Efficient Power Control for Integrated Sensing and Communication Networks with Dual Connectivity

Panagiotis Charatsaris*, Maria Diamanti*, Eirini Eleni Tsiropoulou†, and Symeon Papavassiliou*
{pancharatsaris@netmode.ntua.gr, mdiamanti@netmode.ntua.gr, eirini@unm.edu, papavass@mail.ntua.gr}
* School of Electrical and Computer Engineering, National Technical University of Athens, Athens, Greece
† Dept. of Electrical and Computer Engineering, University of New Mexico, Albuquerque, NM, USA

***Abstract*—Integrated Sensing and Communication (ISAC) has recently emerged as an additional communication service within the Internet of Things (IoT) and Cyber Physical Systems (CPS) era, through which distributed nodes are able to communicate their sensing information to a Base Station (BS) using integrated signals. In this paper, we study the coexistence of ISAC with other communication types of the nodes, by introducing a software-defined framework to control the nodes' uplink transmission powers related to each service. Each node is simultaneously engaged into two types of communications with different BSs for ISAC and generic data transmission to the cloud via dual connectivity. The uplink power splitting/control problem between the BSs is formulated as a non-cooperative game in satisfaction form, through which each node autonomously concludes to a Satisfaction Equilibrium (SE) point that meets its minimum ISAC and pure communication-oriented requirements. Different achievable SE points are analyzed, while an Reinforcement Learning (RL) and a searching-based algorithm are introduced to conclude to the SE and Minimum Efficient SE (MESE) of the studied problem. Simulation results demonstrate the operation of the algorithms and the overall proposed framework in achieving an efficient share of the resources to the different services.**

***Index Terms*—Dual Connectivity, Integrated Sensing and Communication, Game Theory, QoS Satisfaction, Power Control.**

I. Introduction

Radio sensing is a vital functionality of smart-X Internet of Things (IoT) applications and Cyber Physical Systems (CPSs) that determines their intelligence to perform decision making and interact with their surroundings. To create network awareness, sensing data need to be communicated among the networked entities, indicating the necessity for Integrated Sensing and Communication (ISAC) design and underlying enabling technologies [1]. Nevertheless, within this form of distributed networks, sensing-oriented communication (enabled by ISAC technologies) constitutes an additional operation that should be considered along with other types of information or computation task-oriented communications, adding in this way an extra degree of freedom during resource management and optimization. In this context, the dual connectivity interface [2] of IoT/CPS nodes could be utilized to enable their concurrent engagement into different types of communications, which however remains practically unexplored in the literature.

In this paper, our aim is to apply and study ISAC paradigm under a more tangible use case that considers the coexistence of other types of communications, by exploiting the wireless networks' feature of dual connectivity. The IoT/CPS nodes, within the considered network, sense their surroundings and transmit the sensing data to a Base Station (BS) using ISAC signals, for further processing and establishment of network awareness. At the same time, however, they are concurrently connected to a different BS to accommodate data transmission to the core network/cloud, by utilizing their dual-connectivity interface. Subsequently, the problem of power split/control between the BSs arises at each node and is modeled as a game in satisfaction form [3]. The goal is to satisfy both the minimum ISAC and pure communication-oriented performance requirements, while examining different types of satisfaction equilibria to control the performance-energy cost tradeoff.

A. Related Work & Motivation

The convergence of radio sensing and communication has been widely explored from a physical layer perspective (e.g., transceiver, coding, ISAC waveform design), and systematic attempts to classify the different research activities and steer future progress are lately made [1]. In the meanwhile, another stream of research adopts a from-practice-to-theory approach and studies the entangled sensing and communication problems, by considering direct applications to realistic use cases, e.g., [4]–[6]. In [4], multiple-vehicle tracking and vehicle identifier (ID) association is achieved at a Road-Side Unit (RSU), by exploiting ISAC signaling, thus, contributing to the reduction of frequent ID feedbacking from the vehicles to the RSU and the occupation of uplink channels. In [5], the joint IoT device-to-server association and subchannel allocation problem is examined under a general IoT environment setting, where IoT devices concurrently sense their surroundings and wirelessly upload the sensing results to edge servers for further processing. The ultimate objective of this work is to introduce a holistic scheduling method that controls the gains between sensing, communication and computing, while the proper scheduling of sensing, communication and motion for cellular connected Unmanned Aerial Vehicles (UAVs) over mmWave frequencies is pursued in [6].

Although there exist some works that directly apply ISAC to realistic use cases and study optimization problems therein, its application in dual-connectivity wireless networks has not been considered so far. Dual connectivity is a functionality enabled since Long Term Evolution (LTE) networks [2], while being of practical use in state-of-the-art technologies, such as Multi-access Edge Computing (MEC) [7]. The major problem to be tackled in dual-connectivity wireless networks is the efficient power splitting/control among the different entities that provide connectivity. Given that energy resources need to be sparingly managed within an IoT or CPS environment, efficient power control mechanisms that target at Quality of Service (QoS) satisfaction rather than myopic utility maximization (at the cost of higher power consumption) are important. In this context, non-cooperative games in satisfaction form constitute a promising framework [3]. Contrary to games in normal form, a game in satisfaction form concludes to a Satisfaction Equilibrium (SE) point, in which players just satisfy their minimum QoS prerequisites, while other types of equilibria (e.g., Efficient SE, Minimum Efficient SE) can be explored too to strike a good balance between QoS satisfaction and experienced cost [8]. Application examples of satisfaction form games in networking range from subchannel allocation in wireless networks of limited spectrum [9] to the efficient determination of the data perturbation level for secure though accurate distributed classification [10].

B. Contributions & Outline

In this paper, we aim to address the research gap related to the coexistence of ISAC with other types of communications within an IoT/CPS environment. To achieve this, we introduce a software-defined framework to control the wireless resource share (i.e., uplink transmission power) among two types of services, i.e., ISAC and pure-communication, which is technologically and scientifically enabled by the dual connectivity functionality and game theory in satisfaction form, respectively. The main contributions of this paper are as follows:

1) An IoT network/CPS environment consisting of multiple nodes is considered. Each node senses its environment and uploads the respective sensing data by transmitting ISAC signals to a dedicated BS, while preserving its typical connection to the core network through a different BS via dual-connectivity.
2) The power splitting/control problem among the BSs is formulated as a non-cooperative game in satisfaction form, allowing each node to autonomously determine an efficient solution point that meets the minimum performance requirements of the two services, i.e., ISAC and pure communication, while different types of satisfaction equilibria are discussed and analyzed.
3) A Reinforcement Learning (RL) and a searching-based algorithm are introduced to effectively determine the problem's Satisfaction Equilibrium (SE) and Minimum Satisfaction Equilibrium (MESE) points, respectively. Detailed numerical results demonstrate the operation and effectiveness of the proposed framework.

The remainder of the paper is organized as follows. Section II presents the system model. In Section III the power control problem is formulated as a game in satisfaction form and the different types of SE are analyzed. Section IV introduces the algorithms employed to derive the SE and MESE. Section V is devoted to the performance evaluation of the proposed framework, and Section VI concludes the paper.

II. System Model

We consider an IoT/CPS environment consisting of a set of nodes $\mathcal{N} = \{1, \dots, n \dots, N\}$ and two serving BSs denoted by i and j, respectively. Each node performs simultaneously two services, by utilizing its dual-connectivity interface. The first service concerns the sensing of potential targets/obstacles in its vicinity and the wireless upload of the sensing data to BS i for further processing and establishment of network awareness, whereas the second regards the node's n constant data exchange and connectivity to the core network that is achieved through BS j. For the accomplishment of the former service, we assume that each node n is equipped with ISAC technologies and thus, integrated signals are used for the joint sensing of target and communication with BS i. The two services are performed over separate frequency bands of bandwidth W_{ISAC} [Hz] and W_{COM} [Hz], accordingly, while the different nodes' transmissions to both BSs i and j are multiplexed in the power domain, using Non-Orthogonal Multiple Access (NOMA) technique.

Each node n aims to determine its total uplink transmission power p_n [W] and the optimal power split over the two services, where $x_n, x_n \in [0,1]$ indicates the percentage of power investment for the ISAC service. Hence, the transmission power of node n to BS i is $p_n^{ISAC} = x_n p_n$ and the remaining $p_n^{COM} = (1 - x_n)p_n$ refers to the service of BS j.

A. Sensing Model

Focusing on the sensing model related to the first service, we assume that each node n disposes a dual-functional transmitter. To sense a target, each node n radiates an integrated OFDM waveform, which is then reflected back conveying the detection information. The corresponding radiated signal by node n at time instance t is formally written as [5]:

$$s_n(t) = e^{j2\pi f_c t} \sum_{l=0}^{S-1} g_n c_n^l e^{j2\pi W_{ISAC}(t-lT_s)} \times rect\left[\frac{t-lT_s}{T_s}\right], \tag{1}$$

where S is the number of consecutive integrated symbols radiated towards the target, T_s [s] is the duration of a completed OFDM symbol, f_c [Hz] is the center frequency of the wireless channel, g_n is the amplitude of the integrated waveform, c_n^l is the phase code of the modulated symbol l, and $rect[z]$ is a pulse function, giving 1 when $0 \leq z \leq 1$ and 0 otherwise.

The reflected signal by the target to node n is written as:

$$z_n(t) = \int_{-\infty}^{\infty} q_n(\tau) s_n(t-\tau) d\tau + w(t), \tag{2}$$

where $q_n(t)$ and $w(t)$ denote the impulse response and the zero-mean Additive White Gaussian Noise (AWGN).

The performance of each node's n sensing operation is evaluated by calculating the Mutual Information (MI) between the reflected signal $z_n(t)$ and the impulse response $q_n(t)$ conditioned on the initial waveform $s_n(t)$, which is given by:

$$\begin{aligned} MI_n &= I\left(z_n(t), q_n(t) | s_n(t)\right) \\ &= \frac{1}{2} S T_s W_{ISAC} \log_2\left(1+\gamma_{n,sens}^{ISAC}\right), \end{aligned} \tag{3}$$

where $\gamma_{n,sens}^{ISAC}$ corresponds to the radar Signal-to-Interference-plus-Noise Ratio (SINR) of node n:

$$\gamma_{n,sens}^{ISAC} = \frac{p_n^{ISAC} S T_s^2 |Q_n(f)|^2}{I_0 + \sum_{n' \in \mathcal{N}, n' \neq n} G_{n',n} p_{n'}^{ISAC}}. \tag{4}$$

$Q_n(f)$ is the Fourier transformation of impulse response $q_n(t)$, $G_{n',n}$ is the channel gain from node n' to node's n radar receiver, and I_0 is the power of zero-mean AWGN.

B. Communication Models

Without loss of generality, we assume that the channel gains observed by each BS are sorted in ascending order, such as $G_{i,1} \leq \cdots \leq G_{i,n} \leq \cdots \leq G_{i,N}$ and $G_{j,1} \leq \cdots \leq G_{j,n} \leq \cdots \leq G_{j,N}$, and the decoding of the nodes' signals is successfully implemented by employing the Successive Interference Cancellation (SIC) technique, starting from the the highest channel gain node.

The achieved throughput of node n for communication with BS i and the delivery of the sensing data is calculated as:

$$R_n^{ISAC} = W_{ISAC} \log_2\left(1 + \frac{p_n^{ISAC} G_{i,n}}{I_0 + \sum_{n'=1}^{n-1} G_{i,n'} p_{n'}^{ISAC}}\right). \tag{5}$$

Similarly, the node's n achieved throughput during the data exchange with BS j is given by:

$$R_n^{COM} = W_{COM} \log_2\left(1 + \frac{p_n^{COM} G_{j,n}}{I_0 + \sum_{n'=1}^{n-1} G_{j,n'} p_{n'}^{COM}}\right). \tag{6}$$

III. Satisfaction Form Games and Equilibria for Efficient Power Control

In this section, we formulate the problem of power control and splitting among the two BSs as a non-cooperative game in satisfaction form, and examine different satisfaction equilibria to satisfy the minimum ISAC and pure communication-oriented performance requirements.

A. Satisfaction Game Formulation

The non-cooperative game in satisfaction form is characterized by the tuple $G = (\mathcal{N}, \{\mathcal{A}_n\}_{n\in\mathcal{N}}, \{f_n\}_{n\in\mathcal{N}})$, where $\mathcal{N}$ is the set of players, i.e. the nodes, $\mathcal{A}_n = \{(p_n, x_n) | p_n \in [0, p_{max}], x_n \in [0,1]\}$ is each node's n action space of cardinality A_n, where (p_n, x_n) is every feasible combination of power level and split among the services and p_{max} is the maximum feasible power level. Also, f_n is the specific set of actions of player n that satisfy the minimum ISAC and pure-communication requirements given the actions selected by the other players/nodes. In our case, this set is defined as:

$$f_n(\mathbf{a}_{-n}) = \{a_n \in \mathcal{A}_n | u_n(a_n, \mathbf{a}_{-n}) \geq u^{thr}\}, \tag{7}$$

where u_n is the node's n utility function. In other words, f_n includes the actions that allow the utility u_n to be above a threshold u^{thr}.

The utility of node n is dependent on the payoffs gained by the two simultaneously performed services, i.e., the ISAC service in collaboration with BS i and the pure communication with BS j, the latter of which are defined as $u_n^{ISAC} = MI_n \cdot R_n^{ISAC}$ and $u_n^{COM} = c \cdot R_n^{COM}$, with $c \in \mathbb{R}^+$ [bits] being a constant balancing factor. Subsequently, the overall utility of node n is the weighted sum of u_n^{ISAC} and u_n^{COM}, i.e.,

$$u_n = w^{ISAC} u_n^{ISAC} + w^{COM} u_n^{COM}, \tag{8}$$

where w^{ISAC}, w^{COM} are appropriate weight factors, such that $w^{ISAC} + w^{COM} = 1$.

B. Satisfaction Equilibria

In this type of games, each player instead of trying to selfishly maximize its personal utility, aims to reach a minimum threshold and achieve a satisfactory operation for the system. The simplest equilibrium is a Satisfaction Equilibrium (SE).

Definition 1 (Satisfaction Equilibrium). *An action profile $\mathbf{a}^* = (a_1^*, \ldots, a_n^*, \ldots, a_N^*)$ is a SE for game G if:*

$$a_n^* \in f_n(\mathbf{a}_{-n}), \forall n \in \mathcal{N}. \tag{9}$$

When a SE is achieved, all nodes are satisfied and have no incentives to change their action. Apparently, there may exist multiple action profiles that satisfy the nodes' minimum requirements, but are differentiated in the level of effort that the nodes exert to achieve them. It is, therefore, natural for the players to seek to satisfy their constraints with the minimum possible effort. To quantify the effort required by an action, the concept of cost is introduced. For all $n \in \mathcal{N}$, the cost function $c_n : \mathcal{A}_n \longrightarrow \mathbb{R}$ satisfies the following condition: $c_n(a_n) < c_n(a_n') \forall (a_n, a_n') \in \mathcal{A}_n^2$, if and only if, a_n requires a lower effort by device n than action a_n'. Based on this definition, we introduce the Efficient Satisfaction Equilibrium (ESE).

Definition 2 (Efficient Satisfaction Equilibrium). *An action profile $\mathbf{a}^* = (a_1^*, \ldots, a_n^*, \ldots, a_N^*)$ is an ESE for game G, with cost function $\{c_n\}_{n\in\mathcal{N}}$, if:*

$$a_n^* \in f_n(\mathbf{a}_{-n}), \forall n \in \mathcal{N}, \tag{10a}$$

$$c_n(a_n) \geq c_n(a_n^*), \forall n \in \mathcal{N}, \forall a_n \in f_n(\mathbf{a}_{-n}^*). \tag{10b}$$

Particularly, the equilibrium point, in which the players achieve not only the minimum cost for their action but also from the overall system's perspective is called Minimum Efficient Satisfaction Equilibrium (MESE).

Definition 3 (Minimum Efficient Satisfaction Equilibrium). *An action profile $\mathbf{a}^* = (a_1^*, \ldots, a_n^*, \ldots, a_N^*)$ is a MESE for game G, with cost function $\{c_n\}_{n\in\mathcal{N}}$, and set of action profiles that are ESEs $\{E\}$ if:*

$$a_n^* \in f_n(\mathbf{a}_{-n}), \forall n \in \mathcal{N}, \tag{11a}$$

$$c_n(a_n) \geq c_n(a_n^*), \forall n \in \mathcal{N}, \forall a_n \in f_n(\mathbf{a}_{-n}^*), \tag{11b}$$

$$\sum_{n\in\mathcal{N}} c_n(e_n) \geq \sum_{n\in\mathcal{N}} c_n(a_n^*), \forall e \in E. \tag{11c}$$

IV. Learning Satisfaction Equilibria

In this section, we present an RL and a searching-based algorithm that are used to obtain the different SEs and the MESE that exist for the formulated problem. The two algorithms are executed in a fully distributed manner, such that each node knows just its action and the last selected action of the others, while observing its personally achieved utility.

A. Reinforcement Learning-based SE Algorithm

The proposed RL algorithm's aim is to conclude to any SE that at least satisfies all constraints defined by the action set $f_n, \forall n \in \mathcal{N}$ [3]. To facilitate the subsequent analysis, let us index the elements of each node's n set $\mathcal{A}_n$ with the index $k_n \in \mathcal{K}_n = \{1, \dots, K_n\}$. At each iteration τ, each node evaluates its achieved utility and accordingly assigns a probability $\pi_n(\tau) = (\pi_{n,1}(\tau), \dots, \pi_{n,k_n}(\tau) \dots, \pi_{n,K_n}(\tau))$ to each available action $a_{n,k_n} \in \mathcal{A}_n$. In this way, the node indicates its preference towards selecting the specific action a_{n,k_n} in the future. After probabilistically selecting an action a_{n,k_n}, each node examines whether the threshold u^{thr} is satisfied. For the nodes that this holds true, their selected action remains unchanged for the next iteration, otherwise they update their probability distribution using the following rule and proceed to the next RL algorithm's iteration:

$$\pi_{n,k_n}(\tau+1) = \begin{cases} \pi_{n,k_n}(\tau), & \text{if } u_n(\tau) \geq u^{thr} \\ g(\pi_{n,k_n}(\tau)), & \text{otherwise} \end{cases} \tag{12}$$

with

$$g(\pi_{n,k_n}(\tau)) = \pi_{n,k_n}(\tau) + \lambda_\tau r_{n,\tau}(\mathbb{1}_{\{a_n(\tau)=a_{n,k_n}\}} - \pi_{n,k_n}(\tau)). \tag{13}$$

The parameter $\lambda_\tau = \frac{1}{\tau+1}$ represents the learning rate of the algorithm, while $a_n(\tau)$ the action selected by node n at iteration τ. $r_{n,\tau}$ is a reward function calculated as:

$$r_{n,\tau} = \frac{u_n^{max} - u_n(\tau) - u^{thr}}{2u_n^{max}}, \tag{14}$$

where $u_n(\tau)$ is the utility of node n at iteration τ and u_n^{max} is the maximum utility that node n can achieve, as in the single-node system case. The physical meaning and interpretation of probabilities' update rule is that higher probability values are assigned to actions that yield at higher node utilities and thus, it is more likely to satisfy the minimum requirement u^{thr}.

The pseudocode of the RL-based SE algorithm is presented in Algorithm 1. It should be noted that the convergence of this algorithm is highly affected by the initial action chosen by each player. Therefore, in order to avoid running into infinite loops, its operation is terminated if all nodes remain unsatisfied after a predefined number of iterations.

B. MESE Search Algorithm

To determine the MESE of the examined problem, a type of Best Response Dynamics (BRD) algorithm is used, according to which each node selects the specific best response action that achieves the minimum cost [8]. The algorithm comprises two sequential phases, namely the "Preparation Phase" and the "Turn Phase". During the "Preparation Phase" (Algorithm 2), each node determines for each action $a_{n,k_n} \in \mathcal{A}_n$ the minimum cost action between a_{n,k_n} and all subsequent ones in the set $\mathcal{A}_n$. In more detail, after this phase, a list $S_n[]$ is derived for every player n, each element $S_n[z]$ of which expresses the index of action a_{n,k_n} that provides the minimum cost over the actions $\{a_{n,z_n}, \dots, a_{n,K_n}\}$. The player selects its initial action from the list $S_n[]$ minimizing the cost function, regardless of whether this actions satisfies its constraints, i.e., $actions_{initial} = (a_{n,S_1[0]}, \dots, a_{n,S_N[0]})$.

Algorithm 1 Reinforcement Learning-based SE Algorithm

Initialize $\tau = 0$;
for each $n \in \mathbf{N}$ **do**
  for each $a_{n,k_n} \in \mathcal{A}_n$ **do**
    $\pi_{n,k_n}(0) = \frac{1}{A_n}$;
  end for
  Select an action $a_n(0) \sim \pi_n(0)$;
end for
while $\exists n, u_n(\tau) < u^{thr}$ **do**
  for each $n \in \mathbf{N}$ **do**
    Update distribution $\pi_n(\tau+1)$ according to (12)
    if $u_n(t) \geq u^{thr}$ **then**
      $a_n(\tau+1) = a_n(\tau)$;
    else
      $a_n(\tau+1) \sim \pi_n(\tau+1)$;
    end if
  end for
  Update $\tau = \tau + 1$;
end while

Algorithm 2 MESE Search Algorithm Preparation Phase

Initialize $min = c_n(a_{n,K_n})$, $min_{index} = K_n$;
$S_n[K_n] = K_n$;
for $k = K_n - 1, 1$ **do**
  if $c_n(a_{n,k}) \leq min$ **then**
    $S_n[k] = k$;
    $min_{index} = k$;
    $min = c_n(a_{n,k})$;
  else
    $S_n[k] = min_{index}$;
  end if
end for

The Turn Phase (Algorithm 3) aims to find an action that satisfies each node's utility with a minimum cost. To this end, each player is sufficient to perform a binary search from the Minimum Satisfying Action (MSA), i.e., the action that satisfies the node's minimum requirements computed at the previous iteration $\tau - 1$, to a_{n,K_N} (supposing the actions are in increasing order of total cost), searching for the first action that satisfies the requirements. The latter constitutes the Minimum Satisfying Action (MSA) for the next iteration τ that will remain unchanged in case it keeps satisfying the constraint for the particular node. Accordingly with the SE algorithm, we suppose that the iterative process terminates after a defined number of iterations, in case that all devices are unsatisfied.

Algorithm 3 MESE Search Algorithm Turn Phase

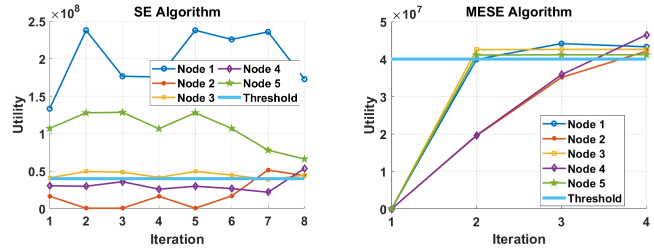
Initialize $\tau = 0$;
while $\exists n, u_n(\tau) < u^{thr}$ **do**
  for each $n \in \mathbf{N}$ **do**
    if $u_n(t) < u^{thr}$ **then**
      Keep the same action
    else
      MSA = BinarySearch($\mathcal{A}_n, MSA, A_n, u_n, \mathcal{A}_{-n}$)
      Change action to $a_{n,S_n[MSA]}$
    end if
  end for
  Update $\tau = \tau + 1$;
end while

V. Evaluation & Results

In this section, we evaluate the performance of the proposed framework, via modeling and simulation. We consider a circular area of 300 m radius, within which two BSs and $N = 5$ nodes are uniformly spatially distributed. Each node senses a target located up to 100 m far from it. The sensing-related parameters are set as: $S = 10$, $T_s = 5$ us, while, for simplicity, we assume that the target frequency response follows the standard normal distribution. The channel gain between any two network entities, i.e., BS, nodes, targets, is set as $G = \frac{1}{d^4}$, where d [m] is the distance between the two entities. The rest constants are set as: $I0 = W \cdot N_0$, with $W = \{W_{ISAC}, W_{COM}\} = 2$ MHz, $N_0 = -174$ dBm/Hz, and $p_{max} = 2W$. For the nodes' utilities, we consider $u^{thr} = 4 * 10^7$ bits^2/s, $w^{ISAC} = w^{COM} = 0.5$ and $c = 1$ bits. The convergence limit of both algorithms is 500 iterations and the cost function used in the MESE algorithm is the total power level $p_n, \forall n \in \mathcal{N}$. The number of power states p_n is 201 (range $[0, p_{max}]$ with step 0.01), whereas the number of power split states x_n is 101 (range $[0, 1]$ with step 0.01).

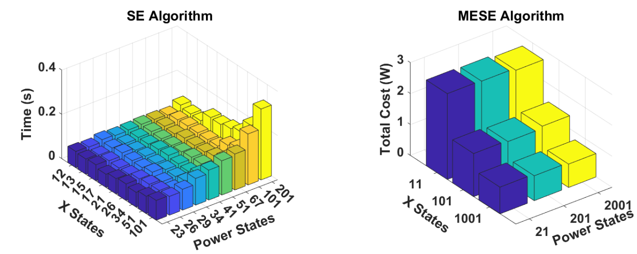
First, we study the convergence behavior of the RL-based SE (Fig. 1a) and the MESE Search (Fig. 1b) algorithms, by examining the progression of the utility value $u_n, \forall n \in \mathcal{N}$ as a function of the algorithms' iterations. As can be observed, the SE algorithm requires twice the number of iterations of the MESE algorithm in order to converge, due to its probabilistic operation. The SE algorithm is, also, differentiated from the MESE in the fact that higher utility values are achieved for the nodes, given that the MESE algorithm's target is to find the SE yielding the minimum possible cost to the system, i.e., total power, results though in more efficient utility levels. At this point, it should be noted that although the nodes persist on their selected action after the minimum utility threshold u^{thr} is exceeded, their utility seems to keep changing values, as it is directly affected by the actions of the remaining unsatisfied nodes via the interference term.

The SE algorithm's convergence behavior is further compared against two different approaches, regarding the probability distribution used for the state selection, namely: a) the "Selection-Based" distribution, where the probability of each action is inversely proportional to the number of times that this action has been already selected, and b) the "Uniform" probability distribution, i.e., $\pi_{n,k_n} = \frac{1}{A_n}$. Table I lists the percentage of successful convergence instances derived out of 500 independent simulation executions under the three approaches. Indeed, the proposed RL-based distribution approach achieves to successfully converge to 73.2% of the instances, significantly surpassing the other two.



(a) (b)

Fig. 1: Convergence behavior of SE and MESE algorithms.



(a) (b)

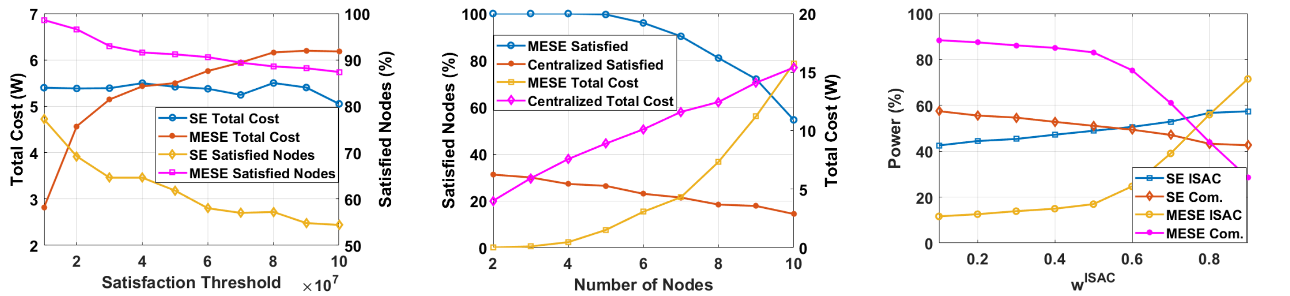
Fig. 2: Number states impact on SE and MESE algorithms.

TABLE I: Comparative evaluation of SE algorithm's percentage of successful convergence instances.

Distribution	Learning-Based	Selection-Based	Uniform
Convergence	73.2%	38.6%	37.4%

Subsequently, we study the impact of the number of states comprising the action set on the behavior of the proposed framework, by selecting different sampling steps. Fig. 2a, depicts the real execution time required for the SE algorithm to converge (z axis) for different combinations of initial number of power states p_n (x axis) and power spilt percentages x_n (y axis), considering sampling steps from 0.01 to 0.09. Obviously, the more states used, the more the increment observed in the algorithm's complexity and hence, real execution time. Fig 2b illustrates the total cost, i.e., total power used in the system, concluded by the MESE algorithm for different numbers of initial states (sampling steps $[10^{-3}, 10^{-2}, 10^{-1}]$). The accumulation of more possible states, especially of x_n states, enables the algorithm to achieve a lower system cost.

Fig. 3 summarizes the proposed framework's pure operation under different values of the nodes' satisfaction threshold u^{thr}



(a) (b) (c)

Fig. 3: Operation of the proposed framework under different satisfaction thresholds, weight factors, and number of nodes.

and weight factor w^{ISAC}, as well as different number of nodes in the system. In particular, Fig. 3a presents the total cost, i.e., total power, (left vertical axis) and the percentage of satisfied devices (right vertical axis) achieved by the final actions concluded by the SE and MESE algorithms, for different values of satisfaction thresholds. As the satisfaction threshold becomes more strict, the percentage of satisfied users decreases, resulting in almost half of the nodes to be satisfied by the SE algorithm that seeks to just achieve higher node utilities, as implied by Eq. (14). Furthermore, the increase in the satisfaction threshold results in higher total power consumption particularly for the MESE algorithm, since the SE algorithm aims to just satisfy the nodes' requirements regardless of the incurred cost. Finally, although for higher threshold values the cost of MESE is higher than that of SE, a much larger number of nodes are satisfied.

In Fig. 3b, the proposed framework is compared against a centralized optimization approach for the power splitting/control problem, whose aim is to maximize the sum of all the devices utility with respect to the constraints defined in action set $\mathcal{A}_n$. The presence of more nodes in the system leads gradually to more and more of them to remain unsatisfied, with the centralized approach resulting in constantly lower satisfaction rates, although achieving higher individual utility values for the nodes. Considering the system's total cost, the centralized method forces some of the devices to consume the maximum permitted power in order to maximize their utility and thus, concludes to always consuming more power.

Fig. 3c illustrates the percentage of power consumed by each service, i.e., ISAC and pure communication, under different values of the weight factor w^{ISAC}. For both algorithms, increasing the weight of ISAC leads to higher amount of the total selected energy level given for this service. Considering the operation of MESE algorithm, the communication service seems to be generally performed with higher power percentages. Given that, in our implementation, the cost function is the total power consumed by each node, then the lowest possible power split factor x_n is chosen at each iteration, when the minimum satisfying power level is computed.

VI. Conclusion & Future Work

In this paper, the power control problem in an ISAC and dual connectivity-enabled IoT/CPS network was modeled as a satisfaction game. The IoT/CPS nodes communicated simultaneously with two BSs for ISAC and pure-communication services, respectively, and aim to satisfy the minimum performance requirements set by each service. Different types of satisfaction equilibria and corresponding algorithms were examined in order to control the tradeoff between the performance and incurred cost. The numerical results demonstrated the convergence behavior of the satisfaction equilibria algorithms, as well as the effect of different parameters on their operation and the effectiveness of the proposed framework. Part of our current and future work focuses on the inclusion of computing-related communication services, and the proper scheduling of sensing, communication and computing resources.

References

[1] A. Liu, Z. Huang, M. Li, Y. Wan, W. Li, T. X. Han, C. Liu, R. Du, D. K. P. Tan, J. Lu, Y. Shen, F. Colone, and K. Chetty, "A survey on fundamental limits of integrated sensing and communication," *IEEE Comm. Surveys & Tutorials*, vol. 24, no. 2, pp. 994–1034, 2022.

[2] Y. Wu, L. P. Qian, J. Zheng, H. Zhou, and X. S. Shen, "Green-oriented traffic offloading through dual connectivity in future heterogeneous small cell networks," *IEEE Communications Magazine*, vol. 56, no. 5, pp. 140–147, 2018.

[3] S. M. Perlaza, H. Tembine, S. Lasaulce, and M. Debbah, "Satisfaction equilibrium: A general framework for qos provisioning in self-configuring networks," in *2010 IEEE Global Telecommunications Conference GLOBECOM 2010*, 2010, pp. 1–5.

[4] Z. Wang, K. Han, J. Jiang, F. Liu, and W. Yuan, "Multi-vehicle tracking and id association based on integrated sensing and communication signaling," *IEEE Wireless Communications Letters*, vol. 11, no. 9, pp. 1960–1964, 2022.

[5] L. Zhao, D. Wu, L. Zhou, and Y. Qian, "Radio resource allocation for integrated sensing, communication, and computation networks," *IEEE Transactions on Wireless Comm.*, vol. 21, no. 10, pp. 8675–8687, 2022.

[6] B. Chang, W. Tang, X. Yan, X. Tong, and Z. Chen, "Integrated scheduling of sensing, communication, and control for mmwave/thz communications in cellular connected uav networks," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 7, pp. 2103–2113, 2022.

[7] C. Li, H. Wang, and R. Song, "Mobility-aware offloading and resource allocation in noma-mec systems via dc," *IEEE Communications Letters*, vol. 26, no. 5, pp. 1091–1095, 2022.

[8] P. Promponas, P. A. Apostolopoulos, E. Eleni Tsiropoulou, and S. Papavassiliou, "Redesigning resource management in wireless networks based on games in satisfaction form," in *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*, 2019, pp. 24–31.

[9] A. H. Arani, A. Mehbodniya, M. J. Omidi, and M. F. Flanagan, "Satisfaction based channel allocation scheme for self-organization in heterogeneous networks," in *2018 IEEE Global Communications Conference (GLOBECOM)*, 2018, pp. 1–6.

[10] L. Xu, C. Jiang, J. Li, Y. Zhao, and Y. Ren, "Privacy preserving distributed classification: A satisfaction equilibrium approach," in *GLOBECOM 2017 - 2017 IEEE Global Comm. Conference*, 2017, pp. 1–6.