Neighbour Discovery for Opportunistic Networking in Internet of Things Scenarios: A Survey

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Abstract—Neighbour Discovery was initially conceived as a means to deal with energy issues at deployment, where the main objective was to acquire information about network topology for subsequent communication. Nevertheless, over recent years, it has been facing new challenges due to the introduction of mobility of nodes over static networks mainly caused by the opportunistic presence of nodes in such a scenario. The focus of discovery has therefore shifted towards more challenging environments where connectivity opportunities need to be exploited for achieving communication. In fact, discovery has traditionally been focused on trade-offs between energy and latency in order to reach an overlapping of communication times between neighbouring nodes. With the introduction of Opportunistic Networking, neighbour discovery has instead aimed towards the more challenging problem of acquiring knowledge about the patterns of encounters between nodes. Many Internet of Things applications (e.g., Smart Cities) can, in fact, benefit from such discovery, since end-to-end paths may not directly exist between sources and sinks of data, thus requiring the discovery and exploitation of rare and short connectivity opportunities to relay data. While many of the older discovery approaches are still valid, they are not entirely designed to exploit the properties of these new challenging scenarios. A recent direction in research is therefore to learn and exploit knowledge about mobility patterns to improve the efficiency in the discovery process. In this survey, a new classification and taxonomy is presented with an emphasis on recent protocols and advances in this area, summarizing issues and ways for potential improvements. As we will show, knowledge integration in the process of neighbour discovery leads to a more efficient scheduling of the resources when contacts are expected, thus allowing for faster discovery, while, at the same time allowing for energy savings when such contacts are not expected.

Keywords—Neighbour Discovery, Opportunistic Networking, Internet of Things, Mobility, Knowledge.

I. INTRODUCTION

The Internet of Things (IoT) is a paradigm concerned with bringing pervasive internet connectivity to real world objects or things [1]. Such a scenario opens up the possibility for a multitude of different devices to communicate and interact with each other. Envisioned applications entail but are not limited to Smart Buildings, Smart Cities, Health-care and Environmental Monitoring as well as Smart Business [2]. In such complex scenarios, it is possible to find heterogeneous static and mobile devices, equipped with different radios which might interact with each other only during certain contact opportunities and relay information between heterogeneous and possibly disconnected static networks. For example, in a Smart City, mobile sinks (e.g. cars) might be collecting data from static nodes (e.g. traffic sensors) or disseminating control information. Moreover, such data might be relayed by any node and forwarded through other nodes (e.g. via smartphones) even in the absence of a predefined end-to-end path between data sources and sinks, exploiting opportunities for communication as soon as they become available. Evidently, such an Opportunistic Networking [3] paradigm plays an important role as an enabler for communication in IoT, where the scope of networks of static devices might be augmented through new communication possibilities with opportunistically present mobile devices [4]. Indeed, without opportunistic routing paths, disconnected networks of devices could not be connected to the Internet world. This shows the need to profit from opportunities for communication in order to pervasively reach any device, thus creating an IoT device.

Neighbour Discovery was traditionally intended for Wireless Sensor Networks (WSN) to address the energy issues of deployments [5], where static nodes released during week-long phases needed to discover each other to form a network topology. During such deployment phases, it became evident that if the devices were to be kept always on and listening, a significant amount of energy would have been wasted in the beginning just for establishing a topology. Initial research has been therefore focused on how to conserve energy in such a discovery phase, typically by trading it with the latency (i.e. the time needed to be aware of the presence of another device). The aim was to perform discovery by putting the radio into sleep and awake modes of operation through the use of different strategies.

Nevertheless, more recently, due to the introduction of nodes mobility, discovery has acquired the meaning of understanding and acquiring knowledge about the availability patterns of opportunities for communication, in order to target only when nodes are effectively in the neighbourhood. This means that Neighbour Discovery for Opportunistic Networking must be able to recognize not only if a node is available at a particular time, but also learn when or where such node will be deemed available. This is consistent with the aim for such
discovery protocols, which should be, to be able to reduce energy wastage when devices are known to be not available while discovering as quickly as possible when they are instead likely to be available. Such an approach allows the exploitation of the entirety of the short contact duration for useful communication. It is known that “Artificial Intelligence” allows for concepts such as cognition, reasoning, knowledge representation, learning and planning. Following such a definition, it is these authors’ opinion, that exploiting learning mechanisms and knowledge about the environment can aid “cognitive” IoT devices to greatly improve the neighbour discovery process in IoT scenarios of Opportunistic Networking.

In order to perform Neighbour Discovery for Opportunistic Networking in IoT scenarios, several challenges must be dealt with:

- **Recognition of Presence:** An important challenge for nodes is being able to recognize the effective presence of other nodes within their reachable communication range. This requires the adaptation of radio resources in order to be able to find neighbours within a finite temporal window even under different contacts duration conditions. Moreover, a secondary challenge is being able to understand when nodes are not present in order to save resources, as well as setting a bound for the latency to discover in order to exploit as much as possible the residual contact time for communication tasks even in presence of short contacts.

- **Mobility Patterns Features:** A challenging objective, currently part of a broad area of research, is to understand the key features of mobility patterns. Mobility models are currently trying to capture temporal and spatial patterns characteristics (e.g. truncated inter contact times power law distributions [6] or Levy nature of human walks [7]) but the research is not limited to such features. Metrics of **Popularity** such as the number of visits to a certain location, their ranking, **Social Behaviour** such as community membership, friendship, **Location Tagging** such as identifying meaningful places (schools, pubs, railway stations) explain a better tale about mobility patterns and could be useful to predict with higher accuracy mobility patterns. Finally, **Geographical Locations** allow also such possibilities: WhereNext [8] or NextPlace [9] are examples exploiting such features.

- **Knowledge Acquisition:** In order to have knowledge about the future returns of nodes in the neighbourhood, being able not only to understand mobility patterns, but also to learn them by storing information about their recurrence and reproducibility is a further challenge. In such a way, it becomes possible to predict future node arrivals and perform power management by planning not only the scheduling of resources for discovery, but also the communication based on the known future arrival times, locations and contact durations.

Neighbour Discovery for Opportunistic Networking in IoT scenarios brings along also several advantages:

- **Extended Lifetime:** An important advantage is avoiding to waste resources when nodes are predicted to be within communication range with low probability, therefore improving the power consumption on both static and mobile devices with respect to a scenario where nodes are supposed to be always available.

- **Communication Time:** A further advantage is allowing the tailoring of resources to the application requirements in useful communication time after discovery by exploiting the knowledge about nodes arrival times and contact durations.

- **Communication Planning:** By having knowledge about mobility patterns, it becomes possible to plan the communication by learning the nodes arrival rates, contact durations, as well as which nodes are more frequently visited (for example, in static networks data might be pre-forwarded to most accessed nodes [10]).

In this survey we focus on providing a taxonomy and classification about such neighbour discovery protocols for opportunistic networking in IoT scenarios. Previous surveys [11], [12], [13] were mainly targeted on traditional WSN discovery scenarios, while instead ours focuses on a broader heterogeneous (different radios based) IoT devices scenario and on knowledge acquisition in the context of learning about mobility patterns for Opportunistic Networking. Moreover, the survey of DiFrancesco et al. [14], focuses mainly on older discovery approaches and only partially on them, since it treats a broader scope including data collection and routing protocols. Our contributions are twofold:

- A first contribution is to provide a classification of neighbour discovery protocols for opportunistic networking in IoT scenarios into classes distinguished by whether and how they make use of knowledge about mobility in order to achieve discovery.

- A second contribution is to discuss shortcomings, advantages and challenges of discovery approaches in IoT scenarios of opportunistic networking and to comment about recent research trends as well as providing ideas for how future discovery protocols should be devised.

It is the belief of these authors that the addition of knowledge within discovery protocols can introduce further optimization and benefits, not only in discovery, but also for opportunistic communications in IoT scenarios. This work is therefore organized as follows: Section II introduces the scenario of discovery, a taxonomy and a classification of discovery approaches. As we will see, discovery approaches can be divided into two main classes based on whether they profit from mobility knowledge or not. Sections III and IV provide a discussion highlighting limitations and possible research interests on Mobility Agnostic and Mobility Aware approaches. Section V concludes this survey.

## II. IoT Scenario and Taxonomy

Opportunistic Networking [15] mutates concepts from Delay/Disruption Tolerant Networking (DTN), where communication over disconnected static and mobile ad-hoc networks comes at a price of additional delay in the message delivery between sources and destinations. Disruptions and intermittent
connectivity due to mobility in fact might introduce delay because of the unavailability of next hops where to relay data in order to reach its intended destination. While the introduction of a delay in communication due to disruptions could be seen as a penalization, many applications tolerate such an end-to-end latency. Famous DTN applications include the InterPlaNetary Internet [16] or Tactical and Battlefield Military Networks [17].

While Opportunistic Networks are often used interchangeably with DTNs, Opportunistic Networks usually describe one of its facet. In particular, the main assumption is that end-to-end routes are built dynamically by forwarding agents, without the need of knowledge about network topology. In fact, Opportunistic Networking assumes that each device acts as a gateway/forwarding device and hop-by-hop relays messages between sources and destinations. Famous real world applications of Opportunistic Networking include Wildlife Tracking and Monitoring (e.g. ZebraNet project [18]) or Internet provision for rural and development areas (e.g. DakNet project [19]).

Opportunistic Networking is however not limited to such applications, but, for example, in an IoT scenario such as a Smart City, could introduce further connectivity and benefits to the deployed networking infrastructure. Smart Cities were envisioned as a way to ameliorate city-wide infrastructures in order to create new services for their citizens as well as to improve the existing ones. In such a scenario, IoT devices might roam and opportunistically encounter several different statically deployed networks and perform either data collection or dissemination as well as relaying data between these networks, thus introducing further connectivity for disconnected networks. This, in fact could be seen as the delay tolerant message ferrying approach where nodes deliver data across several networks [20].

Figure 1 shows only few of the many possible applications, ranging from data collection or dissemination to and from infostations, buses and mail trucks relaying, environmental and pollution levels monitoring or police cars surveillance for safety reasons. For example, as seen in the figure, a car could opportunistically encounter roadside sensors, collect information from them and relay it until it finds an available access point where it can upload the information. Similarly, a person might collect information from home-based weather stations and relay it through several other people, cars and buses until it reaches its intended destination, i.e. a meteorological center. Finally, law enforcement officers entering shops could collect information from disconnected surveillance cameras in order to relay them to their police stations.

Evidently, one fundamental characteristics of such an IoT scenario is that devices will be heterogeneous and generally equipped with multiple radios, therefore capable of connecting to various different networks, thus increasing the scope of traditionally homogeneous networks. For example, a recent trend is to exploit opportunities for offloading traffic from cellular networks by profiting from contacts between devices in order to allow network operators traffic reduction. It is well known that, with the advent of the big data era, the amount of network traffic is about to increase exponentially. In order to satisfy such requirements, projects such as the OneFIT project [21] were concerned with extending the wireless infrastru-
ture with cognitive management techniques for opportunistic networks suitability determination, creation, maintenance and forced termination. Similarly, the MOTO project [22] was involved in offloading operators infrastructure by exploiting geographical location knowledge and social knowledge with the objective of reducing communication delays and improve traffic. Recent standardization efforts are trying to include neighbour discovery within different networks, such as the one of the 6LoWPAN Internet Engineering Task Force (IETF) group [23] or of the 3GPP LTE Device-to-Device (D2D) communications group [24], thus allowing bridging between such networks. By building on well established IETF IoT communication protocols (i.e. CoAP) [25], IoT devices could therefore be used to store-carry-forward across multiple networks in a cost-effective way thus increasing the possibility to exploit communication opportunities, but also increasing the energy demand on IoT devices to be able to power such multiple radios, thus requiring optimization. Alternatively, new solutions for IPv6 integration in IoT scenarios such as Glowlab IP [26], allow for exploitation of heterogeneous and legacy devices by adopting a session layer protocol on top of the application layer, thus increasing the scope and reachability of the Internet of Things.

In IoT scenarios of Opportunistic Networking, IoT devices could be statically deployed or moving, typically without a readily available power supply for recharging. Therefore, increasing lifetime of such battery operated devices, while guaranteeing the same networking performance of un-optimized devices is of paramount importance. In addition, IoT devices might be subject to different mobility patterns, which could be more or less periodic, depending on how they are generated. In fact, by interacting with many IoT devices, a single IoT device might experience the overlapping of many mobility patterns. For example, IoT devices can be mounted on public transportation or robotised systems (i.e. drones) or, simply, carried by humans.

As an example, in Figure 1, a mobile IoT device (i.e. mounted on a car) can opportunistically encounter statically deployed sensors along the road (i.e. roadside traffic sensors). Such IoT devices are defined to be in contact when both their radios are within communication range with each other. Moreover, we define the arrival time of an IoT device as the time at which another device enters communication range (point A). Similarly, the departure time is defined as the time at which another device leaves the communication range (point B). Therefore, we can define the contact duration as the time which lasts between the arrival and the departure of another IoT device (between points A and B). Finally, it is possible to define the inter contact time as the time that lasts between two consecutive arrivals (between points C and D).

This scenario dictates the requirements of a desirable neighbour discovery algorithm, which is to exploit the entirety of the opportunities for communication, while at the same time optimizing power consumption. Neighbour discovery for IoT devices should therefore be capable of:

- **Learning**: A first requirement for neighbour discovery is to acquire knowledge about the periods of time in which future contacts are to be expected, in a distributed fashion, both on static and mobile IoT devices.
• **Prediction:** A further requirement for neighbour discovery is to store in an efficient way this knowledge, without requiring too many resources and exploiting it to know about future occasions in which communication will be available by exploiting features of mobility patterns.

• **Low Latency:** Neighbour discovery should allow for a lower discovery latency of devices (see Figure 2) when they are learned to be present with a high probability, therefore guaranteeing more useful contact time to be used for communication, according to communication time requirements.

• **Energy Efficiency:** Neighbour discovery should allow saving energy during discovery when devices are supposed to be absent with high probability in order to allow for extended lifetime without compromising communication possibilities.

Starting from these requirements, it becomes evident that there is a need for techniques capable of learning the contact patterns of IoT devices in order to predict future contact
opportunities. For example, in Figure 1, an IoT device mounted on the car should be able to learn about such patterns over time and exploit such knowledge with the objective of forecast of the next predicted arrival (point D) or the next predicted departure (point E), therefore, also the next predicted contact duration. Such an aim could be achieved, for example, by means of recent pattern recognition and machine learning algorithms. More precisely, there is demand for techniques capable of learning online, avoiding long training phases and the need to collect data for them. In addition, mobility patterns could change over time, even abruptly, due to a deviation in the habits of device’s carriers: an ideal learning algorithm should therefore be able to adapt quickly to such situations. Reinforcement Learning ([27], [28]) shows a method for acquiring information more inclined towards such features, rather than several other learning paradigms. Indeed, a few works have already successfully applied such techniques to the problem of neighbour discovery ([29], [30], [31]) in order to learn contact patterns.

Another problem for such algorithms is the decision of which mobility features to incorporate in the learning process in order to increase the accuracy of the predictions. Ideally, incorporating more features might lead to better accuracy in the predictions, but could introduce additional complexity (a problem for resource constrained IoT devices). In addition, it requires obtaining detailed contextual knowledge which might not always be available on every IoT device. While temporal features (inter contact times, arrival times, arrival rates, contact durations) could be easily computed on a per node basis, spatial features would require additional hardware, such as GPS receivers or accelerometers. Those might not always be available on IoT devices and need to be taken into account for their power consumption in the overall computation. Examples of algorithms that use such features under a different objective than discovery are, WhereNext by Monreale et al. [8], which introduces a location predictor based on trajectory-pattern mining relying on GPS data, and the combined spatial and temporal predictor NextPlace of Scellato et al. [9]. However, these algorithms usually require long training phases with the extensive use of data and high computational capabilities.

Popularity metrics could also be used to increase accuracy in predicting mobility patterns. For example predictors could use the number of visits a mobile node does to locations of interests, or the ranking a particular location has, based on the number of its visitors. It is evident that these features, combined with spatial and temporal features, might achieve better accuracy in predicting encounters in a learning-based approach founded on mobility patterns, only at the cost of keeping a count on the number of nodes encountered and sharing it between nodes. In addition, by knowing how popular users are, the discovery process on their IoT device could be adjusted as well. Even more challenging is the use of social behaviour metrics such as community membership and the notion of friendship between IoT devices’ carriers, which would require algorithms for inferring such features. However, eventually, this could lead to better accuracy in the predictions. Finally, being able to exploit predefined knowledge about locations (e.g. tagging places as schools, pubs, railway stations) could further introduce higher resolution. This, together with temporal information about mobility, could help to distinguish the rush hours of the day from hours in which few contacts are expected and adjust the discovery process accordingly. For example, a pub might be crowded at night, whereas a school might be empty in the same hours. An example of an algorithm that uses such data for prediction of next place is the work of Noulas et al. [32]. By introducing such features in an online learning environment, it could be possible to optimize discovery.

![Diagram of Duty Cycled Neighbour Discovery Process](image)

Fig. 2. Duty Cycled Neighbour Discovery Process with $d = \frac{T_{ON}}{T}$

The problem in itself, however, is more complex than it seems, since gathering all such contextual knowledge requires probing the environment continuously, therefore requiring energy to understand the behaviour of the real world environment in which the algorithm needs to operate. However, in neighbour discovery, IoT devices are usually duty cycled. Figure 2 shows a generic (asynchronous) duty cycled discovery process, where IoT devices may schedule different radio states over time in order to provide a lower power consumption. IoT devices typically schedule for an arbitrary time, $T_{ON}$, their radios in an awake state where their radio can either listen (receive) for incoming communication requests or transmit packets with limited information content (i.e. address, location) on a channel, usually called beacons, or even do a combination of both transmission and listening. In order to preserve energy, radios can also be put in a standby (sleep) state for a time $T_{OFF}$, in which their consumption is reduced by few orders of magnitude and can be considered negligible. Such mode of operation is called duty cycling with value $d = \frac{T_{ON}}{T}$ and represents the percentage of energy the device is using with respect to a non duty cycled device. Finally, in an IoT scenario such as the one of the previous figure, we identify the discovery latency as the time difference between the instant in which the mobile node enters communication range with a static node and the instant in which their awake times overlap. The residual contact time after such instant is therefore called the useful communication time, since it is the remaining contact time available for communication after discovery. These last two metrics are of evident importance because, while from an energy point of view duty-cycled operation aims at improving lifetime, it also impacts the design of algorithms for data communications [33].

Discovery protocols can sometimes adopt a time slotted approach (see Figure 3), where a temporal slot represents
The main objective of a discovery process should be to recognize all the contacts up to a certain minimum contact duration under duty cycling assumptions. In addition, it should be able to gather contextual knowledge contained in beacons, exchanged between devices, in order to gain a better insight on the mobility patterns. Therefore, energy efficiency in discovery can be achieved by not wasting resources when contacts are known to be not present, usually obtained by allowing a higher latency discovery duty cycle, while at the same time being able to discover most of the contacts in order to understand the mobility dynamics. Finally, in order to still guarantee the highest useful time available for communication, the aim of a discovery algorithm should be to provide a lower latency but more power consuming schedule when nodes are known to be within communication range. Jointly optimizing latency and energy by relying on the mobility patterns will therefore allow the introduction of additional savings with respect to a discovery algorithm which is agnostic to such patterns. However, such a daunting task requires to be able to acquire accurate knowledge about recurrence of contacts between devices in order to adapt the resources, which could be achieved by a higher intelligence agent (e.g. machine learning and artificial intelligence techniques). This clearly shows the need for new techniques capable of learning, reasoning and acting by allowing schedules which could overall benefit the communication in IoT scenarios of opportunistic networking.

Based on such considerations, we classified recent advances in research according to the taxonomy reported in Figure 4. A first differentiation is based upon how the algorithms make use of mobility knowledge in order to schedule resources for finding devices within communication range. We identify two main classes:

- **Mobility Agnostic** protocols which perform neighbour discovery without making any particular assumption on the mobility of devices in order to achieve it. They rely only on information about the scheduling of the radio wake up and sleep times between nodes or on the possibility of indirectly recognizing the presence of nodes in the neighbourhood.

- **Mobility Aware** protocols that instead benefit from domain knowledge about the mobility either derived through temporal features such as time or frequency of arrivals or derived from spatial features in the form of colocation and positioning patterns. This allows a more efficient and tailored discovery process.

Among the first category of mobility agnostic discovery protocols, a second differentiation can be made on the basis of the requirement of a time reference for nodes in order to achieve discovery. In particular, we identify two main groups:

- **Time Synchronized** protocols that require and exploit the use of a common time reference, shared between all devices and ultimately used with the aim of reaching a common communication scheduling for the neighbour discovery process. Time references are commonly available through the use of Global Positioning System (GPS) receivers or Network Time Protocols (NTP).

- **Asynchronous** protocols which do not need any common time reference but depend on the capability of either overlapping temporal awake timeslots or waking up asynchronously through an indirect request from their neighbours. Some of them do not require any particular hardware to achieve synchronization, which makes them the most generally applicable.

Asynchronous approaches divide further into two categories based on the method for reaching discovery:

- **Indirect Request** based protocols that achieve discovery by waking up neighbouring nodes either by relying on indirect or alternative lower power reception capabilities of a device, capable of triggering communication scheduling when nodes are recognized to be into range. This typically requires the use of either ad-hoc customized or secondary radios.

- **Temporal Overlap** based protocols which are the most generally applicable protocols capable of allowing the overlap of temporal awake slot between unsynchronized devices. They generally rely on mathematical properties of overlapping between sequences of numbers within a finite time with high or guaranteed probability.

Within indirect request protocols it is possible to further differentiate within two major classes:

- **Multiple Radios** driven protocols which exploit the availability of off-the-shelf, non-customized secondary radios on IoT devices in order to trigger the wakeup of a primary radio for communication. More precisely, they profit from the lower power of the secondary radios (e.g. Bluetooth, ZigBee) with the objective to achieve discovery on a higher power radio (e.g. Wi-Fi).
Fig. 4. Taxonomy of Neighbour Discovery for Opportunistic Networking in IoT scenarios

- **Energy Triggered** discovery approaches that recognize through customized and ad-hoc receivers the energy contained in a radio signal and use it to trigger the wake up of the IoT device for communication. This is similar to what happens in a Radio Frequency Identification (RFID) tag, where the signal is used as a trigger for the whole system wake-up.

Finally, within temporal overlap based protocols we can identify two more categories:

- **Probabilistic** approaches that exploit statistical properties in order to guarantee high probability of scheduling the communication in the same temporal slots on neighbouring IoT devices which need to discover each other and which are not synchronized. However, they do not guarantee (with a 100% probability) an overlap of communication between unsynchronized devices.

- **Deterministic** approaches, which exploit mathematical properties deriving from combinatorics or number theory in order to generally guarantee (with a 100% probability) an overlap of communication between unsynchronized devices. They also require a time slotted scheduling of the communication.

In mobility aware discovery protocols, it is instead possible to distinguish between two main classes as follows:

- **Temporal Knowledge** based discovery protocols that profit from knowledge about temporal contact patterns of movement of nodes in order to understand the future availability of devices in the neighbourhood and tune the discovery process accordingly. They typically exploit statistical analysis or machine learning techniques to learn about such patterns.

- **Spatial Knowledge** based approaches which use the knowledge about the position of nodes, their movement and the knowledge about IoT devices’ co-location in order to optimize the discovery process. They usually exploit additional hardware to gather such knowledge, such as GPS receivers, accelerometers or, in general, neighbour to neighbour communication.

Within the temporal knowledge based discovery protocols we can differentiate between:

- **Arrival Times** based discovery protocols that exploit knowledge about the mobility patterns of neighbouring devices in order to take advantage of learning how to adapt and optimize their scheduling, therefore scheduling less or more resources depending on IoT devices’ future arrival times.

- **Rate of Encounters** based approaches that exploit the knowledge about the number of contacts encountered within a finite window of time in order to either relax or intensify the contact probing sequence process. They usually do not require much computational resources to be implemented.

Lastly, in spatial knowledge driven approaches, we can find two classes:
• **Positioning** based approaches that exploit knowledge about either the spatial geographical location or the movement between devices in order to schedule their resources in an optimal way. However, they often require additional hardware which cannot always be present in resource constrained devices.

• **Colocation** based protocols which rely on spatial co-location knowledge between nodes in order to optimize and coordinate the discovery process. They often rely on multiple node scenarios where nodes flock and benefit from the sharing of schedules across nodes.

While mobility agnostic neighbour discovery protocols generally profit from established techniques, we argue that incorporating knowledge about the patterns of mobility and about the environment that surrounds IoT devices can bring several advantages in IoT scenarios of opportunistic networking. The aim of this survey is to present recent advances in this sense and argue that, in an IoT scenario where a massive amount of devices move and interact with each other within the deployed infrastructure, incorporating contextual knowledge can optimize discovery approaches and allow applications to pursue a longer lifetime and obtain a longer useful communication time. We will also show that introducing mobility knowledge within discovery can benefit approaches which were not initially thought from that point of view. Energy efficiency, longer useful communication periods, higher throughput and, in general, the possibility to plan the communication in advance, are the advantages to be expected when a discovery approach considers the addition of knowledge about the patterns of encounters.

### III. MOBILITY AGNOSTIC APPROACHES

In this section we present works which do not make assumptions about the mobility patterns in order to achieve neighbour discovery. The main principle is that they can achieve discovery without exploiting knowledge concerning the level (or the lack) of mobility of the device in which they are running. Therefore, they can be applied to either static or mobile nodes and their success in discovering another node is not dependent on whether neighbouring nodes are more or less mobile.

#### A. Time Synchronized Protocols

Time synchronized discovery approaches rely on the use of synchronization methods to agree communication scheduling between neighbouring nodes. With such methods, it is indeed possible to derive a common time reference, known to all, which is used to overlap communication timings based on a schedule agreed on every device. Several techniques exist in order to derive time references, usually with more or less precision depending on the robustness of the device against clock drifts and skews.

For example, in the ZebraNet experiment [34], [35] GPS time reference aided calibration is used in order to allow node synchronization. A major issue for devices that need to be deployed in such wildlife scenarios is power consumption, since they should require minimal intervention from operators and cannot be recharged promptly. In such a scenario, the strategy followed for collecting the data recorded by the sensors is to adopt synchronization and wake the nodes accordingly every two hours for five minutes to search for sink nodes in the neighbourhood where data might be downloaded. In such a way, the authors achieve data collection in an energy efficient fashion by exploiting both the delay tolerant nature of the application and the availability on resource constrained devices of GPS receivers, which are also used as a means to track the mobility of zebras. However, not every application might need GPS receivers and not every IoT device might feature such an additional hardware module, therefore limiting the applicability of this protocol to such scenarios or introducing the need to account for GPS receivers power consumption in the total energy expense. Finally, from the viewpoint of delay sensitive applications, the frequency of the synchronization updates should be taken into account, in particular its trade-off with energy and its dependence on how fast the clock drifts in IoT devices.

When GPS receivers are not available and IoT devices require delay sensitive data collection, time synchronized wakeup patterns such as the ones of Keshavarzian et al. [36] could instead be used. Such algorithms leverage existing lightweight ad-hoc synchronization techniques, such as the ones of Ganesar et al. [37], to guarantee efficient and timely wakes up of devices. From the point of view of delay sensitive applications, such as fire detection systems, time synchronized discovery protocols might achieve faster discoveries and lower end-to-end communication delays in comparison with unsynchronized approaches. These protocols leverage the presence of multi-hop paths where various wakeup patterns are considered: i.e. Fully Synchronized, Shifted Even and Odd, Ladder, Two Ladder and Crossed-Ladders patterns where wake up times are interleaved and combined or staggered. An important shortcoming of this approach is that it requires the possibility to reach devices in order to communicate with them and update their synchronization clock. While on a static scenario this might be achievable periodically, it might be more difficult to achieve it in mobile networks or in sparse networks where devices might be unreachable for long times, thus requiring additional strategies.

A more integrated approach combining neighbour discovery with time synchronization are the self-stabilizing protocols of Herman et al. [38]. Assuming that nodes will be temporally partitioned, with misaligned wakeup patterns, the protocol chooses sleep periods and additional extra time slots in order to achieve neighbour discovery and synchronization by slot alignment. A *no cost* approach in the number of additional slots is proposed, which leverage a duty cycling based on relatively prime numbers. A second probing approach, introduces additional slots for accelerating the convergence of the synchronization between devices, either by deterministically placing them or by randomization techniques. While these self-stabilization protocols provide a way to reach fast discovery, in opportunistic IoT scenarios where nodes could have very short contacts, there could be issues due to the relatively short available time to reach convergence. In addition, clock skews of devices might neutralize the positive effects when node contacts are scarcer or missed due to their short duration.

Ghidini and Das [39] instead rely on a time synchronized randomized probing on top of which they add a memory element in the form of a Markov chain which optimizes
the schedule between dormant and active states. The main objective of such work is to accelerate the discovery, while, at the same time, optimizing a time efficiency parameter which represents the ratio of the active time (without radio setup and teardown times) to the total time in which the radio is actually on, therefore including setup and teardown times. This is achieved by adjusting the transition probabilities of the Markov chain in order to have a higher chance to have consecutive active slots, therefore reducing the total number of teardown and setup times. At the same time, by reducing slot lengths it is possible to achieve a lower discovery latency. A partial limitation of this approach is that in IoT scenarios of opportunistic networking (i.e. mobile sink), it would be more challenging to achieve synchronization due to the short timed and intermittent connectivity of such scenarios. It would be also be interesting to understand how the Markov chain memory element would adapt to the mobility of nodes.

The Recursive Binary Time Partitioning (RBTP) by Li and Sinha [40] also aims at minimizing the discovery latency, however between more “smartphone-like” IoT devices. On such devices, it is indeed possible to leverage NTP protocols to achieve time synchronization: the authors showed such synchronization achieve an accuracy of up to 100ms by connecting to NTP servers every six hours, therefore accounting for negligible power consumption. In order to minimize latency, a uniform separation of the wake up instances has been shown effective by the authors. Such separation has been previously proven effective also to reduce contact misses by Wang et al. [41]. To achieve such an objective, IoT devices with different numbers of wakeup instances can recursively halve in a binary fashion the wake up period, as shown in Figure 5. In such a configuration, a time frame is divided into $n_i = 4$ wake up instances for node $i$ and into $n_j = 6$ wake up instances for node $j$, therefore minimizing the contact latency between such nodes without requiring each node to know the wakeup pattern of the other node. The authors show in the paper that the protocol generally outperforms other protocols for asynchronous discovery. However, while in a smartphone the use of an NTP server for periodical re-synchronization is easily achievable through a cellular network, for other IoT devices such task might not be easily performed. For example, resource constrained IoT devices deployed in remote or rural zones might not have neither precise clocking nor cellular connectivity or the means (GPS receivers) to maintain synchronization.

Another option for deriving time references is to opportunistically exploit available Wi-Fi based IoT devices. For example, in WizSync by Hao et al. [42] ZigBee based IoT devices profit from the overlapping radio frequency bands in the 2.4 GHz unlicensed spectrum in order to detect Wi-Fi beacons as a means to achieve synchronization. A similar idea is proposed by Camp-Murs [43] where the synchronization achieved is between Wi-Fi based IoT devices in order to enhance existing asynchronous discovery protocols such as random, quorum-based or U-Connect (to be discussed later in this section) showing improvements in the number of discovered devices with little energy cost. Camp-Murs and Loureiro [44] later present Energy Efficient Discovery (EED) Wi-Fi as a driver level extension protocol benefiting from access point (AP) synchronization, though only needing a Wi-Fi radio and not an internet connectivity such as RBTP. In such an algorithm, neighbouring nodes within a cluster can overhear announcement frames with cluster IDs, local clocks timestamps and periods, thus synchronizing their schedule to the reference clock of an announcement master. Due to the dense scenario considered, mechanisms for avoiding collisions such as tuning the contention window and temporal load spreading according to denseness are considered. Leveraging synchronization, this protocol can achieve lower latency discoveries with respect to unsynchronized approaches. The authors argue that their protocol has large applicability due to the large presence of AP in urban scenarios. However, if the scenarios are not dense, or do not include Wi-Fi radios, its use could be limited.

A new completely integrated solution for discovery, link management and distributed scheduling is FlashLinQ [45] which builds a new PHY/MAC layer synchronous architecture operating in the licensed spectrum. Leveraging orthogonal frequency-division multiplexing (OFDM), energy-level driven signalling and existing infrastructure, it allows coordination between nodes to achieve synchronization of nodes within propagation delay errors (up to a maximum of 5μs). FlashLinQ’s discovery allows finding up to a few thousand devices over a 1 kilometre communication range radius within roughly 10 to 15 seconds. This long range is accomplished by exploiting rateless codes to broadcast nodes IDs, therefore allowing an extremely low signal-to-noise ratio (SNR) operation. In addition, time slotted synchronized communication on a discovery channel, combined with OFDM orthogonalization allows for energy efficient operation. The authors show that by designing from scratch a new channel-aware, synchronous opportunistic system it is indeed possible to achieve gains over conventional protocols such as 802.11.

**B. Asynchronous Protocols**

Asynchronous protocols do not require the presence of an accurate time reference in order to achieve discovery between neighbouring devices. Therefore, they do not need additional hardware or computationally expensive synchronization protocols. They differ from the time synchronized approaches in the capability of not needing agreement between IoT devices on the temporal intervals at which to schedule their awake instances. They rely on either on the capability of being woken up through an indirect request or in the capability of guaranteeing overlapping awake slots without prior agreement.
1) Indirect Request Based Protocols: Indirect request based protocols achieve discovery by exploiting either the use of customized or secondary radios in IoT devices. The wake up is triggered either indirectly by the energy contained in RF signals or by means of a lower power radio, thus introducing energy efficiency for a higher power radio. The main principle is that IoT devices radios can be indirectly woken through a request coming from a neighbouring device either via a secondary or ad-hoc radio. However, such technologies do not relieve the communication-initiating device from the burden of starting the wake up process and do not introduce any optimization on such a device.

a) Multiple Radios Based Approaches: Multiple radio based approaches rely on radio diversity, a trait on the rise since the advent of complex IoT devices such as smartphones. Indeed, in many IoT devices a lower power radio such as Bluetooth or ZigBee is sometimes present in combination with a higher power radio such as Wi-Fi. While theoretically adding a secondary radio should account for higher energy expense, exploiting it for saving power on a higher power radio in the discovery process ultimately reduces power consumption. In addition, a secondary radio allows reaching and bridging between a higher number of networks in IoT scenarios of opportunistic networking.

The Sparse Topology Energy Management (STEM-B) by Schurgers et al. [46] proposes the use of two different radios operating in parallel at different frequencies. A wake up radio or wake up plane is used to initiate the communication, whereas a data radio or data plane is used to perform the actual communication between nodes. Since in many applications the primary objective is to promptly detect events (e.g. brush fires detection, battlefield surveillance), the authors argue that, by introducing the data plane, they still allow for communication while continuously listening for other nodes to connect on the wake up plane. However, the planes differentiation allows a reduction in power consumption on the wake up plane, which can be considered the biggest contribution to the total power consumption if communication events are sporadic. The authors propose also a secondary protocol, STEM-T [47], which differs in the use of a tone (the signal’s energy with no information) rather than a beacon to wake up its neighbour. If the tone is sent by the initiator for a sufficient long time, no acknowledgement is needed by receiving nodes, assuring wakeup of all neighbouring nodes in dense scenarios. In resource constrained devices for opportunistic networking IoT scenarios, however, the requirement of a secondary plane for wake up might not always be satisfied.

Wake on Wireless, [48] instead reports a multiple radio protocol where a secondary low power and low data rate radio (Amplitude Shift Keying (ASK) radio in the 915MHz ISM band) is used in combination with higher power 802.11 radios with the objective of reducing the overall consumption for the discovery of devices. This secondary radio is able to achieve a standby time of 30 hours in a PDA-like IoT device, therefore improving by 115% over a 802.11 radio in power save mode (PSM) and overcoming the limitations of a protocol such as Wi-Fi which was not designed for low power communications. The use of a secondary radio, however, might not always be possible, either for cost reasons or for the physical impossibility to modify off-the-shelf IoT devices (e.g. Wi-Fi AP). Nonetheless, in many scenarios secondary lower power radios are available (e.g. Bluetooth in smartphones) or it is easy to add them without heavy hardware modifications.

Geographic Random Forwarding (GeRaF) by Zorzi and Rao [49], [50] leverages high node density to decrease wakeup frequencies. Indeed, if N nodes are present, duty cycles could have N times slower rate with respect to a single node wakeup. The nodes also use the dual plane setup of STEM, but do not allow for longer tones at the initiator, instead relying on a collision avoidance scheme, necessary due to the dense scenario hypothesis. Such a scheme profits from busy tones issued by the receiver: if the sender finds the receiver busy, this will prevent it from transmitting. In IoT scenarios for opportunistic networking, the availability of a secondary radio for collision avoidance might not always be possible due to a higher cost or because it would require hardware modifications. In addition, scenarios might not always be dense, such as in remote or rural areas.

Pipeline Tone Wakeup by Yang and Vaidya [51], similar to STEM, uses two different radio planes, one for data and one for tone detection. The objective of such work is to construct a wakeup pipeline to minimize end-to-end communication delay. The initiator node sends a tone on the wakeup plane for a duration necessary to wake up all of its neighbours. The initiator then starts the communication on the data plane with one of the neighbouring nodes while the others shut down. In parallel with communication, the destination node will start to wake up all of its neighbours on the wakeup plane, thus minimizing end-to-end delay. From the point of view of IoT scenarios for opportunistic networking, such an approach could allow fast wake up in dense and multi-hop scenarios, but for sparse scenarios the uncertainty on the duration of contacts might pose problems in understanding the duration of the wakeup tones.

Perring et al. [52] further enhance the concept of Wake on Wireless by experimenting on a customized platform the use of Bluetooth, Wi-Fi and ZigBee in different combinations, under the general assumption that a lower power radio in conjunction with higher power radio optimizes discovery and communication. The lowest power consumption is achieved by employing ZigBee and Wi-Fi, while Bluetooth and Wi-Fi introduce a slightly increased connection delay. However, Bluetooth and Wi-Fi are the most generally available radios (e.g. in smartphones), therefore the most vastly applicable solution. Finally, ZigBee and Bluetooth allow for both a reduction in connection latency and power consumption, however at a cost of lower communication throughput compared to Wi-Fi. While many IoT devices feature multiple radios (i.e. smartphones), adding a secondary radio might not always be feasible. For such reasons techniques generally applicable for a single radio scenario might be the only viable option for certain IoT scenarios.

ZiFi by Zhou et al. [53], similar to WizSync [42], exploits how beacons are structured to find interference signatures in the signals received by a low power ZigBee radio when in presence of a high power radio such as Wi-Fi Access Point. The authors’ basic idea is that Wi-Fi beacons will present some periodicity and by measuring the received signal strength (RSS) in a common ZigBee radio it is possible to detect such recurrence through a low computationally expensive Common
The problem of interference at 868MHz band from near GSM bands was shown to be reduced by Van Der Doorn et al. [59], which presented the first realistic prototype of a wake-up radio. The interference is mitigated by combining a band-pass filter on the receiver with a digital filter on the opposite side. However, such an approach is limited to a very short range of 3m. In order to overcome such a constraint, the authors added a charge pump based circuit to store energy over time. By slightly increasing the latency to discover, it is possible to reach higher distances: i.e. 55ms latency would reach up to 30m, reasonable for certain scenarios. They also propose that by adding an ultra low power amplifier, therefore increasing by a little the standby current (i.e. 0.8%), it is possible to reach higher ranges. Finally, by exploiting multiple frequencies, they propose a method for distinguishing between different devices requesting wakeups. Such approaches are useful, especially from the viewpoint of opportunistic networking in IoT scenarios, because they are capable of guaranteeing the wake up of nodes (even though in limited ranges) even in presence of scenarios with short contact duration or high speed of interaction. However, most of the approaches just reduce the power consumption of the receiver shifting the burden to the sender, which would still need optimization.

**Radio Triggered Wakeup radios with Addressing Capability** (RTWAC), are presented by Ansari et al. [57], where the addressing capability is intended as a way to differentiate senders on the receiver, thus avoiding unnecessary wakeups. Nodes are therefore woken up only if the sending node belongs to a particular wake up set. To derive such information, wake up packets are organized in frames containing addresses and commands for the receivers, plus cyclic redundancy check (CRC) field. Every bit is encoded through a Pulse Interval Encoding scheme which allows decoding and recognition of bits based on pulse lengths on the receiver side. Similarly, Takiguchi et al. [58] uses a bloom filter, a space-efficient probabilistic data structure for testing the membership of an element to a set, in order to achieve ID matching with very low false wakeup probability. Such an approach, like the previous one, however suffers from a low detection range, which, from the viewpoint of opportunistic networking, could result in lower contact durations, therefore further reducing the duration of short and rare contacts, posing a threat on communication possibilities. In addition, interference from near bands (i.e. cellular networks bands) could trigger false wakeups, even though the addressing capability could mitigate such effect.
microcontroller to filter out spurious frequencies from GSM bands. An evaluation showed very short operating ranges (3m) but good robustness from GSM interference with little cost for the hardware modifications. However, a solution for the problem of “friendly-fire” interference from neighbouring nodes (i.e. addressing capability), was not presented.

Gamm et al. [60], also presented a prototype for a wake up radio receiver in the 868MHz band which however introduces the possibility to modulate a lower frequency (125KHz) wake up signal on the main radio carrier at high frequency through an On-Off Keying (OOK) modulation, to be provided at the transmission interface. At the receiver side, instead, a passive demodulation circuit reconstructs the low frequency signal and uses it to wake up the system. Such a wake up signal, similar to previous works, contains the addressing information for distinguishing between different nodes. The prototype is shown to achieve a wakeup range of 20 times further and to have a 100 times smaller current consumption than Van Der Doorn’s previous work. To achieve such lengths and consumptions, the authors leverage a low frequency (125KHz) ASK wake-up receiver coming from an automotive application, which was previously used by other authors in wakeup radios but for preamble detection purposes only at the receiver (Liang et al. [61]) or in frequency diversity based wakeup (Wendt and Reindl [62]).

Several other different front-end implementations are present in the literature, with the aim of the reduction of the standby current. Fletcher et al. [63], [64] reported a 2GHz customized front-end using Bulk Acoustic Wave (BAW) filtering and envelope detector reducing power consumption from 65µW to 52µW. Similarly, Huang et al. [65] showed a 51µW receiver, though capable of working at both 915MHz and 2.4GHz frequencies with different inductor configurations. Le-Huy and Roy [66] present an implementation which further reduces consumption towards on average 20µW by using a Pulse Width Modulation (PWM) demodulator and comparator for address decoding, while Durante and Mahlknecht [67] showed a different implementation reaching power consumptions of the order of 10µW. Finally, Marinkovic and Popovic [68] showed it is possible to reduce this consumption to 270µW in Body Area Networks (BAN) applications at 433MHz. Lastly, Oller et al. [69] report a sub-1µA receiver exploiting a Surface Acoustic Wave (SAW) filter along with a modified transmitter, however still reaching up to 10 meters range. Indeed, most of these architectures will neither reduce the range gap between a wakeup radio and a conventional radio, nor introduce optimization at the transmitter to reduce its consumption but, instead, sometimes modify it to increase its output power further penalizing the balance between transmitter and receiver.

A few other works employ an RFID tag in order to wake up a wireless sensor, such as in CargoNet by Malinowski et al. [70] where signals above -65dbm were detected at only 2.8µW of power with readers located 8 meters away. Ba et al. [71] also built a completely passive wakeup radio by combining an RFID tag with a Telos-B node. The authors showed that in scenarios of sparse nodes with mobile sinks, while their solution achieved significant packet delay due to the limited range at higher duty cycles (> 0.1%), they reached similar delays at lower duty cycles (< 0.1%) but consuming less energy. Similarly, Kamalinejad et al. [72] report a recent front-end which is fully passive as well, therefore harvesting its entire required energy from the wake-up signal. Finally, Boaventura and Carvalho [73] present a prototype wake up radio which is shown to introduces advantages in indoor positioning applications. In such short-range scenarios, they showed that node lifetime can increase from the 200 days of a periodic duty cycled based operation to the 8000 days of a wake up radio based operation.

2) Temporal Overlap Based Protocols: Temporal overlap based protocols are the most general methods, relying on the capability of overlapping awake temporal slots between unsynchronized devices. They usually exploit duty cycling (sleep scheduling) techniques combined with mathematical properties such as numbers theory and combinatorics. They can be divided into probabilistic approaches that guarantee a high probability of overlapping awake slots and deterministic approaches that guarantee an assured overlap under certain conditions.

a) Probabilistic Approaches: Probabilistic approaches exploit statistical properties in order to guarantee with high probability the temporal overlap of awake slots between devices within communication range. While such approaches usually achieve effective discoveries with high probability and good average latency, they sometimes miss a few contacts or discover nodes with relatively high latencies.

Birthday protocols by McGlynn and Borbash [5] exploit the Birthday Paradox property from probability theory stating that between a certain number of people randomly selected, the probability of finding two of them with the same birthday grows as the number of people grows. In particular, with just 23 people this probability already exceeds 50%, before reaching 99% with 57 people. The same principle is applied by the authors to the probability of overlapping communication scheduling between nodes. In detail, if two nodes select randomly k awake slots out of n for turning on the radio for either transmitting or listening, if the ratio k/n is small because n is large, then with high probability the nodes will hear each other as well as simultaneously benefit from sleeping for a long time. A shortcoming of such protocols is that, even though discovery has high probability, it cannot be completely guaranteed, hence in some cases the devices might experience misses and latency issues, especially in scenarios of short opportunistic contacts. In addition, since in opportunistic IoT scenarios nodes could be disconnected for long times, probing during such times could waste a lot of energy. A mechanism for saving energy in such cases should therefore be introduced.

Similarly, Random Asynchronous Wakeup (RAW) by Paruchuri et al. [74], defines a protocol that exploits randomization in dense scenarios with the objective of maximizing the probability that nodes will hear each other. Nodes wake up at random times, stay awake for a predefined time and then sleep again, but also maintain a neighbour list and allow wakeup time sharing to be used by a routing protocol based on greedy geographical routing. Due to the probabilistic nature of this protocol, it is shown to perform well in the average case, especially when there are high neighbour densities, allowing a good average latency with respect to deterministic protocols such as [75], which will be discussed later in this section. A known limitation of these approaches is that they fail to guarantee a worst case bound on latency to discover, which
can be a problem in opportunistic IoT scenarios where nodes are not particularly dense and contacts might be short and rare.

Balachandran and Kang [76], instead, investigated a dynamic spectrum access protocol for time-slotted probabilistic discovery between nodes. The authors aimed to discover at multiple frequencies, showing that as the number of frequencies increases, the average discovery time increases as well, though showing as well a reduction in latency for crowded scenarios. Four approaches for selecting frequency hopping are presented: randomized, policy based, sequential energy detection and simultaneous energy detection. The last, which employs simultaneous energy detection and decoding on multiple frequencies, achieves better latencies than the others, though the policy based prevails at higher node densities. This approach could be interesting in IoT scenarios for opportunistic networking given the fact that a node moving might encounter many different networks to discover, relying on different frequencies. However, its practical feasibility should be investigated.

Vasudevan et al. [77] analyse the ALOHA-like probabilistic protocol of [5] showing that it reduces to the classical Coupon Collector’s problem (which is of finding the expected number of trials needed to collect all the coupons in an urn) in dense scenarios. The protocol is proven to allow a node to discover all its \( n \) neighbours with an expected time of \( ne(\ln n + c) \), where \( e \) is Euler’s constant and \( c \) a generic constant. Furthermore the authors propose an extension where nodes are capable of detect collisions, distinguishing them from idle slots, thus showing an improvement on the expected time which reduces to an \( ne \) bounded time. The authors also show that the lack of knowledge concerning the number of neighbours or the lack of slot synchronization introduces a factor two slowdown in the algorithm. However, it allows for an asynchronous discovery, even with misaligned starting times and in presence of clock offsets.

You et al. [78] further extend the previous work by adding the possibility of nodes to duty cycle, showing that the protocol then reduces to a \( K \) Coupon Collector’s problem, where \( K \) is \( 3\log_2 n \) and \( n \) the number of nodes. In such a problem, if each coupon is collected \( K \) times (slots), it means the discovery has been successful with high probability. The analysis shows that, in such cases, the expected time is lower bounded by \( ne \ln n + c n \) and upper bounded by \( ne(\log_2 n + (3\log_2 n - 1)\log_2 \log_2 n + c) \). The authors then propose a method to allow discovery in the presence of an unknown number of neighbours by progressively reducing in every phase the probability by which it is activated, thus resulting in only a factor two slowdown.

Finally, Vasudevan et al. [79] extend their previous work to a general multi-hop network, showing an upper bound of \( O(\Delta \ln n) \) for the running time of the ALOHA-like algorithm, where \( \Delta \) is the maximum degree of the network and \( n \) the number of its nodes. In addition, a lower bound of \( \Omega(\Delta + \ln n) \) on the running time for any randomized discovery algorithm is shown, therefore implying that the ALOHA-like algorithm is, at most, a factor \( \min(\Delta, \ln n) \) worse than the optimal. While such approaches guarantee discovery with good average latency, in IoT scenarios of opportunistic networking, where contacts are rare and short, such analysis should be extended by applying considerations deriving from mobility patterns.

In addition, probabilistic methods for guaranteeing worst case bounds on discovery latency, while still performing well for the average latency could be introduced.

\( b) \) Deterministic Approaches: Deterministic approaches profit from mathematical properties (i.e. combinatorics or number theory) in order to have an overlap of awake slots between unsynchronized devices. They often guarantee overlap, though in general they require higher latencies in order to discover. However, they do not require synchronization or a customized radio and are completely generally applicable.

Quorum based protocols were originally introduced by Tseng et al. [80] as a power saving protocol for 802.11 MANETs. The authors derived a quorum based wake up scheduling algorithm that guarantees a time slot overlap between two devices at least twice every \( n^2 \) slots. This can be achieved by considering an \( n \times n \) matrix of beaconing intervals and selecting a row and a column for every host resulting in \( 2n - 1 \) beaconing intervals and \( n^2 - 2n + 1 \) sleeping intervals. For example, in Figure 8, node \( i \) selects the fourth row and column while node \( j \) selects the second row and column, resulting in two overlaps every \( n^2 = 25 \) slots in the \( 5 \times 5 \) grid. More recently Jiang et al. [81] generalize the concept of Quorum systems by analysing the \( n \times n \) grid quorum of [80], the \( t \times w \) torus quorum of [82] where \( tw = n \), the difference-sets based cyclic quorum of [83] and the hypergraph based finite projective plane quorum of [84]. Such quorum based protocols are all shown to respect a Rotational Closure property which, if satisfied, allows for overlaps between slots. The Adaptive Quorum-Based Energy Conserving (AQEC) protocol by Chao et al. [85], also uses a grid-based quorum, but adaptively increases the grid size in order to prolong sleep when the traffic is light and conversely, when the traffic load is heavier.

Block Design based methods were introduced by Zheng et al. [86] in order to provide the optimal wake up schedule function (WSF) with the objective of discovery between devices. By defining the block of intervals in which the devices have to wake up, such methods ensure at least one overlapping slot between nodes with probability one by making use of difference sets from combinatorics theory. A drawback of these approaches is that, though providing bounded discovery in the symmetric case, they still need to cope with the asymmetric case, i.e. the case in which each device independently schedules (or changes) its own duty cycle, as might happen...
in heterogeneous IoT scenarios of opportunistic networking.
This problem was partially solved by the recent work of Lai et al. [87]
which allows different patterns and cycle lengths between two devices
by constructing quorum pairs for grid and cyclic quorums. However, the
work limits the choice to only two different schedules between the entire
network, which could be restrictive in a heterogeneous and opportunistic
IoT environment, where several devices need to interact with each
other and where every each one of them might come from
different vendors, presenting different features.

The work of Choi et al. [88] introduces an adaptive hierarchical approach
based on multiplicative and exponential difference sets, allowing the possibility
to select among several different levels of power savings. This shows to be useful
in scenarios in which several degrees of energy efficiency must be considered,
such as in opportunistic and mobile IoT environments. In a similar way, Carrano et al. [89]
introduces over block design methods by aiming at addressing their
problems with asymmetry and operation at low duty cycle by
allowing the presence of slots nested within superslots which are both active or not based on different (or identical) outer
and inner block designs.

A protocol which improves the heterogeneous duty cycles
selection granularity problem is Disco by Dutta and Culler [90]. It proposes a method for selecting duty cycles on nodes
with the only condition of respecting a prime numbers rule.
If such a rule is respected, nodes have guaranteed discovery
within bounded time thanks to the property of the Chinese Remainder Theorem. For example, Figure 9 shows that discovery
time between two unsynchronized nodes with primes and duty cycles
$p_i = 2 (d_i = \frac{1}{2} = 50\%)$ $p_j = 3 (d_j = \frac{1}{3} = 33.3\%)$ is guaranteed within $2 \times 3 = 6$ slots. Furthermore, since the fact

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c|c|c|c|c}
\hline
\text{t=0} & \text{t=1} & \text{t=2} & \text{t=3} & \text{t=4} & \text{t=5} & \text{t=6} & \text{t=7} & \text{t=8} & \text{t=9} \\
\hline
i & & & & & & & & & & & & & & \\
\hline
j & & & & & & & & & & & & & & \\
\hline
\end{array}
\]

Fig. 9. Disco between nodes $i$ and $j$ with primes $p_i = 2 (d_i = \frac{1}{2} = 50\%)$ $p_j = 3 (d_j = \frac{1}{3} = 33.3\%)$

that duty cycles need to be selected as the reciprocal of a prime
counter could be seen as a resolution limitation, the authors
provide a method for selecting additional primes in order to
increase such resolution. In addition, the protocol allows a very practical way to select different latencies by adjusting slot size
and prime numbers schedule.

A more recent work, U-Connect by Khandalu et al. [91]
improves the performance of the previous works by providing
a new algorithm whose power-latency metric is asymptotically
a 1.5 approximation of the optimal discovery approach. Indeed, the
authors show that Quorum protocols and Disco are instead a
2.0 approximation of the optimal discovery algorithm theo-
etically proposed in [86], therefore having lower performance.
The introduced algorithm allows both asymmetric and symmetric
discovery by extending the wake up schedule of Disco
by one slot every prime number $p$. In fact, the algorithm still
wakes up for Low-Power Listening every $p$ slots, but also on

\[
(p + 1)/2 \text{ slots every } p^2 \text{ slots for Low-Power Transmit.}
\]

This allows improvements over the previous works but only in the
symmetric case: in the asymmetric case the performance is still comparable with Disco. However, differently from Disco, the
authors propose the use of a very short slot size of 250μs for
their Friend Finder application in order to achieve a very low
latency (which is proportional to number of slots). The authors
showed such a slot duration as the minimum allowable for a
reliable clear channel assessment (CCA) using their platform.
However, a partial drawback of such solution is the clock
drift occurring in such a platform, observed to be roughly 1
slot every 17 seconds (using a crystal with 15ppm resolution
precision) which is due to inaccuracies in the very short slot
design.

Bakht et al. [92] proposed a new protocol, named Search-
light, which can ensure discovery within a bounded latency
by deterministically searching the time slots for discovery in
a sequential fashion. By leveraging constant offsets between
slots, it allows systematically probing and discovering in the
symmetric case within $t \cdot \lceil \frac{1}{2} \rceil$ slots, where $t$ is defined as the
number of slots in one period. In Figure 10, the basic principle
is shown where every period each node schedules $t$ slots
and wakes up always the first (anchor) slot and sequentially searches with a (probe) slot until it finds an overlap, thus
having only two awake slots per period. A striped probing

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c|c|c|c|c}
\hline
\text{t=0} & \text{t=1} & \text{t=2} & \text{t=3} & \text{t=4} & \text{t=5} & \text{t=6} & \text{t=7} \\
\hline
\text{T=0} & \text{A} & \text{P} & & & & & & & & & & & & \\
\hline
\text{T=1} & \text{A} & \text{P} & & & & & & & & & & & & \\
\hline
\text{T=2} & \text{A} & \text{P} & & & & & & & & & & & & \\
\hline
\text{T=3} & \text{A} & \text{P} & & & & & & & & & & & & \\
\hline
\end{array}
\]

Fig. 10. Searchlight with period $t = 8$

enhancement further reduces the discovery latency to $t \cdot \lceil \frac{1}{2} \rceil$ slots by using evenly interleaved slots and adding an $\epsilon$ length
to the slot to account for the worst case in which slot edges
are synchronized. To deal with the asymmetry of duty cycles,
the nodes adopt a minimal common reference number of slots
$t$ and introduce multiplicative factors such as $2t$, $4t$, $8t$, etc.,
thus guaranteeing that every two nodes have periods which are
multiple of each other. Finally, the proposed algorithm also
adapts randomization techniques to counterbalance the slower
average case discovery latency in respect to a randomized
approach, such as the ones presented previously. Given that
a complete randomization would introduce a higher bound,
a restricted randomization is chosen to improve average case
latency while still guaranteeing a worst case latency bound.
 Lastly, McDis by Zhang et al. [93], reports a multi-channel
protocol for discovery. Two algorithms are provided: a ran-
domized version, which switches randomly between channels
and a deterministic version which sequentially allocates them.
The authors show that such a protocol is more reliable than
previous work when high packet loss conditions exist.

The work of Jain et al. [94] shows that, by placing
the responsibility for discovery on the mobile element, it is possible to minimize the power consumption load on static nodes. This asymmetric discovery therefore places the burden on the mobile element (deemed easily rechargeable) and saves energy on the static (deemed difficult to recharge). However, in some scenarios, it might be the mobile nodes which have lifetime constraints while the static nodes might be attached to a power supply. In addition, the duty cycle affects the discovery probability, together with the speed of interaction and the duration of listening times. Indeed, the works of Anastasi et al. [95], [96] analyse more deeply such issues, showing that shorter interactions due to higher speeds, with fixed duty cycling and inter-contact times, lead to a lower residual useful time for communication. This might be a problem since, when there is a need to exploit more of short contacts to collect data after long periods of absence, there is a shorter temporal window to do so. This clearly shows that a lower duty cycle does not always imply a lower power consumption, or it does only at lower speeds or higher duration of interactions. The objective of a discovery protocol in IoT scenarios for opportunistic networking is to discover short and rare contacts with low latency.

A more general approach for deriving the optimal asynchronous probing scheme is presented by Yang et al. [97] where an analytical formulation for the energy-optimal latency-bounded asynchronous duty cycle for discovery is presented. A more accurate evaluation in the case of realistic mobility patterns should be reported, considering also the possibility to adapt towards such patterns. Similarly, in the work of Zhou et al. [98], under the assumption that the contact duration is power law distributed, it is shown that the contact miss probability is not affected by a reduction in duty cycles if $T_{ON} \geq T_{OFF}$ and $\tau \geq 2(T - T_{ON})$, where $T$, $T_{ON}$ and $T_{OFF}$ are, respectively, the period, the awake and sleep times and $\tau$ is the minimum contact duration. The authors show indeed they can achieve 50% energy savings without affecting the miss probability.

Trullols-Cruces et al. [99] analyse the trade-offs of power consumption with miss probability and dissemination times. An analytical model of contact miss probability based on duty cycles shows that node lifetime can be doubled while still maintaining contact probability one. However, a more realistic analysis could have been considered by using notions about latency of discovery and radio throughput.

Feng and Li [100] also analyse a trade-off in the miss probability but with the different parameters of probing interval and radio detection range. The authors show that, as the probing frequency increases, there are more chances to detect nodes, however at a higher energy cost. Similarly, as the detection range increases, the contact duration increases and therefore nodes are more likely to be detected (the miss probability decreases). The authors then propose a utility function for trading off probing energy and miss probability based on a weight factor, therefore allowing adjustment to meet different requirements.

C. Discussion and Lesson Learnt

Time synchronized protocols for discovery require the availability of a common time reference and the ability to maintain synchronization over an arbitrary period of time, depending on the IoT device clocks accuracy. In order to accomplish such a synchronization, devices might require additional hardware such as GPS radios to retrieve a time reference. This, however, might introduce an energy cost that could be too high for ultra low power applications. In addition, many resource constrained devices do not incorporate real time clocks in their design and might use inaccurate crystals, making it difficult to maintain an accurate time reference. This means that, IoT devices that want to maintain their time reference for long periods of time require the availability of network connectivity to periodically update their internal clocks as well as incurring an energy cost for such communication. Nevertheless, in more powerful IoT devices, these components are usually present (i.e. smartphones) thus opening the possibility to employ synchronization methods that achieve advantages in energy with respect to asynchronous methods. However, since IoT scenarios will be inherently heterogeneous in nature, this means that the requirement for an internet connection might not be persistently covered by every device, therefore hinting at the need of techniques for opportunistic synchronization between devices.

While most of the common works in research try to employ different strategies to derive such a time reference (i.e. GPS or Wi-Fi of smartphones, or resource constrained wireless sensors ad-hoc techniques), an interesting research objective could be the understanding of how to change the synchronization schedule of IoT devices in order to comply with varying applications requirements. Indeed, coordination between devices is still needed in a synchronized environment and could be used to such an objective. However, while synchronization allows for a potential lower latency discovery with respect to asynchronous protocols, it could be limited by the heterogeneity of hardware (i.e. batteries capacity) and asymmetric schedules (lower or higher power) within IoT scenarios. In addition, many devices are disconnected and only rarely interface with other devices which opportunistically enter within communication range. Without understanding the mobility behaviour of devices, it becomes a daunting task to organize the efficient scheduling of the discovery resources and cope with the limitations of the hardware inaccuracies (i.e. reference oscillators clock drifts compensations). Therefore, a dynamic way of scheduling the resources for discovery in such a challenging environment could be introduced, with the objective to maintain distributed coordination and, at the same time, allow the satisfaction of application requirements. For example, game theoretic approaches or evolutionary algorithms could be used. In particular, such algorithms could understand when the encounters between devices are occurring in order to bring synchronization across several networks, thus allowing them to rely on faster time synchronized approaches in IoT scenarios of opportunistic networking.

Within indirect request protocols, energy triggered approaches are the ones most promising for the engineering of new radio receivers. Such customized radios provide very low discovery latency, due to high speed wakeups based on RF signals detectors. In addition, they provide a quasi-negligible power consumption on the receiver side due to the use of the energy present in a radio signal to wake up a system either directly or through a power amplifier, therefore achieving higher energy savings with respect to other asynchronous
approaches. However, they still require energy, sometimes even higher than a standard radio, at the transmitter in order to achieve acceptable discovery ranges, therefore simply moving the energy-burden from the receiver to the transmitter. While in many applications low range and the need to shift the burden of consumption on one device (the advertiser, in such cases) can be seen as a limitation, for other applications it might be considered an advantage. For example, this could be the case of an indoor scenario in which mobile nodes equipped with a wake up radio communicate with statically deployed nodes, which advertise their presence thanks to a potentially unlimited power supply availability. However, we argue that the communication range is of primary importance from the viewpoint of a IoT scenario of opportunistic networking since such range dictates the available contact time useful for communication. Another interesting opportunity for research, instead of concentrating on the reduction of the receiver power consumption, is to focus on achieving farther communication ranges. For example, research could explore alternative frequency band design opportunities or integrate such receivers with customized directional antennas and beamforming techniques in order to achieve higher communication ranges.

Multiple radios based approaches also allow an indirect wakeup of the system. Since in IoT scenarios, the vast heterogeneity of devices will require methods to bridge communication between different networks, from that point of view, radio hierarchies will gain importance due to their necessity to recognize both others radios technology presence and exploit the performances of such technologies in achievable communication range, lower power consumption, energy per transmitted bit and latency to setup and teardown communication as well as throughput. Similarly to the energy triggered approaches, it could be interesting to understand, for example, how to apply beamforming techniques and how frequently or how much to adjust the power of the transceiver according to the range to be achieved by multiple radios.

Temporal overlap based protocols, instead adopt a time slotted approach in order to overlap awake slots between neighbouring devices without any constraint about availability of time references or particular hardware. Such protocols have limitations due to the presence of clock drifts, or in the granularity or asymmetry of selectable duty cycles, as well as non guaranteed discovery. However, from the point of view of using them in real IoT scenarios, their major limitation is the general applicability to any radio technology. While such approaches are generally applicable in scenarios where ZigBee radios are used, their use with Bluetooth or Wi-Fi radios is yet to be completely understood. Indeed, when slotted protocols are used, fast radio turn on (setup) and turn off (teardown) times are required to achieve a short discovery latency, which require access to low level drivers. For example, in Searchlight [92] experiments have shown that Wi-Fi requires about 1 second for turning on from user space applications, therefore limiting the protocol. In addition, short listening and beaconing intervals are required to guarantee short slots and a low discovery latency, which is an important property in opportunistic scenarios where contact might be short. Indeed, in Bluetooth radios, by protocol definition the inquiry phase duration should be of multiple of 1.28s and recommended at a default value of 10.24s, which can be reduced to 5.12s as a minimum time to scan all frequencies and still be able to locate 99% of devices, as shown in [101]. However, slot durations in ZigBee can go as low as 10ms [90] (less than 5ms will introduce jitter) or lower (80µs) if the device only performs a carrier sensing as in Wi-Flock [102].

Many of the temporal overlap protocols are generally designed without the relying of information about the mobility pattern of the devices in which they are deployed. An interesting analysis of such approaches could lead to a higher degree of integration between them and intelligent approaches capable to adapt the discovery process according to the mobility patterns. In addition, while many deterministic approaches guarantee latency bounds on the discovery time therefore allowing a customizable useful time for communication, probabilistic approaches do not guarantee such bounds. This means that, in an opportunistic IoT networking scenario where contact durations between devices are relatively short and rare, randomized protocols may not guarantee the correct operation of applications that might have low latency requirements or may require higher power consumption with negative impact on devices’ lifetime. However, these approaches have better average case performances, suggesting that future research should be made in order to design optimal approaches which guarantee not only latency bounds but also low average latency.

IV. MOBILITY AWARE APPROACHES

In this section we present mobility aware protocols, which differ from the mobility agnostic of the previous section in the ability to exploit knowledge about IoT devices mobility patterns. These approaches use contextual information to infer devices’ availability over time, therefore organizing the schedule of the resources in an efficient fashion. They can be divided into protocols that profit either from temporal features, such as the frequency of arrivals or the arrival times, or from spatial features, such as knowledge of position and movement or colocation.

A. Temporal Knowledge Based Approaches

Temporal knowledge based approaches make use of knowledge about temporal features of mobility of IoT devices in order to adapt the schedule to save resources. Contact patterns of node movements are used to understand the availability of other devices in the neighbourhood in order to adjust the discovery process. We can differentiate between two main categories, namely, those based on arrival times and the ones based on the rate of encounters between devices.

1) Arrival times Based Approaches: Arrival times based approaches exploit knowledge about contact patterns of previous nodes discoveries in order to learn how to adapt their temporal schedule to save energy. Their aim is to derive knowledge about contact arrival times in order to achieve better efficiency than non-adaptive duty cycling approaches.

Knowledge about predictable and recurrent mobility of a mobile device, such as a shuttle bus, is used by Chakraborti et al. [103] to design a protocol for power efficient communication. The authors model the data collection process of a mobile device as a queuing process with random arrivals and study it to quantify power efficiency, in particular by making considerations about transmission ranges, speed, minimum
contact duration and nodes distribution. They show that if the nodes spatial distribution guarantees minimum separation distance, zero miss probability can be guaranteed. Moreover, they report an analysis which shows that knowing about predictable mobility achieves one third of the consumption with respect to a static multi-hop network. A collection protocol is then presented, having a startup phase where knowledge about how long and how often a mobile node comes within range is accumulated on the static devices, while the mobile learns the static node presence in order to understand when to wake them up. Subsequently, a steady phase, where learned knowledge is exploited by the nodes to introduce additional power savings, is performed. A drawback of this approach is that it assumes mobility comes only from a single device recurrent pattern, such as a public transportation system while, in general, more complex and overlapping patterns may be present. However, significant power savings are shown by employing such methods. An evaluation on a real world platform or by making use of simulations with realistic mobility traces is however lacking.

Jun et al. [104], instead, introduced a framework for power management based on knowledge about contacts between IoT devices. Starting from the assumption that an Oracle would have a perfect knowledge of contact arrival times and duration, the authors derive first a zero knowledge approach that adopts a beaconing searching strategy under clock synchronization hypothesis. A second proposed algorithm, exploits partial knowledge about the contacts in the form of statistics previously collected about the mean and variance of contacts duration and waiting times between contacts to save energy in discovery. Evidently, a shortcoming of such an approach is that it is limited to scenarios in which the mobility patterns do not present abrupt changes over time and also needs the statistical data to be collected previously (offline) and not continuously updated in accordance with a changing mobility scenario. Furthermore, the authors simulated only synthetic mobility models while a more accurate evaluation could have been carried out by employing real world mobility traces.

A more recent work from Dyo and Mascolo [29] instead, exploits Reinforcement Learning (RL), which allows to collect online data regarding mobility patterns. As can be seen in Figure 11, in RL, an agent learns online, in a step-by-step approach, to schedule its actions based on states reached by the environment and whether actions have been more or less rewarding. In this work, the days are divided into time slots and at each time slot of the day, the device learns how to adjust its beacons frequency based on the encounters frequency of the time slot of the previous day. This is achieved by updating a moving average for each of the timeslots (according to an energy budget) in which a day is divided into. While this work has been simulated with real world traces, these were low resolution Bluetooth traces of one sample every 5 minutes. A more accurate evaluation and real world experiment with RFID for detecting badgers has been presented by Dyo et al. in [105], even though a comparison with other approaches could better quantify advantages and eventual shortcomings.

Jun et al. [106] show a hierarchical approach where a long range high power radio (HPR) such as 802.11 and a very low range and low power radio (LPR) such as the ZigBee radio are used for discovery. Several different discovery strategies are presented, in particular a Continuous Aware mechanism which uses only the HPR always on and a Power Saving Mode, which instead alternates the HPR between sleep and awake. In addition, they present a Short-range-radio-dependent Power Saving Mode which uses both HPR and LPR, but the HPR is only woken by the LPR when a discovery is made. Finally, a Generalized Power Saving Mode sleep schedules both radios but only the HPR is the one woken, either by a beacon or by the LPR. Furthermore, the authors provide traffic aware optimization methods for such strategies, where statistical knowledge about mobility patterns is used in conjunction with traffic load knowledge, which is supposed to be available, for example by exploiting routing protocols. In such a way, contact arrival rates and durations as well as expected bandwidth are used to estimate the wake up temporal intervals under the assumption that arrivals are modelled as a Poisson Process.

While Dyo’s approach works in a completely mobile scenario, Resource Aware Data Accumulation (RADA) by Shah et al. [30] exploits a Q-Learning based framework for energy efficient discovery in sparse network scenarios with static devices learning about mobile devices presence. In particular, the framework learns to schedule a higher or lower duty cycle by learning the inter-contact times and the time of day at which the contacts were made, exploiting the inherent periodicity of patterns of mobility to optimize resources. A drawback of this approach is that while learning is available on the static sensor, on the mobile element that is not possible, since the device is dedicated to advertising its presence. In addition, an evaluation with real world mobility traces could be carried out to highlight its performance in realistic environment and how to adjust its parameters.

Sensor Node Initiated Probing for Rush Hours (SNIP-RH) by Wu et al. [107] leverages the authors’ previous work (SNIP [108]) to provide an efficient algorithm which exploits knowledge about rush hours during a day to concentrate effort and energy, thus scheduling a faster probing when there is more probability to interact with other elements. This is performed by dividing days into time frames and by understanding the average contact duration and marking the rush hours to be exploited by the algorithm, which will exchange data during these slots. However, the selection of the rush hours in this algorithm is to be achieved at deployment time by engineers and not performed online. Therefore, a more accurate evaluation in a dynamic environment with changing rush hours, should be carried out to understand its adaptability and performance.

![Fig. 11. Reinforcement Learning based Discovery Approach](image-url)
More recently, Kondepu et al. [109] combined the reinforcement learning of [30] with the dual beaconing approach of previous works [110], [111] which uses a single radio but with dual transmission power for beaconing, which is therefore capable of transmitting either long or short range beacons. By exploiting an interleaved short and long range beaconing strategy at the transmitting node and different duty cycles at the receiving node, the node implements a knowledge-based learning algorithm which, based on mobility, learns when to schedule a higher duty cycle for receiving short range beaconing by benefitting from the lower duty cycle for receiving long range beaconing. In addition, when there is no beacon reception the node will either sleep or schedule a low duty cycle to be executed. An evaluation of the algorithm in a real world scenario and with real world mobility traces should be provided to better quantify its gains, as well as its trade-offs in energy and latency to discover.

The work of Gao and Li [112] reports an opportunistic scheduling algorithm which adaptively schedules resources based on knowledge about mobility patterns. Their approach is capable of predicting in a probabilistic fashion the next arrivals on both a pairwise or aggregated contact behaviour. In such a way the nodes can sleep during absence of contacts and wakeup only when there is a high probability of contact. While showing the possibility to achieve a high trade-off between energy consumption and accuracy, it may be desirable to have an approach which achieves high discovery ratio with low energy consumption, as well as with short latency to discover a contact. Therefore, an evaluation in comparison with recent learning approaches in terms of accuracy and missing ratios as well as a real world implementation could be provided to quantify better the benefits of such algorithm.

Recently, the work by Zhang et al. [113], models the contact arrival process according to the well known statistical properties for intercontact times of following a power law distribution. It defines a wakeup schedule based on knowledge of arrivals in order to save energy when nodes are not in range by predicting the optimal contact arrival and departure times in order to have a contact happening with high probability. However, rather than focusing on average delivery ratio, it would be interesting to understand the discovery latency and the cumulative contact time provided by such approach.

Finally, Context Aware Resource Discovery (CARD) by Pozza et al. [31], showed that by exploiting Q-Learning it is possible to define a learning algorithm that tries to schedule low latency discovery actions when the node is learned to be in communication range in opportunistic IoT networking scenarios. This provides not only energy efficiency, but also optimization of the discovery latency, subject to application requirements. A real world implementation of such algorithm could be provided to quantify its applicability to heterogeneous IoT devices, thus using multiple radios.

2) Rate of Encounters Based Approaches: Rate of Encounters based approaches profit from information such as the number of node encounters over a finite time window in order to increase or decrease probing frequency. They distinguish themselves from the ones in the previous section from the fact that no knowledge about arrival times is used, but rather just a number of arrivals over a certain temporal window.

Druła et al. [114] derived an adaptive energy saving discovery algorithm for opportunistic networks capable of dynamically adjusting Bluetooth protocol parameters. Firstly, the authors propose an analysis of the Bluetooth parameters exploring the trade-offs between mean discovery time and power consumption. By varying the residence time in the inquiry and scan phases of Bluetooth as well as the scan interval and scan window the authors identify five different modes of use for Bluetooth from the most to the least aggressive. The authors then proposed, two adaptive opportunistic discovery protocols, one based on knowledge of the recent activity level and another on the location information about previous contacts. The recent activity level scheme schedules the most aggressive mode whenever a node is discovered while relaxes the discovery mode if a node has not been seen for a while. The second protocol instead exploits positioning information, which the authors presume is available from, for example, GPS receivers. Such a protocol works by keeping a count of the number of discovered nodes in each location (cell). The accumulated knowledge is exploited to select the optimal discovery mode when returns of a cell are made, also according to the maximum contact count of any cell. An evaluation with real world mobility traces or in a realistic environment on a hardware platform could be considered to evaluate the assumption of persistent presence/absence of devices in time. This assumption poses the basis for adaptive approaches to work on changing the frequency of discovery.

A similar work by Choi et al. [115] adopts a beaconing strategy based on knowledge about the history of discovered contacts, named Adaptive Exponential Beacon (AEB) protocol. In particular, as fewer contacts are discovered and until a certain maximum beacon interval $h_{max}$, the discovery process is relaxed by doubling the beaconing interval. As a contact is discovered, the beaconing interval is set to its minimum $T_{min}$ value. To update the value of the $h_{max}$ parameter, the authors use a moving average of the contact discovery rate and calculate its slope on a finite window. A method for selecting the optimal $h_{max}$ is then presented, based on the cumulative distribution function (CDF) of contact durations calculated (in this work) for a random waypoint model, to cover a certain number of possible contacts (i.e. 98%) while saving as much energy as possible.

Kam and Schurgers [116] adopt the baseline beaconing method of AEB [115] but introduce as well a local knowledge based sleeping protocol. The protocol decides to sleep or not at each beacon based on favourable or unfavourable states which are determined by information concerning packet queue length, packet expiration times, history of contacts, battery conditions or a mobility map. Indeed, many protocols for routing in delay tolerant networks (DTN) provide this kind of information which can be exploited to judge whether a node should discover or sleep. A geographic convergecast application is evaluated with state information such as rate of progress, sink proximity and packet expiration time and showed a two times energy reduction in comparison with an application without such knowledge. A partial drawback of this approach is however that it needs the information from routing protocols. This can be seen as a good point as it allows cross-layer knowledge integration, while on the other side reduces flexibility since different routing protocols might have different performances. An evaluation with other protocols and in more
realistic mobility scenarios could quantify better such benefits.

A further work by Wang et al. [41] proposes adapting the frequency of probing based on knowledge about the rate of encounters of the contact arrival process. A first analysis shows that for independent and identically distributed (i.i.d.) contact durations and stationary inter contact times, among all contact probing strategies, the one that minimizes contact miss probability is the one that probes at constant intervals. Furthermore, a second analysis of real world traces of mobility shows that the contact arrival process presents a self-similarity property which can be used to adapt the probing interval for maximizing the discovery process while respecting constraints on energy. Therefore, an optimal contact probing interval formulation for non stationary inter contact times is made, which only needs the estimated arrival rate in a particular time slot. Adaptive algorithms for Short Term Arrival Rate (STAR) estimation are further presented, based on previous time-of-day information (STAR-TOD), on previous time slot information (STAR-PTS) and on linear and non-linear minimal error estimator techniques (STAR-LMMSE, STAR-MMSE).

This method, however, is based on the assumption that the contact duration distribution decay coefficient is known but this is dependent on the underlying patterns, even though the authors demonstrate resilience to changes of the parameter. However, if different or overlapping mobility patterns are considered, this might raise issues. Moreover, while on a large temporal scale the algorithm has low miss probability, the algorithm may miss significant contacts over a short time scale, which might be useful in rare and short contact scenarios. Latency of discovery is also an important parameter which needs investigation.

More recently, eDiscovery by Han and Srinivasan [117] firstly reports an experiment with smartphones showing that the Bluetooth standard is preferable over Wi-Fi to perform discovery from the point of view of the power consumption. The authors then devise an adaptive protocol that, similarly to the work of Drula et al. [114], changes the duration and interval of the Bluetooth inquiry times according to knowledge about the history of discovered nodes, mainly in the form of the number of devices discovered. Therefore, the protocol progressively concentrates the discovery effort when there are more contacts and viceversa decreases it when there are fewer contacts. An example of Bluetooth discovery intervals and windows can be seen in Figure 12. In this work, the inquiry window parameter is set to 8 (corresponding to $8 \times 1.28 = 10.24$s) if at least $N + 1$ are discovered. On the contrary, if there is a number of peers discovered less or equal to $N$, such a parameter is adjusted to be $5 + r$, where $r$ is a constant equal to 0 with probability 0.8 and equal to $\pm 1$ each with probability 0.1. The inquiry interval parameter, instead is increased by $10 + r$ when no peers are discovered in two intervals and reset to $10 + r$ after a peer is discovered. In addition, if more or fewer peers are discovered with respect to the previous interval, then the inquiry interval is respectively decreased or increased by a different parameter $I$. A possible extension of this approach is that while using Bluetooth might be more efficient in energy than Wi-Fi, since the latter is still widely available on IoT devices such as smartphones, its use as a standalone or in combination with Bluetooth might reach higher communication ranges and provide higher throughput for communication. Therefore a hierarchical radio approach might allow a higher discovery rate or could even achieve better energy savings, for instance, by supporting ZigBee radios.

The adaptive working schedule of Zhou et al. [118] adopts a slotted model, with a working schedule consisting of the combination of awake slots within a fixed period, which is the same across nodes. In this work, nodes use knowledge about previous contact history in order to predict future contacts. In particular, each node records the history of the encounter times and computes a table for the inter contact times. Such nodes, will then compute the expected encounter values EV (the number of nodes to be seen in future) based on the inter contact times history and, every period, adaptively set the working schedules to guarantee overlap based on the EV for every slot. In fact, the algorithm selects the slots within a period which have the highest EV. A more accurate analysis taking into account discovery latency considerations as well as comparison with relevant state of the art protocols, could quantify better the benefits achievable.

Finally, Wi-Fi Sensing with Aging (WiSaG) by Jeong et al. [119], proposes an optimization problem for the optimal sensing process capable of adapting the probing frequency based on inter-arrival times and contact durations. The work exploits the aging property, stating that, if the time elapsed from last arrival increases, the nodes should sleep longer. The optimal sensing interval is increased or decreased according to knowledge about, respectively a negative or positive aging of the inter-arrivals distribution. While this and previous approaches achieve substantial gains over a mobility agnostic protocol, they can still be improved by incorporating additional knowledge (i.e. spatial) to further improve accuracy.

B. Spatial Knowledge Based Approaches

Spatial knowledge based approaches exploit geographical location or movement knowledge coming from additional sources, such as neighbouring nodes or hardware modules such as GPS receivers or accelerometers, in order to understand how to adjust the scheduling of resources. They can be divided into positioning based and colocation based according to the knowledge source they exploit.

1) Positioning Based Approaches: Positioning based approaches exploit knowledge about relative or absolute position
of IoT devices in order to optimize the discovery process. In such approaches, knowledge about geographical locations of encounter, movement or its absence with respect to neighbours is used to optimize the schedule of resources.

The Connection-less Sensor-Based Tracking System Using Witnesses (CenWits) by Huang et al. [120], reports of a search and rescue application for hikers. In such an application, IoT devices are loosely synchronized via GPS or opportunistically with deployed access points. The probing frequency for power management is adjusted based on knowledge about hikers movement speed (derived from opportunistic encounters with other devices) and radio transmission range. For example, if the hikers move at 1 mile/hour with Mica2 nodes range of 150 feet, the nodes emit one beacon every 1.7 minutes, while if the hikers are moving fast, such a rate could be increased, or vice versa relaxed if the users are not moving at all (i.e. at night).

Banerjee et al. [121] present a hardware platform for DTN throwboxes. DTN throwboxes are static infrastructure nodes used for collecting data from mobile nodes, mainly for increasing capacity of DTN networks. The platform adopts a hierarchical radio structure relying on a long range low power radio in the 900MHz band in combination with a higher power but shorter range 802.11 radio as can be seen in Figure 13. By receiving beacons through the low power radio, the system can decide based on a prediction algorithm whether to wake up in advance the shorter range Wi-Fi radio to exploit the contact. Such a hierarchical architecture provides power savings thanks to the information contained in the beacon of the mobile device (location, speed, direction) approaching, which is used for predicting its trajectory and to wake up the short range radio when the mobile element is supposed to be in range. In particular, the mobile node movement pattern is assumed Markovian inside a square area defined by the long range radio. Thanks to beacons, which contain positioning information, i.e. from GPS, the probability the node will enter the short range area will be calculated, allowing prediction of the data communication time and the duration of contact. This information is used by a token bucket scheduler which decides which of the opportunities to exploit based on average power constraints. A drawback of this approach is however that it relies on the mobile node to be equipped with a GPS receiver, therefore limiting its applicability.

**Blue-Fi** by Ananthanarayanan and Stoica [125] devised an algorithm to efficiently predict on a mobile node the availability of Wi-Fi based on knowledge about both Bluetooth and Cell ID information. In this algorithm, the devices periodically log contact pattern information with timestamps about Cell IDs, Bluetooth IDs and Wi-Fi MACs. The authors argue that predicting Wi-Fi availability based on Bluetooth has higher accuracy but lower coverage due to the lower range of Bluetooth. Moreover, Cell Tower based predictions have lower accuracy but higher coverage due to their higher range. Therefore, a hybrid method is presented by combining first Bluetooth based prediction and then relying on Cell Tower based prediction. In addition, since the absence of movement can not change the outcome of the predictions, the authors present a method which uses the received signal strength indication (RSSI) of the cell towers. Therefore, only if a euclidean distance computation shows enough movement, the protocol triggers the discovery. Finally, a diversity measure based on the K-medians clustering algorithm is used to capture similarity between locations a device visits to identify similar entries between a list of locations. Thanks to such measures, the algorithm will be able to identify lower diversity static devices with Bluetooth, from mobile ones, the latter to be discarded as non-useful for prediction. A partial limitation of such an approach is that it is application dependent and requires that devices have three radios with different characteristics (see Table I), which is common in smartphones, but might not be on more resource constrained IoT devices. A more accurate energy analysis which accounts for the power consumption of the multiple radios could be provided to quantify the energy savings effectively achievable and to compare against state of the art.

**Footprint** by Wu et al. [126] uses mobile phone location knowledge to trigger Wi-Fi access point scans only if the mobile device has been moving more than a threshold distance with respect to its previous position. Movement knowledge is gained through cell ID and RSSI historical information, which the authors call footprint. A limitation of such an approach is that relying on cellular networks might limit its general applicability only to devices which have ad-hoc hardware. In addition, a more accurate evaluation of power consumption, could be performed.
Sivaramakrishnan et al. [127] introduce an algorithm for discovery in which mobile devices are equipped with accelerometers which are sampled to understand position displacements. Such data is used to train an artificial neural network (ANN) which learns the distribution pattern of the nodes in the area and predicts the displacements. The work exploits the intuition that the probability of a successful discovery increases as the node density increases and proposes an adaptive sampling algorithm which saves energy in comparison with a regular sampling technique. However, this work lacks an accurate evaluation in terms of the energy used by employing accelerometers, as well as of a real world implementation.

Li et al. [128] use an autoregressive model for time series analysis which exploits historical location knowledge from GPS equipped nodes. Each node estimates its mobility and velocity time series based on GPS observations and shares them with its neighbours in a hello message. Each node will then predict its own mobility and advertise it only when it predicts a false topological change, therefore correcting the prediction on other nodes. An accurate analysis of the advantages of predicting mobility of a node in terms of energy savings and in scenarios where this knowledge is shared could be introduced, thus better highlighting the benefits of this approach.

In WiFisense by Kim et al. [129], firstly, an optimal Wi-Fi sensing interval analysis is made by analysing a connectivity model based on a Markov Chain where the distribution of Wi-Fi access points is hypothesized as a Poisson Process. Under these assumptions, the key factors that affect the sampling interval are the knowledge of movement and of access points density. On this basis an algorithm that uses knowledge of movement from an accelerometer to determine the sensing strategy in an energy efficient way is presented.

Hu et al.[130] introduced Mobility Assisted User Contact (MAUC) detection, which leverages the fact that movement recognition based on accelerometers uses very little energy in comparison with Bluetooth scans. From this starting point, the authors propose an algorithm which triggers Bluetooth scans only when user movements have a high probability of causing contact changes, showing energy savings in respect to a mobility agnostic scheme. In particular, the accelerometers samples are classified based on a decision-tree technique which classifies users as moving or static. If the user is found moving, then Bluetooth scans are triggered according to an exponential increase, multiplicative decrease backoff technique. In addition RSSI knowledge is used to detect boundaries of communication ranges, such as, for example, when the node is moving out of range. An evaluation of such algorithm in combination with different other radio technologies should also be performed, and compared to other approaches.

Hess et al. [131] introduces a discovery protocol for opportunistic networks which uses local knowledge about velocity of a device, acquired from either GPS or accelerometer sampling, with the objective of adjusting the beaconing process. The authors argue that short unmeaningful contacts might be not worth discovering since they do not affect significantly the communication time. In addition, due to long communication setup and handshake times between devices, their effective contribution to the total residual contact time could be neglected. However, this might depend on the mobility scenarios, and in some applications, short contacts between highly dynamic devices might be the only solution for relaying data across different networks.

Finally, PISTONS [132] and PISTONSv2 [133] by Orlinski and Filer report movement speed based adaptation for adjusting the discovery process. PISTONS exploits knowledge about the maximum speed at which devices travel and adjusts the discovery process based on the intuition that contacts occur in a burst. When a contact is found the probing frequency is adjusted to maximum and then relaxed progressively. In PISTONSv2, the authors assume that nodes can estimate their average speed or mode of transportation, i.e. walking or driving. Therefore, PISTONSv2 alters the neighbour discovery schedule based on movement speed, adapting to changing conditions. However, on a device perspective, knowing its movement is not beneficial to recognize all other devices, because they could move at different speeds (i.e. when stationary). An improvement could be learning other devices speed consequently their contact durations.

2) Colocation Based Approaches: Colocation based protocols profit from knowledge coming from neighbouring nodes in order to coordinate the schedule between such nodes for the optimization of the discovery process. For example, in multiple nodes scenarios where nodes tend to flock together, they can accelerate the discovery of all the nodes by exchanging their schedules or by estimating the number of neighbours.

Borbash et al. [134] introduce a randomized discovery approach based on their previous work (Birthday protocols [5]) therefore adopting a time slotted protocol where acquired knowledge about the number of neighbours is used with the purpose of maximizing the number of discoveries in a fixed running time. However, in IoT scenarios of opportunistic networking, topology changes and mobility could cause problems with the time needed to acquire knowledge and its re-use. In addition, in such a scenario, the algorithm might present difficulties in complying with the assumption of having an initial estimate of the expected number of neighbours.

Xi et al. [135] define a Context Aware Power Management (CAPM) scheme which determines an optimal sleep/wake up pattern that minimizes energy consumption to be integrated with routing algorithms for DTNs. In particular, the beaconing strategy is based on parameters $W, C$ and $K$, where $W$ represents the wake up period, $C$ the wake up cycle and $K$ the number of cycles to be counted after which a full wake up cycle will be scheduled. Each node builds a neighbour

<table>
<thead>
<tr>
<th>Throughput</th>
<th>Transfer Energy(J/MB)</th>
<th>Idle Energy(W)</th>
<th>Scan Energy(W)</th>
<th>Range(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cellular</td>
<td>few 100 kbps</td>
<td>100</td>
<td>0</td>
<td>500</td>
</tr>
<tr>
<td>Wi-Fi</td>
<td>11-54 Mbps</td>
<td>0.77</td>
<td>0.12</td>
<td>10</td>
</tr>
<tr>
<td>Bluetooth</td>
<td>700 kbps</td>
<td>0.01</td>
<td>0.10</td>
<td>10</td>
</tr>
</tbody>
</table>

TABLE I. SMARTPHONE RADIOS FEATURES
table by receiving beacons containing information concerning the awake patterns. Based on an analysis, rules for selecting optimally $W$, $C$ and $K$ based on traffic load requirements are presented. Similarly, Tumar et al. [136], [137], try to apply concepts of multiple radios to the work of context aware power management of [135] by using low power ZigBee radios for discovery and high power Wi-Fi radio for communication. Since the low power radio has a further range for communication than the high power radio, it allows for a lower power discovery. An evaluation with Random Waypoint Mobility and realistic traces shows that energy savings can reach 55% to 68% compared with a single radio protocol. However, these approaches do not profit from temporal knowledge about mobility but just from colocation knowledge, therefore leaving room for potential improvement.

Luo and Guo [138] instead try to solve the problem of efficient multiple user detection in neighbour discovery by making use of a Code Division Multiple Access-like (CDMA) technique for discovery. In such an environment, multiple nodes send their unique on/off signatures, which are known to the receiver. Two algorithms are proposed for testing the observations of the receiver and recognizing the presence of other nodes signatures: the direct algorithm and a reduced complexity binning algorithm. They both show a faster and reliable discovery (based on group testing) than probabilistic access discovery methods, which requires only non-coherent energy detection.

Zhang and Wu [139] instead introduce an algorithm that adapts the duty cycle for discovery if a flocking condition occurs. Indeed, since in IoT scenarios nodes might tend to flock together, if each node shares the information about its duty cycle, the occurrence of a flock can be easily identified by each node and actions can be taken if present. Therefore, the authors proposed to schedule faster duty cycles (limited by an energy budget) when flocking occurs in order to adjust to increasing nodes demand, and, vice versa if it does not. A shortcoming of this approach is that no temporal knowledge about the flocking occurrence is used to predict in advance their occurrence and take actions accordingly.

In WiFiLock by Purohit et al. [102], the flock discovery and maintenance is also achieved by sharing knowledge about neighbours between nodes. However, at the same time, nodes synchronize the listening phase and transmit evenly spaced beacons to coordinate communication between nodes, thus allowing group formation. Listening synchronization is achieved by adapting the schedule based on beacon reception, in particular, by calculating the distance between beacons. Evenly spaced transmission is achieved by coordinating the slots based on priority. The node with the smallest ID picks an arbitrary time slot as slot zero and the other nodes adapt their slot based on the number of nodes in the group and their ID. In addition, node departure is handled with a time-to-live entry in the group membership table and removed at expiration. A limitation of such an approach, however, is that it does not exploit predictability about the temporal occurrence of flocking conditions, which comes from mobility patterns.

NetDetect by Iyer et al. [140], proposes an algorithm for adapting dynamically the beaconing rate based on neighbour density estimation, achieved by making use of a maximum likelihood estimator (MLE) in order to compute transmissions probabilities. The algorithm is founded on a distributed consensus mechanism for which, nodes will converge to the average of each other’s probabilities (shared across nodes), which will then be pushed to the reciprocal of the local density of nodes by basing the MLE on the distribution of slots where packets where successfully transmitted.

Karowski et al. [141] report a linear programming (LP) optimization in order to define when to listen, on which channel and for how long. In addition, they exploit information overheard because of the sharing of listening schedules, therefore accelerating the discovery of neighbours operating with smaller beaconing intervals. However, since the authors’ first optimized (OPT) strategy results in many possible switches between channels, they also propose a switched optimized (SWOPT) strategy which reduces the number of such switches by increasing a sustainability period parameter representing the minimum number of slots a node stays awake on a channel.

More recently, in Cooperative Duty Cycling (CDC) by Yang et al. [142], knowledge of community metrics such as clustering of people is incorporated with a strategy for duty cycling to save energy which differentiates between travelling and clustering mode. In travelling mode, nodes will independently wake up with a certain active ratio parameter, whereas in clustering mode the active ratio is reduced thus saving power but introducing delay. A method for configuring the active ratio in clustering mode is then presented, based on a Monte Carlo experiment showing that as the active ratio in clustering decreases, the benefits are still achieved but with an increasingly higher number of clustered nodes.

United we find by Bakht et al. [143] leverages the presence of a multiple radio scenario of low power radios (LPR) such as Bluetooth radios and high power radios (HPR) such as Wi-Fi to define a protocol that optimizes power consumption by making use of knowledge about clustering between nodes. The algorithm first identifies in a probabilistic way the optimal coverage by building a scanner set which identifies the HPR nodes to be scanned, mainly by coordinating through the LPR nodes. Therefore, as HPR and LPR scanning are performed, beacons containing knowledge about the neighbours table are exchanged between nodes. In such a way, nearby nodes not reachable by short range radios, can therefore be found by making use of HPR, thus maximizing discovery of nodes with a lower energy consumption.

Finally, in Acc by Zhang et al. [144], a framework built on top of a deterministic discovery protocol such as Disco and U-Connect is used in order to share knowledge about neighbour tables for accelerating discovery. How this can be achieved, is shown in Figure 14, where node $i$ discovers $j$ at $t = 0$ and subsequently can activate a further slot at $t = 6$ accelerating the next discovery of $j$ by 4 slots and also gaining at such temporal slot the information of $j$’s discovery of $k$ at previous slot $t = 3$. The algorithm determines a slot gain parameter for acceleration based on spatial similarity (how many neighbours are shared) and temporal diversity (how much schedules are different) between nodes thus showing that by choosing accurately the slots it is possible to accelerate discovery. However, a prediction algorithm which also uncovers the temporal patterns of nodes mobility could extend such work in order to achieve better performances when no nodes are close.
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WLAN-Opp by Trifunovic et al. [145] provides an opportunistic networks discovery solution for smartphones based on a probabilistic approach profiting from knowledge of the current number of neighbours. The solution leverages the possibility for a smartphone to either behave as access point (AP) or to connect to a network as a station (STA) according to a state machine with different transition probabilities. The probability of switching to another network while in STA or AP modes decreases as the number of neighbours increases. However, for AP mode the probability of being turned on (or off) also depends on the time elapsed since the device was in the previous off (or on) AP mode. An integration of such an approach with solutions which consider also temporal knowledge, might introduce further benefits.

C. Discussion and Lesson Learnt

Mobility Aware approaches profit from knowledge about the features of mobility patterns in order to provide IoT devices resource scheduling, thus enabling their adaptive, autonomous and smart operation in an optimized fashion. It is obvious that many such approaches could be coupled with older, well-established, non-adaptive discovery protocols in order to introduce further optimization thanks to the added knowledge. Within mobility aware protocols, many of the temporal knowledge based approaches rely on statistical analysis of the underlying mobility patterns temporal characteristics in order to derive arrival times or adapt the probing frequency in order to minimize contact miss probability and, at the same time, optimize resources. However, few recent algorithms, exploit learning approaches with the objective of learning from the history of mobility patterns, therefore acquiring knowledge about temporal recurrence of IoT devices’ patterns of encounters in order to predict (usually online) future contacts arrivals.

Arrival times based approaches exploit temporal mobility features in order to predict how to adjust the resource schedule, but present an intrinsic limitation due to their time-based nature, which is the accuracy in deriving the arrival times of the forecast contacts. Evidently, relying only on temporal features such as inter contact times, time of arrivals and contact durations limits the understanding of the mobility patterns of the IoT devices’ carriers. This translates into a negative impact on the accuracy of the learning algorithms that run on such devices. To overcome such an obstacle, additional research on high level knowledge and new types of features in order to improve the accuracy of discovery protocols could be carried out but also with the aim of aiding to identify the best nodes to discover to relay information, while avoiding the need to find the less important ones. For example, knowledge about social behaviour such as community membership or friendship between IoT devices carriers could be used to infer knowledge about patterns of encounters if combined with arrival times information, therefore improving accuracy and identifying the best nodes worth discovering. This will introduce energy savings when unimportant encounters are happening. Moreover, in an IoT scenario for opportunistic networking, by exploiting more powerful Internet-connected nodes (i.e. smartphones or connected-cars) it is possible to share this information and enhance or annotate additional knowledge in order to further optimize the discovery process. Ant colony gossiping, currently used in data collection protocols (i.e. EDAL by Yao et al. [146]) to spread status information, could also be used to propagate knowledge between nodes in order to find optimal routes for discovery and communication. In addition, Quality of Service (QoS) knowledge, in the form of available bandwidth, congestion and duration of the predicted contacts, could aid the discovery process to select which opportunity to exploit, subject to application requirements. In fact, such knowledge, sometimes is made available by exploiting routing protocols, therefore advocating the need for a tighter integration between routing protocols and discovery mechanisms in IoT scenarios for opportunistic networking which could optimize both discovery and routing techniques.

Rate of Encounters based approaches adapt the beaconsing frequency according to the history of arrival rates, therefore concentrating more resources if a burst of arrivals condition is forecast. Such approaches however fail to guarantee a bound on discovery latency, but rather adapt the discovery frequency based on the changing environment in order to minimize the miss probability, regardless of the useful communication time remaining to be exploited after discovery. However, such approaches, in comparison with arrival times based protocols are usually very simple to implement and require little computation capabilities, i.e. only the recording of the activity level under an arbitrary temporal window. Nevertheless, such protocols could be improved in accuracy by incorporating a few notions about the quality of the encounters they face. For example, a popularity-based measure could be used, in order to understand the number of visits of a mobile IoT device to a certain static IoT device or, in general, the number of interactions any device has with each other. This could represent a more accurate picture about the mobility patterns. Similarly, knowledge about ranking of IoT devices based on their degree of mobility could be employed, for example, by tagging and discovering the devices which interact with the highest number of different devices or the ones which provide the highest cumulative communication time estimate and discarding the ones which only interact with few devices, thus saving energy. Moreover, from the viewpoint of opportunistic forwarding, this approach could be integrated with protocols that discover devices that will likely meet other devices soon, instead of routing messages towards potentially slower hops in terms of end-to-end delay.

Spatial knowledge based approaches differ from the temporal features based protocols mainly from the fact that they often require additional hardware components, thus requiring energy and the additional cost to include such hardware. If discovery approaches can be limited to exploit temporal mobility features, they typically do not require additional hardware and energy, since these are the most general form of context.
that can be learned even on resource constrained devices. Spatial approaches allow recognizing relative positioning and colocation between devices in order to adapt the discovery process accordingly, as shown in the previous sections.

Positioning based approaches are able to understand movement and, under certain conditions, even geographical location. However, when GPS geographical coordinates are required, GPS hardware needs to be used, therefore hinting that such approaches need techniques to reduce their energy demand, for example, as shown by Paek et al. [147] or Liu et al. [148]. The former proposes, in fact, a sleep scheduling algorithm for GPS based on velocity and location-time history, while the latter leverages cloud offloading of raw GPS data to aggressively duty cycle GPS receivers as well as to have a fast GPS position fix. Other works require cellular network radios in order to exploit location knowledge to establish when to discover for Wi-Fi AP based on the cellular base stations location information. It is obvious that requiring such radios on a resource constrained device might pose problems for the power consumption needed to derive such spatial knowledge. Finally, using RSSI or accelerometers in order to derive knowledge about movements provides a lower power solution, but does not allow understanding geographical locations such as in GPS based approaches.

Concerning the algorithms for predicting about mobility patterns, many works in the state of the art, already exists, especially under GPS data mining approaches (see Lin and Hsu for a survey [149]). However, such algorithms often require high volumes of historical data for training, as well as high computational requirements. Therefore, an adaptation of such approaches from the point of view of discovery protocols could be considered, however, requiring modifications to cope with the online learning and low computational requirements. Knowledge about the context in which nodes are moving could also be inferred by employing additional sensors, which are more and more often being pervasively diffused in IoT devices. Indeed, thanks to the advances in manufacturing, they require increasingly less energy as well as provide new sensing capabilities. For example, audio microphones, acoustic and ultrasonic sensors or passive infrared sensors, could be used to infer people presence and turn on radios accordingly for communication. Alternatively, photoelectric or luminosity sensors could be used to infer knowledge about movement in a building or a room in order to adapt the discovery accordingly.

These sensors could be used also to devise new colocation based protocols, which exploit knowledge about neighbouring devices in order to optimize the discovery process. Many of these approaches, however do not exploit temporal knowledge about the mobility patterns. In fact, these approaches use knowledge about colocated (flocking) nodes’ schedules piggybacked on devices’ beacons. Such knowledge could also be learned by devices along with their temporal mobility patterns with the objective of adapting to the forecast approaching nodes with the best schedule in terms of required latency/energy trade-off, therefore coordinating the flock discovery. Finally, in order to improve the accuracy of colocation based protocols, tagging locations and dividing them into different groups (e.g. schools, pubs, railway stations) could be useful to differentiate potentially crowded locations from unimportant and rather empty places, in which resources could be saved. This would require adding temporal knowledge along with location since the density of mobile nodes could vary during the day; i.e. a pub would be crowded during the weekend or in the evening, whereas a school would be crowded during the days of the week.

V. CONCLUSION

In this survey, neighbour discovery approaches for opportunistic networking in IoT scenarios were presented. A scenario and taxonomy illustrating a classification between mobility agnostic and mobility aware discovery protocols was reported, highlighting the distinction between approaches that do not profit from knowledge about mobility, from the ones which exploit it for optimization. While mobility agnostic protocols can be applied in IoT scenarios where a device’s availability is not considered, in mobility aware protocols the objective is to understand and exploit patterns of availability in order to introduce optimization. It is these author’s opinion that exploiting mobility knowledge is the preferred option in the light of the highly dynamic nature of opportunistic networking within IoT scenarios.

Future discovery protocols should be able to acquire knowledge and learn about the availability of IoT devices in order to predict future encounters of nodes in a distributed fashion by relying on contextual knowledge. Such contextual knowledge should aid the devices in optimizing both latency and energy by reducing power consumption when devices are learnt to be absent and by discovering as fast as needed when they are predicted to be in range to allow for the maximum possible useful time for communication, especially when contacts are short and rare. New frameworks for discovery should be devised by incorporating in the learning and prediction algorithms both new features capable of describing intrinsic properties of mobility and new knowledge sources capable of explaining better the envisioned patterns of encounters. By gaining a better knowledge about the environment and by combining approaches it will be possible to gain a better understanding of the context surrounding IoT devices, therefore achieving better accuracy in prediction and introducing further optimization for opportunistic networking in IoT scenarios.

In conclusion, it is these author’s opinion that the knowledge acquired via neighbour discovery impacts not only such protocols, but also opportunistic routing techniques [150]. If such knowledge was exploited and applied to routing in IoT scenarios of opportunistic and disruption tolerant networking, it could help in devising new autonomic and smart protocols, thus moving towards a knowledge driven store-carry-forward paradigm. Moreover, service discovery protocols [151] could also be influenced by the availability of knowledge about patterns of encounters between IoT devices, thus aiding IoT applications in resource discovery and selection based on the opportunistic availability of such resources [152]. For example, the ElasticSearch engine by Jara et al. [153] offers a resolution infrastructure called “digcovery”, which allows colocated resources pertaining to different domains to be discovered based on geo-location and context-awareness. Finally, in IoT scenarios for opportunistic networking where knowledge is shared across heterogeneous networks, trust management [154] becomes a new challenge which needs to be addressed in order.
to preserve privacy of data and of users within data fusion processes.

**APPENDIX A**

**CLASSIFICATION**

In light of the taxonomy previously introduced, we report in Table II a summary of neighbour discovery approaches highlighting their key mechanisms. The table serves the purpose of showing areas of overlap between works as well as their categories which allowed us to construct the current taxonomy. Such differentiation clearly shows that there is potential to devise new approaches, capable of offering the desirable properties that a discovery approach should have (see Section II). In fact, an ideal approach should be able to integrate spatio-temporal learning and prediction in a latency and energy efficient discovery protocol for opportunistic networking in IoT scenarios.

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