply the Kuramoto model into resource allocation in a wireless network. Consider the discrete-time Kuramoto model designed to operate at a unit time of ΔT, given by

$$\theta_i(t+1) = \theta_i(t) + w_i - \frac{K\Delta T}{N}\sum_{j=1}^{N}\sin(\theta_j(t) - \theta_i(t)), \quad i = 1, \ldots, N. \tag{3}$$

To simplify this discrete-time Kuramoto model equation, we use a complex-valued order parameter given by

$$re^{i\psi} = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_j}. \tag{4}$$

Multiplying by $e^{-i\theta_k}$ yields

$$re^{i(\psi-\theta_k)} = \frac{1}{N}\sum_{j=1}^{N} e^{i(\theta_j-\theta_k)}. \tag{5}$$

Taking the imaginary part of (5) gives

$$r\sin(\psi - \theta_k) = \frac{1}{N}\sum_{j=1}^{N}\sin(\theta_j - \theta_k), \tag{6}$$

where $r \in [0, 1]$ is the coherence of the object group and ψ is the average phase. Then, (3) can be simplified by

$$\theta_i(t+1) = \theta_i(t) + w_i - rK\Delta T\sin(\psi(t) - \theta_k(t)). \tag{7}$$

Fig. 2 shows the phase synchronization in the discrete-time Kuramoto model.

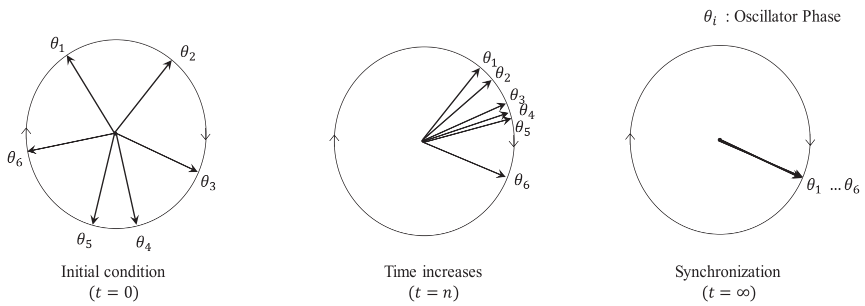


FIGURE 2. Synchronization in Kuramoto model.

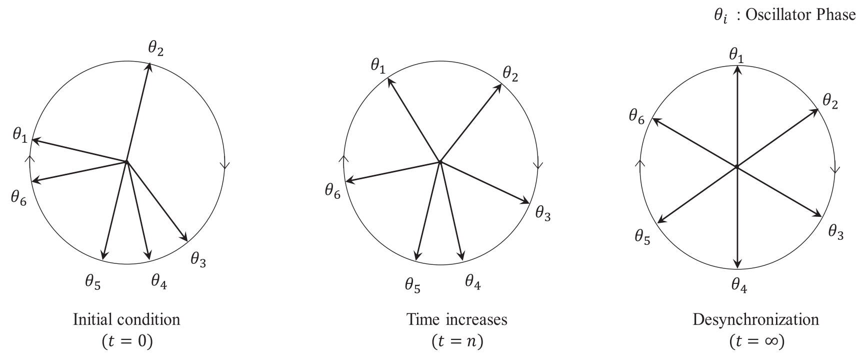


FIGURE 3. De-synchronization in Kuramoto-Desync model.

C. THE PROPOSED KURAMOTO-DESYNC MODEL

In this subsection, we propose the Kuramoto-Desync model for fair resource allocation. While synchronization phenomena obtained by Kuramoto model makes the phases of all the objects converge to the same, the proposed Kuramoto-Desync model is designed to achieve de-synchronization, which means that the phase difference between any two consecutive objects are the same and evenly spaced. The phase update equation of the Kuramoto-Desync model is proposed by

$$\theta_i(t+1) = \theta_i(t) - rK\Delta T \sin(\psi(t) - \theta(t) + (a_0 + \frac{i-1}{N})2\pi), \tag{8}$$

where $\theta_i(t) \in [0, 2\pi)$ is the phase of object i at time t, $a_0 \in [0, 2\pi)$ is a random initial value and $i = 1, 2, \ldots, N$ is a sequence with ascending order according to the phase of each object. It is noticed that in the proposed Kuramoto-Desync model, it is assumed that the firing periods is the same for all nodes, thus the natural frequency of a node is a constant and is set to zero without loss of generality.

Achieving de-synchronization in the proposed Kuramoto-Desync model is interpreted as to make node i to have the phase of $(a_0 + \frac{(i-1)}{N})$ from the average phase at the time when node i fires. Fig. 3 illustrates the phase de-synchronization in the Kuramoto-Desync model.

The following Theorem 1 describes the necessary condition for the convergence of the proposed Kuramoto-Desync model.

Theorem 1: Suppose that each object updates its phase according to (8). If $K\Delta T$ satisfies $-2 < K\Delta T < 0$, de-synchronization is always achieved regardless of the initial phase value of each object.

Proof: Suppose that there are N objects in a network. We construct a Lyapunov function given by

$$V(t) = 1 - \vec{\psi}(t)\vec{u}(t), \tag{9}$$

where $\vec{\psi}$ is the average phase vector of all N objects and $\vec{u}$ is the unit vector of the average phase. Then, $\vec{\psi}$ and $\vec{u}$ are respectively calculated by

$$\vec{\psi}(t) = \frac{1}{N}\sum_{i=1}^{N}\begin{bmatrix}\cos(\theta_i(t) - (a_0 + \frac{i-1}{N})2\pi) \\ \sin(\theta_i(t) - (a_0 + \frac{i-1}{N})2\pi)\end{bmatrix}^T, \tag{10}$$

$$\vec{u}(t) = \begin{bmatrix}\cos(\phi(t)) \\ \sin(\phi(t))\end{bmatrix}. \tag{11}$$

In the above equation, $\phi(t)$ is the angle of the average phase vector $\vec{\psi}(t)$, so $\phi(t) = \angle\vec{\psi}(t)$. Let the difference between two discrete-time steps be ΔV given by

$$\Delta V(t) = V(t+1) - V(t). \tag{12}$$

According to (9) and (12), we have

$$\begin{aligned}\Delta V(t) &= \vec{\psi}(t)\vec{u}(t) - \vec{\psi}(t+1)\vec{u}(t+1) \\ &\leq \vec{\psi}(t)\vec{u}(t) - \vec{\psi}(t+1)\vec{u}(t).\end{aligned} \tag{13}$$

Here, inequality in (13) holds because the projection of $\vec{\psi}(t+1)$ on $\vec{u}(t+1)$ is always larger than the projection of $\vec{\psi}(t+1)$ on $\vec{u}(t)$. According to (13), ΔV is expressed by

$$\Delta V(t) \leq -\Delta\vec{\psi}(t)\vec{u}(t). \tag{14}$$

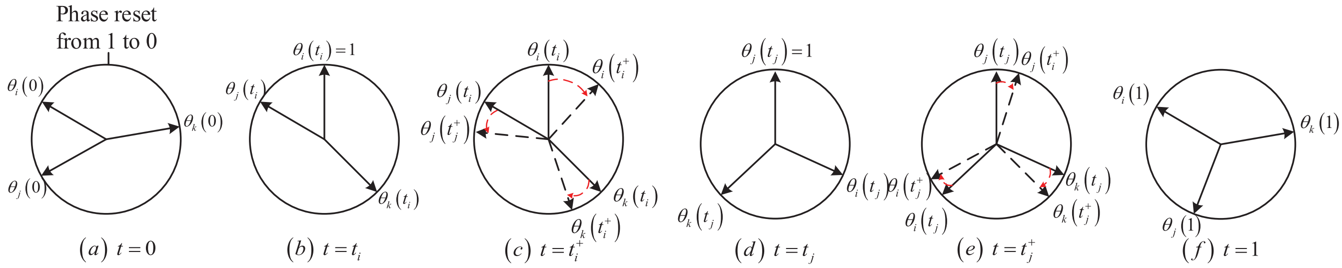


FIGURE 4. Phase update under the Kuramoto-Desync model.

Therefore, by substituting (10) and (11) into (14), the following inequality is established.

$$\begin{aligned}\Delta V(t) &\le \frac{1}{N}\sum_{i=1}^{N}\left\{\begin{bmatrix}\cos(\theta_i(t)-(a_0+\frac{i-1}{N})2\pi)\\ \sin(\theta_i(t)-(a_0+\frac{i-1}{N})2\pi)\end{bmatrix}\right.\\ &\quad\left.-\begin{bmatrix}\cos(\theta_i(t+1)-(a_0+\frac{i-1}{N})2\pi)\\ \sin(\theta_i(t+1)-(a_0+\frac{i-1}{N})2\pi)\end{bmatrix}\right\}^T\begin{bmatrix}\cos(\phi_i(t))\\ \sin(\phi_i(t))\end{bmatrix}. \end{aligned} \tag{15}$$

Let $S_i := (a_0 + \frac{i-1}{N})2\pi$ and $\rho_i(t) := \psi(t) - \theta_i(t) + S_i$. Substituting (8) into (15) yields

$$\begin{aligned}\Delta V(t) &\le \frac{1}{N}\sum_{i=1}^{N}\begin{bmatrix}\cos(\phi_i(t))\\ \sin(\phi_i(t))\end{bmatrix}^T\\ &\quad\cdot\left\{\begin{bmatrix}\cos(\theta_i(t)-S_i)\\ \sin(\theta_i(t)-S_i)\end{bmatrix}-\begin{bmatrix}\cos(\theta_i(t+1)-S_i)\\ \sin(\theta_i(t+1)-S_i)\end{bmatrix}\right\}\\ &= \frac{1}{N}\sum_{i=1}^{N}\cos(\phi(t))\{\cos(\theta_i(t)-S_i)-\cos(\theta_i(t+1)-S_i)\}\\ &\quad+\sin(\phi(t))\{\sin(\theta_i(t)-S_i)-\sin(\theta_i(t+1)-S_i)\}\\ &= \frac{1}{N}\sum_{i=1}^{N}\cos(\phi(t)-\theta_i(t)+S_i)-\cos(\phi(t)-\theta_i(t+1)+S_i)\\ &= \frac{1}{N}\sum_{i=1}^{N}\cos(\phi(t)-\theta_i(t)+S_i)-\cos(\phi(t)-\theta_i(t)\\ &\quad+K\Delta T\sin(\phi(t)-\theta_i(t)+S_i)+S_i)\\ &= \frac{1}{N}\sum_{i=1}^{N}\cos(\rho_i(t))-\cos(\rho_i(t)+K\Delta T\sin(\rho_i(t))). \end{aligned} \tag{16}$$

Assuming $\rho_i(t) > 0$, (16) always becomes negative when $\sin(\rho_i(t)) \neq 0$ for all i and

$$\begin{aligned}&\cos(\rho_i(t))-\cos(\rho_i(t)+K\Delta T\sin(\rho_i(t)))<0\\ &\Leftrightarrow \cos(\rho_i(t)+K\Delta T\sin(\rho_i(t)))>\cos(\rho_i(t)). \end{aligned} \tag{17}$$

The condition for (17) to hold is given by

$$\begin{aligned}&2n\pi-\rho_i(t)<\rho_i(t)+K\Delta T\sin(\rho_i(t))<2n\pi+\rho_i(t)\\ &\quad\Leftrightarrow -2\rho_i(t)<K\Delta T\sin(\rho_i(t))<0. \end{aligned} \tag{18}$$

From (18), we have

$$\frac{-2\rho_i(t)}{\sin(\rho_i(t))} < K\Delta T < 0, \tag{19}$$

which ends the proof. ■

IV. FAIR RESOURCE ALLOCATION UNDER THE KURAMOTO-DESYNC MODEL

In this section, we explain how the proposed Kuramoto-Desync model is applied to TDMA-based networks to achieve fair resource allocation. Suppose that there are N nodes in a network, which fires periodically with a period of TDMA frame size. Actually, a firing event corresponds to a node broadcasting a firing message that all other nodes can hear. A node in a network recognizes phase information of its neighboring nodes by overhearing their firing. A node updates its phase according to the Kuramoto-Desync model. When a node's phase becomes 1, it computes its new phase using (8), transmits this calculated phase to all nodes via a firing message, and adjusts its own phase to the calculated phase. The phases of all nodes are successively updated in the same manner until de-synchronization is achieved. Fig. 4 shows how the Kuramoto-Desync update procedure works when there are three nodes i, j, and k. Suppose that the initial phases of nodes are randomly aligned as in Fig. 4 (a). When the phase of node i becomes 1 at time t_i ($\theta_i(t_i) = 1$), this phase is updated to $\theta_i(t_i^+)$ according to the Kuramoto-Desync model. The updated phase $\theta_i(t_i^+)$ is shared with nodes j and k via node i's firing message and these other nodes update their phases as well. Subsequently, node j, whose phase immediately follows the phase of node i, updates its phase when it becomes 1 at time t_j, and the other nodes i and k update their phases as well.

The proposed Kuramoto-Desync model permits nodes to automatically regulate slot sizes for fully utilizing bandwidth without incurring any collisions. The mapping relation between the phase of a node and resource allocation in a TDMA frame is as follows. First, we decouple the ring in Fig. 4 into the line segment depicted in Fig. 5. At time $t = n$ for a non-negative integer n, node i is allocated TDMA time slots by mapping the two consecutive phase differences from $\theta_i(n)$ to $\theta_j(n)$. If there are M time slots in a TDMA frame, a node i occupies the data time slots that ranges from $\lfloor(\theta_i(n))\cdot M\rfloor$ to $\lfloor(\theta_j(n))\cdot M\rfloor - 1$, where $\lfloor\cdot\rfloor$ is the floor function. This operation guarantees the mutually exclusive and

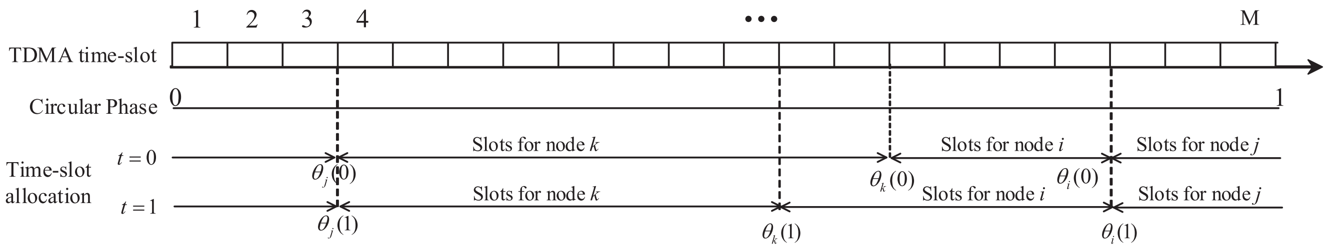


FIGURE 5. **Resource allocation under the Kuramoto-Desync model.**

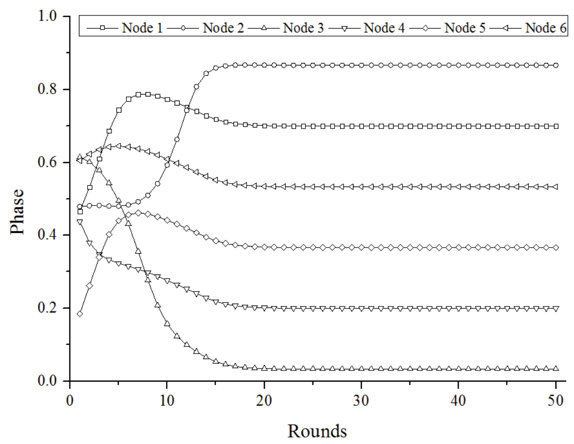


FIGURE 6. **De-synchronization under the Kuramoto-Desync model.**

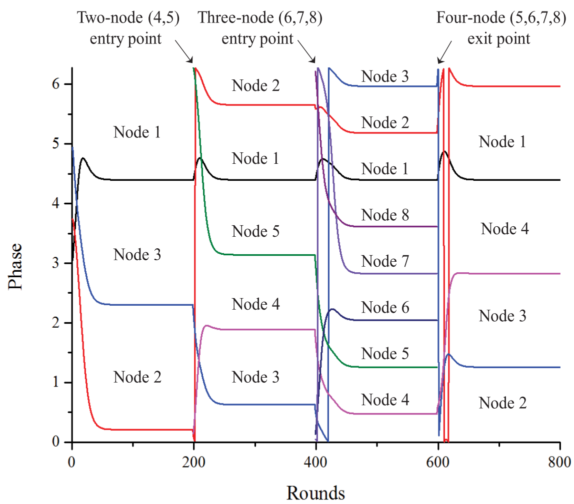


FIGURE 7. **Variation of phases with the change of network topology.**

collectively exhaustive resource allocation among nodes in a network even though de-synchronization is not yet reached.

V. PERFORMANCE EVALUATION

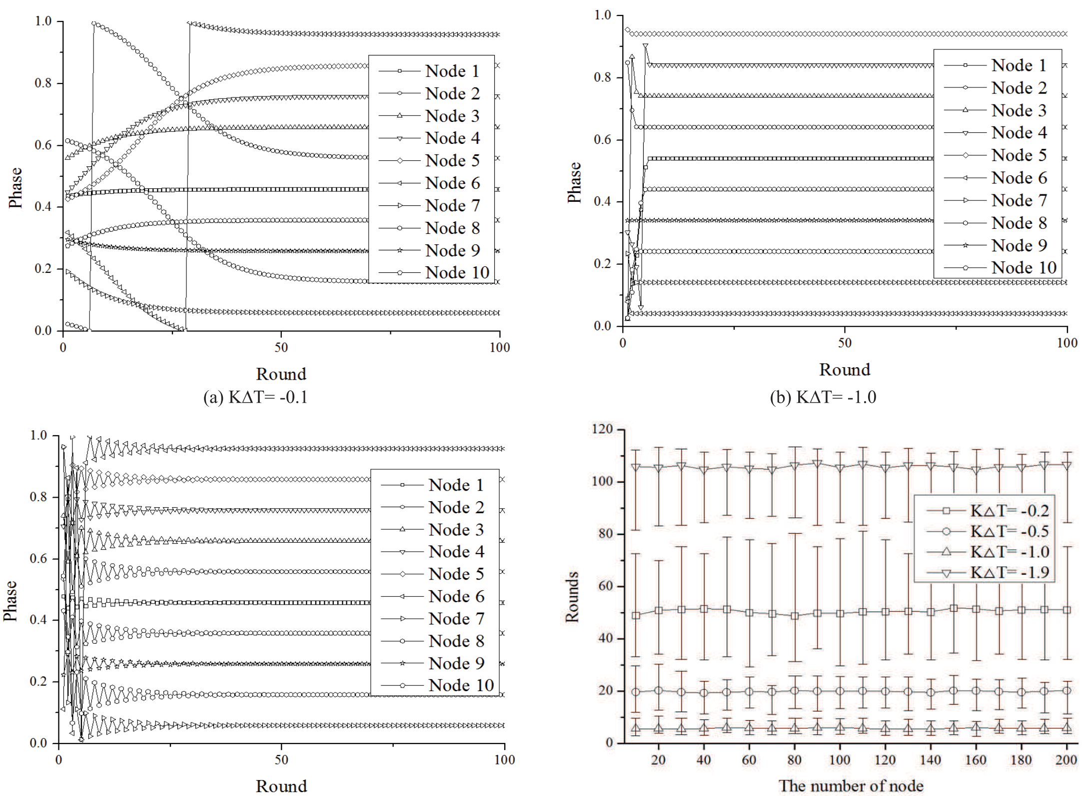
Fig. 6 shows phase de-synchronization under the proposed Kuramoto-Desync model when there are six nodes in a network. We use $r = 1$, $a_0 = 0.2$, and $K\Delta T = -0.2$ for simulation runs. The results show phase de-synchronization of all nodes and the convergence of the Kuramoto-Desync model.

Fig. 7 shows the variation of phases with dynamically changing network topology under the same parameter set as used in Fig. 6. In this simulation run, nodes 1, 2, and 3 initially enter the network simultaneously. At the 200-th iteration, nodes 4 and 5 enter the network for the first time. Nodes 6, 7, and 8 enter at iteration 400. Nodes 5, 6, 7, and 8 then exit the network at the same time, at iteration 600. The simulation results show that the proposed Kuramoto-Desync model adaptively adjusts the phase of each node as the network topology dynamically changes, and demonstrating the robustness of the Kuramoto-Desync model against changes in network topology.

Fig. 8 shows how the convergence speed of the Kuramoto-Desync model varies as a function of $K\Delta T$ when parameters are set as $N = 10$, $r = 1$, and $a_0 = 0.2$. From Fig. 8(a)-(c), we can verify that $K\Delta T$ significantly affects the convergence speed of the Kuramoto-Desync model. Fig. 8(d) shows the average, maximum, and minimum number of iterations required to achieve convergence as a function of the number of nodes in a network, together with the values of $K\Delta T$. From the figure, we verify that (i) the number of nodes in a network does not have much of an impact on the convergence speed of the Kuramoto-Desync model, (ii) the convergence speed becomes faster as $K\Delta T$ approaches 1, and (iii) the convergence speed becomes slower as $K\Delta T$ approaches 0 or -2.

Finally, we compare the Kuramoto-Desync model with that of the De-synchronization model described in Section II. The simulation parameters used for the De-synchronization model are set to be the same as those used for our proposed model for a fair comparison. For the performance metric, we compare the convergence speeds of the two models, which is an important factor in evaluating the real-world applicability of the model. Fig. 9 shows the convergence speeds of the proposed and De-synchronization models as a function of the number of network nodes. Taking into account that the convergence speeds of the Kuramoto-Desync and De-synchronization models are affected by $K\Delta T$ and the weight factor $\alpha \in (0, 1)$, respectively, we choose the values of α values for the De-synchronization model so that $\alpha = \left| \frac{K\Delta T}{-2} \right|$ holds.

Simulation results show that the number of iterations required to obtain de-synchronization using the De-synchronization model increases as the number of nodes increases, while the convergence speed of the Kuramoto-Desync model is stable irrespective of the node density of a network. This characteristic of the Kuramoto-Desync model



(a) KΔT= -0.1 (b) KΔT= -1.0
(c) KΔT= -1.9 (d) The number of convergence round

FIGURE 8. **Convergence speed of the proposed Kuramoto-Desync model.**

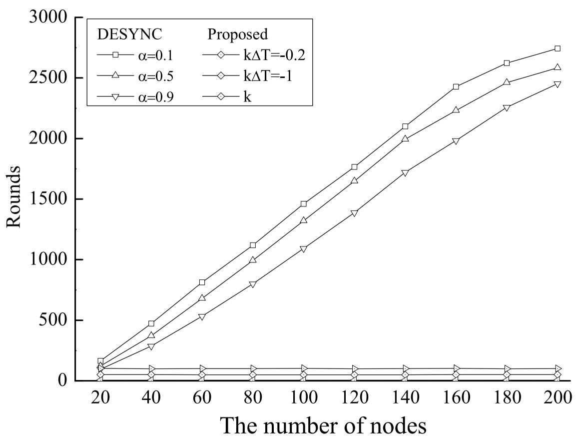


FIGURE 9. **Convergence speed of the Kuramoto-Desync and the De-synchronization model.**

is explained by the fact that all nodes in a network update their phases when any node fires under the Kuramoto-Desync model, by contrast, only the single node having the nearest phase to the phase of the firing node updates its phase under the De-synchronization model. This result allows us to verify the scalability of the Kuramoto-Desync model for resource allocation to large-scale wireless networks.

VI. CONCLUSION

In this paper, we proposed a Kuramoto-Desync model inspired by the Kuramoto model with the purpose of achieving distributed and fair resource allocation across all nodes in a network. We analytically derived the necessary condition for the proposed Kuramoto-Desync model to fully desynchronize and proposed a resource mapping scheme under the Kuramoto-Desync model in a TDMA-based network. Performance evaluation showed that the Kuramoto-Desync model successfully performs fair and distributed resource allocation in a network. Furthermore, we verified that the Kuramoto-Desync model shows robust adaptivity against dynamic network topology changes and scalability against an increasing number of nodes in the network; this shows that the Kuramoto-Desync model is expected to be an efficient resource allocation scheme for large-scale wireless networks.

On the other hand, considering the real-world applicability of the proposed model, it would be an important future research to derive a direct relation between convergence speed and $K\Delta T$ and to obtain the exact value of $K\Delta T$ which achieves the fastest convergence in the Kuramoto-Desync model. Furthermore, it is noted that the Kuramoto-Desync and the De-synchronization models both function in the context of fully-connected networks in which every node can hear the other nodes' firing signals. In wireless multi-hop network environments, one node's firing cannot be propagated to all other nodes immediately, which may accordingly result in duplicated resource allocation and hidden-node problems. Therefore, another important future goal would be to enhance the Kuramoto-Desync model to cover wireless multi-hop networks.

APPENDIX
DEMO VIDEO FOR THE KURAMOTO MODEL & KURAMOTO-DESYNC MODEL

We provide simulation demo video of Kuramoto model and Kuramoto-Desync model. To see our demo video, please visit the following link.

Kuramoto Model: https://youtu.be/DmF6oRPzW-U,
Kuramoto-Desync Model: https://youtu.be/AkqyS4bikHo.

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