Interference Aware Optimal Power Allocation for Industrial IoT: A Self-triggered Approach

Zohaib Ijaz, Md. Noor-A-Rahim, Dirk Pesch

***Abstract*—One of the key use cases for 5G cellular communication is wirelessly connected smart factory applications as part of the Industry 5.0 vision. Such applications require high throughput, low latency, and highly reliable communication for critical control applications. With limited private spectrum available for Industry 5.0 use cases, scarce wireless network resources (e.g., bandwidth, channel capacity, etc.) need to be used efficiently. In this paper, we optimize wireless channel resources, in particular the secondary control channel, by increasing channel capacity in the presence of interference through power control and self-triggered control (STC) based message transmission. We aim to maximize control channel efficiency and minimize secondary control communication. Our simulation results demonstrate that STC-based communication can achieve the same system performance as periodic communication while preserving about 85% of the control channel bandwidth.**

***Index Terms*—Industry 5.0, Industrial IoT, Network Resource Management, Smart Manufacturing, Energy Efficient System, Self-Triggered Control.**

I. Introduction

As industrial control applications have a low tolerance for communication delays or errors, the industry has traditionally used wired communication to connect sensors, actuators, and control systems. However, wireless communication offers many advantages over wired communication, as it does not require wiring, allows device mobility, and reduces costs. The Industrial Internet of Things (IIoT) is driven by wireless communication, a key ingredient of Industry 5.0 [1]. Most recently, 5G connectivity has gained attention across many industries as it offers dependable communication services. Ultra-reliability and low latency are now possible with the evolution of cellular 5G connections, albeit at a hefty cost. As the industry has a strong emphasis on cost control, optimal network resource utilization and spectrum efficiency for industrial IoT devices [2]–[5] is paramount due to the high cost of 5G spectrum licenses.

Numerous solutions have been proposed to maximize channel capacity. Industrial customers often receive power from third-party grids, which imposes significant costs on customers due to high transmission and generation costs. The industry is also required to buy license spectrum for their communication channels. As a result, in order to save costs, the user (or device) must maximize channel capacity while limiting the use of maximum power by the system. Several preliminary attempts have been made in [6]–[14] to optimize channel capacity while taking into account various power supply constraints.

Optimal power control with channel capacity maximization is a major challenge because the channel is shared by all the devices, and the devices are not intelligent enough to calculate the number of devices connected to the system and then allocate resources accordingly. As a result, in order to optimally distribute resources to all the devices, the concept of a Central Control Unit (CCU) was established, which will monitor and collect data on all devices present in the system [15], [16]. CCU will then be incharge of determining the resources that can be made available to individual users [15].

While the primary control of channel capacity has been adequately discussed in the literature, secondary control, in which the CCU communicates with different users to allocate resources, has been overlooked. Although secondary control does not need much bandwidth as it operates on a low-frequency shared channel, it may occupy the channel continuously, leading to congestion. This secondary channel of communication has been largely ignored, with less emphasis on resource minimisation. The current design requires the CCU to communicate with each user at specific, predetermined periodic rates to obtain user requirements and distribute resources. This can require a large amount of bandwidth to ensure reliability, often leading to over-dimensioning of the given channel [17].

Recent efforts have been made to switch from time-based communication to a needs-based, aperiodic communication strategy, i.e., only transmitting messages when necessary. One interesting aperiodic communication strategy is Event-Triggered Communication (ETC), in which the controller continuously monitors the state of the system and communicates only when an event occurs. The issue with ETC is that it is proactive in nature and reacts to any change in the system, necessitating additional hardware resources such as sensors that will continuously monitor the system state in order to detect events, leading to an increase in the

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cost of the system. To address this issue, [18]–[20] proposed STC, in which the CCU calculates the next communication instance on the current triggering time and the controller remains silent between two communication instances, offsetting the need for additional continuous monitoring of the state. In STC, the CCU receives information from all devices at the STC communication time, calculates the next STC time, and updates the controller actuator signal based on the difference in states of all devices. Therefore, we propose an STC technique that decreases the CCU's communication requirements by up to 85% while maintaining the same performance in resource optimization as in the time-periodic approach.

The remainder of this article is organized as follows: Related work is discussed in section II; the optimal channel capacity maximization problem is formulated in section III; the communication strategy is introduced in section IV, with STC formulation in subsection IV-1; simulation results are presented in section V; conclusion and future work are discussed in section VI.

II. Related Work

The architecture of IIoT is addressed in [21]–[26], with a 5G-based IIoT model being proposed in [27]. The authors examine various smart manufacturing designs using 5G connectivity to get enhanced mobile broadband (eMMB), ultra-reliability and low-latency communication (URLLC), and communication between massive machine-type communication (mMTC). In [28], a technique for dealing with delays while transmitting through the uplink channel of the IIoT was presented. Mobile robots communicate through 5G between the controller and the production line. In [29], channel assignment and power optimization for the IIoT are covered. The authors suggest a technique for partial resource multiplexing in which a cellular user can multiplex its resources using a single device-to-device (D2D) pair. The authors address the power optimization problem using the Lagrange dual optimization technique. In [30], a joint D2D paring and power allocation problem is decomposed into multiple min-max local functions to obtain a URLLC network. Additional issues with power allocation have been examined in [29], [31], [32].

The aforementioned works use URLLC, power allocation, eMMB, and mMTC to address the primary control issues. However, they do not consider the secondary control channel, whereas in [18], secondary event-based control was introduced, in which communication between the CCU and the users is not periodic but event-based. Unfortunately, the proposed model solely considers linear systems. Additionally, [33], [34] discuss the STC for linear systems. In [35], a switched linear system based on ETC and STC is discussed. The majority of existing research on STC is limited to linear systems, with less discussion of nonlinear systems. In [19], a simple self-triggered sampler for nonlinear systems was introduced, in which a self-triggered sampler with time delays is designed. A self-triggered sampler for non-linear cognitive radio networks, in which an STC is proposed for the control channel in a cognitive radio network scenario, is discussed in [20]. To achieve the same performance as with periodic communication, the optimal resource allocation is performed via the control channel using STC. We proposed an STC sampler for a non-linear system deployed in industry, in which our proposed model works well in a real-time non-linear system. This proposed model can be applied to any nonlinear real-time system.

III. Problem Formulation

Consider a smart factory in which numerous wireless IoT devices are deployed across the site. We suppose that the wireless IIoT network has N_i active devices. Fig. 1 illustrates the proposed configuration. A device transmits data over a channel, which is received by the CCU and other neighboring devices. The same holds true for all devices. Due to the fact that all devices share the same wireless channel, their transmissions may cause interference with one another. To maintain high communication quality, we must maximize the Signal to Interference plus Noise (SINR) ratio. SINR is defined as the ratio of a device's transmitted power to the interference and noise generated by other devices. The interference strength is determined by the connection matrix H_i, which can be calculated using the channel gain and other characteristics such as the distance and path loss between devices [36].

$$SINR_i = \frac{H_{ii}P_i}{\sum_{j=1}^{L} H_{ij}P_j + n_i} \tag{1}$$

where P_i is the power of device i and P_j is the power of device j interfering with the device i, n_i is channel noise for device i, H_{ij} is a path loss matrix between devices i and j, where $i, j \in \{1, 2, \ldots, L\}$. The path loss matrix captures attenuation due to distance and slow or shadow fading, i.e., lognormal distributed fading.

We are now attempting to optimize network resource management by introducing an optimization problem with the goal of maximizing channel capacity. The constraint we are considering is a wireless IoT device's power supply such that the total power consumed by all devices must not exceed $\overline{P}_{max}$. Additionally, we assume that all devices are operational, which results in a positive power consumption for each device [37].

$$\begin{array}{rl} \max & \sum_{i=1}^{L} log_2(1 + SINR_i) \\ \text{s.t.} & \sum_{i=1}^{L} P_i \leq \overline{P}_{max} \\ & P_i \geq 0 \end{array} \tag{2}$$

To find the optimal solution, we will solve P(2) using the Lagrangian dual function approach, which will result in an iterative solution and will allow us to eliminate unnecessary communication [37]. The problem's Lagrangian function is as follows:

$$\mathscr{L}(P_i,a_i,v_i) = -\sum_{i=1}^{L} log_2(1+SINR_i) + v_i(\sum_{i=1}^{L} P_i - \overline{P}_{max}) - a_iP_i \quad (3)$$

where a_i and v_i are Lagrangian multipliers that aid in the optimization process. We can find the primal-dual algorithm using the gradient descent method.

$$\begin{aligned} \dot{P_i} &= \left(\frac{-H_{ii}}{P_i(H_{ii}+H_{ij})+n_i}\right) - v_i + a_i \\ \dot{a_i} &= -P_i \\ \dot{v_i} &= \sum_{i=1}^{L} P_i - \overline{P}_{max} \end{aligned} \quad (4)$$

where P(4) are the dynamic equations describing the system states as they change with each iteration. $\dot{P_i}$, $\dot{v_i}$ and $\dot{a_i}$ are the respective terms' derivatives.

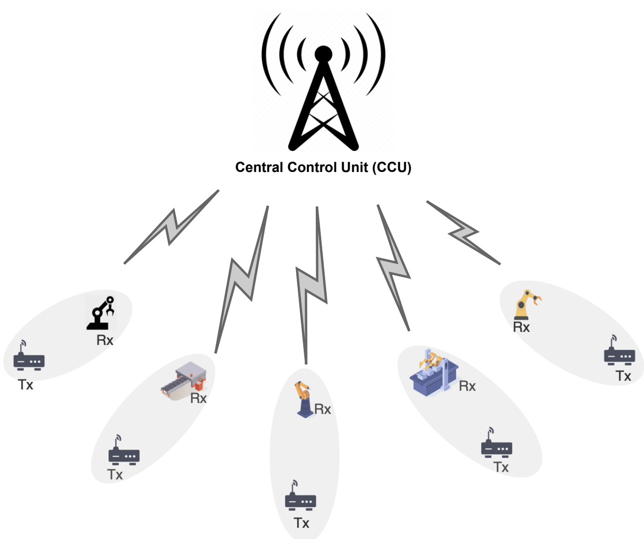

Fig. 1: An example of Industrial Internet of Things (IIoT) network.

IV. Communication Strategy

To find the optimal solution to the equation set P(4), it is required that all users communicate with one another via the CCU, and that communication be time-periodic. In the following, we argue that periodic communication is not the most resource-efficient strategy and propose an STC-based alternative.

1) Self-Triggered Communication: STC operates on the basis of forecasting the next sampling instance based on the system's current state at the current time instance. We base our STC technique on the dynamic equations P(4) developed in the section III.

Consider a state-feedback system in which the state is controlled by the system's control input.

$$\dot{g} = f(g,u) \quad (5)$$

where $g \in D_g \subset \mathbb{R}$ denotes the system's state-space equation and $u \in D_u \subset \mathbb{R}^+$ denotes the control input trajectory, where, $\mathbb{R}$ is a set of real numbers and $\mathbb{R}^+$ is a set of positive real numbers. Consider now a differentiable state feedback law $k : D_g \to D_u$, which transforms the closed loop system into the following:

$$\dot{g} = f(g,k(g)) \quad (6)$$

We need to discretize the system so that the control input can be updated at discrete time intervals. This is accomplished by sampling and holding at $t = t_k$ and maintaining a constant control input $u = k(g_k)$ for $t \in [t_k, t_{k+1})$, i.e. until the next sampling time.

$$\dot{g} = f(g,k(g_k)) \quad (7)$$

The next sample time is determined by defining a constant error signal $e(t)$ equals to the difference in the state of the system between the current and next time instants.

$$||e(t)|| = ||f(g(t);k(g_k)) - f(g(t);k(g(t)))|| \leqslant \delta \quad (8)$$

Every time $e(t)$ becomes equal to δ the system triggers, the control law is updated and $g(t)$ becomes g_k causing g_k updates to $g_{t_{k+1}}$. Our discretized error in eq.(8) is the difference between the state at two time instances, which is the state when it was previously triggered and at the current triggered time. There are multiple ways to define δ, which can be state-dependent, continuously changing, time-dependent, Lyapunov-based, and static. For the sake of simplicity, we will use the constant static threshold in this article.

We need to compute the self-triggered sampler based on eq.(8), which will determine the next sampling time t_{k+1} for the controller at which users communicate their state and the control input is updated. For STC, we begin by defining the control input for the power $u_p = k(g_p(t))$. Using eq.(8) we get $e_p = f(g(t),u(t_k)) - f(g(t),u_p)$. Differentiating yields:

$$\frac{d}{d_p(t)} e_p = -\frac{d}{d_p(t)} f(g(t),u_p) = \phi(g(t),u_p) \quad (9)$$

The solution of the above equation after integration yields

$$\begin{aligned} e_p &= \int_{p_k}^{p} \phi(g(t),u(n))dn \\ &= \int_{p_k}^{p} (\phi(g(t),u(n)) - \phi(g(t),u_k))dn + \int_{p_k}^{p} \phi(g(t),u_k)dn \end{aligned} \quad (10)$$

By taking the norm of both side it holds

$$\begin{aligned}||e_p(t)|| &\leq \int_{p_k}^{p} ||\phi(g(t),u(n))||dn \\ &= \int_{p_k}^{p} (||\phi(g(t),u(n)) - \phi(g(t),u_k)||)dn \\ &+ \int_{p_k}^{p} ||\phi(g(t),u_k)||dn \\ &\leq \int_{p_k}^{p} L_{\phi,u}||f(g(t),u(n)) - f(g(t),u_k)||dn \\ &+ \int_{p_k}^{p} ||\phi(g(t),u_k)||dn \\ &= \int_{p_k}^{p} L_{\phi,u}||e(n)||dn + \int_{p_k}^{p} ||\phi(g(t),u_k)||dn \end{aligned} \quad (11)$$

Using Leibniz Theorem, we get

$$\frac{d}{d_p(t)}||e_p(t)|| \leq L_{\phi,u}||q_p|| + ||\phi(g(t),u_k)|| \quad (12)$$

and solving for $||e_p||$ we obtain

$$||e_p|| \leq \frac{||\phi(g(t),u_k||}{L_{\phi,u}}(\exp^{L_{\phi,u}(p-p_k)} - 1) \quad (13)$$

we can get the upper bound by replacing g with g^* where g^* is the optimum value of g.

Now the self-triggered sampler becomes

$$t_{k+1} = t_k + \frac{1}{L_{\phi,u}} \ln(1 + \frac{\delta L_{\phi,u}}{||\phi(g^*,k(v_k))||}) \quad (14)$$

where $L_{\phi,u}$ is the Lipschitz constant. It is possible to obtain t_{k+1} at t_k from the self-triggered sampler eq.(14) provided that we have g^* and $L_{\phi,u}$.

V. Simulation Results

We are evaluating our proposed STC approach with a use case of three active users sharing the same wireless network. We are defining the $x-y$ coordinates of the users to obtain the distance between them by:

$$\begin{aligned} X_{Tx} &= \begin{bmatrix} 0.0 & 3.0 & 3.2 \end{bmatrix} \\ Y_{Tx} &= \begin{bmatrix} 1.0 & -1.0 & 2.0 \end{bmatrix} \end{aligned} \quad (15)$$

and

$$\begin{aligned} X_{Rx} &= \begin{bmatrix} 1.0 & 1.75 & 2.5 \end{bmatrix} \\ Y_{Rx} &= \begin{bmatrix} 1.0 & -0.5 & 1.0 \end{bmatrix} \end{aligned} \quad (16)$$

where X_{Tx}, Y_{Tx} denote the $x-y$ positions of the transmitters and X_{Rx}, Y_{Rx} denote the $x-y$ positions of the receivers. We assume a path loss exponent of α equals 4. With that, the connection matrix becomes:

$$H_i = \begin{bmatrix} 0.250 & 0.091 & 0.019 \\ 0.016 & 0.304 & 0.055 \\ 0.029 & 0.014 & 0.450 \end{bmatrix} \quad (17)$$

The initial primary power P_i, and Lagrange multipliers a_i, v_i are:

$$P_i = \begin{bmatrix} 0.02 & 0.02 & 0.02 \end{bmatrix} \quad (18)$$

$$a_i = \begin{bmatrix} 0.1 & 0.1 & 0.1 \end{bmatrix} \quad (19)$$

$$v_i = \begin{bmatrix} 0.01 & 0.01 & 0.01 \end{bmatrix} \quad (20)$$

the primary noise n_i is

$$n_i = \begin{bmatrix} 0.01 & 0.01 & 0.01 \end{bmatrix} \quad (21)$$

with δ set equal to 0.1 in eq.(8).

As we consider mobile devices moving in the factory environment, we assume that the transmitter and receiver's $x-y$ positions are continuously changing. At time $5(s)$, we assume the following changed positions:

$$\begin{aligned} X_{Tx} &= \begin{bmatrix} 0.0 & 3.0 & 3.2 \end{bmatrix} \\ Y_{Tx} &= \begin{bmatrix} 0.0 & -1.0 & 2.0 \end{bmatrix} \end{aligned} \quad (22)$$

and

$$\begin{aligned} X_{Rx} &= \begin{bmatrix} 1.0 & 1.75 & 2.5 \end{bmatrix} \\ Y_{Rx} &= \begin{bmatrix} 1.0 & -0.5 & 0.0 \end{bmatrix} \end{aligned} \quad (23)$$

which results in the new connectivity matrix

$$H_i = \begin{bmatrix} 0.250 & 0.091 & 0.026 \\ 0.016 & 0.304 & 0.640 \\ 0.029 & 0.014 & 0.049 \end{bmatrix} \quad (24)$$

At a subsequent time interval of $10(s)$, we shall notice the transmitter's and receiver's $x-y$ positions.

$$\begin{aligned} X_{Tx} &= \begin{bmatrix} 0.0 & 3.0 & 3.2 \end{bmatrix} \\ Y_{Tx} &= \begin{bmatrix} 0.0 & -1.0 & 2.0 \end{bmatrix} \end{aligned} \quad (25)$$

and

$$\begin{aligned} X_{Rx} &= \begin{bmatrix} 1.0 & 1.75 & 2.5 \end{bmatrix} \\ Y_{Rx} &= \begin{bmatrix} 0.0 & -0.5 & 1.0 \end{bmatrix} \end{aligned} \quad (26)$$

which yields the connectivity matrix as

$$H_i = \begin{bmatrix} 1.000 & 0.091 & 0.019 \\ 0.040 & 0.304 & 0.055 \\ 0.029 & 0.014 & 0.450 \end{bmatrix} \quad (27)$$

We implemented the optimal power allocation problem from P(2). We assume that the communication channel is perfect, meaning there is no delay and no packet loss in the system. We use both periodic and self-triggered centralized control as shown in Fig. 2.

Three users are occupying the channel at varying distances from the base station. After a period of time, as users move, the distance between them changes, resulting in transients in the power allocation system. As illustrated in Fig. 2, the system performance when users communicate on a periodic basis is similar to that when users communicate on a self-triggered basis, but the communication resources

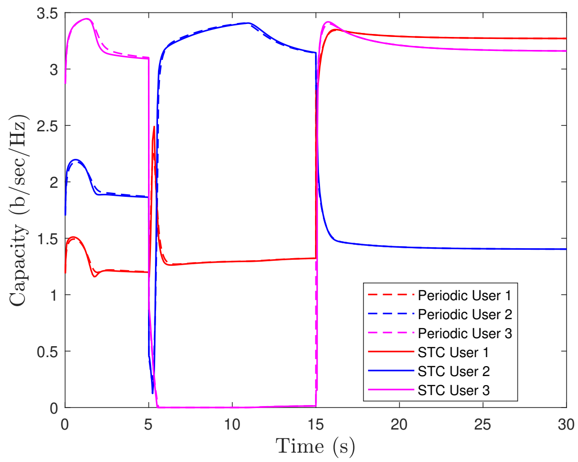

Fig. 2: Channel capacity using periodic and self-triggered communication.

required for both approaches are significantly different, as illustrated in Fig. 3.

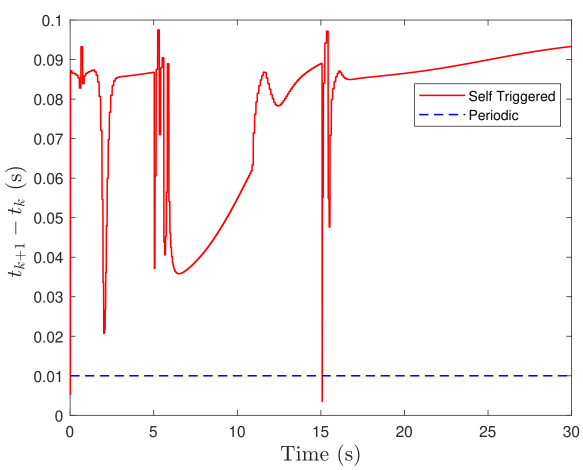

Fig. 3: Inter-sampling time using periodic and self-triggered communication.

As illustrated in Fig. 3, the inter-sampling time for periodic transmission is fixed at $0.01(s)$. On the other hand, the inter-sampling time for self-triggered communication varies according to the system's transients. Time-triggered communication requires 3000 packets for the complete simulation time to calculate the accurate power levels, whereas our STC technique requires only 340 packets, resulting in an 85% reduction in control channel communication.

VI. Conclusion

In this study, we design an optimal energy-efficient resource allocation problem by maximizing channel capacity in the presence of interference and setting limits on the system's maximum available power. Using the Lagrange multiplier method, we obtain a dynamic model of the system. The CCU's communication approach for control purposes is aperiodic STC, which considerably reduces communication while maintaining the system's quality of service (QoS). Our intention is to improve this STC technique, in which each user's communication time is calculated independently and distributively. Additionally, we will investigate the implications of an imperfect communication channel and study the system's response to packet loss and delays in the future. We will also study continuously moving users and assess the performance of our suggested technique when the mobility model is continuous.

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