A Distributed Hybrid Event-Time-Driven Scheme for Optimization Over Sensor Networks

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***Abstract*—In sensor networks (SNs), how to allocate the resources so as to optimize data gathering and network utility is an important and challenging task. This paper studies the distributed optimization problem in SNs. A distributed hybrid-driven algorithm based on the coordinate descent method is presented for the optimization purpose. The proposed optimization algorithm differs from the existing ones since the hybrid driven scheme allows more choices of actuation time, resulting a tradeoff between communications and computation performance. Applying the proposed algorithm, each sensor node is driven in a hybrid event time manner, which removes the requirement of strict time synchronization. The convergence and optimality of the proposed algorithm are analyzed, and then verified by simulation examples. The developed results also show the tradeoff between communications and computation performance.**

***Index Terms*—Distributed algorithm, hybrid event-time-driven scheme, optimization, sensor network (SN).**

I. Introduction

The Internet of Things (IoT) has emerged as a powerful, integrated solution to interconnected devices that are embedded for critical applications in industry and in our life. There are many smart devices connected over sensor networks (SNs), exhibiting favorable collective behaviors, such as formation, consensus, and optimization [1]–[3]. As the IoT becomes more and more complicated, the scale of SNs goes even bigger. How to allocate limited resources for sensing, communication, and control actuation among sensor nodes thus becomes more important and urgently need to be addressed [4], [5]. There are lots of practical problems in SNs that can be cast to optimization problems, such as data gathering, estimation, localization, tracking and coverage control, and network utility maximization [6], [7], [12], [17].

One well-studied optimization model is the constrained minimization of additive convex functions subject to constraints on convex sets [8], [9], [14]. In general, each convex function is nonnegative, representing a local cost of one sensor node, and the state of each node belongs to an individual constraint set. For convex programming, most existing distributed optimization algorithms resort to consensus-based dynamics and calculation of subgradients [9], [16], [26], [33]. However, networked nodes may not have consensus dynamics, meanwhile the subgradients of cost functions are difficult to calculate precisely at each iteration. Considering the network communication in the IoT, the cost functions associated with SNs are typically of a coupled type, i.e., containing both self part (only with the state of the node) and social part (with the states of neighboring nodes) [10], [11]. It is known that, in the case of a coupled cost, consensus-based subgradient algorithms cannot be applied directly. This motivates the present study for developing distributed optimization algorithms such that coupled cost functions can be optimized while relaxing the troublesome requirement of consensus-based dynamics or subgradient calculation.

On the other hand, due to practical resource demands, the IoT framework prefers asynchronous sensing, communication, and control actuation rather than the difficult time-synchronous ones [2], [9], [12], [25], [27]. The event-triggered method has been proven to be an effective approach to distributed coordination with asynchronous updates, especially in networks with limited resources [18], [20]–[23]. An excellent survey on the event-driven paradigm for control, communication, and optimization is presented in [18].

In this paper, concerning the tradeoff between communication and computation performances, we develop a distributed algorithm for solving the above-discussed optimization problem. Contributions of this paper are summarized as follows.

1) A hybrid event-time-driven scheme is developed for solving distributed optimization in SNs with limited resources. The considered triggering event is defined by a measurement-based condition, meanwhile restricted by a triggering cycle, like the sampling period. The driven scheme is hybrid and integrated at both time and event

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levels, and is Zeno-free, thus allowing more feasibility in that more choices of actuation time are provided.

2) Based on the direct block coordinate descent method [29], a distributed optimization algorithm is designed along with the hybrid event-time-driven scheme. Compared with the works in [10], [11], and [29], the present algorithm incorporates asynchronous hybrid driven updates. The important convergence analysis has been performed, which also shows the influence of the hybrid scheme on distributed optimization.

3) In the hybrid scheme, the triggering cycle is used to ensure the communication requirement in the asynchronous network environment. In addition to the known advantages of event-driven methods, the hybrid optimization algorithm brings a tradeoff between communication and computation/convergence performances.

The rest of this paper is organized as follows. Section II briefly reviews the related works on distributed optimization. Section III describes the network model and formulates the problem of this paper. Section IV presents the new hybrid event-time-driven optimization algorithm with detailed convergence analysis. Section V provides the simulations results, and Section VI concludes this paper.

Notations: Let $\Re$ be the set of all real numbers, and $\Re^m$ the set of all $m \times 1$ real vectors. $y = \text{col}(y_1, \ldots, y_m)$ denotes an $m \times 1$ column vector, $\|\cdot\|$ denotes the 2-norm. $\prod_{i=1}^{N} S_i$ denotes the Cartesian product of sets $\{S_1, \ldots, S_N\}$. $\arg\min\{\cdot\}$ represents the operator yielding an argument, at which a function attains minimum.

II. Related Works

In recent years, extensive research efforts have been devoted to distributed communication, control, and optimization [4], [9], [13], [16], [32], [33]. For example, the data gathering optimization of SNs was studied by a balanced energy allocation scheme in [4]. A distributed linear iterative algorithm was presented for ensuring average consensus in SNs [15]. A distributed coordinated control algorithm was designed for multivehicle systems in [13]. Based on the projected gradient/subgradient method [8], a randomized distributed algorithm was designed for optimal consensus in [9]. Distributed approaches are designed for solving random convex programs, i.e., convex optimization problems with multiple randomly extracted constraints in [16]. A distributed primal–dual subgradient method was used to handle inequality constraints in [33]. Moreover, a distributed alternating direction method of multipliers was presented in [11]. A distributed random optimization algorithm was developed with an application to random field estimation in [10]. The distributed filtering and performance evaluation problems of Markovian jump nonlinear systems over SNs was studied in [32]. However, one common limitation of the aforementioned works is that the distributed algorithms rely on continuous-time communication and control actuation, i.e., linked nodes communicate continuously. This requirement may not always be available, especially in large-scale SNs.

There are many interesting works on event-triggered communication and control for networked systems [2], [20]–[24], [31]. For example, recent advances in consensus of networked multiagent systems have been surveyed and analyzed in [2]. An event-based sensor data scheduling scheme was presented, showing a tradeoff between communication rate and estimation quality in [31]. In [24], both centralized and distributed control algorithms were designed for ensuring consensus of multiagent networks. In [20], a novel distributed event-triggered scheme was proposed for ensuring leader-following consensus. In [22], consensus of multiagent networks was studied with a novel distributed event-triggered coordination algorithm. Particularly in [23], a hybrid time-event-triggered transmission and control strategy was designed for stabilization of networked control systems over SNs.

Meanwhile, there are also some works concerning distributed optimization algorithms with discrete-time communication, i.e., linked nodes communicate only at certain time instants [18], [19], [26], [30], [34]. For example, in [26], a type of distributed optimization algorithms was presented with asynchronous discrete-time communication including an event-triggered scheme. In [34], a distributed optimization algorithm using asynchronous event-driven communication was proposed with an application to the coverage problem in SNs. In [30], a distributed event-triggered optimization method was developed for solving economic dispatch problem in smart grids. These works assumed that the cost function of each node is local, related only to its own state variable, thus the existing algorithms cannot be applied directly to the case of additively coupled cost functions. Besides, the simplex event-triggered scheme may not work all the time due to the existence of triggering actions and event detections.

Based on the above observations, this paper studies distributed optimization problems on sensor networks such as sensor data gathering and multiple vehicle localization that fit into the coupled, constrained minimization setup. The objective is to develop a distributed optimization algorithm concerning tradeoff between communication and computation performances. To this end, a hybrid event-time-driven scheme is designed and incorporated in the algorithm iterations. This study differs from the existing works in that more choices of actuation time can be included with the proposed hybrid driven scheme. Detailed convergence analysis and simulations are given to show the efficiency of the proposed hybrid optimization algorithms.

III. Network Model and Problem Formulation

A. Network Optimization Model

Consider an SN of N nodes, with an undirected communication topology $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where $\mathcal{V} = \{1, 2, \ldots, N\}$ is the set of nodes, and $\mathcal{E} = \{(i,j)|i, j \in \mathcal{V}\}$ is the set of edges. Let $\mathcal{N}_i = \{j \in \mathcal{V}|(i,j) \in \mathcal{E}\}$ be the neighboring set of sensor node i. Each node i has an initial state variable $x_i(0) \in \Re^m$ and a wireless module. And each node has access to the state information of its neighboring nodes $\{x_j(0) : j \in \mathcal{N}_i\}$ in $\mathcal{G}$. The initial state $x_i(0)$ can be the amount of resource/energy, or cost

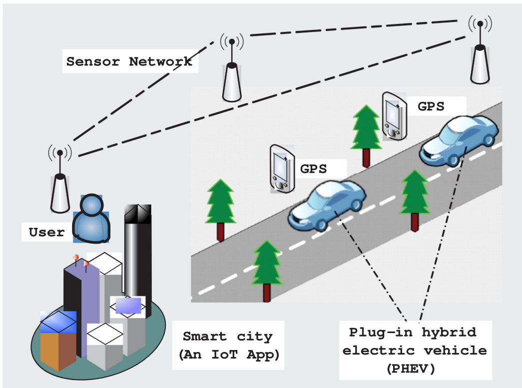


Fig. 1. Architecture of an IoT application over SNs: Multivehicles in smart city.

from sensing and communication that are used for certain control objective. Denote $x = \mathrm{col}(x_1, x_2, \ldots, x_N)$ the state vector.

Fig. 1 presents a multivehicle application. In this scenario, there are distributed vehicles, and each vehicle is equipped with one sensor node. The vehicles are interconnected through wireless SNs with the communication topology $\mathcal{G}$. Let all sensors be equipped with the same wireless module, like TelosB from Crossbow [4].

It should be noted that, in the real world, the IoT is subject to physical limitations, such as resource/state constraints. Practical examples include economic dispatch in smart grids, cost/performance control of mobile vehicles, data gathering, and estimation and localization in SNs (see Fig. 1). These constrained scenarios have inspired a substantial part of research on constrained consensus and optimal consensus of networked nodes [9], [16]. In particular, many problems in SNs can be cast into the following optimization problem [7]:

$$\begin{cases} \text{minimize} & f(x) = \sum_{i\in\mathcal{V}} f_i(x_i, y_i) \\ \quad \text{w.r.t.} & x \\ \text{subject to} & Ax \le g \end{cases} \tag{1}$$

where y_i denotes a measurement local to node i, $f_i(x_i, y_i)$ denotes a local cost function of node i, depending on both x_i and y_i, and $Ax \le g$ denotes certain coupling constraints or balance in the SN.

In this paper, the following constraints will be taken into account. Assume that the state x_i of node i belongs to a constraint set $S_i \subseteq \Re^m$. The state vector then is constrained by $x \in \prod_{i=1}^N S_i$. For example, one can envisage the SN as a vehicle community propagating information over a network. The cost function associated with each sensor consists of two parts since sensor not only has a selfish cost but also has to entail a consequence of mutual communication, like a social cost. Thus, differing from the formulation in (1), a coupled type of cost function is introduced as follows.

Using the state x_i, each sensor node i contains a cost function $h_i(x_i) : \Re^m \to \Re^+$, and each linked pair of nodes (i, j) also has a cost function, denoted by $h_{ij}(x_i, x_j) : \Re^m \times \Re^m \to \Re^+$. In this case, for node i, minimizing $h_i(x_i)$ implies a selfish attempt, while minimizing $h_{ij}(x_i, x_j)$ represents a social cost, a consequence of mutual communication. Let

$$F_i(x_i, x_{N_i}) = h_i(x_i) + \sum_{j\in\mathcal{N}_i} h_{ij}(x_i, x_j) \tag{2}$$

where $x_{N_i} = \{x_j | j \in \mathcal{N}_i\}$. This paper considers the scenario of coupled cost functions, which differs from other existing work concerning only local cost function like $F_i(x_i)$ [7]–[9], [34]. Write $F_i(x_i, x_{N_i})$ as $F_i(x)$, $x = \mathrm{col}(x_1, x_2, \ldots, x_N)$. $F_i(x)$ then represents the coupled cost function, local to node i, $i = 1, 2, \ldots, N$.

B. Problem Formulation

In this paper, by combining the aforementioned constraints, the following minimization problem (MP) is studied:

$$\begin{cases} \text{minimize} & \sum_{i=1}^N F_i(x_i, x_{N_i}) \\ F_i(x_i, x_{N_i}) = h_i(x_i) + \sum_{j\in\mathcal{N}_i} h_{ij}(x_i, x_j) & \\ \text{subject to} & x_i \in S_i, \quad i = 1, 2, \ldots, N. \end{cases} \tag{3}$$

The main *objective* of this paper is to design a new distributed optimization algorithm for solving MP (3).

Definition 1: The distributed optimization problem for MP (3) is said to be solved asymptotically if, for any initial condition $\{x_i(0), i \in \mathcal{V}\}$, there exists a distributed algorithm such that the state vector of SN satisfies $\lim_{k\to\infty} x(k) = s^*$, where s^* is the global optimum ensuring that $\sum_{i=1}^N F_i(s^*) = \min \sum_{i=1}^N F_i(s)$ subject to $s \in \prod_{i=1}^N S_i$.

To proceed, the following assumption is needed.

Assumption 1: For any $x, y \in \prod_{i=1}^N S_i$, the following statements hold:

i) S_i and $F_i(x_i, x_{N_i})$ are closed and convex;

ii) $F_i(x_i, x_{N_i})$ is continuously differentiable and strongly convex w.r.t. x_i, i.e., there exists $m_0 > 0$ such that

$$\begin{aligned}\big(\nabla_1 F_i(y_i, x_{N_i}) - \nabla_1 F_i(x_i, x_{N_i})\big)(y_i - x_i) \\ \ge m_0 \|y_i - x_i\|^2\end{aligned}$$

iii) there exists $M_0 > 0$ such that

$$\big\|\nabla_1 F_i(y_i, x_{N_i}) - \nabla_1 F_i(x_i, x_{N_i})\big\| \le M_0 \|y_i - x_i\|$$

where $\nabla_1 F_i$ denotes the gradient of $F_i(x_i, x_{N_i})$ at x_i, $i = 1, 2, \ldots, N$.

From Assumption 1, it follows [10], [35] that there exists $s^* = \mathrm{col}(s_1^*, s_2^*, \ldots, s_N^*) \in \prod_{i=1}^N S_i$ ensuring a global optimum of MP (3), i.e., $\sum_{i=1}^N F_i(s^*) = \min \sum_{i=1}^N F_i(s)$ subject to $s \in \prod_{i=1}^N S_i$. The above assumption (i)–(iii) are widely used to describe real sensor systems, such as social models and robotic systems [9], [10], [29]. More specifically, in terms of MP (3), these assumptions ensure that each cost function has a unique minimum, and also has a desirable rate of descent when accelerating the convergence process toward the minimum.

To solve MP (3), some effective optimization algorithms have been developed, including the alternating direction method and the coordinate descent method [10], [11], [35]. Among these algorithms, the coordinate descent method is a direct optimal method with the best convergence property. The coordinate descent algorithm is introduced as follows.

Take an initial state $x_i(0) = x_i^0 \in S_i$ and assume that each sensor node updates itself according to the following:

$$x_i(k+1) = \arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k)), \quad i \in \mathcal{V}. \tag{4}$$

Based on Weierstrass' Theorem [28], [29], MP (3) can be solved by algorithm (4) in a time-synchronous manner, if the initial set $S^0 = \left\{x | \sum_{i=1}^N F_i(x) \le \sum_{i=1}^N F_i(x(0))\right\}$ is compact, and $\sum_{i=1}^N F_i(x)$ is closed and convex on set S^0.

Remark 1: Note that, the iterations of algorithm (4) are time-synchronous. One may take $t_k = kh$ or $t_k = kh_k$ according to the time clock, where h and h_k denote the time-unit constant and time-varying sampling period, respectively. Sensors are assumed to share the same clock, requiring strict time synchronization in the loops of sensing, communization, and control actuation. However, as mentioned previously, time-synchronous continuous communication and control actuation may not be realizable in real SNs. Meanwhile, the IoT framework prefers time-asynchronous updates since better robustness can be achieved. The event-triggered scheme provides an effective time-asynchronous mode, by which each node can determine how and when to sense, communicate, and actuate in a relatively independent way [7], [20], [22], [24].

Due to the decentralized feature of sensors associated with multivehicles, solving MP (3) is actually a distributed optimization problem. Thus, the communication load in SNs is an important issue that should be taken into account in the algorithm design. Therefore, asynchronous updates will be one main concern of this paper, as well as a tradeoff between communication load and convergence performances.

IV. Distributed Hybrid Event-Time-Driven Optimization Algorithm

In order to solve MP (3), this section presents a distributed algorithm, which consists of an effective coordinate descent scheme and a hybrid event-time-driven scheme without Zeno behavior.

A. Distributed Hybrid Event-Time-Driven Algorithm

The focus of this paper is to design a distributed optimization algorithm, by which MP (3) can be solved asymptotically. According to the optimal iterations associated with algorithm (4), if each node i updates along the block coordinate descent direction regarding its own cost function $F_i(x)$, then an estimate of the optimum s_i^* can be obtained after certain iterations. Then, each node will take on the optimal-response dynamics directly with respect to MP (3).

From practical consideration of resource demands [27], [30], asynchronous updates would be preferable comparing with time-synchronous ones [18], [21], [22], [24]. Especially in an event-driven setting [20], [31], the fault tolerant control can be achieved by choosing proper triggering conditions [36]. Following this line of thinking, an improved distributed version of algorithm (4) is designed, with hybrid event-time-driven communication and updates. It is expected that the hybrid event-time-driven scheme is capable of reducing unnecessary

TABLE I
Distributed Hybrid Event-Time-Driven Scheme

i) Initialization: $t_0^i = 0$, $x_i(t_0^i) = x_i^0$

ii) Event-time-driven trigger:

$$t_{k+1}^i = \begin{cases} \inf\Big\{t > Ck \big| \rho\big(x_i(t), x_{N_i}(k)\big) \ge \theta_i^k, \\ \qquad\qquad t < C(k+1)\Big\} \\ C(k+1), \qquad \text{otherwise} \end{cases} \tag{5}$$

C is a positive integer

iii) Asynchronous iteration:

$$x_i(k+1) = \arg\min_{x_i \in S_i} F_i\big(x_i, x_{N_i}(k)\big) \tag{6}$$

Repeat $k \leftarrow k+1$

communication and computation burdens while guaranteeing the optimal convergence in MP (3).

The proposed hybrid event-time-driven coordination algorithm consists of the three phases, as sketched in Table I.

Differing from algorithm (4), iteration (6) is triggered by the hybrid event-time-driven scheme (5). Here, $x_i(k) = x_i(t_k^i)$ denotes the kth state measurement of node i, and $x_{N_i}(k) = \{x_j(t_{k'}^j) | t_{k'}^j \le t_k^i, j \in \mathcal{N}_i\}$ denotes the set of the most recent state measurement of neighboring nodes of node i, $k = 0, 1, 2, \ldots$, $t_0^i = 0$, $x_i(t_0^i) = x_i^0$. Particularly, $\rho\big(x_i(t), x_{N_i}(k)\big)$ represents a triggering function determining when node i should communicate with its neighbors and do the iteration (6), and $\theta_i^k > 0$ denotes the triggering threshold.

Precisely, in (5), one has

$$\rho\big(x_i(t), x_{N_i}(k)\big) = \Big\| x_i(t) - \arg\min_{x_i \in S_i} F_i\big(x_i, x_{N_i}(k)\big)\Big\|.$$

Thus, an interpretation of the hybrid driven scheme (5) is: when the difference between the current state $x_i(t)$ and the last argument measurement $\arg\min_{x_i \in S_i} F_i\big(x_i, x_{N_i}(k)\big)$ exceeds a given threshold θ_i^k, a communication event is triggered. Then, node i communicates with its neighbors, collects the latest state measurement, and updates its state information according to the iteration (6). Similarly, to the event-triggered method [20], [22], once a communication event is triggered, the measuring error will be reset to zero, till the end of the corresponding circle, namely $\rho\big(x_i(C(k+1)), x_{N_i}(k)\big) = 0$ will be enforced.

Without loss of generality, assume that in (5) the thresholds $\{\theta_i^k\}_k$ satisfy

$$\sum_{k \ge 0} (\theta_i^k)^2 < \infty, \quad \theta_i^k > 0 \tag{7}$$

for $i = 1, 2, \ldots, N$. Then, under the triggering condition given in (5), it can be verified that $Ck < t_{k+1}^i \le C(k+1)$. This is because, in (5), if there exists an $\tilde{t} \in (Ck, C(k+1))$ such that $\rho\big(x_i(\tilde{t}), \hat{x}_{N_i}(k)\big) \ge \theta_i^k$, then $t_{k+1}^i = \tilde{t}$; otherwise, $t_{k+1}^i = C(k+1)$.

Remark 2: The algorithm (6) contains asynchronous updates based on hybrid event-time-driven sampling data, which differs

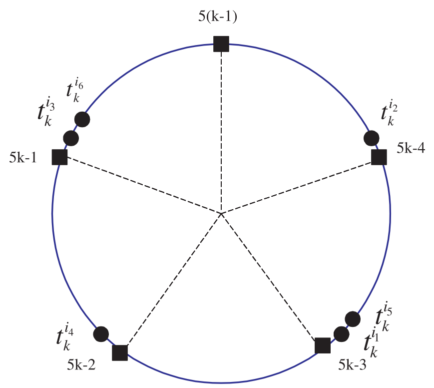


Fig. 2. Configuration of hybrid event-time-driven scheme for six agents: $C = 5$, squares denote clock time, and dots denote event instants.

from the algorithm (4) that depends on time-synchronous sampling data. The asynchronous algorithm (6) thus is superior to the time-synchronous algorithm (4) in terms of less actuation time. Applying (6), the optimal-response dynamics in MP (3) is imposed on each node. It can be seen that each node only uses the neighboring information from the coupling configuration of $F_i(x_i, \hat{x}_{N_i})$. In this setting, to solve MP (3) iteratively, each agent takes only local information regarding the local cost function $F_i(x_i, \hat{x}_{N_i})$. The hybrid driven algorithm (6) then requires no consensus-based dynamics, which was used in [2], [9], and [33]. Thus, no further requirement of the network connectivity is needed, as will be further discussed in the simulation. In addition, an observer-based technique such as the one developed in [36] can be used to improve the algorithm (6) to handle the sensor fault case.

Since each node uses its own state measurement to evaluate the triggering condition, the hybrid driven scheme (5) involves asynchronous updates with a new estimate for the optimum of MP (3). In (5), in order to ensure sufficient amount of communication and updating, each node is supposed to communicate and update at least once in every C consecutive time slots, which is confirmed by the constraint $t \le C(k+1)$. Combining the hybrid driven scheme (5) and the typical event-triggered method, it follows that $t^i_{k+1} \in (Ck, C(k+1)]$, which implies that all N nodes are activated exactly once in every C time slots, as illustrated in Fig. 2. In this context, the interevent time $t^i_{k+1} - t^i_k$, implicitly defined by (5) is positively lower bounded, i.e., no Zeno behavior exists.

Remark 3: In the hybrid driven scheme (5), C is referred to as the triggering cycle. More precisely, C represents the partial asynchronism described in [35]. The usage of the triggering cycle is to ensure that sensor nodes can communicate and update sufficiently often in asynchronous manner. The hybrid driven scheme (5) then can be viewed as an improved event-triggering approach since it may contain more triggering events with different choices of θ^k_i and C. In particular, by choosing a small threshold θ^k_i satisfying (7), the triggering scheme (5) becomes the typical time-synchronous case. The triggering scheme (5) is hybrid at both time and event levels, akin to the hybrid impulsive control method [25]. Thus, comparing with traditional time-clocked method or event-triggered method, the hybrid event-time-driven algorithm (5)–(6) has more flexibility and better robustness, allowing a tradeoff between communication/updating and optimal coordination, as studied in [23] and [31].

B. Convergence Analysis

In the subsequent part, denote $x(k) = \mathrm{col}(x_1(k), x_2(k), \ldots, x_N(k))$, representing the sampled data at the end of time circle Ck. In view of the hybrid driven algorithm (5)–(6) and by the zero-order holder (ZOH), one has $x_i(k) = x_i(t^i_k)$, $i = 1, 2, \ldots, N$. Let $F^* = \sum_{i=1}^N F_i(s^*)$ be the optimal value of MP (3). The resulting global error with respect to MP (3) is given by

$$\Phi(x(k)) = \sum_{i=1}^{N} F_i\big(x_i(k), x_{N_i}(k)\big) - F^* \tag{8}$$

where $k = 0, 1, 2, \ldots,$. Clearly, $\Phi(x(k)) \ge 0$, due to the fact that F^* is the minimum in MP (3).

To show the optimal convergence of the hybrid driven algorithm (5)–(6), the following theorem demonstrates a decreasing trend of the error sequence $\{\Phi(x(k))\}_k$ given in (8).

Theorem 1: Suppose that Assumption 1 is satisfied, and $\{x_i(k)\}_k$ is generated by the hybrid driven coordination algorithm (5)–(6). Then

$$\Phi(x(k+1)) \le \Big(1 - \frac{m_0}{M_0 C}\Big)\Phi(x(k)) + M_0\Big(C + \frac{1}{C}\Big)\sum_{i=1}^{N}(\theta^k_i)^2. \tag{9}$$

Proof: From the iteration (6), it follows that:

$$\begin{aligned} &F_i\big(x_i(k+1), x_{N_i}(k)\big) \\ &= F_i\Big(\arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k)), x_{N_i}(k)\Big) \\ &= \min_{x_i \in S_i} F_i\big(x_i, x_{N_i}(k)\big) \end{aligned} \tag{10}$$

By Assumption 1 (i)–(iii), one has the following two relationships: For any $x_i \in S_i$

$$\begin{aligned} F_i\big(x_i, x_{N_i}(k)\big) \le\ & F_i\big(x_i(k), x_{N_i}(k)\big) \\ &+ \nabla_1 F_i\big(x_i(k), x_{N_i}(k)\big)(x_i - x_i(k)) \\ &+ \frac{M_0}{2}\|x_i - x_i(k)\|^2 \end{aligned}$$

$$\begin{aligned} &\Big\|\nabla_1 F_i\Big(\arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k)), x_{N_i}(k)\Big) \\ &\qquad - \nabla_1 F_i(x_i(k), x_{N_i}(k))\Big\| \\ &\le M_0\Big\|\arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k)) - x_i(k)\Big\|. \end{aligned}$$

Since $\nabla_1 F_i(\arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k)), x_{N_i}(k)) = 0$, one gets

$$\begin{aligned} &\|\nabla_1 F_i(x_i(k), x_{N_i}(k))\| \\ &\quad \le M_0\Big\|\arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k)) - x_i(k)\Big\|. \end{aligned}$$

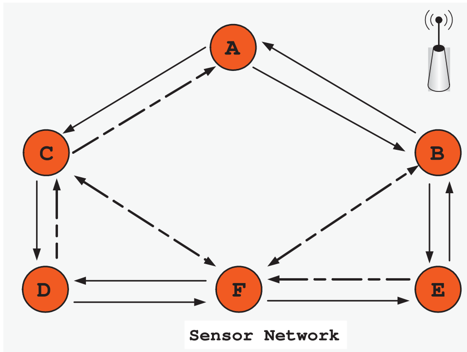


Fig. 3. Communication topology: An SN with 6 nodes.

Note that on each time slot $(Ck, C(k+1)]$, according to the triggering scheme (5), all nodes are supposed to update only once. In other words, from time Ck to $C(k+1)$, all nodes are triggered to take the optimal iteration (6), in which each node is activated only once in every C time slots. Thus, substituting $x_i = \arg\min_{x_i \in S_i} F_i(x_i, x_{N_i}(k))$ into (10) gives

$$\begin{aligned}
&F_i\big(x_i(k+1), x_{N_i}(k)\big)\\
&\le F_i\big(x_i(k), x_{N_i}(k)\big) + \nabla_1 F_i\big(x_i(k), x_{N_i}(k)\big)\\
&\quad\times \Big(\arg\min_{x_i\in S_i} F_i\big(x_i, x_{N_i}(k)\big) - x_i(k)\Big)\\
&\quad+ \frac{M_0}{2}\Big\|\arg\min_{x_i\in S_i} F_i\big(x_i, x_{N_i}(k)\big) - x_i(k)\Big\|^2\\
&\le F_i\big(x_i(k), x_{N_i}(k)\big) - \frac{1}{2M_0C}\big\|\nabla_1 F_i\big(x_i(k), x_{N_i}(k)\big)\big\|^2\\
&\quad+ \Bigg\|\frac{1}{\sqrt{2M_0C}}\nabla_1 F_i\big(x_i(k), x_{N_i}(k)\big)\\
&\quad+ \sqrt{\frac{M_0C}{2}}\Big(\arg\min_{x_i\in S_i} F_i\big(x_i, x_{N_i}(k)\big) - x_i(k)\Big)\Bigg\|^2.
\end{aligned}$$

Then, by the triggering condition given in (5), one obtains

$$\begin{aligned}
F_i\big(x_i(k+1), x_{N_i}(k)\big) &\le F_i\big(x_i(k), x_{N_i}(k)\big)\\
&\quad- \frac{1}{2M_0C}\big\|\nabla_1 F_i\big(x_i(k), x_{N_i}(k)\big)\big\|^2\\
&\quad+ M_0\Big(C + \frac{1}{C}\Big){\theta_i^k}^2.
\end{aligned}\tag{11}$$

Thus, it follows that:

$$\begin{aligned}
\sum_{i=1}^{N} F_i\big(x_i(k+1), x_{N_i}(k)\big) &\le \sum_{i=1}^{N} F_i\big(x_i(k), x_{N_i}(k)\big)\\
&\quad- \frac{1}{2M_0C}\sum_{i=1}^{N}\big\|\nabla_1 F_i(x_i(k), x_{N_i}(k))\big\|^2\\
&\quad+ M_0\Big(C + \frac{1}{C}\Big)\sum_{i=1}^{N}{\theta_i^k}^2.
\end{aligned}$$

On the other hand, by Assumption 1 (i) and (ii), one gets

$$\begin{aligned}
&\sum_{i=1}^{N}\big\|\nabla_1 F_i(x_r(k), x_{N_i}(k))\big\|^2\\
&\quad\ge \Big\|\sum_{i=1}^{N}\nabla_1 F_i(x_r(k), x_{N_i}(k))\Big\|^2\\
&\quad\ge 2m_0\left(\sum_{i=1}^{N} F_i(x_i(k), x_{N_i}(k)) - F^*\right).
\end{aligned}$$

Therefore

$$\begin{aligned}
\sum_{i=1}^{N} F_i\big(x_i(k+1), x_{N_i}(k)\big) &\le \sum_{i=1}^{N} F_i\big(x_i(k), x_{N_i}(k)\big)\\
&\quad- \frac{m_0}{M_0C}\left(\sum_{i=1}^{N} F_i(x_i(k), x_{N_i}(k)) - F^*\right)\\
&\quad+ M_0\Big(C + \frac{1}{C}\Big)\sum_{i=1}^{N}{\theta_i^k}^2.
\end{aligned}\tag{12}$$

Consequently, subtracting F^* from both sides of (12) yields the result. ■

Based on Theorem 1, we show that the distributed optimization problem in MP (3) can be solved asymptotically by the hybrid event-time-driven algorithm (5)–(6). In view of condition (7), more precise characterization of θ_i^k will be given below for the optimization purpose.

Theorem 2: The hybrid event-time-driven algorithm (5)–(6) asymptotically solves MP (3), if the triggering threshold $\{\theta_i^k\}_k$ satisfies

$$\sum_{i=1}^{N}(\theta_i^k)^2 < \frac{m_0}{(C^2+1)M_0^2}\Phi(x(k)) \tag{13}$$

where $\Phi(x(k))$ is defined by (8), $k = 0, 1, 2, \ldots,$.

Proof: Since the triggering threshold θ_i^k satisfies condition (13), there exists a constant $1 > \varepsilon > 0$ such that

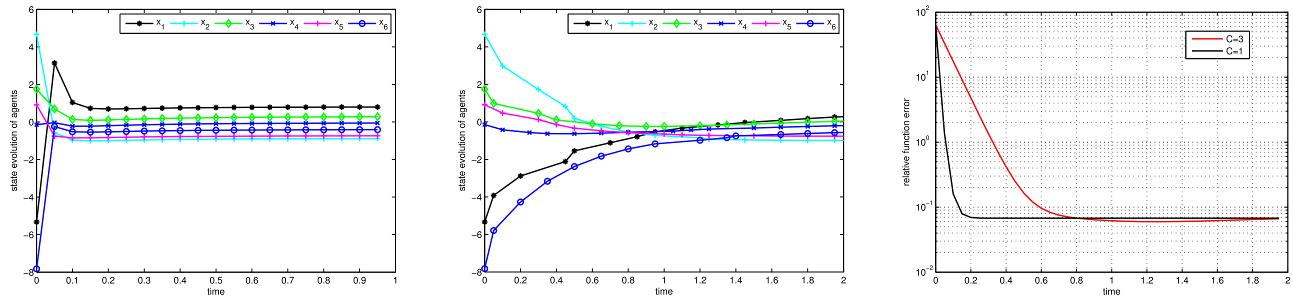
$$\sum_{i=1}^{N}(\theta_i^k)^2 = (1-\varepsilon)\frac{m_0}{(C^2+1)M_0^2}\Phi(x(k)).$$

Substituting the above equation into (9) gives

$$\Phi(x(k+1)) \le \Big(1 - \frac{\varepsilon m_0}{M_0C}\Big)\Phi(x(k)). \tag{14}$$

Therefore, with $0 < 1 - \frac{\varepsilon m_0}{M_0C} < 1$, one has $\Phi(x(k)) \to 0$ as $k \to \infty$, which implies $x(k) \to s^*$. That is, MP (3) is solved asymptotically by the hybrid algorithm (5)–(6). ■

Remark 4: Theorem 1 provides a recursive estimate of error function $\Phi(x(k))$, which is necessary for qualifying the convergence rate associated with algorithm (5)–(6). Based on the relationship developed in Theorem 1, the asymptotic stability property of error function $\Phi(x(k))$ is naturally obtained in Theorem 2. It is easy to find one θ_i^k to satisfy condition (13). For example, one may choose $\theta_i^k = \frac{1}{k+1}, \frac{1}{\sqrt{(k+1)(k+2)}}$ or $\frac{1}{2^{k+1}}$ [14]. Based on the recursive relation (9), it can be verified that



(a) (b) (c)

Fig. 4. State evolutions and error comparison using the hybrid driven algorithm (5)–(6). (a) $C = 1$. (b) $C = 3$. (c) Error comparison.

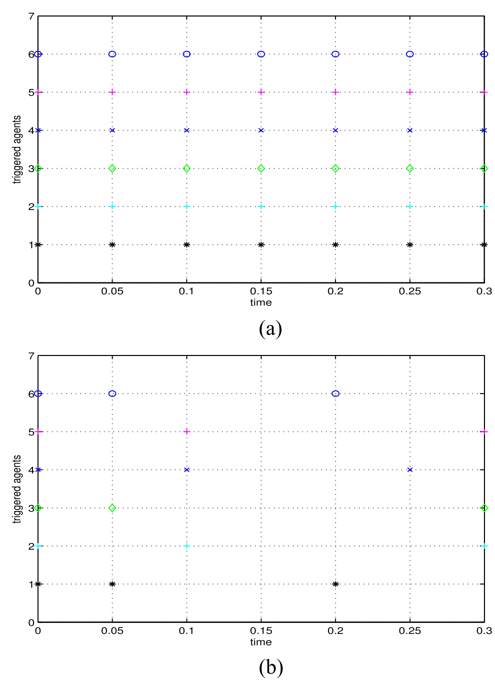


Fig. 5. Triggering instants of nodes under the hybrid driven scheme (5) within two circulations. (a) $C = 1$. (b) $C = 3$.

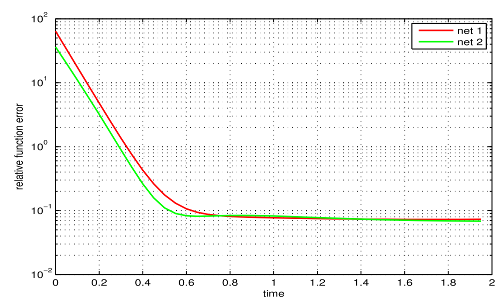


Fig. 6. Error comparison under different network topologies: 'net 1' is from the full communication graph $\mathcal{G}$, as shown in Fig. 3, while 'net 2' is the variant after removing the dashed links.

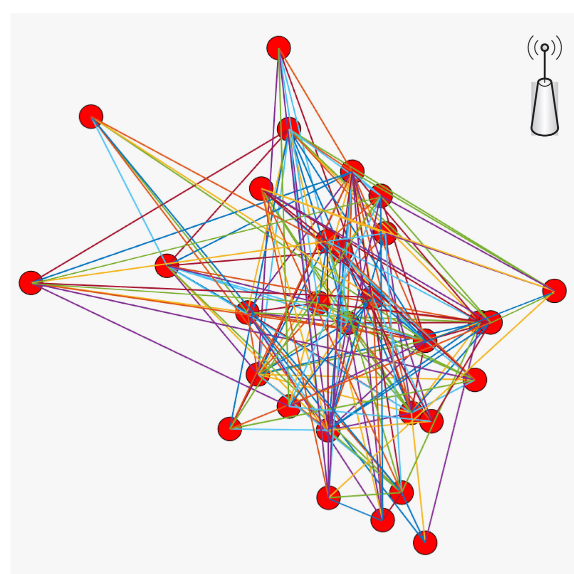


Fig. 7. Communication topology: An SN with 30 nodes

$\sum_{k\geq 0} \Phi(x(k)) < \infty$ under condition (13). This implies that $\Phi(x(k)) \to 0$ as $k \to \infty$. Condition (13) is reasonable since the sensors are activated to communicate and update by the hybrid event-time-driven scheme (5).

Remark 5: In Theorem 1, C represents the triggering cycle, which describes how often sensor nodes communicate and update. In this sense, Theorem 2 together with Theorem 1 demonstrate that the distributed hybrid event-time-driven algorithm (6) admits a tradeoff between the communication effort and the resulting optimality with MP (3). Specifically, considering the approximated convergence factor $1 - \frac{m_0}{M_0 C}$, smaller values of C would result in better convergence performance. When $C = 1$, the triggering scheme (5) becomes the time-synchronous case, since each node will be activated in every time slot. The tradeoff thus is developed through the integration of the triggering condition and the triggering circle C. This balanced phenomenon distinguishes the hybrid driven coordination algorithm (5)–(6) from those optimization algorithms developed in [10], [11], [14], and [16].

V. Performance Evaluation

In this section, simulation results are given to show the convergence performance of the hybrid event-time-driven coordination algorithm (5)–(6) when solving MP (3).

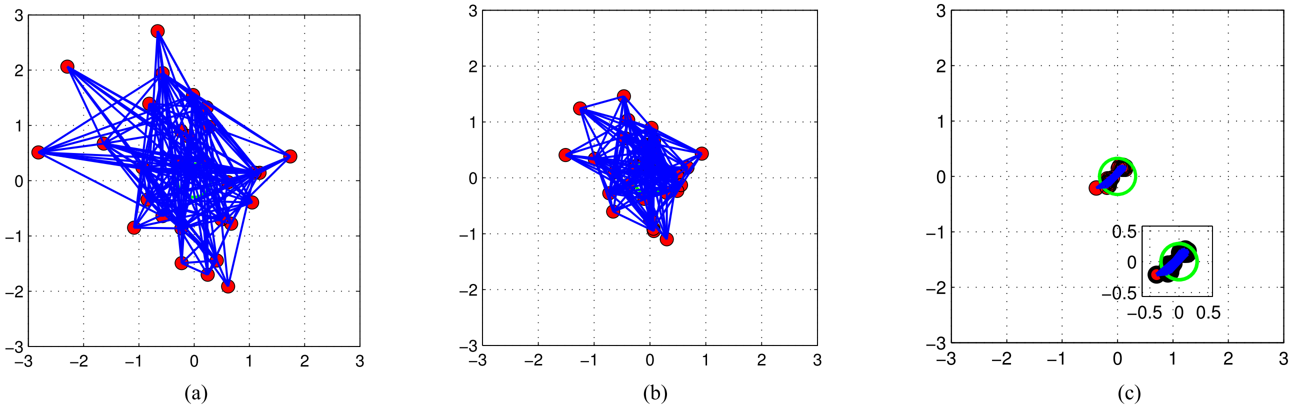


Fig. 8. Snapshots of phase diagrams of nodes using the hybrid driven algorithm (5)–(6). (a) $t = 0$ s. (b) $t = 5$ s. (c) $t = 30$ s.

Example 1: Consider an SN consisting of six nodes, where the communication topology $\mathcal{G}$ is an undirected graph, as shown in Fig. 3. This example takes into account the data gathering problem of SNs that MP (3) can fit in.

Specification of the MP (3) is summarized as follows. The cost functions and the constraint sets are given as.

1) $h_1(x_1) = 0.5(x_1 - 3)^2$, $h_2(x_2) = (x_2 + 2)^2$
$h_3(x_3) = e^{-x_3} + 0.8e^{0.2x_3}$
$h_4(x_4) = 0.5x_4^2 + 0.2x_4^2 \ln(1 + x_4^2)$
$h_5(x_5) = 0.2(x_5 + 3)^2 + \frac{x_5^2}{\sqrt{(x_5+3)^2}}$
$h_6(x_6) = 0.2(x_6 + 1)^2$.
2) $h_{ij}(x_i, x_j) = 0.5\|x_i - x_j\|^2$ $(i \neq j)$.
3) $S_i = \{x_i \in \Re | x_i \in [-8, 10]\}$, $i, j = 1, \ldots, 6$.

In this case, MATLAB yields the optimal value of MP (3): $s^* = \text{col}(0.3926, -0.6313, 0.1129, -0.0874, -0.5865, -0.3315)$, and $F^* = 9.9656$. Take the initial condition: $x^0 = \text{col}(-5.3335, 4.6686, 1.7516, -0.1450, 0.9123, -7.8253)$.

According to condition (7), choose the threshold $\theta_i^k = 1/2^{k+1}$, satisfying $\sum_{k\geq 0}(\theta_i^k)^2 < \infty$. Following the iteration (6), condition (13) is satisfied at each time k. Applying the hybrid driven coordination algorithm (5)–(6), simulation results are obtained, as presented in Fig. 4. Considering different values of triggering cycle C, Fig. 4(a) and (b) shows the state evolutions of nodes that converge to the optimum s^*. To show the optimality with the coordination algorithm (5)–(6), Fig. 4(c) further depicts and compares the dynamical evolutions of the relative function error $\text{err}(k) = (\sum_{i=1}^{6} F_i(x_i(k), x_{N_i}(k)) - F^*)/F^*$ for different triggering cycles. These simulation results demonstrate that MP (3) is solved by using the coordination algorithm (5)–(6), which is consistent with Theorem 2. Together with Fig. 4(c), Fig. 4(a) and (b) suggests that the optimal convergence of the hybrid driven algorithm (5)–(6) can be ensured under different driven scenarios.

For different choices of C, the triggering instants of nodes are depicted in Fig. 5, showing how the hybrid event-time-driven scheme (5) works. In this example, each time slot is assumed to be 0.05 s. Fig. 5(a) represents the case of $C = 1$, i.e., the time-synchronous scenario, while Fig. 5(b) corresponds to the case of $C = 3$ over two circulations. Combining Fig. 5(a) and (b), it suggests that smaller value of the triggering cycle C would result in better convergence, which is consistent with the approximated convergence rate $1 - \frac{m_0}{M_0 C}$ derived in Theorem 1.

Fig. 6 compares the evolutions of the relative function error $\text{err}(k)$ in the case of $C = 3$, where different network topologies are taken into account. In contrast to 'net 1', 'net 2' has a weaker connectivity but results in a relatively better optimality, in solving MP (3). This phenomenon confirmed that the hybrid driven coordination algorithm (5)–(6) requires no more connectivity beyond the original topology $\mathcal{G}$.

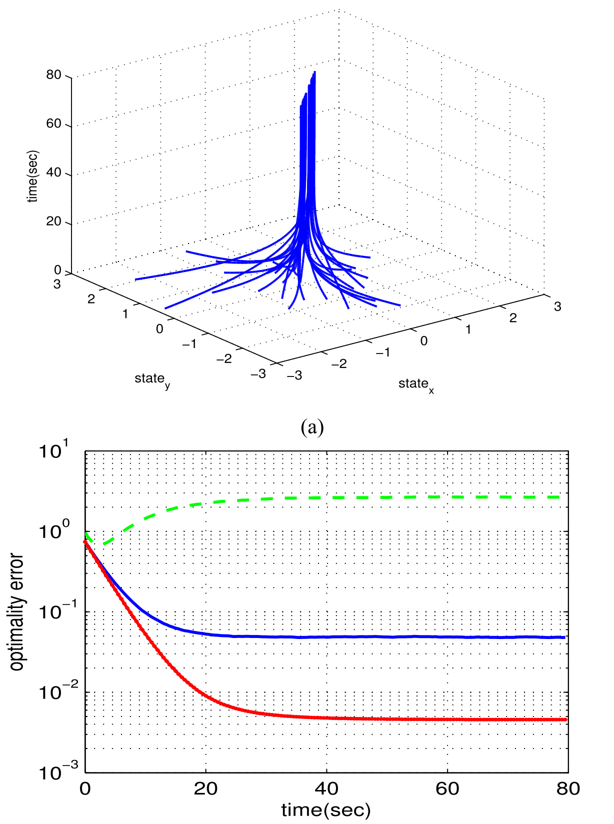
Example 2: Consider the estimation and localization problem of an SN, where multivehicles cooperate to search for and localize one source (a destination or a food site) at minimum cost [10]. To show the scalability with the coordination algorithm (5)–(6), an SN consisting of 30 nodes is simulated.

The distributed optimization to MP (3) is settled over 30 nodes, as depicted in Fig. 7. Consider the social foraging model that was widely studied in the literature, we choose the following cost functions:

1) $h_i(x_i) = \frac{1}{2}\|x_i + (5; 5)\|^2$, if i is an odd integer,
$h_i(x_i) = \frac{1}{2}\|x_i + (-5; -5)\|^2$, otherwise.
2) $h_{ij}(x_i, x_j) = \frac{1}{2}\|x_i - x_j\|^2$ $(i \neq j)$.
3) $S_i = \{x_i \in \Re^2 | x_i \in ([-10, 10]; [-10, 10])\}$
$i, j = 1, \ldots, 30$.

Similar to related work [10], the above functions are chosen based on the fact that between individual nodes, attraction force is dominant at large distances, while for short distances repulsion force dominates. Applying the hybrid driven coordination algorithm (5)–(6), the triggering threshold is given by $\theta_i^k = 2/(k + 1)$, satisfying $\sum_{k\geq 0} \theta_i^k)^2 < \infty$, and the triggering cycle is $C = 3$.

Fig. 8 provides the optimal state evolutions of nodes using the coordination algorithm (5)–(6), where nodes are placed over an $[-3, 3] \times [-3, 3]$ square. It is shown that nodes can aggregate to the optimum s^* step by step, see Fig. 8(a)–(c). Moreover, the convergence curves in the phase diagram are presented in Fig. 9(a), while the dynamical evolutions of the relative error function $\text{err}(k)$ is depicted and compared in Fig. 9(b), for different choices of C. It can be observed from Fig. 9(b) that the optimal approximation can be better as the triggering cycle C goes smaller, i.e., with more communication requirement. With scheme (5), an explicit characterization of triggering instants on



(a)

(b)

Fig. 9. State evolutions using the coordination algorithm (5)–(6): In (b), different triggering cycles C are considered, where red-line denotes $C = 1$, blue-line denotes $C = 3$, and green-line denotes $C = 100$. (a) Phase diagram. (b) Error comparison.

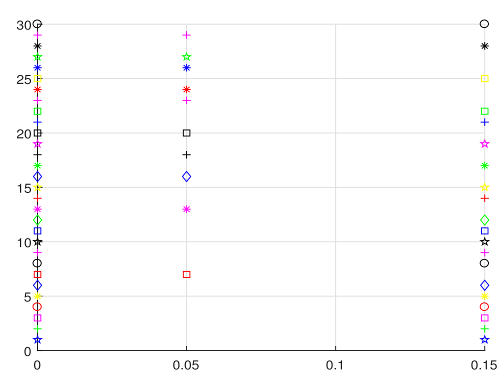


Fig. 10. Triggered instants within one circulation: $C = 3$.

one circulation is presented in Fig. 10, where each node is driven only once in every C time slots. Recalling that one circulation has C time slots, with each time slot $h = 0.05$, Fig. 10 has well verified the hybrid driven scheme given in (5).

VI. Conclusion

In this paper, a distributed hybrid driven algorithm was developed and analyzed, with which the optimization problems of data gathering and localization in SNs can be solved efficiently. A new distributed optimization algorithm was developed based on the hybrid event-time-driven scheme, exhibiting no Zeno behavior. For the hybrid driven scenario, the event-triggered scheme was applied to sensors equipped with limited resources, while the time-clocked restriction was imposed to ensure necessary communication and updating in time-asynchronous setting. It was shown that, under convexity assumptions, convergence of the proposed optimization algorithm is guaranteed with an estimated rate of convergence. Meanwhile, a tradeoff between communication cost and computation performance can be ensured by taking proper triggering cycle and triggering threshold. Simulation results were given to verify the effectiveness of the proposed hybrid driven algorithm for different optimization problems in SNs. Future research includes relaxing the convexity assumption, and developing intelligent event-driven methods for network optimization.

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