Task Allocation among Connected Devices: Requirements, Approaches and Challenges

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***Abstract*—Task allocation (TA) is essential when deploying application tasks to systems of connected devices with dissimilar and time-varying characteristics. The challenge of an efficient TA is to assign the tasks to the *best* devices, according to the context and task requirements. The main purpose of this paper is to study the different connotations of the concept of TA *efficiency*, and the key factors that most impact on it, so that relevant design guidelines can be defined. The paper first analyzes the domains of connected devices where TA has an important role, which brings to this classification: Internet of Things (IoT), Sensor and Actuator Networks (SAN), Multi-Robot Systems (MRS), Mobile Crowdsensing (MCS), and Unmanned Aerial Vehicles (UAV). The paper then demonstrates that the impact of the key factors on the domains actually affects the design choices of the state-of-the-art TA solutions. It results that resource management has most significantly driven the design of TA algorithms in all domains, especially IoT and SAN. The fulfillment of coverage requirements is important for the definition of TA solutions in MCS and UAV. Quality of Information requirements are mostly included in MCS TA strategies, similar to the design of appropriate incentives. The paper also discusses the issues that need to be addressed by future research activities, i.e.: allowing interoperability of platforms in the implementation of TA functionalities; introducing appropriate trust evaluation algorithms; extending the list of tasks performed by objects; designing TA strategies where network service providers have a role in TA functionalities' provisioning.**

***Index Terms*—Task allocation, Sensor and Actuator Networks, Multi-Robot Networks, Mobile Crowdsensing, Internet of Things, Umnanned Aerial Vehicles**

I. Introduction

It is a matter of fact that we depend more and more on applications that help us in our everyday activities and that rely on the sensing, actuating, processing, and communications tasks performed by connected devices with different capabilities [1]. Enlarging the set of devices that can be inquired makes the applications more powerful because this increases their potentials and their robustness, as devices may suddenly fail, and then some others should be activated and inquired [2]. The applications we refer to are the more disparate, from those that are needed to manage the domestic environment (for heating rooms and controlling multimedia devices, for instance) to those for making the industrial plant secure and comfortable (e.g., alerting the worker about dangerous maneuvers).

The technology drivers for this scenario are connected devices with heterogeneous functionalities, capabilities, and often limited resources (e.g. battery-powered, low processing speed) that cooperate to achieve the common objective of executing applications made of one or more tasks. In this scenario, properly allocating the required tasks to the available devices is critical, as severe issues may arise when this is not done. Indeed, the selected devices may not be able to fulfill the minimum task requirements, thus jeopardizing the achievement of the task goals. On the other hand, when task allocation (TA) does not ensure fair use of resources, the risk of overloading some devices increases. Under these circumstances, such devices may not be able to work properly and this may eventually lead to failures. Accordingly, the strategy for the allocation of the tasks has a significant impact on the performance of the whole application, in terms of accuracy of information provided, reliability of the services, and robustness to failures.

It is quite straightforward that an *efficient* TA strategy has a heavy impact on the application execution outcome, as well as on the performance of the whole network. However, the concept of efficient TA is not univocal, and the same TA solution can be optimal in some cases and inadequate in others. Therefore, to choose an efficient TA strategy, it is first necessary to determine which design principles need to be considered, and which factors most affect its efficiency.

Based on these considerations, the main objective of this paper is to define some guidelines that support the design of an efficient TA strategy among connected devices. Indeed, this work has the ambition to be the first to address the challenge of analyzing how the concept of TA *efficiency* changes based on the reference domain and on the application requirements. According to the results of such study, the paper determines which design principles need to be applied for an efficient TA strategy, according to a combination of factors, which depend on the system infrastructure and on the required application.

Papers such as [3][4][5][6] have also surveyed the solutions for TA but limited their analysis to one or two specific domains. On the other hand, [1] widens the analysis to TA in distributed systems, describing the approaches based on their: control model, resource optimization method, method for achieving reliability, coordination mechanism among heterogeneous nodes, and model considering network structures. As compared to previous works, this paper is a comprehensive study of the TA strategies present in the literature for all the domains that rely on connected devices. Furthermore, it considers the impact that the specific domain, along with its characteristics and typical applications, has on the design choices of a TA mechanism.

Based on the increasing importance of the TA functionalities, in this paper we analyze the major challenges, characteristics, and approaches. With respect to similar past works, we provide key significant novel contributions:

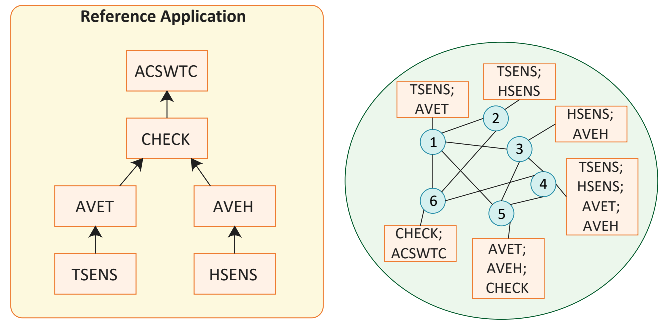
- the analysis of the state of the art has been conducted by identifying and scrutinizing all the five major domains where TA has a key role, i.e., Internet of Things (IoT), Sensor and Actuator Networks (SAN), Multi-Robot Systems (MRS), Mobile Crowdsensing (MCS) and Unmanned Aerial Vehicles (UAV);
- the distinctive factors that characterize these domains with respect to the TA functionalities are identified and extensively discussed, together with the design elements that have driven the definition of the proposed solutions;
- the issues that need to be addressed by future research activities are also discussed, which are: the interoperability of platforms in the implementation of TA functionalities, the introduction of appropriate trust evaluation algorithms, an extension of the list of tasks that the object could perform, and the involvement of network service providers.

The paper is organized as follows. In Section II, the paper briefly presents the key characteristics of applications and tasks and the relationships among them. In Section III, the distinctive factors of the IoT, SAN, MRS, MCS, and UAV domains are analyzed to understand how these impact the TA functionalities, as discussed in Section IV. In Section V, the main proposed TA algorithms are surveyed, by providing a relevant classification in terms of challenges that are addressed by the TA problem and proposed approaches. Section VI discusses the challenges for future research activities. Conclusions are finally drawn.

II. Key Characteristics of Applications and Tasks

Many applications rely on the execution of tasks by connected devices, e.g., monitoring the temperature in a given room, analyzing the context in a specific area, detecting security threats in a public square, conducting collaborative jobs by robots in an industrial plant. Accordingly, the set of possible applications is quite variegated and goes from very simple sensing tasks to those where the collaboration of intelligent objects is needed. Most of the time, the devices to which allocate specific tasks are not statically determined but appropriate algorithms are required to identify the best ones based on those that are actually available and that have the right attributes. To better understand the relationship between tasks, applications, and TA to network devices, assume that the application to be executed is: *turn on the air conditioning when the average over 10 minutes of temperature and humidity sampled at least every minute go higher than respectively 25° C and 75%.* This application, which has to be assigned to the nodes of the network depicted in Fig. 1b, can be subdivided into the following tasks, as shown in Fig. 1a:

- TSENS: temperature sensing;
- HSENS: humidity sensing;
- AVET: average temperature computation;
- AVEH: average humidity computation;



(a) Example application (b) Example network

Fig. 1: Example of (a) subdivision of a reference application into tasks and (b) network of nodes with the related tasks that they can perform. A TA strategy associates each task in (a) to one or more nodes in (b) so that the application is executed

- CHECK: average temperature and humidity check;
- ACSWTC: switch on and off the air conditioning according to the average temperature and humidity values.

As it can be seen in Fig. 1a, a hierarchical dependency can be identified among these tasks, where the higher-level tasks need as input the outputs of the lower-level tasks.

Suppose that the network is made of the devices represented in Fig. 1b, where the tasks that each device can perform are indicated in the labels connected to them. As it is shown in the Figure, only nodes 1, 2, and 4 can perform TENS, nodes 2, 3, and 4 can perform HSENS, nodes 1, 4, and 5 can perform AVET, nodes 3, 4, and 5 can perform AVEH, nodes 5 and 6 can perform CHECK, and node 6 can perform ACSWTC. The aim of a TA solution is to assign each application task to the combination of network nodes that can perform them, by also satisfying their requirements.

The relationship between an application and its tasks is regulated by three main criteria [7][4][3]:

- *Task interconnection:* the application to be executed can be either *single-task* or *multi-task*, i.e. made by multiple tasks (as in the example of Fig. 1a). In multi-task applications, tasks can be made in parallel (e.g., temperature sensing from sensors in a given area when the average value should be computed and provided), or they can depend on one another, i.e. the output of one or more tasks is used as input for other tasks (e.g., tasks in a production chain);
- *Same task assigned to multiple devices:* some applications may request the same task to one device (*single-device* tasks) or more than one at the same time (*multi-device* tasks), e.g. the same sensing can be assigned to multiple sensors to increase information accuracy by leveraging location diversity.
- *Task repetitiveness:* tasks can be categorized either as *event-driven tasks*, whose result is required only once by the application (e.g., ring a bell when a host arrives), or as *periodic tasks*, which repeat themselves after a fixed time interval and are generally associated with a frequency (e.g., periodic acquisition of video shots to detect the presence of intruders).

Application tasks can be grouped into five main categories:

- *Data collection:* it can be performed either by sensors, which provide a measurement of a physical quantity, or by user interface devices, which request data directly to users;
- *Data delivery:* it entails the communication of data from one device to another;
- *Processing:* it consists of producing output by processing some input data. It can be performed by any device with sufficient computing capabilities;
- *Storing:* it requires storing data in a device with sufficient memory capacity;
- *Actuating:* it is performed by actuators, which are usually energy-consuming line-powered nodes, whose function is to convert energy into motion. This includes also showing the output of the application in a given display.

Each task is characterized by some quality requirements, mainly in terms of: Quality of Service (QoS), i.e. the service requirements of end-to-end communications; and Quality of Information (QoI), i.e. the degree of accuracy of the provided information. Such requirements are typically related to ranges of time (e.g. information collected within a precise time window, task finished before a specific deadline), location (e.g. close to a point of interest, inside a specific room), or information quality (e.g. accuracy, completeness). Sometimes, these are also represented by Quality of Experience (QoE) requirements which are combinations of the previous ones, to describe the desired quality as an overall acceptability level as perceived subjectively by end-users, depending on their expectations and context.

Based on these considerations, an *effective* TA technique assigns application tasks to the *system*[1] devices taking into account devices capabilities of executing the tasks with the required quality. Nevertheless, there can be many possible combinations that solve this problem, with utterly different outcomes both on the application results and on the state of the system once the execution of the application is completed. In other words, the same application can be executed in compliance with its requirements but selecting devices to perform tasks more *efficiently* so that, for instance, the impact on energy consumption or communication overhead is reduced. To assess the impact of different TA schemes on different application scenarios and the final system status, in the following Section the factors that mainly affect the TA design are analyzed.

III. Factors Impacting on Task Allocation

As it is evident from the previous Section, and in particular from the example shown in Fig. 1, the performance of a TA solution depends on both the application (Fig. 1a), mainly in terms of requirements, and the system infrastructure, corresponding to the network in the example of Fig. 1b. Indeed, from the analysis of the literature about TA among cooperating connected devices, some factors that depend either on the system infrastructure or on the required application can be identified as particularly critical, as they severely affect the system efficiency and fulfillment of application requirements. Therefore, such factors are also crucial for efficient TA. In this Section, these factors and their impact on TA are examined in detail.

Heterogeneity: it is typical of scenarios where cooperating devices have very different characteristics (e.g. available resources, functionalities, communication protocols) [8][9][10]. The higher the heterogeneity, the higher the number of elements that need to be considered simultaneously by the TA strategy, as it needs to encompass different device capabilities, characteristics, and functionalities, often at the same time (i.e. *multi-objective* TA).

Device resource availability: especially for scenarios with resource-constrained devices, mainly in terms of battery [11][12], computing [13], storage [14], and bandwidth [15], *efficient resource management* is one of the main objectives of TA. Indeed, inefficient use of resources can cause their depletion, leading to faults and failures that may be difficult to cope with.

Mobility: for systems characterized by mobile devices such as smartphones, vehicles, robots, or drones, the TA strategy has to be designed so that it can easily *adapt to topology changes*, also integrating device mobility tracking and prediction [16][17]. Speed-related issues need to be considered: devices whose speed is very high (e.g. vehicles) are less likely to provide *reliable information* about a specific location, especially when the area to be covered is narrow [18][19]. Another issue is related to periodic tasks, which cannot be assigned permanently to mobile devices as these are not always located in the area of interest. This means that tasks need to be recurrently reallocated according to the dynamism of the scenario.

Communication range: whenever the application includes processing tasks, some or all of these can be executed by devices located in the route between the source(s) and the destination, including the sources themselves, according to the selected TA scheme [20][21]. This is the concept behind *fog and edge computing*, which is particularly suitable for systems characterized by short-to-medium-range communications such as Low-Power Wireless Area Networks (LP-WAN) or Device-to-Device (D2D) communications, where devices can interact directly and cooperate autonomously. Indeed, when source devices communicate directly with remote destination devices (e.g. with the cloud) through long-range communications, intermediate processing is generally not possible nor convenient.

User involvement: whenever a user is involved in task execution and is thus requested to take an action (e.g. provide feedback, move to a point of interest to take a photo), a *reward* is offered in return [22]. Such a reward is typically proportional to the effort required to complete the task. Accordingly, TA strategies are designed so that a fair trade-off between task costs and outcome is identified.

Application complexity: it depends on the task interconnection and the number of devices that can be involved in TA. Straightforwardly, multi-task multi-device applications are much more complex than one-task one-device ones. Therefore, in the former case, also TA is much more *complex* and needs

[1]From now on, we refer to "system" as the set of available devices and relevant interconnecting infrastructure, as well as the algorithm for TA

to consider also the order in which tasks are expected to be executed [23].

Stringent requirements: for TA to be effective, *constraints* on QoS [18], QoI [24], and QoE [25] requirements need to be included when designing the TA strategy. Stringency on requirements is directly related to the number of devices that can be selected to allocate tasks to. Indeed, the more stringent the requirements, the lower the likelihood to find many devices that can fulfill them, and this can also affect the probability of disruption of the system.

Task repetitiveness: TA can either be *instantaneous*, i.e. it is valid for one single task execution and is based on the current state of the system, or *time-extended*, i.e. tasks are scheduled over a planning horizon [4]. While event-driven tasks can only exploit instantaneous TA, for periodic tasks, either instantaneous or time-extended TAs can be chosen. In the former case, the TA strategy is evaluated with the same frequency as the task, and therefore it needs to be *lightweight*, in order not to overload the system. In the latter case, the strategy is more complex, as it also needs to predict the future state of the system with enough accuracy, so that faults and failures are prevented. Furthermore, also in this case reallocation needs to be expected whenever *unpredicted changes* to the system are experienced.

IV. Domains of Cooperating Connected Devices

As mentioned in the previous Section, the key factors that affect TA efficiency depend on both the application to be performed and the system infrastructure. Therefore, combinations of applications and system infrastructures with common impacting factors are likely to have common TA design principles. The objective of this Section is thus to analyze the literature to find whether there is some categorization of applications and system infrastructures, hereinafter called *domains*, characterized by common factors' impact. Accordingly, in the following Section, the identified categorization will drive the study of the common TA design principles.

In order to identify the domains, the papers present in the Scopus database that have in the title, abstract or among their keywords the words "network" and "task allocation" or "task assignment" have first been selected[2]. The keywords of the resulting papers have then been analyzed, and the ones that describe the types of system infrastructure considered in the papers have been selected. The resulting papers have then been grouped according to the keyword(s) they are associated with. To be easier to determine the differences between the domains, the subdivision into domains has been made so that the overlapping among the groups of papers, i.e. the ratio of papers that are associated with more than one domain, is less than 5%. According to these criteria, five main domains have been identified: IoT, SAN, MCS, MRS, and UAV. The association between domains and related keywords is enlisted below:

- IoT: Internet of Things
- SAN: Wireless Sensor Networks, Sensor Networks, Wireless Sensor Network, Wireless Sensor Network (WSNs), Ad Hoc Networks, Mobile Ad Hoc Networks
- MCS: Crowdsourcing, Spatial Crowdsourcing, Crowdsensing
- MRS: Multi-robot Systems, Robot Applications, Industrial Robots
- UAV: Unmanned Aerial Vehicles (UAV)

TABLE I: Domain overlapping expressed as the ratio of papers in each pair of domains

	IoT	SAN	MCS	MRS	UAV
IoT	–	2.7%	2.3%	0.0%	2.5%
SAN	2.7%	–	1.6%	3.8%	3.2%
MCS	2.3%	1.6%	–	0.0%	0.0%
MRS	0.0%	3.8%	0.0%	–	1.9%
UAV	2.5%	3.2%	0.0%	1.9%	–

As it is confirmed by Table I, such overlapping is almost always lower than 3%, with the only exceptions of 3.8% and 3.2% corresponding respectively to the pairs WSN-MRS and WSN-UAV. It is important to highlight that, even though the categorization presented in this paper emphasizes the differences among the domains, the boundaries among them are rather blurred, and real case scenarios often present nuances that cannot be thoroughly represented by restricting them to one single category.

Keyword analysis has been later carried out for each domain, to assess how much the factors impacting on TA, defined in Section III, affect them. In particular, for each factor, the papers with the following keywords have been selected:

- Heterogeneity: Diverse, Heterogeneity, Heterogeneous;
- Device resource availability: Battery, Computation Constrained, Computation Constraint, Energy Harvesting, Energy Conservation, Energy Constrained, Energy Constraint, Energy Saving, Lifetime, Low Computation, Low Capacity, Low Capability, Low Capabilities, Low Power, Low Energy, Low Processing, Power Constrained;
- Mobility: Aircraft, Mobility, Mobile, Vehicle, Transport, Movement, Motion, Smartphone, Wearable;
- Communication range: papers that do not have the keywords 6LoWPAN, 802.15.4, 802.15.1, BLE, Bluetooth, Body Area Network, D2D, Device-to-device, Infrared, NFC, Personal Area Network, Short range, RFID, UWB, Ultra wideband, WirelessHART, Z-WAVE, ZigBee;
- User involvement: Man machine, Human-machine, Human-machine interaction, Human computer, Private Information, Privacy, Sensitive Information, User;
- Application complexity: Artificial Intelligence, Big Data, Complex, Computation intensive, Data Intensive, Data Fusion, Data Mining, Large Dataset;
- Stringency of requirements: Accurate, Data Quality, Delay-sensitive, Emergency, High quality, Information Quality, Quality Assessment, Quality Control, Quality of Information, Quality Requirements, Real Time, Reliable, Time-constrained, Timing Constraints, Trust, Trustwor-

[2]The result of this search on 17/02/2021 is of 2395 documents

thy, Trustworthiness;
- Task repetitiveness: Data collection, Monitor, Monitoring, Periodic, Repetitive.

Fig. 2 depicts the level of importance of each factor as the percentage of papers characterized by the keywords that are relevant to that factor, for each domain. More specifically, the innermost level corresponds to percentages from 0% to 20%, and each intermediate level differs by 20% from the others up to the outermost level, which corresponds to 80% to 100%.

A similar analysis has been made also to define which applications are more common in each domain. Fig. 3 shows the stacked bar chart of several applications that are typical in some of the considered domains, with the related percentages of papers per domain. The keywords that were used to select the papers on TA among connected nodes for each application are:

- Intelligent Buildings: Intelligent Buildings, Smart Home, Smart Building;
- Smart Healthcare: Health Care, Healthcare, Health, Structural Health Monitoring, Mhealth;
- Security Systems: Access Control, Intrusion Detection, Security Systems, Identification;
- Smart Grid: Electric Power Transmission Networks, Smart Power Grids, Smart Grid, Electric Network;
- Smart City: Air Quality, Noise Pollution, Smart City, Smart Cities, Roads and Streets, Traffic, Urban Planning;
- Indoor Localization: Indoor Positioning Systems, Indoor Localization;
- Accident Prevention: Accident prevention;
- Industry 4.0: Industry 4.0, Industrial Internet of Things (IIoT), Supply Chains, Manufacture, Factory;
- Smart Agriculture: Agriculture, Agricultural, Crops;
- Photogrammetry: Photogrammetry, Image processing, Aerial Photography, Optical Radar, Image Segmentation, Image Enhancement, Satellite Imagery, Spectroscopy;
- Environmental Monitoring: Environmental monitoring, Forestry, Vegetation;
- Disasters Management: Disasters, Search And Rescue, Uncertain Environments, Unknown Environments;
- Military Operations: Military Operations, Military Vehicles, Suppression Of Enemy Air Defense, Cooperative Combats, Military Applications, Fighter Aircraft.

With the support of Fig. 2 and Fig. 3, in the following subsections, each domain will be discussed by considering its characteristics, main applications, and factors impacting on TA.

A. *Internet of Things*

The IoT is characterized by heterogeneous devices that communicate using the Internet [26] (see Fig. 4). IoT scenarios encompass connected objects such as low-cost low-complexity sensors (e.g. thermometers, smart meters), expensive complex medical equipment, and smart hand-held devices, which cooperate to create smart environments (e.g. smart homes [27], smart transport [28], smart hospitals [29]). Since the IoT is based on Internet communications, the communication range is generally long [30]. Nevertheless, before reaching the

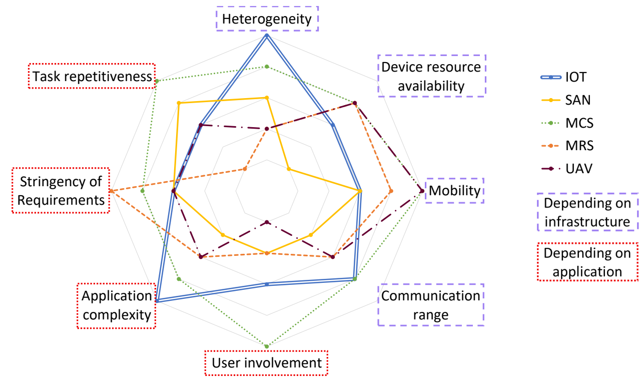


Fig. 2: Major factors impacting the reference domains: this radar chart shows the level of importance of each factor which goes from very low values (center of the graph, corresponding to 0%-20%) to very high (perimeter of the graph, corresponding to 80%-100%)

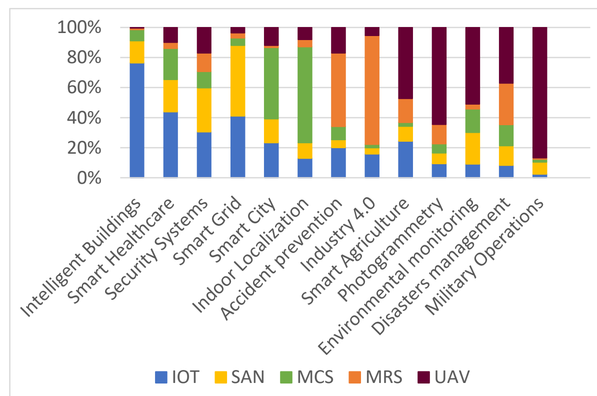


Fig. 3: Stacked bar chart of the papers on TA among connected nodes belonging to each domain per considered application

backbone network, in some cases, IoT devices communicate directly creating ad-hoc and peer-to-peer networks [31]. Even though device resource availability is moderate, especially in terms of battery, computing, and storage, the IoT is usually supported by edge and cloud computing, which provide the required intelligence and memory. The heterogeneity is very high, as different types of devices using different communication protocols at the same time are involved. Such heterogeneity is also reflected in a good balance between fixed (e.g. servers, gateways, actuators) and mobile (e.g. smartphones, smart vehicles) devices, hence the mobility can be considered moderate. User interfaces are often provided to interact with users, either to request data, accept commands/settings, or show information (moderate user involvement). As compared to the other domains, IoT applications are much more complex, with moderate constraints at QoS, QoE (especially for infotainment applications), and QoI levels. Task repetitiveness is moderate, as the IoT includes both periodic [32] and event-driven [33] tasks with almost equal proportions.

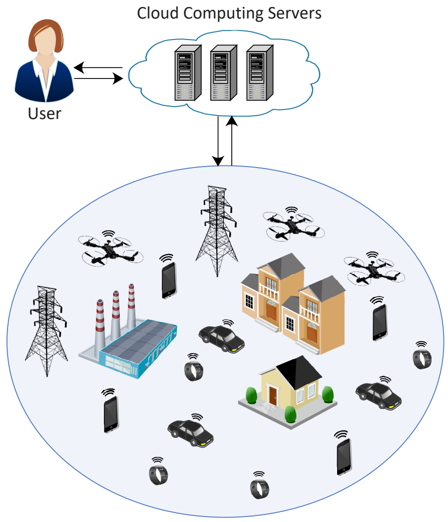


Fig. 4: A typical IoT Scenario

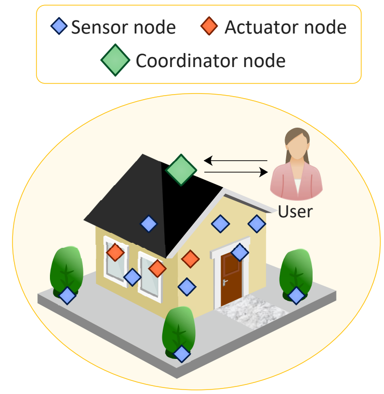


Fig. 5: A typical SAN scenario

B. Sensor and Actuator Networks

As the definition itself states, the most representative devices of SAN are sensors and actuators [34], which are connected, often through routing devices, to a grid-powered central unit, i.e. the coordinator (see Fig. 5). Besides collecting data from sensors and sending commands to actuators, the coordinator manages its network and allocates tasks. It may be connected to a backbone network or the Internet and it is usually the only node in the SAN that has a long-range communication link. Indeed, SAN typically create ad hoc short-range networks [35] among its nodes. Heterogeneity, in terms of device types, their functionalities, and communication technologies involved, is moderate [36]. Sensors and actuators have very low device resource availability: they are typically battery-powered, often non-rechargeable, and have very low computing and storage capabilities. Even though there may be mobile devices, mobility can be considered moderate, as devices are typically fixed. Typical SAN applications are made of simple periodic sensing tasks (low application complexity and high task repetitiveness) such as smart grids [37] or security systems [38]. The collected data are usually not associated with a specific user, but rather to an area: when present, user interfaces are generally installed on coordinators and used to show information and to accept simple commands (low user involvement). Application requirements are moderately stringent, especially for applications related to security and healthcare.

C. Mobile CrowdSensing

MCS is devised to take advantage of crowds of smart mobile devices (e.g. smartphones, smartwatches, smart vehicles) performing location-specific sensing tasks [39]. Typical applications go from outdoor Smart City scenarios [40] to indoor localization and navigation [41][42]. Heterogeneity is high since the involved devices have different characteristics and functionalities. Even though battery-powered (frequently recharged), smart devices typically have high computing and storage capabilities, which are mainly used for other multi-purpose applications. Accordingly, even though device resource availability is high, MCS applications need to be designed so that they do not interfere with device usage. MCS applications are based on continuously collecting huge amounts of data from many devices at the same time (very high task repetitiveness). As depicted in Fig. 6, data are usually transmitted to the cloud through the Internet (e.g. using WiFi or mobile communications), where they are processed to obtain the required information (high application complexity). Even though devices may coordinate autonomously using peer-to-peer (e.g. device-to-device – D2D –) communication protocols [43], they usually rely on long-range communications towards a central coordinator residing in the cloud. The data, collected from personal user devices, can be either objective (e.g. a photo) or subjective (e.g. personal feedback). Furthermore, users may be requested to reach a specific location to perform tasks. It is evident that MCS applications can require very high user involvement, with disclosure of personal data such as identity and location. Indeed, a reward is often envisaged for each task accomplished. Requirements are stringent, particularly in terms of reliable and trusted measurements.

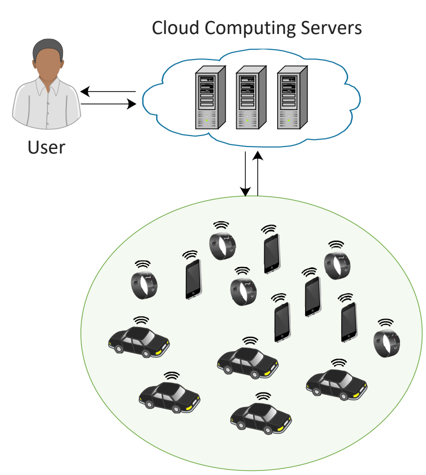


Fig. 6: A typical MCS Scenario

D. Multi-Robot Systems

MRS are made of quite homogeneous robots, equipped with sensors and actuators, which can create ad-hoc networks and/or connect to the Internet [44]. As shown in Fig. 7, depending on the application scenario, robots can be grid-powered and static (e.g. industrial robots [45]) or battery-powered (usually rechargeable) and mobile (e.g. disasters management [46]), with mobility that, similar to SAN, is usually limited and often indoor. Hence, the communication range is considered moderate. Tasks can be either repetitive (typical of industrial applications) or event-driven (more common in disasters management). According to the tasks they are assigned to, mobile robots are requested to move to specific locations to execute them. Robots' computing and storage capabilities are usually much higher than those of sensors in SAN. Thus, they are usually able to coordinate autonomously, either directly or through a coordinator. Similar to SAN, robots usually do not collect data about specific users, and user involvement is very limited. MRS applications are moderately complex, with very stringent requirements, especially in terms of robustness and resilience to errors. Indeed, such requirements are particularly stringent for critical applications such as accident prevention, disaster management, and Industry 4.0.

Fig. 7: A typical MRS scenario

E. Unmanned Aerial Vehicles

UAV, also known as Unmanned Aerial Systems (UAS), are networks of drones or remotely operated aircraft that cooperate either for monitoring purposes or to support cellular networks and enhance their QoS [47] (see Fig. 8). UAV have been historically used mainly as relay networks to support military operations [48]. Thanks to the advances in technology, they have recently found application in civilian and commercial environments, in particular for smart agriculture [49], photogrammetry [50], environmental monitoring [51], and disasters management [52]. Applications are mainly made of data collection and delivery tasks, without much complexity. Even though they are battery-powered, UAV's aircraft generally have good computation and storage capabilities [53] (i.e. device resource availability is high). Heterogeneity is low, as the involved devices have quite homogeneous equipment and functionalities. Similar to SAN and MRS, UAV are usually made of short-range ad-hoc networks of locally cooperating objects. Long-range communications are typically assigned to coordinator nodes, which also act as sinks by collecting data and communicating them through a backbone network. Humans rarely interact with UAV, therefore user involvement is very low. UAV applications can include either event-driven tasks with stringent requirements (e.g. emergency- and military-related applications), or periodic monitoring tasks with more relaxed requirements (e.g. photogrammetry, environmental monitoring, and smart agriculture). Thus, task repetitiveness and stringency of requirements are considered moderate.

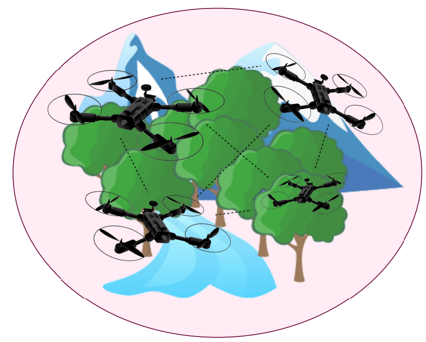


Fig. 8: A typical UAV scenario

V. Discussion About Task Allocation Approaches

Based on the study of the literature on TA among connected devices in the different domains and on the discussion about the impact on the design of a TA strategy of the eight factors characterizing the domains (see Fig. 2), it is possible to infer four challenges that can be addressed by TA solutions among connected objects, and that are discussed in the following. Table II shows to which extent each of these challenges has characterized the proposed solutions so far. The percentage values have been assessed by analyzing the ratio of papers, belonging to each domain, with keywords related to the considered challenge. More specifically, analogously to what has been done in Section IV, the keywords of the papers that have in the title, abstract or among their keywords the words "network" and "task allocation" or "task assignment" were analyzed and the papers with the following keywords were selected:

- Resource management: Bandwidth, Communication Cost, Communication Overheads, Computation Offloading, Computational Complexity Costs, Efficiency, Efficient Allocations, Energy Aware, Energy Balance, Energy Conservation, Energy Efficiency, Energy Efficient, Load Balancing, Optimal Processing, Power Management, Resource Allocation, Resource Aware, Resource Management, Resource Utilizations;
- QoS: Delay Constrained, Delay Constraints, Delay-sensitive, Latency Constrained, Latency Constraints, Low-latency, Quality Of Service, QoS, Real Time, Real Time Systems, Task Completion Time, Timing Constraints;
- QoI: Accuracy, Accurate, Data Quality, Information Management, Information Quality, QoI, Quality of Data,

TABLE II: How frequently the TA challenges are considered in the different domains

Domain	Resource mngmt.	Quality rqmts.			Coverage	Incentive
		QoS	QoI	QoE		
IoT	91%	53%	22%	6%	16%	10%
SAN	67%	34%	20%	1%	27%	14%
MCS	60%	12%	33%	2%	60%	34%
MRS	35%	16%	13%	1%	37%	12%
UAV	45%	25%	9%	0%	53%	10%

Quality of Information, Quality of Sensing, Quantity of Samples, Reliability, Reputation, Trust, Trustworthiness, Trustworthy;

- QoE: Quality Of Experience, QoE, Satisfaction;
- Coverage: Coalition Formation, Communication Relays, Coverage, Destination-aware, Dynamic Alliance, Dynamic Coalition, Fleet Operations, Location Based Services, Location Information, Motion Planning, Multi-robot Coordination, Path Planners, Path Planning, Path-planning Algorithm, Route Planning, Self Organizations, Self Organizing Maps, Target tracking, Trajectory Planning;
- Incentive: Auction, Budget Balance, Budget Constraint, Budget Constraint, Budget Control, Incentive, Incentive Mechanism, Incentive Models, Profit, Reward.

The percentages that are shown in Table II report the number of papers that have these keywords as compared to the total number of papers for the considered domain.

The following two subsections discuss respectively the identified challenges and the main approaches that are commonly used in TA algorithms.

A. Challenges Typically Addressed by Task Allocation Approaches

Resource management: it is included in TA approaches that need to ensure that the available resources are not used *unfairly*, causing their early depletion in the overloaded devices while others are barely used. The necessity of considering resource management depends on the amount of resources required to execute an application in relation to their availability: high-demanding applications in scenarios with limited resources require including their management into TA. As indicated in Table II, IoT, SAN, and MCS are the domains where this challenge is more frequently addressed. Whereas in SAN the main issue is represented by very low resource availability, IoT and MCS are characterized by very high to high application complexity. Since communication ranges in SAN are low, nodes that are close to one another often form a cluster to cooperate and share their resources [3][10][54]. As opposed to SAN, in the case of MCS, the resource availability is high, therefore the resource management problem is typically solved by just assigning the tasks to the most capable devices that participate in the task execution [17][55]. On the other hand, thanks to its very high heterogeneity, the IoT can make use of the concepts of *Edge Computing* and *Fog Computing*, also under the form of *Mobile Edge Computing* (MEC). In such architectures, complex tasks that cannot be performed by resource-constrained end nodes are offloaded to more capable devices that are located close to the end nodes [21][24][56]. This enables not only a more efficient use of local resources but also a lower overload of the network as compared to the case where complex tasks are offloaded remotely to the cloud.

Quality requirements: they are included in TA approaches that need to ensure that QoS, QoI, and QoE requirements are fulfilled. As demonstrated by Table II, QoS requirements are more predominant in the IoT [18][57] and SAN [58][59] domains, which encompass delay-sensitive applications such as smart healthcare and security systems (refer to Fig. 3). Besides being beneficial for resource management, Edge and Fog computing are proved to be advantageous also for QoS-constrained applications, as opposed to Cloud Computing solutions [13][60]. Indeed, they not only keep the data closer to the sources, i.e. the place where they are most likely to be needed, but also reduce the network overhead towards the Cloud.

With reference to QoI requirements, they are most frequently included in TAs where data reliability and information quality are paramount, i.e. those that are applied to applications where data are massively collected by potentially unknown devices. This is the case of the MCS domain, where tasks need to be assigned to reliable and trustworthy users [61][62].

Finally, QoE is only considered in applications that have an impact on users' satisfaction such as infotainment applications. For this reason, it is rarely considered into TA, with IoT being the domain where it is more frequently included [24][63].

It is important to note that, even though MRS is characterized by very stringent requirements, especially in terms of robustness and resilience to errors, quality requirements are not frequently included in MRS TA strategies. The reason for this is that such requirements are typically intrinsically satisfied by the infrastructure, which is appropriately designed for this purpose.

Coverage: it characterizes TAs of location-based tasks that have to be assigned to mobile devices, whose position changes with time. Hence, as it is reported in Table II, coverage is a crucial challenge of MCS, UAV, and, albeit to a lower extent, MRS. The main difference in the type of mobility of these three domains is that in MCS it depends on the user's will or likelihood to move to a specific location, whereas in MRS and UAV the mobile devices are controlled to satisfy the application requirements. Accordingly, MRS and UAV TA strategies to optimize coverage are characterized by coalition formation [64][65] and path planning [66][67]: task target locations are assigned to robots or vehicles according to their capability to perform the task and to the resources needed to do it efficiently. As far as MCS is concerned, spatio-temporal coverage is optimized by assigning the tasks to the devices that are more likely to collectively cover the requested area, either because they're already there or because they are predicted to be there at the right moment. For this reason, TA in MCS often incorporates mobility prediction algorithms [17][68][69].

TABLE III: Task allocation approaches in the different domains

Approach	IoT	SAN	MCS	MRS	UAV
Heuristic/ Greedy/ Genetic Algorithms	13%	28%	43%	13%	33%
Machine Learning	42%	8%	12%	28%	10%
Game Theory	5%	29%	8%	25%	23%
Integer Linear Programming/ Branch & Bound	13%	11%	18%	20%	13%
Swarm Intelligence	10%	15%	8%	3%	12%
Markov Processes	10%	1%	6%	3%	4%
Others	7%	8%	5%	8%	5%

Incentives to task execution: reward-based TAs are characteristic of location-based *participatory* tasks, where devices move to specific places to complete the tasks [70][71]. Indeed, rewards can be also provided when devices participate in tasks *opportunistically*, i.e. unintentionally while they move to their destination [72][73], without the need to change their route, but in this case the outcome of the task does not depend on the incentive, but rather on the already defined trajectory. On the other hand, in participatory sensing, the reward is usually proportional to the desired QoI, according to the assumption that higher-quality data is worth more. This is the reason why incentive-based TA approaches are mainly implemented into MCS scenarios (see Table II), which are the only ones where participatory tasks are envisaged. Nonetheless, it is important to note that the user involvement in location-based tasks often raises concerns on location privacy: indeed, the higher the precision on device location, the higher the risk of location privacy leaks. Techniques such as spatial cloaking, differential geo-obfuscation, and blockchain are often included in MCS TA to preserve location privacy [5][74][75][76]. Nevertheless, such techniques tend to reduce the QoI. For this reason, some MCS TA approaches are designed to provide rewards high enough to compensate for potential privacy loss and stimulate the production of reliable data [70][77].

B. Approaches Typically Included in Task Allocation Algorithms

Table III identifies the most typical approaches used to solve TA problems in the literature, subdivided by domain. Also in this case the percentage values of the Table are computed according to the ratio of papers for each domain with keywords related to the specific approaches. The keywords associated with each TA approach are:

- Heuristic/Greedy/Genetic Algorithms: Approximation Algorithms, Genetic Algorithms, Greedy Algorithms, Heuristic Algorithms, Heuristic Methods, Metaheuristic, Meta-heuristic, Numerical Methods, Search Algorithms, Simulated Annealing, Simulated Annealing Algorithms;
- Machine Learning: Clustering, Clustering Algorithms, Deep Learning, K-means, Learning Algorithms, Learning Systems, Machine Learning, Multi Armed Bandit, Neural Networks, Reinforcement Learning;
- Game Theory: Auction, Dynamic Alliance, Game Theory;
- Integer Linear Programming/Branch & Bound: Branch & Bound, Branch and Bound, Integer Programming, Linear Programming, Mixed Integer Linear Program, Mixed Integer Non-linear Programming Problems, Polynomial Approximation;
- Swarm Intelligence: Ant Colony Algorithms, Ant Colony Optimization, Binary Particle Swarm Optimization, Discrete Particle Swarm Optimization, Particle Swarm Optimization, PSO, Particle Swarm Optimization Algorithm, Swarm Intelligence, Swarm Robotics;
- Markov Processes: Markov Processes, Monte Carlo Methods;
- Others: all the remaining, including Contract Net Protocols, Convex Optimization, Evolutionary Algorithms, Fuzzy Logic, Hungarian Algorithm, Nonlinear Programming.

Heuristic, greedy and genetic algorithms are overall the most commonly used approaches for TA. Even though they are designed to converge to sub-optimal results, they are characterized by very low computational complexity, which makes them a satisfactory solution especially for resource-constrained scenarios and/or mobile scenarios [17][64][78], or time-constrained applications [60][79].

The second category of most common approaches for TA is that of machine learning techniques. Although they are not simple in terms of computational complexity, as opposed to machine learning, they enable to include in the TA strategy complex evolutions of the application scenarios to which the TA is applied. In dynamic environments such as IoT, adaptive TA is accomplished thanks to reinforcement learning [80][81][82][83]. Neural networks, and in particular Self-Organizing Maps (SOM) are mostly used in MRS [67][84].

Game theory-based TA mechanisms are distributed approaches where the devices negotiate to maximize their own utility, either cooperatively or non-cooperatively. With specific reference to TA, a device utility expresses its degree of benefit associated with the execution of a task, i.e. a task is assigned to a device only if its related utility is sufficiently high. Given its distributed nature, game theory is mainly applied in application scenarios where devices coordinate autonomously [54][85][86].

Another approach that is very frequently used in TA is Integer Linear Programming, along with the related sub-optimal solutions such as Branch & Bound. Indeed, such approaches are particularly suitable to model TA problems where a specific cost can be associated with each involved device. This is the case, for instance, of trajectory planning problems, which are typical of MCS [87][88], MRS [16], and UAV [89], and are often solved using graph-based approaches (e.g. Traveling Salesman Problem, Traveling Repairman Problem) [90][91].

As it is evident in Table III, the other approaches are more related to one or two specific scenarios, and only marginally used in the other ones. This is the case of Swarm Intelligence (e.g. Ant Colony Optimization, Particle Swarm Optimization), which is typical of SAN [92] and UAV [93], in particular in monitoring applications where sensing devices move and coordinate similar to a swarm. Markov processes are used when the application scenario can be modeled as a set of possible states with a probability of transition between states. As for Table III, they are mainly used in IoT and MCS [18][94].

Other less common TA approaches, reported in Table III under the heading "Others", are present in the literature. It encompasses some well-known approaches, which however are applied in less than 5% cases, among which fuzzy logic [95], nonlinear programming [96], evolutionary algorithms [97], and Hungarian algorithms [98].

VI. Discussion about challenges for future research efforts

The current solutions of TA suffer from key shortcomings that need to be addressed by future research activities. These are related to the interoperability of platforms, inclusion of trust evaluation, support from the network service providers, and extension of the list of considered tasks, which are discussed in the following. Fig. 9 illustrates the discussed challenges.

A. Platform interoperability

Platform interoperability has been the subject of research and development in the last years, especially in the IoT domain. Standards have also been defined in this area by proper standard development organizations (SDOs), such as ETSI, oneM2M, W3C, IETF. A major platform (FIWARE[3]) has also been defined to create a large ecosystem with open-source implementation of generic enablers based on open specifications to realize smart environments in several application domains. These organizations have also addressed the interoperability issue, especially in terms of APIs which allow for connecting devices and services belonging to different platforms. However, this interconnection is possible only between platforms that follow the architectural specification of the reference SDO. For instance, in [99] the authors have explained how two platforms that followed the FIWARE and oneM2M architectural solutions may be interconnected. It results that specific modules had to be defined and deployed in the two platforms so that services of one platform could be used by the other. This required a significant amount of time; additionally, replicability is quite limited as the developed components apply only to this specifically considered scenario. Other works have brought to the same conclusions [100], [101]. Such an issue is discussed in the oneM2M standard, where discovery is considered a common service function (CSF) which should foster interoperability, but then detailed discussions on how this inter-platform procedure outside of the oneM2M world should function has not been analyzed further.

Indeed, the following aspects need to be addressed:

- A *shared format or syntax to describe the available resources* in terms of types of tasks that can be performed and characterizing parameters, such as: energy consumption; computational, processing, and storage capacity; communication capabilities; assured level of QoS.
- *Common APIs* to be used to involve devices belonging to external platforms, which should provide access to the following services (among others): list of available devices, tasks that can be performed with given QoS requirements, description of the interface for the provisioning of tasks results, authorization and authentication functions. Additionally, these should allow for the management of the rewards when used.
- The device *discovery results should be described with accepted metadata*, which can be used internally by the platforms running the requesting application(s).
- *Authorization and authentication standards* are not defined yet in this context. This should allow for setting the access parameters for different categories of users, services, and objects.

[3]https://www.fiware.org/

B. Inclusion of trust evaluation

When TA is applied to a multi-platform scenario (each platform belonging to a different organization), the resulting application relies on resources owned by different administrations. For this reason, the evaluation of trust is of paramount importance. However, when selecting the devices to which allocate the execution of a given task, the evaluation of the device trust level is rarely performed, except from a few works [102] [103]. The reason is due to the fact that most of the time the proposed solutions apply to an intra-platform scenario. However, as we mentioned before, the inter-platform scenario is the most powerful, and in this case trust evaluation becomes of vital importance.

To achieve this objective, past works proposed in other settings can be considered [104]. These are typically aimed at *collecting the feedback* by systems that in the past received services by the devices under evaluation. Such feedback is related to the quality of service level (measured in terms of latency in the provisioning of the service) and the quality of information (measured in terms of accuracy of the provided results and the relevant correctness). Feedbacks are collected from a community of peers, which in turn have been already selected as being of high reliability. With the diffusion of TA in inter-platform settings, specific malicious attacks may happen to be performed (e.g., discrimination attack, on-off attack, bad-mouthing attack, just to cite a few) [105]. The trust evaluation algorithms *should be able to detect the potential types of attacks* and isolate the relevant group of entities involved. Then, the TA algorithm may decide either to exclude the nodes with a trust level lower than a given threshold or to *combine the estimated trust level with other factors* characterizing the considered approach (e.g,, required amount of resources, expected level of QoS, communication overhead). When integrating the trust evaluation in the TA logic, an important aspect to be considered is to assign it with the appropriate weight when compared to the other considered factors; to this, the possible damage caused by a malicious behavior of the selected task provider should be estimated by considering the characteristics of the deployed application (number of involved nodes, type of shared data, type of service requested).

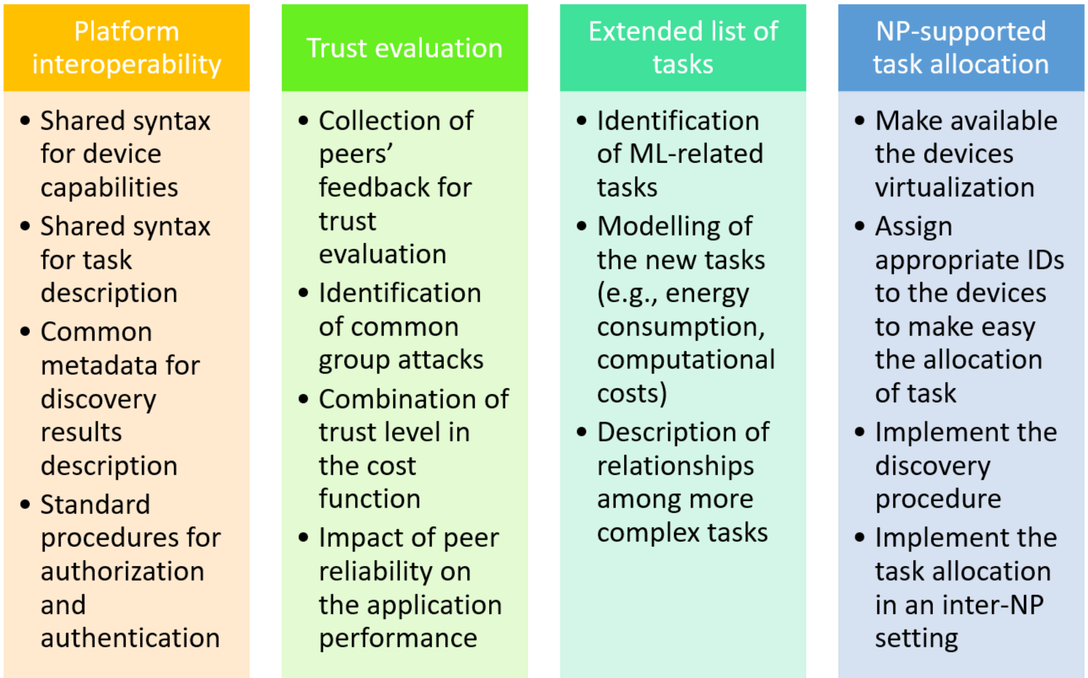


Fig. 9: List of challenges for future research activities

C. Extended list of tasks

The types of tasks that have been considered in most proposals so far are restricted to the five categories we mentioned in Section II. However, with the increasing processing and storage power of the edge devices and the need for reducing the latency (and then the distances) between the users and the provider in distributed applications, there is a strong need for the deployment of more complex data processing tasks in the edge connected devices. Additionally, more and more application tasks are driven by ML (Machine Learning) operations to exploit the power of available huge amounts of data. These more complex processing tasks are mostly related to ML model training (federated learning, model aggregation, distributed learning coordination), inference, and merging of datasets. Accordingly, tasks allocation strategies cannot focus only on the collection of data from sensing devices so that central units can process and analyze the data; indeed, it should also consider the allocation of inference-related tasks that can be allocated dynamically so as to improve the overall application QoS. A representative scenario is that of a group of UAV with the mission to detect threads in a given area where a public event is held. The video cameras and audio sensors have to be activated in the UAV to maximize the detection performance while considering also the consumed energy; the acquired data is processed with pre-trained models to detect dangerous events. However, some data pre-processing modules have to be trained with the local data for calibration of the system. Finding the right node that can perform the analysis of the acquired data should be included in the TA objectives.

The above considerations call for future research activities focused on the *identification of the additional ML-related tasks* and the *definition of proper models* that can characterize the additional tasks in terms of: computation complexity and consequent every consumption, generated data, and contribution to the overall quality of service. The latter is the one that requires significant efforts as the relationship of the relevant contribution to the overall benefit in terms of better inference performance or improvement in the model training is not straightforward. Additionally, this calls for a *more complex description of the relationships among a different and more heterogeneous set of tasks* that need to be combined for the deployment of the final application.

D. NP-supported distributed approach deployment

The widespread adoption of Mobile-Edge Computing (MEC) facilities by the network providers (NP), also as key components of the currently deployed 5G network solutions, can help the deployment of TA solutions. Indeed, the MEC infrastructure facilitates the provisioning of the following services: *hosting the device virtualization*, *assigning and managing unique IDs* for the devices, implementing the *device discovery*, and fostering *inter-NP TA* procedures.

Device virtualization is important to augment the capabilities of the physical entities with the power of the edge cloud in terms of computing, storage, and intelligence resources. With these additional resources, the devices become virtually always reachable, even if the physical entity is not reachable at the moment (but as far as cached data is enough). Additionally, it can take part in TA processes and provide the relevant services when alive. The assignment of the IDs to the devices has been a subject of long research activities in the last years which did not allow for reaching effective solutions. The discovery solutions are strictly connected with the TA and are aimed at finding the devices which can provide the required services based on the service description. The discovery can be performed by relying on the device virtualization as the physical device is not needed at this point. The NPs can provide an important contribution in this respect as they can support the deployment of interoperable services by addressing the issues discussed in the previous Section VI-A. Once the devices that may fulfill a given task have been found, then the allocation can take place in an inter-NP setting with the involvement of different MEC platforms.

E. Highlights on the future research directions

To address the mentioned issues there is the need to pursue the following research activities:

- Contribute to SDOs' standardization processes in the fields where distributed sensing and actuating have an impact, such as: ITU-T SG20 (on IoT, smart cities & communities) and IEEE Standards Activities for Smart Cities.
- Design appropriate trust evaluation methodologies that should exploit the ML/AI technologies and rely on extensive datasets generated from real IoT-based deployments.
- Analyze ML-based applications in different domains (smart cities, sustainable mobility, smart building, and others) to define the requirements in terms of ML-related tasks that should be assigned to single objects. This should then be used to define the list of additional tasks to be considered in TA frameworks.
- Leverage 5G infrastructures to deploy NP-supported strategies to make TA available to over-the-top service providers.

VII. Conclusions

The conducted extensive analysis of strategies of TA among connected devices has highlighted that different factors and design principles have characterized the different domains. The strategies proposed so far in the SAN domain have mostly focused on the efficiency in energy management, due to the low robustness of the relevant infrastructure and the task repetitiveness in the deployed applications. In the MRS domain, the fulfillment of QoS requirements is the one that has driven the definition of solutions as the relevant applications often pose stringent conditions. In the MCS domain, the QoI is instead the most important design principle. In the IoT domain, the heterogeneity of devices and the complexity of deployed applications have mostly driven the research and design efforts, so that multi-objective approaches that target efficient energy management and the fulfillment of QoS requirements have been mostly followed. As expected, in the UAV domain the level of coverage of the area of interest has been the most important challenge considered.

Whereas effective solutions are now available for TA, these do not cover all the scenarios of interest. Accordingly, several challenges that need to be addressed by future works have been identified. It results that the current solutions do not cover the multi-platform scenario, so that appropriate interoperability TA-related functionalities need to be devised. Strictly related to this aspect, there is the need to introduce the evaluation of trust in the allocation of tasks, especially when objects with allocated tasks and the application that requests these belong to different platforms. Additionally, the types of tasks considered so far should be extended to include some ML-related operations, such as: inference, training, dataset merging. Finally, the devised strategies should consider the deployment in the scenarios where the network operator can support the deployment of the TA algorithm by exploiting the ever-increasing MEC infrastructures.

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