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# Peer-to-peer energy sharing in mobile networks: Applications, challenges, and open problems

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ABSTRACT

Energy is a scarce resource in mobile wireless networks that consist of devices mainly powered by their batteries. Providing energy ubiquitously to these devices for making them functional for a long time is a challenging task. With the advent of energy sharing techniques, either by wired or wireless mediums, it is possible to extend the lifetime of such networks by utilizing the energy from other energy sources (e.g., chargers, other devices) within the network. In this paper, we explore the utilization of peer-to-peer energy sharing in various applications of mobile networks that consist of agents from low-power devices such as sensors to high-power ones such as electric vehicles. We provide an overview of the current research directions and developments of new protocols and algorithms that exploit the energy sharing techniques to solve the scarce energy problem in mobile networks. For each mobile networking domain, we highlight the specific challenges and describe the approaches followed to address them under various research problems. We also discuss open problems yet to be solved in each specific application.



## 1. Introduction

Energy is a scarce resource in mobile wireless networks as the devices mostly run on batteries. Thus, many research efforts [1] have been made for the efficient utilization of energy at mobile agents to prolong the network life time. However, these solutions only delay the need of energy replenishment. For a continuous operation of nodes, energy harvesting [2,3] from various sources (e.g., vibration, radio waves, solar) has been considered but it has limited application in practice due to the predictability issues and small amount of energy that could be harvested most of the time. Similarly, battery replacement [4] can be an immediate remedy but it is costly and may not be practical. Mobile chargers, which are special devices having high energy supplies compared to mobile agents in the network have been recently considered as an alternative solution. That is, they charge themselves from energy sources, navigate to the locations of mobile agents and transfer energy to them periodically. While this approach helps solving the continuous energy needs of mobile devices, it comes with many challenges (e.g., efficient scheduling) and also depends on special devices.

Taking this approach further, energy sharing among all kinds of mobile agents in the network has been studied very recently, relaxing the need of special charger devices and providing a ubiquitous access opportunity to energy. While there are different challenges (e.g., hardware extension of ordinary mobile devices, incentive for sharing) in its application, there is a growing number of interesting research studies on its utilization to solve the energy problem in mobile networks. The research community has recently considered energy sharing between different types of mobile agents including the chargers in a *Wireless Sensor Network (WSN)*, smartphones in a *Mobile Social Network (MSN)* or electric vehicles (EV) in a *Vehicular Ad-hoc Network (VANET)* or between unmanned aerial vehicles (UAV's) and ground devices. However, due to the nature of networking scenario as well as the form of energy sharing, different problems have been studied.

### 1.1. Motivation

The charging of battery powered devices has gained a different perspective with recent breakthroughs in the areas of wireless power transfer (WPT) [5,6] and rechargeable lithium batteries [7]. Thanks to both academic and industrial efforts, wireless charging has been adopted for the charging of various mobile nodes including not only the low-power devices such as RFID tags, sensors or other Internet-of-Things (IoT) devices but also other devices and vehicles that operate with moderate and high capacity batteries such as smartphones, tablets, and cars. There are many commercial products that can be charged wirelessly in the market today and it is expected that the global wireless charging market is

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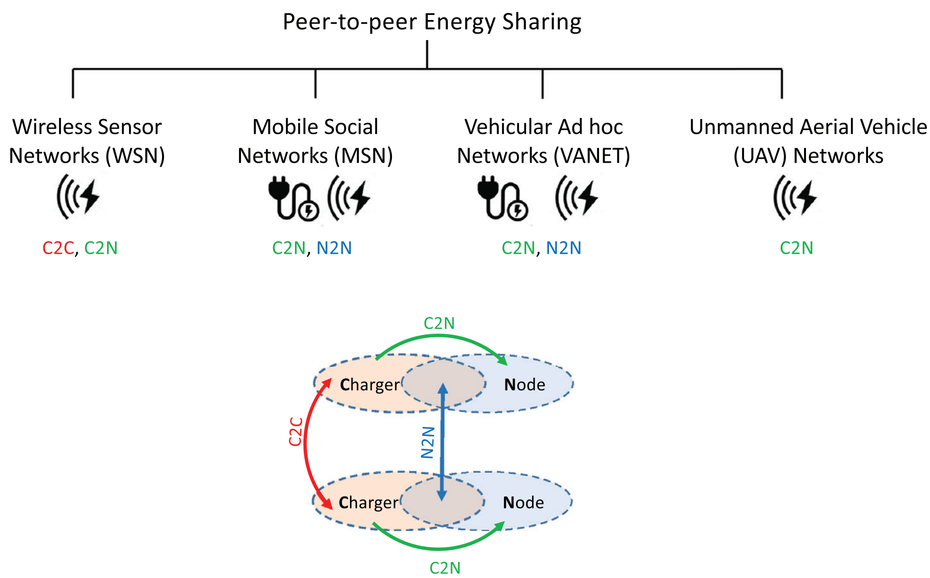


**Fig. 1.** The scenarios considered for energy sharing in different mobile network applications.

projected to reach $71,213 million by 2025, with a compound annual growth rate (CAGR) of 38.7% from 2018 to 2025 [8].

In this paper, motivated by the recent growing number of studies, we overview the usage of energy sharing between the agents in mobile networks to prevent the energy depletion problem. We refer to *energy sharing* as the transfer of energy from the battery of one member of the mobile network to the battery of the another member. Thanks to the convenience and better user experience provided, wireless charging technologies have been recently adopted for the sharing of energy among peers. However, energy sharing not necessarily be achieved via wireless power transfer. Conductive (wired) way could also be possible and a better option for efficiency in some networks consisting of high-power vehicles (e.g., electric vehicle to electric vehicle [9]). Moreover, this energy sharing could be between some specific type of agents (e.g., mobile charger to mobile charger (*C2C*) [10]), between ordinary *nodes* (*N2N*) when they are equipped with necessary hardware (e.g., phone to phone [11]) or from specific agents to ordinary nodes (e.g., mobile charger to a sensor node [12] (*C2N*)). The scenarios considered for energy sharing in different mobile network applications are summarized in Fig. 1.

Depending on how the energy sharing is used within a specific application, it also comes with different design challenges including optimal trajectory planning, scheduling of multiple chargers as well as providing incentives for the sharing. Moreover, if wireless power transfer is used, the energy transfer efficiency should be taken into account during the development of protocols and algorithms. The consumption of the energy may also need to be optimized not just in terms of its distribution to other peers but also for the mobility of agents in some scenarios. For example, while in the case of smartphones the mobility is provided by people carrying them, in the case of mobile robots or vehicles as mobile chargers in a sensor network, the energy is also consumed for their movement, thus, a joint optimization is required.

### *1.2. Contributions*

The main contribution of this paper is to provide the first holistic and comprehensive overview on the utilization of peer-to-peer energy sharing in different applications of mobile networks. There are some surveys that specifically focus on the wireless charging technologies [13], and its utilization specifically in wireless sensor networks [14,15]. However, there is a growing number of research studies that adopt the energy sharing for several energy optimization problems in different types of mobile networks. To the best of our knowledge, there is no study that surveys the usage of energy sharing between peers in mobile networks in a comprehensive manner. Moreover, the research community utilizing the concept of energy sharing among peers are not connected and misses the opportunity to benefit from each other's findings. To this end, the goal is (i) to collect the state-of-the-art research contributions that exploit peer-to-peer energy transfer, (ii) highlight the challenges met and how they are addressed in each application and (iii) discover the open research problems for the community. The applications range from recharging of sensor nodes using a mobile charging robot [16] or from an unmanned aerial vehicle (UAV)-mounted energy transmitter [17] to balancing the energy among smartphones [18] in mobile social networks and supplying of energy needs of electric vehicles (EV) with low remaining range from electric vehicles (EV) with high and excessive range [9].

The rest of the paper is structured as follows. In Section 2, we provide a brief overview on existing methods for energy sharing among peers in a mobile network. In Section 3, we discuss on the current research trends and directions of peer-to-peer energy sharing in different mobile networks. We also provide the open research problems not addressed within each application. Finally, we conclude with a summary and suggestions to the research community in Section 4.

## 2. Energy sharing technologies

In this section, we review the various technologies and methods used to achieve energy sharing between the batteries of mobile devices in different mobile network applications. Due to its practicability and recent advances, several *wireless* charging technologies adopted recently, however, *wired* energy transfers through conductive cables or gadgets have also been considered.

Wireless power transfer (WPT) or simply wireless charging is a technology of transmitting power through the air to electrical devices for energy replenishment. There are several ways of achieving wireless charging (e.g., inductive coupling [19], magnetic resonant coupling [5] and radio frequency (RF) based charging [20]), each with advantages and disadvantages to one another. For example, RF based charging is radiative charging and uses electro-magnetic waves like RF waves and microwaves to deliver energy in the form of radiation. As it can be unsafe due to the RF exposure [21,22], it is usually offered for low-power devices like sensor nodes and medical implants [23]. Inductive coupling based charging can provide good efficiency but has a short range. Magnetic resonance coupling based wireless charging can operate at larger distances but with less efficiency. Other forms of wireless charging (e.g., ultrasound [24], or lasers [25]) are also possible but none of those approaches yet made it available for consumers while staying in the safety limits defined by FCC [22]. A comprehensive overview of the existing and emerging wireless charging technologies and their applications in wireless communication networks could be found in [13].

Wireless charging has also been utilized for energy sharing between mobile devices. However, due to the efficiency issues with wireless charging at larger distances, it has been mostly considered for sensor networks consisting of devices with low power requirements. A mobile robot or a vehicle usually charges itself and navigates to the sensors in the network to charge them. As sensor nodes are considered stable most of the time, peer-to-peer energy sharing among sensor nodes is not applicable. However, to increase the number of sensors that could be charged, energy sharing among charger vehicles [10] has been considered as an example of peer-to-peer energy sharing.

With the introduction of new generation mobile devices such as smartphones with built-in wireless charging capability, the adoption of wireless charging beyond sensor networks as well as its research has gained momentum. However, current common usage scenarios are very limited. For example, smartphone users need to place their devices on a charging pad and start charging their devices without the hassle of cables. While several additional convenience could be provided by embedding charging equipment in other things such as a desk [26] or a cup holder in a car [27], as the charging equipment still needs to be plugged into a power source, it does not really achieve an *energy sharing* as defined in this survey. Energy sharing between smartphones could indeed simply be achieved by power sharing cables [28], and power equalizer gadgets [29] in a conductive way. However, it comes with the burden of carrying such accessories. There are some recent studies [11,30] demonstrating that current wireless power transfer technologies can easily be utilized to create an on-the-go power sharing system between mobile devices. While, due to the efficiency problems this is achieved at very close distances (i.e., almost touching), it can provide the flexibility to users for finding energy ubiquitously from other users' devices.

Energy sharing between high-power mobile agents has also been studied recently. With the rise of electric vehicles (EV), charging of vehicles has been one of the major problems. Wireless charging has been considered as an option for electric vehicle charging by several means (e.g., convenient charging while parking [31], dynamic wireless charging on roads [32]). However, such solutions require heavy investment and high labor costs [33]. Recently, vehicle to vehicle charge sharing has been considered to address the immediate charge needs of vehicles especially in the absence of nearby charging stations. While wireless charging based energy sharing between EVs has been claimed with a recent study [34], there is actually no practical implementation due to aforementioned challenges and limitations. However, the possibility of energy exchange between two EVs has already been introduced to the market through different products by a few companies, such as Andromeda Power (AP) [35] and eMotorWerks (EMW) [36]. There are also recent academic efforts that focus on the development of more compact and efficient solutions [37,38]. These products provide a direct V2V charge sharing with a DC/DC converter and a charging cable that tie the batteries of both EVs through their fast charging ports. However, these products are mainly developed for the purpose of rescuing stranded vehicles. Building on top of these solutions, there is a growing number of studies that aim to solve charging problem of EVs through V2V charge sharing. However, understanding the potential benefits of such V2V charging among a network of EVs at a large scale is a challenging question, thus several specific aspects of this problem are focused on these studies. Furthermore, recent research studies also look at the utilization of Unmanned Aerial Vehicles (UAV) to solve the charging problem. Energy sharing solutions using UAVs is more effective since UAVs can hover around a large place significantly increasing the charging coverage. However, the high speed of drones and energy constraints make energy sharing a challenging problem. Moreover, due to the longer charging distances from UAVs, the charging efficiency will be lower. Thus, most research studies focus on tackling these aspects of the problem.

## 3. Mobile network applications utilizing peer-to-peer energy transfer

In this section, we provide the state-of-the-art for the utilization of peer-to-peer energy sharing in different mobile network applications, namely, (i) Wireless sensor networks (WSN), (ii) Mobile social networks (MSN), (iii) Vehicular ad hoc networks (VANET), and (iv) UAV networks.

### *3.1. Wireless Sensor Networks (WSN)*

The major mobile network application in which wireless energy transfer has been extensively utilized is wireless sensor networks. For the energy replenishment of sensor nodes, which are most of the time considered static, a mobile charging vehicle (MCV)[12] or multiple of them are used to visit and charge the sensor nodes periodically and keep them operational. Usage of static sensors can be seen in situations where sensors are hung on trees or buried underground (e.g., wildlife monitoring [39]). Mobile charging vehicles with wireless charging technology can recharge these sensors on their way. Mostly, discovering alternative optimal paths for MCVs and finding efficient charging strategies have been the problem of interest in this area. In contrast, some research also considers a scenario where a charging node is static and the mobile agents are moving around to get recharged. Mobile sensor nodes can be deployed for addressing coverage problems like sweep coverage [40] and barrier coverage [41]. Placement of static chargers and coverage without interference are some challenges to be addressed for designing these type of models. Recently, there is also an interesting scenario considered in which charger nodes collaborate and share energy with each other in order to maximize the number of sensor nodes charged. Fig. 2 shows an illustration of these different charging scenarios in wireless sensor networks.

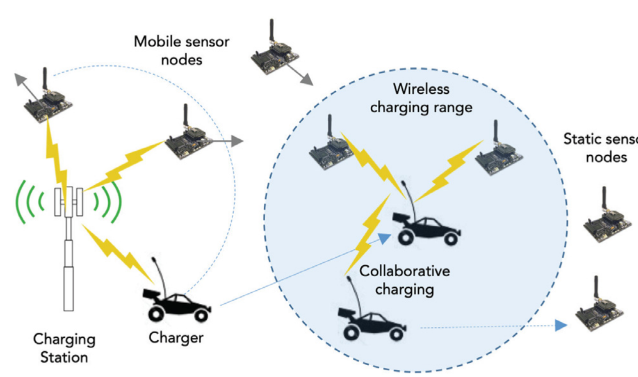


**Fig. 2.** Different scenarios of charging in wireless sensor networks: (i) A static charging station charging the mobile sensor nodes, (ii) a mobile charger vehicle charging the static nodes, and (iii) mobile chargers collaboratively charging the sensor nodes.

The research that utilize energy sharing in wireless sensor networks could be categorized in several ways. One way could be based on the mobility of the chargers. In static charger case, the sensor nodes are usually considered as mobile, however, there are some studies that also consider static sensor nodes. With mobile chargers, it is most of the time assumed that the sensor nodes are static. Another way of categorization could be based on the number of chargers employed. With single charger, most of the time the problem focuses on the optimization of a single problem (e.g., path optimization) while with multiple chargers the coordination among them is also considered. As both of these features determine the key problems studied and highly affect the performance of the proposed system, we consider both categorization together. However, due to the distribution of the literature we only consider three classes. In all of these classes, the energy transfer is considered unidirectional and from chargers to sensor nodes (i.e., C2N). Bidirectional energy transfer which takes the full advantage of peer-to-peer energy sharing is only considered among chargers (i.e., C2C) in multiple mobile charger scenario. Next, we discuss some of the key studies in each category and summarize the contributions.

#### 3.1.1. Static charger(s)

This scenario usually considers the charging of sensor nodes through energy harvesting from the static charger(s). When the sensor nodes are also assumed static, usually the electromagnetic radiation (EMR) safety issue is studied (i.e., keeping it under a certain threshold for human health) while achieving an efficient charging [42–44] of sensor nodes. Moreover, it is also jointly studied with charging task scheduling in [45] with a charging deadline for sensor nodes.

The benefit of a single static charger could be extended with multiple static chargers, however, this requires a coordination among the chargers. In [46], this has been modeled in terms of both point and path provisioning. However, the authors do not consider the potential interference problems among chargers due to the concurrent charging process. This problem is mitigated in [47,48] by providing new MAC schemes. However, in these works, the sensor nodes are only charged when they have communication requests, which may result in delay in communication. In [49], a solution is given with a system that charges sensors in advance and a genetic algorithm based near-to-optimal solution is provided.

In [50], two new protocols are provided considering either the charging efficiency or the energy balance of the chargers. They also provide results on an actual testbed in which it is shown that the charging efficiency protocol achieves higher efficiency whereas the energy balance protocol is able to supply energy to the network perpetually even if the efficiency is less. The authors also look at radiation aware wireless charging in [51] and present algorithms for deploying wireless chargers while achieving a good trade-offs between efficient charging and electro-magnetic radiation (EMR).

There are also some interesting recent works that consider different aspects. For example, in [52], the impact of mobility on the problem of efficient wireless power transfer to mobile sensor nodes is studied. A key problem in this setting is the dynamic computation of the range of the wireless charger depending on the mobility of agents. This is because even nodes move based on a random mobility model, some agents may never be recharged, thus a dynamic adjustment of the charging range is required. Another interesting extension is studied in [53] using a multi-hop charging strategy. However, this may potentially increase the loss in wireless power transfer. Thus, the authors study the optimization problem that minimizes the required chargers by taking into account the energy loss incurred during energy transfer as well as the capacity of the chargers. To this end, a shortest path tree is constructed with the charger as the root of the tree and the number of nodes in the range of the charger as its children. Multi-hop based charging is also applied for radiative based charging in [54–56] in which charging performance increase is shown over direct transfer under some specific deployment scenarios.

#### 3.1.2. Single mobile charger

This is the most common charging scenario considered in the literature for wireless sensor networks. The goal is to prolong the network lifetime by employing an MCV that will visit sensor nodes in some order and charge them (i.e., *C2N*) without depleting their energies [12,16]. The optimization problem studied is the maximization of the ratio of the MCV's vacation time (i.e., when the charging vehicle is back at the station for recharging purpose) over the cycle time (i.e., when the charging vehicle is moving around sensors). It has been shown that the optimal traveling path for the MCV is the shortest Hamiltonian path.

There are also several variations considered both in the scenario and the optimization problem. For example, in [57] a multi-node charging scheme is introduced in which multiple nodes can be charged at the same time and a near-optimal solution is obtained via a Reformulation-Linearization Technique (RLT). In [58] it is generalized to on-demand charging. However, in these works it is assumed that the mobile charger has enough energy to charge all sensors, which may not be true in reality. In [59], this drawback is addressed by converting the problem to the Traveling Salesman Problem with Neighborhoods (TSPN). In some studies this problem is also jointly studied with data gathering [60,61].

Charging from a single mobile charger has also been studied [62–65] specifically for RFID based systems consisting of RFID tags and a reader (also energy transmitter). In these scenarios, the optimal path with stopping locations and duration for the transmitter is found using several different approaches (e.g., linear programming [62]). They also differ from each other with some nuances (e.g., charging sensors above a threshold energy [62]) in their optimization settings.

Most of these works, however, study the offline scheduling problem, that is, the traveling path of the MCV is usually calculated in advance under given optimization goals. However, offline scheduling may not perfectly align with the energy demand and supply due to unpredictable energy consumption in real life scenarios and may cause performance degradation. To address this, in some studies [66–68], online or on-demand mobile charging problem, where the sensors request charging from the MCV only when their energy runs low, has been studied. Another interesting direction followed by some studies [69,70] is the relaxation of fully charging requirement when an MCV visits a sensor node. Instead, a partial [69] or a mixed [70] partial and full charge model is used in order to reduce traveling cost and increase survival rate of sensors.

#### 3.1.3. Multiple mobile chargers

The problems studied with a single mobile charger can naturally be extended with the usage of multiple chargers to take the advantage of parallel charging process. For example, the charging scheduling problem of multiple MCVs with the goal of minimizing the total traveling distance has been studied in [71]. In other works, different objectives (e.g., optimal charging and routing [72], minimum charger count [73]) as well as different limitations (e.g., velocity control of MCVs [74], itinerary selection [75]) are considered to find the solution in different scenarios. Some studies have also considered joint optimization of multiple objectives (e.g., optimal scheduling, moving time and charging time [76]).

Besides these works in which peer-to-peer energy only considered in one way (i.e., charging of sensors from special charger devices or *C2N*), some recent studies [10,77–82] have considered bidirectional energy sharing between chargers (i.e., *C2C*) to increase the charging performance. Multiple chargers are used to replenish static sensor nodes but the chargers also collaborate with each other by exchanging energy during their trips to make the charging process more energy efficient. It has been shown that such a collaborative approach can help charge more sensors under a given total energy capacity of chargers [10,77]. In [80], a new concept of *shuttling* is introduced and the minimum number of chargers needed for a given charging problem is found with an additional proven guarantee of minimum energy consumption. On the other hand, the major drawback in these methods is the large traveling cost of chargers as they need to go back and forth between a charging station and sensors. In order to address this, a hierarchical charging model is introduced in [78], with two kinds of chargers, where one type charges the nodes only while the other type charges these node-chargers. While this approach is targeted to achieve scalability and flexibility, it fails in addressing the situations in which only a node-charger is present in the area with many sensor nodes in need of energy, thus no energy can be supplied.

To address that drawback, in [81], a game theoretical collaborative charging system is developed converting the problem into a collaborative game taken between chargers. This enables a dynamic decision process for chargers to charge a node or another charger and lets the chargers pursue for the maximum profit when fulfilling charging tasks. As a result, a better charging performance is obtained. On the other hand, this study does not consider a limit on the chargers' energy capacity which may not allow them to able to charge the distant sensors. In order to address this, a hop-based mobile charging policy is introduced in [82] to minimize the charger count while considering the sensors' unbalanced energy consumption rates and the limited energy capacity of chargers. By dividing the network into several circular regions according to nodes' energy consumption, the number of chargers is aimed to be minimized and an integer linear programming (ILP) based solution is provided. In another interesting study [83], the dispatching of a charging vehicle that carry multiple low-cost removable chargers is also proposed to reduce the unnecessary travel by multiple chargers. Moreover, in a recent study [84], the charging of sensors from the smartphones of the users has been studied following a crowdsourcing approach and several solutions for allocation of mobile users to optimize the total charging quality of all sensors are proposed.

### 3.1.4. Open problems

Table 1 provides a summary of major research problems studied using peer-to-peer energy sharing in wireless sensor networks. While several aspects of charging have been covered in these networks, there are still some open problems that are not addressed yet. Some of them are discussed below.

*Mobile chargers charging mobile nodes:* One of the missing scenarios in literature is the charging of mobile sensor nodes from mobile chargers. Such situations may apply to sensor deployments in dynamic environments such as underwater sensor networks [85]. There are a few works [86,87] that consider harvesting in underwater sensor networks, however, a general model for such environments is still an open problem.

*Online collaborative charging:* Existing studies on collaborative charging usually take the periodical and deterministic approach, without considering the online requests dynamically. However, in real deployments the nodes may demand energy continuously and their demands may not be predicted due to the uncertainty in environments. To address this research gap, the routes as well as the energy sharing decisions both among chargers and with nodes should be determined dynamically and distributedly.

**Table 1**
An overview of current research using energy sharing in WSNs.

| Scenario | Research problems<br>(Common objective: network energy replenishment) |
|---|---|
| Static charger(s) | • Radiation-aware charging [42–44,51,52]<br>• Interference-aware charging [47,48,50]<br>• Multi-hop charging [53–56] |
| Single mobile charger | • Charger route optimization [12,16,62–65]<br>• Multi-node charging [57,59]<br>• On-demand charging [58,66–68]<br>• Partial charging [69,70] |
| Multiple mobile chargers | • Charger scheduling [71,72,74,75]<br>• Optimal charger count [73]<br>• Collaborative charging [10,78–82] |

### 3.2. Mobile Social Networks (MSN)

With the proliferation of mobile devices used by people, a new form of networking, called mobile social networks (MSN) [88], has appeared. The unique feature of these networks is the mobility of the nodes, which is provided freely (i.e., without energy consumption from their batteries) by humans carrying them. Moreover, thanks to the growing peer-to-peer communication technologies (e.g., Bluetooth Low Energy (BLE), WiFi Direct), these devices can talk to each other when they are within the wireless ranges of each other. However, most of the time, this type of interaction is determined by the social relations of people carrying these types. Leveraging these properties of MSNs, many studies have been conducted focusing on different problems such as opportunistic routing [89,90], friend discovery [91] and user tracking [92].

One bottleneck in the operation of these complicated mobile devices (e.g., smartphones) constituting the MSNs is their limited battery capacity. They struggle to reconcile their increasing capabilities with their battery lives. While there are ways to optimize the use of battery [93,94] in mobile devices, the need of frequent charging of these devices by their users to keep them operational is inevitable. However, charging facilities may not be continuously accessible (e.g., when the user is outside). In response to this, for example, some crowdsourcing based apps are developed to find out the nearest available plugs (e.g., ChargeItSpot [95], Airport Power [96]). Alternatively, external power banks [97], solar chargers [98] or other eco-friendly chargers like mobile hand generators [99] are also considered but they provide limited solutions in practice and come with the cost of carrying additional accessories.

To provide a more comprehensive solution, opportunistic peer-to-peer energy sharing among mobile devices is considered recently (see Fig. 3). That is, users with high energy in their devices (i.e., recently charged) can share energy with other user devices

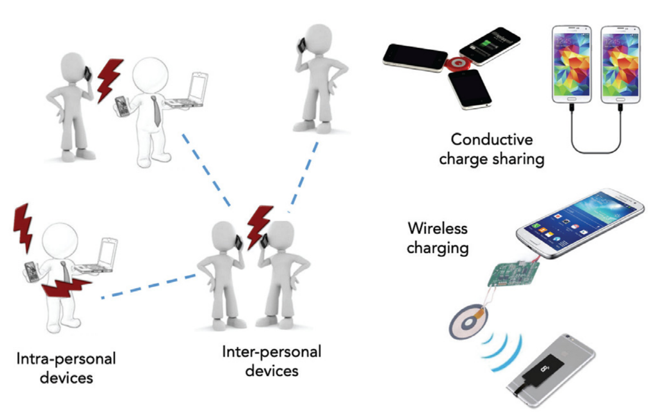


**Fig. 3.** Energy sharing scenarios in a mobile social network consisting of smart mobile devices. The energy sharing could be achieved in a conductive manner via a sharing cable or a gadget or through near-field wireless power transfer.

(i.e., N2N) having less energy and can consider getting it back in another time when they need. This brings flexibility to users for finding power ubiquitously and can potentially mitigate the risks of facing an emergency situation with depleted battery. Conductive energy sharing solutions could be considered but with the increasing number of mobile devices that have built-in wireless charging feature, this could be achieved in a more convenient way. While the current wireless charging application on commercial mobile devices is considered from charging pads and unidirectional only, in some recent studies [11,30] prototype systems managing and controlling bidirectional energy exchange among mobile phones are presented.

Recently, there is a growing number of studies that utilizes the peer-to-peer energy sharing in mobile social networks. We categorize them based on the objective of the research. Below, we first overview the studies in each category, then provide open problems not addressed yet.

#### 3.2.1. Optimal energy usage

The studies in this group aim to take the advantage of opportunistic interaction of nodes in a mobile social network for energy sharing. Their goal is to optimize the energy usage at nodes in general but different approaches are considered. Some studies aim to reduce the burden of frequent charging of mobile devices from charging stations, and some aim to keep the devices functional as long as possible. Users can share energy when they travel and encounter each other such that mobile users don't run out of energy on the way or before reaching to its charging point. Thus, to maximize the benefit from opportunistic energy sharing, not only the mobility and encounter patterns of users but also energy levels of the user devices' batteries at their encounter times should be taken into account.

In [100,101] a constrained Markov decision process is used to formulate the optimal energy sharing policy that minimizes the energy outage probability. Users are ranked based on the potential mutual benefits to each other in terms of shareable energy and the best pairs of nodes are found using stable matching. However, this concept is studied without an integrated analysis of charging habits of individual user devices and meeting patterns between the users that can exchange energy. To address this, in [102], the limits of energy sharing among mobile devices is investigated by analyzing the current charging patterns and the social interactions between these mobile users. The nodes are paired as *power buddies* and energy sharing is achieved only among them similar to [101]. Interestingly, this model is able to show that these power buddies can provide a good percentage of energy needs allowing users to delay their charging decisions and increase average charging cycle duration. Following a similar concept, [103] and [104] also focus on finding the potential of peer-to-peer energy sharing to reduce the burden of traditional cord-based charging process. The burden of charging is defined in terms of the number of periods that the devices stay plugged to the outlet (i.e., wall charging). The study aims to minimize the number of these periods exploiting the energy shared by other users without changing the charging habits of any user and while keeping the device's energy more than a threshold value. Utilizing a dynamic programming [105] approach, optimal energy sharing and skip patterns are found in a deterministic manner to show the potential energy saving with peer-to-peer energy sharing. They also utilize real mobility traces and an Android log dataset that contains battery information to analyze the potential benefits in a real setting. In [106], a group-based charging system is introduced and assuming two separate battery units at nodes, the burden of charging is given to only some lead nodes who are responsible for charging their second units overnight and providing energy during the day to others.

#### 3.2.2. Energy distribution for balancing

One important problem studied exploiting peer-to-peer energy sharing in mobile social networks is to distribute the available energy in a desirable way. Mostly, the goal of such distribution is to achieve the energy balance in the network or to reach a certain target energy distribution. However, the distributed cooperation of the nodes towards collectively achieving global computational and communication goals can be challenging. In this effort, some studies offer peer-to-peer energy exchange between agents to achieve approximate *energy balance* [18,107–109] in the network with minimum energy loss whereas some advocates on constructing a *network structure* [18,110,111], basically a star structure to reach a desired energy distribution in the network. Next, we discuss these approaches, respectively.

Energy balancing can provide efficient utilization of scarce energy in mobile social networks and can prolong the network lifetime (e.g., especially when network lifetime is defined as the duration until the first node dies). Distributing energy such that each node in the network has access to similar level of energy or energy proportional to its weight (e.g., importance in the network) can be thought of a fair way of collaboration among mobile users in efficient utilization of energy resource. Studies focusing on energy balance mostly investigate on interactive, peer-to-peer wireless energy exchange in populations of resource limited mobile agents, without use of any special chargers with the main goal of achieving the energy balance among the mobile nodes [18,107–109].

In these works, it is assumed that the agents are capable of achieving bi-directional wireless energy transfer acting both as energy transmitters and receivers. Both loss-less and lossy cases are considered for energy sharing where the energy loss follows a fixed linear law. Under these assumptions, various interaction protocols are proposed that will achieve the energy balance. These include sharing half of the available energy or only a small amount of energy. When the average of the available energy in the network is also known, more smart sharing rules such as sharing between the agents on the opposite sides of the average, are also considered to speed up the convergence. There are also weighted versions of these protocols considered when the significance of nodes are not the same. In a more recent study [112], it has been shown that sharing of energy in every opportunistic meeting of opposite side nodes will result in unnecessary energy loss during the energy balancing process. Thus, new algorithms that define the opposite side nodes based on the final achievable optimal energy balance in the network and let one of the encountered nodes reach that balance immediately have been proposed. As in networks with heterogeneous node relations, not all nodes may reach the same energy balance, in a follow up study [113], a Mixed Integer Linear Programming (MILP) based model is used to compute the optimal possible energy balance and new algorithms that consider this balance and the limitations in node relations have been proposed. Through real dataset based simulations, it has been shown that the proposed protocols can reach the optimal possible balance quickly and with less energy loss than previous algorithms. Another recent study [114] also suggests on utilizing the online social information to enhance the wireless crowd charging process. In fact, they make use of available self-reported online social network data of groups of people and propose wireless crowd charging protocol with the goal of balancing the available energy among the mobile users in the crowd with minimum loss.

Energy distribution among peers has also been studied [18,110,111] within a network formation problem considering the roles of the nodes and their energy needs. For example, in a star topology, nodes are organized in a cluster, and a cluster head is selected to which all communication is forwarded. In view of this, the fair distribution of energy in the network could be when the energy level of the cluster head is proportional to the number of mobile nodes in its cluster. In networks, where the central agent knows the number of actual peripheral nodes, this could be easily managed by finding the proportional energy needs of nodes, however, this may not be the case always in practice. Thus, naive (e.g., transferring all or half of the energy from the peripheral nodes to the central node) solutions are simply adopted mostly favoring the heavy-duty nodes such as cluster heads. Similarly, [111] proposes construction of binary and arbitrary trees to achieve different energy distributions in the network. Here, the authors also provide and evaluate several energy distribution protocols that exploit different levels of knowledge to achieve the desired distribution of energy in the network.

Apart from these works, there is also an interesting work [115], which studies the fair charging of smartphones (e.g., balancing energy distribution based on their current energies) from the wireless chargers deployed at subways (i.e., C2N). This study applies a similar uni-directional charging model as considered in WSNs and aims to increase the energy gain by making the phones charged from the closest chargers during the passengers' trip times.

### 3.2.3. Energy sharing for content delivery

There is a group of studies that exploits energy sharing in the context of content delivery in sparsely connected mobile networks such as Delay Tolerant Networks (DTN) [116] or Mobile Social Networks (MSN). The communication between the nodes in such networks is achieved in opportunistic manner. That is, when a source node has a message to send to a destination node, the message is forwarded or copied to other nodes in the network with some decision rationale [116–119] to achieve the minimum possible delay. Then, the message is stored in the relay node, carried until another better relay node or destination node is met and forwarded again. While routing is the main problem studied in such networks, as the nodes in these networks require energy for storing, carrying and forwarding the message contents to other nodes in the network, energy management is also a major issue. Thus, there are many studies that aim to develop energy efficient routing protocols. Besides these works, recently several studies have considered the scenario in which a mobile user transfers not only the content but also energy (see Fig. 4) to intermediate users [120–122], as an incentive to them to carry this content to the destination. However, this makes the problem more challenging as the nodes need to determine not only the forwarding of the content but also the amount of energy to be given to relay nodes.

Several approaches are adopted in the literature to address this challenging problem. In [120], the problem is formulated using a Markov decision process (MDP) based on the contact state of content source to obtain the optimal energy sharing policy. The content source moves and visits a charger to receive energy and when it meets with a messenger (e.g., relay), asks for the delivery of the content to the destination node by sharing some energy to the messenger. If the energy depletes before reaching to the destination, the content is discarded by the messenger. MDP is used to carefully select a messenger node and transfer optimal energy so that the content is delivered to the destination with highest probability. Extending this study in [123] the authors show that the optimal strategy obtained by MDP is a threshold policy. In order to avoid the cumbersome of centralized solutions and achieve a decentralized decision policy, authors also formulate the problem using a decentralized partially observable Markov decision process with constraints and a decentralized learning algorithm is proposed to obtain an optimal local policy at nodes [124].

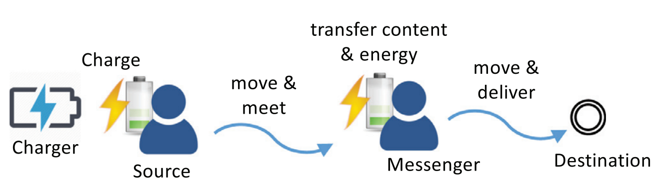


**Fig. 4.** Source node charges itself at a charger and when it meets with a messenger offering better delivery option for its message to a specific destination, it transfers the message as well as the sufficient energy for the messenger to carry it to the destination.

The interaction between the source and the messenger nodes has also been modeled using game theoretical models in several studies. In [121] the peer-to-peer relations between mobile nodes is exploited to form a coalition to help one another on delivering packets. They also look at the cases when these coalitions might not be beneficial and some nodes might decide to deviate away from the coalition. A different approach based on forming a non-cooperative game model is considered in [122]. The source node holds an auction for wireless energy and the nodes send their bids for it. In return of service, the nodes have to pay certain cost to the source. A stochastic dynamic response algorithm that allows nodes to adapt their strategies to the Nash Equilibrium is presented and proved to be the optimal policy. In a recent study [125], energy sharing among relay nodes is also considered and an Optimal Stopping Theory (OST) based solution is proposed. The results show that energy sharing based content delivery can potentially increase the delivery performance.

Different than the focus of the aforementioned works, in [126], a charging-aware mobility model is studied to integrate the charging needs of mobile nodes during their mobility. To this end, nodes are motivated to move towards energy sources when they have low energies while they are motivated to move towards the destination node when they have sufficiently high energy. Moreover, as the deadline for delivery gets close, the weight for moving towards destination increases to achieve timely delivery. It has been shown that this approach lets the nodes maintain high energy and achieve better packet delivery ratios depending on the location and the number of charger nodes in the network.

### 3.2.4. Open problems

The summary of the current work using peer-to-peer energy sharing in mobile social networks is given in Table 2. However, there are still many open challenges not addressed yet in current research.

*Interest/social relation aware energy balancing*: The problem of energy balancing has been studied in several aspects but these works assume that the nodes in the network interact randomly. However, in practice, the interaction patterns of different pairs might be totally different. Moreover, some nodes may act selfishly and deviate from the collaboration significantly diverging the stability of the system. Thus, designing protocols considering the heterogeneous node relations and differences in their interests is still an open research problem.

*Reactive charging with controlled mobility*: The notion of energy sharing in MSNs has been considered mostly in uncontrolled mode as the mobility of devices is maintained by the humans carrying the devices. While this is an advantage compared to other networking scenarios in which the mobility also causes energy consumption on the mobile nodes, it makes the energy sharing possible only opportunistically, i.e., when nodes encounter. A more interesting scenario could be when the mobility of the agents are controllable at least partially through incentives.

*Incentive Models.* In most works, it is assumed that the nodes are motivated to share energy between each other. However, users may need incentives (e.g., money, credit) for energy sharing with others, otherwise sharing of energy can be restricted to among friends or within family members. This may also help address the privacy concerns of users as the process of transferring energy be-

**Table 2**
A summary of current research using energy sharing in mobile social networks.

| Research Objective | Key features |
| --- | --- |
| Optimal Energy Usage [100–104,106] | • Limits the energy sharing only among assigned pairs.<br>• Allows opportunistic energy exchange at meeting times only.<br>• Aims to reduce traditional charging from outlets by benefiting from others' energy. |
| Energy Distribution for Balancing [18,107–114] | • Energy is shared in certain (e.g., half, small amount) portions between all or some (e.g., in the opposite sides of average network energy) of the interacting nodes.<br>• Roles of nodes within a network formation problem is jointly considered for a weighted distribution.<br>• Final achievable optimal energy balance is computed for networks with homogeneous and heterogeneous node relations.<br>• Online social information is utilized for wireless crowd charging. |
| Energy Sharing for Content Delivery [120–126] | • Energy is provided to relay nodes to carry content to destination.<br>• Optimal amount of energy to be transmitted is determined jointly with the decision of forwarding. |

tween mobile devices require them be in close proximity of each other and can reveal some sensitive information.

*Long-distance charging*: In the current form, wireless energy sharing has been mostly considered between the devices that are within close-proximity of each other ($<1$ cm). While it is possible to charge sensor networks at higher distances, due to the higher power requirements of smartphone like devices (e.g., 5–10 W h [127]), it cannot be applied directly. In some recent studies [128,129] it has been shown that long distance charging for such devices is possible through beamforming the magnetic field. Moreover, when it is applied to multiple devices simultaneously, an increasing efficiency could be achieved (e.g., 6 devices at distances of up to 50 cm). However, such concept has not been considered for peer-to-peer energy sharing which could be challenging but can provide more flexibility.

*Multi-hop energy/content sharing.* Utilizing energy as a payoff to the service of carrier nodes has currently been considered only for two-hop delivery. That is, the source node decides and waits for the best carrier node, transfers the appropriate energy and content, and waits for the delivery by that carrier. However, in a more realistic setting, carrier nodes can also distribute this energy and content to other relay nodes, thus a multi-hop joint energy and content sharing strategy has yet to be developed.

### 3.3. Vehicular Ad-hoc Networks (VANET)

Electric vehicles (EVs) have received increasing attention in the past decade because of their potential to provide a sustainable and eco-friendly alternative transportation system. They can help realize the foundation of smart and green cities of the future, thus, auto-manufacturers have been increasingly introducing new models with competitive prices.

Despite such excitement and potential about EVs, there are still challenges that need to be addressed for the widespread adoption of EVs by consumers. These include relatively smaller driving ranges, longer duration for charging, and non-ubiquity of charging stations. There are several interesting solutions proposed recently such as dynamic/stationary wireless charging [130–132], and fast charging [133] but they most of the time require heavy investment and high labor costs.

Recently, an alternative approach based on the exchange of energy between EVs has been studied. The vehicle-to-vehicle (V2V) charging[35,37,134] is realized through discharging of energy (as in V2G operation) from the battery of one EV (thanks to the bidirectional chargers), and supplying the energy to the other EV's battery. While the concept of energy sharing will also apply to the cases when a AAA truck [135] comes and provides a charging service to a stranded EV (i.e., *C2N*), research community has mainly focused on the V2V charging between the actual EVs (i.e., *N2N*). The V2V charging aims to connect EVs having excessive electric energy on their boards with the EVs in need of charge. This can provide more flexibility to EV charging by releasing the obligation of charging from grid-connected stations. Note that there are also other forms of peer-to-peer energy sharing between vehicles.

Note that due to efficiency and high amount of energy needs, the V2V energy transfer has been realized in a conductive way through the connection of the EVs via cables. This is different from the form of peer-to-peer energy transfer (i.e., wireless) in other networking applications. While there are a few studies [34] that consider wireless power transfer based energy exchanges between EVs, they do not provide much details on how this could be realized in practice efficiently and mostly focus on the theoretical problems with some assumptions.

There are two different forms assumed for the conductive V2V charging in the literature: (i) Infrastructure-dependent and (ii) infrastructure-free. In the former, as it is illustrated in Fig. 5, it is assumed that the transfer between vehicles happen at pre-installed stations (with connection to grid) or swapping centers (without connection to grid). On the other hand, in the infrastructure-free case, a charging cable and a DC/DC converter is used to transfer energy between vehicles directly at any location. Fig. 6 shows an example of this scenario, where the charging process is also controlled via a mobile app.

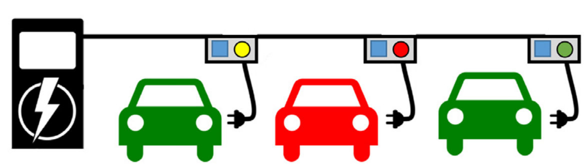

**Fig. 5. Infrastructure-dependent case:** Peer-to-peer energy exchange between electric vehicles at a local charging/swapping station.

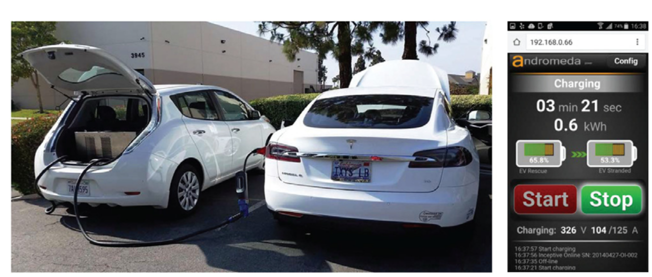


**Fig. 6. Infrastructure-free case:** Electric vehicles can exchange energy anywhere through a DC/DC converter and a conductive charging cable. A mobile app communicates with both vehicles and lets the drivers control the charging process [35,141].

In the infrastructure-dependent case, the energy sharing between vehicles has been considered in different scenarios. In a set of studies [136–138], it is considered to happen at regular charging stations for temporary sharing of energy between EVs to benefit from the flexibility on the charging requirements of EVs, and reduce charging costs. For example, an EV with a later deadline to be charged is discharged initially to provide energy to the other EVs connected to the same station and charged later without passing the charging deadline. In another set of studies [9,139,140], it is assumed that there are some pre-installed designated parking lots in which an aggregator, a control device that collects all information from EVs and the grid status and executes the V2V operation [134], coordinates the charging and discharging of a group of EVs connected to it through V2V transfer without directly drawing power from the grid. However, in both of these forms, there is still a requirement of pre-installing such an infrastructure.

In the infrastructure-free case, a more flexible (e.g., anywhere, anytime) and less costly way for V2V charging is achieved through a direct V2V charge sharing with a DC/DC converter that ties both EV batteries through their fast charging ports. The studies [9,142,143] working under this form of V2V charging, then mostly focus on forming a Vehicular Ad hoc Network (VANET) based communication framework [142] between EVs and developing efficient [9] and secure [143] matching of demander and supplier EVs within their spatio-temporal constraints.

Next, we look at the specific research problems under these different forms of V2V charging and discuss the details of various proposed solutions.

### 3.3.1. Charging price control

There are several works [136–138] that aim to leverage V2V charging for the optimization of charging costs. To this end, they study the optimal charging scheduling of multiple EVs at a charging station (i.e., with grid connectivity) to reduce the charging cost while meeting the charging requirements. The EVs with far charging deadlines are initially discharged to provide energy to other EVs connected to the station to avoid high electricity prices from the grid and charged later at a lower rate while still meeting the deadline for charging. In [140,144], a semi-distributed V2V charging strategy is developed for electric vehicles exchanging energy at a swapping station (i.e., no grid connectivity). While the prices are determined at the swapping center in a centralized manner, charging decisions are made by individual vehicles in a distributed way. However, the study focuses on price control at a single swapping station and does not provide a scalable solution. In [145], spatio-temporal dynamics of such a system is also considered and revenue maximization for supplying EVs and charging cost minimization for demanding EVs are studied. The price control strategy is modeled using Oligopoly game and the charging coordination among all vehicles is formulated as a time-coupled mixed-integer non-linear programming (MINLP) under a given price. Similarly, in [139], a peer-to-peer energy trading system is developed between electric vehicles and a more realistic evaluation is conducted using the data-driven mobility model for vehicles in Belgium's Flanders region. The results in these studies in general show that more EVs could be charged at lower prices thanks to the local trading between EVs.

### 3.3.2. Supplier/demander matching

In V2V charging, one significant challenge is how to match the demander EVs and supplier EVs efficiently. In some studies [142] this is simply handled via first come first serve manner. However, this could be inefficient and can result in unnecessary traveling costs for the users. Thus, in several studies different efficient matching algorithms are proposed. These algorithms could mainly be categorized under two different goals. In the first group of studies, a system-oriented optimization is aimed in terms of several metrics such as total traveling distances [145–147] or social welfare [9]. In the second group [9,148], the matching problem is targeted from individual user's point of view, and preferences of each user are considered in the matching process. Then, a matching making all users satisfied with their assignments is found by adopting stable matching algorithms from economic context. In some of these works [139,146], the impact of commuting patterns of EV drivers, and city (transportation and charging) infrastructure is also realistically modeled in order to understand the true benefits of V2V charging under spatio-temporal constraints. In a recent study [147], the performance of these two algorithmic approaches have also been compared using real data based simulations in three US metro areas and the pros and cons of each are discussed.

### 3.3.3. Security and privacy management

As there is an interaction between multiple parties in V2V charging context, the security and privacy of EV owners should also be modeled properly. For example, with a long-term analysis of charging schedules and information exchanges, users' driving patterns could be exposed. This may then hinder the successful application of V2V charging as users see privacy as an important human right when using technology [149]. To address these concerns, several privacy-preserving and secure solutions are proposed for different aspects of V2V charging.

In [150,151], a localized P2P electricity trading system among EVs is proposed using consortium blockchains. An iterative double auction based mechanism is also used to optimize electricity pricing and the amount of traded electricity among vehicles, with a goal of maximizing social welfare while protecting privacy of EVs. Similarly, a payment network formation based on bitcoin is studied between electric vehicles [152]. The privacy concerns should also be considered during the matching process. Thus, in some studies privacy-preserving matching algorithms are developed. For example, in [143] an efficient and privacy preserving matching is proposed through utilization of bichromatic nearest neighbor based assignments and partially homomorphic encryptions. During the V2V charging operation, there may also be a need to authenticate each other before they actually start charge sharing. This has been addressed in [153] and a distributed Diffie-Hellman (DH) based authentication protocol is proposed.

### 3.3.4. Open problems

Table 3 provides a summary of the key contributions in the literature studying V2V energy sharing. While many different problems have been studied, the topic is still in its infancy and there are many open issues. Below, we discuss some of the potential new research directions in this area.

*Sharing economy based modelling of V2V charging:* Similar to other sharing economy based applications (e.g., Uber, AirBNB), V2V charge suppliers could help supplying the demands of EVs in need of charge, without building new charging stations. This can reduce infrastructure costs and provide business opportunities to V2V charge suppliers. On the other hand, there will be more and fast deterioration in the batteries of their vehicles due to increased energy cycling on the batteries. Thus, this problem has to be analyzed in a holistic manner and corresponding parameters (e.g., energy price) has to be carefully determined to have a sustainable system.

*Demand response management via V2V charge sharing:* V2V charging can potentially be utilized to shift the peak-time power demands to off-peak times in coordination with the grid operator. V2V suppliers can be provided incentives to adopt delayed charging strategies (e.g., after midnight) and can provide on-demand charging service to the EVs in need of charge during peak times.

**Table 3**
Summary of research studying peer-to-peer energy sharing between electric vehicles.

| Research objective | Key features |
|---|---|
| Charging price control [136–140,144] | • Develops local markets and aims to reduce charging costs and impact to the grid.<br>• Differentiates by local and global price modeling. |
| Supplier/emander atching [9,142,145–148] | • System level optimization is aimed using bipartite matching based solutions.<br>• User participation and satisfaction is aimed using stable matching based solutions. |
| Security and privacy management [143,150–153] | • Multiple aspects of V2V charging are studied including authentication and matching.<br>• New technologies such as blockchain and payment networks are utilized. |

This can help reduce the stress on the grid, however, there are challenges that need to be addressed such as the amount of incentives and management of such a system.

### *3.4. Unmanned Aerial Vehicle (UAV) networks*

Unmanned aerial vehicles (UAVs), which are also known as drones, have recently found many promising usages in our society thanks to many advantages they offer such as high mobility and flexible deployment associated with low costs. They have been used for various applications including surveillance for public safety [154], search and rescue operations [155], agricultural purposes [156], providing/extending communication (e.g., Facebook Aquila [157]) and data collection from IoT devices [158] or sensor networks.

There have been many works in the literature utilizing UAVs for facilitating different operations in these aforementioned applications. Beyond these works, there are also studies [17,159,160] that aim to benefit from UAVs for recharging of low-power Internet-of-things (IoT) devices such as sensors and tags. Such a service could be invaluable especially in remote and hard to access locations [161], which UAVs can easily reach. UAVs are assumed to be equipped with various forms of wireless power transmitters and charge the ground sensors or IoT devices having wireless power receiving capabilities. In other words, a uni-directional (from UAVs to sensors) energy sharing is assumed as in the case of mobile charging vehicles (MCV) used in the charging of wireless sensor networks (i.e., *C2N*). However, UAVs as MCVs, provide additional benefits over standard ground MCVs, while having some constraints. For example, a UAV can move in 3D space and can jump or fly over obstacles, which could be a significant limiting factor for ground MCVs. On the other hand, using UAVs in the charging of sensors brings additional challenges as UAVs run on batteries and flying and hovering is more costly than moving on the ground. Moreover, most of the time, the charging is assumed to happen in longer distances, which heavily affects the charging efficiency at the receivers on the ground. To address these challenges, there have been several solutions proposed recently in a growing number of studies. These solutions mostly differ in terms of the optimization goals in specific use cases and the assumptions made for the environment (see Fig. 7).

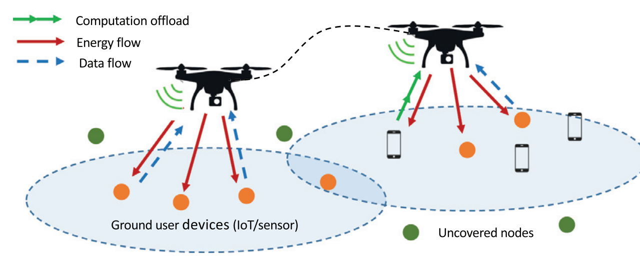


**Fig. 7.** UAV-equipped transmitters charge the ground devices considering their trajectory and energy limits. They are also considered jointly for optimization of communication needs and computation offloads from the devices.

#### *3.4.1. Network energy replenishment*

In several works, the main objective is to supply the necessary energy to ground devices by finding the optimal trajectories of UAVs including the hovering locations and the actual paths. For example, in [17] the maximization of the sum of the energy received by all ground energy receivers is aimed by optimizing the UAV's trajectory which is subject to its maximum speed constraint. The authors show that UAV should hover over a set of fixed locations with optimal hovering time allocations among them. It is also observed that when the distance between two receivers is smaller than a certain threshold, the pareto boundary region is obtained but when this distance is larger, to obtain the boundary of the energy region, the UAV needs to hover and fly between two different locations above the line connecting them [159]. Optimal hovering location is also studied in [162] in order to improve the stability and reliability of wireless sensor networks in emergency areas and reduce the maintenance costs. It is assumed that there are separate UAV energy points and UAV information points and a centralized algorithm is developed to determine the optimal UAV hovering positions for each service group of sensors. Similarly, in [163] minimization of the number of drone positions by adjusting the altitude of drones is studied before drones are out of charge. A time-efficient heuristic with low computation costs is developed and close-to-optimal results are obtained with significant performance gains. A more generalized coordinated charging problem with heterogeneous chargers in a three-dimensional space is also studied in [160]. The problem is formulated as a minimum total sleep time problem with the goal of ensuring network functionality by minimizing the total sleep time of sensors. There are also some works that model the problem as a joint optimization problem considering the other characteristics of sensor networks. For example, in [164], recharging of sensors on a bridge is jointly studied with the optimal selection of the sink node to improve the network lifetime. Similarly, in a recent study [165], the schedules of UAVs are determined considering both sensing coverage of the area (i.e., moving to an area not covered by sensors) and the charging needs of the sensors and heuristic scheduling algorithms that target both goals have been proposed.

As a UAV provides energy to sensor nodes, sensor nodes can provide more data back to the UAV. However, the more energy provided to sensor nodes, the shorter trip time it gets, resulting in low coverage of the area. This dilemma between data gathering and recharging ground IoT devices is studied in [166] by modeling the battery level of the devices as a birth and death process depending on the device activity rate. An optimal scheduling algorithm is defined based on the data sensitivity or energy requirements of nodes modeling it as a traveling salesman problem within a certain time window. The energy constraints of the UAVs while recharging the sensor nodes are also studied in a route association problem [167]. The selection of routes and the associated sensor nodes to be charged are discovered using a greedy algorithm with the goal of maximizing the overall charging coverage utility for a multi-drone wireless charging system.

Most of these works, however, assume that there is a central authority, which has the full knowledge of the ground nodes' power levels so that it can identify the nodes to charge easily and control the UAV accordingly. However, collecting this power information adds overhead to the network and limits scalability. Thus, in some studies [168,169] this assumption is relaxed and solutions with partial or no prior knowledge are presented. For example, in [168], the charging of sensor networks with UAVs has been studied with no knowledge of sensor nodes' power levels and without fully exploring the network. Thus, a probabilistic stopping and charging algorithm is used based on the observed power levels of sensors during the flight of the UAV. However, this study is limited as it assumes a line topology and does not fully benefit from the three dimensional movement capabilities of UAVs.

#### 3.4.2. Wirelessly-powered communication

There is a group of studies that specifically focus on the optimization of communication needs of ground devices that can receive energy from the UAVs. We consider them under a different category as they focus on throughput maximization from devices rather than just recharging of devices. For example, in [170], the authors aim to find the optimal hovering locations in order to maximize the uplink common throughput of a TDMA-based system over a certain UAV flight period with given UAV speed constraints. In a similar study [171], the maximization of the system's minimum throughput performance is aimed by jointly considering the UAV trajectory, uplink power, and time resources. Such an energy harvesting based communication approach is also studied specifically for device-to-device (D2D) communication pairs [172] using a static UAV deployed at varying altitudes with a similar goal of maximizing the average throughput within a time window while satisfying the energy constraints of devices under a generalized harvest-transmit-store model. In [173], weighted harvest-then-transmit model is introduced as far-apart nodes from the UAV cannot harvest energy as the near ones and require more energy for the same throughput due to distance-dependent signal attenuation (known as doubly near-far problem). To this end, UAVs are modeled to perform weighted energy transfer in order to receive information from all nodes properly. This problem is also studied jointly with other problems in IoT networks. For example, in [174] a new system for wirelessly-powered public safety IoT devices is proposed to improve the energy efficiency for distributed non-orthogonal multiple access (NOMA) together with the optimal role assignments (e.g., head, member) of IoT devices in a coalition. A game-theoretic approach is adopted to determine the optimal uplink transmission power of IoT devices while a reinforcement learning based technique is used for better coalition formations.

#### 3.4.3. Wirelessly-powered mobile edge computing

There is also a few recent works that study efficient mobile edge computing (MEC) models using wireless energy transfer from UAVs. MEC enables mobile devices to offload partial or all of their computation-intensive tasks to MEC servers that locate at the edge of the wireless networks. MEC and wireless power transfer (WPT) in conjunction can be promising in enhancing the computational capability and prolonging the life time of low-powered wireless devices. In this setting, the UAVs not only charge ground users but also provide computation service to them. While the computation performance will be limited due to limited flight time, this can be a significant service especially in remote and rural environments or disaster areas. In one of the first studies [175] that looks at the resource allocation problem in such a setting, the problem is modeled under both partial computation offloading mode, where the mobile nodes only offload part of the computation to the MEC servers and binary computation mode, where the computation task is either done locally or completely offloaded. Considering the harvesting constraints and the maximum speed of UAVs, different multi-stage algorithms are proposed for these two modes to maximize the weighted sum computation bits by jointly optimizing the CPU frequencies, the offloading times and the transmit powers of users as well as the UAV trajectory. In another work [176], a different system model based on cooperation of nodes is presented to improve the computation performance of active devices. That is, the idle devices are considered as helper nodes and modeled to use their harvested energy from UAV to help active nodes for their computation needs while staying within their energy constraints. The proposed system specifically aims to maximize the computation rate by jointly optimizing the transmit energy at the UAV and the communication and computation resource allocations at both the active users and helpers (i.e., idle users). Optimal solution is found by leveraging the Lagrange duality method and simulation results are provided showing the improved computation rate for users. In another recent work [177], a time division multiple access (TDMA) based resource and workflow scheduling has been studied for UAV-enabled wirelessly powered MEC systems for IoT devices. The problem is modeled as a joint optimization problem aiming to minimize the energy consumption due to association with ground IoT devices, allocation of computing resources, UAV hovering time, wireless charging duration and the servicing of the IoT devices and several efficient heuristic based solutions are proposed. While there are also other works that provide systems for UAV-assisted edge computing [178] or energy harvesting based edge computing [179–181], to the best of our knowledge, the joint consideration of energy transfer from UAVs and computation offloading to UAVs is very new and there are limited number of studies yet.

#### 3.4.4. Open problems

The research interest in UAV-assisted wireless charging has been growing rapidly. We have summarized the current work in the literature in Table 4. Since it is a relatively new area of research, there are several open research problems that need to be

**Table 4**
Summary of current research using energy sharing in UAV networks.

| Research Objective | Key features |
|---|---|
| Network energy replenishment [17,159,164–169] | • Aims efficient path planning and charging scheduling with optimal hovering locations and duration for maximization of energy by receivers.<br>• Considers cooperation between aerial and ground chargers in a 3-D space.<br>• Differentiates based on full, partial or no prior knowledge about the network. |
| Wirelessly-powered communication [170–174] | • Aims to maximize throughput in communication with ground users.<br>• Considers weighted charging models for fair charging and proper data collection. |
| Wirelessly-powered mobile edge computing [175–177] | • Aims to optimize computation offloading from ground devices to UAVs which also provide energy to the devices.<br>• Considers different offloading modes and cooperation among nodes. |

**Table 5**
Summary of major research problems and common technical approaches.

| Application | Major research problems | Common technical approaches |
|---|---|---|
| Wireless Sensor Networks (WSN) | • Radiation/interference-aware charging [42–44,47,48,50–52]<br>• Charger route optimization and scheduling [12,16,58,62–67,69–72,74,75]<br>• Collaborative charging [10,78–82] | • Traveling Salesman/Hamiltonian Path Problem [12,16,59]<br>• Reformulation-Linearization Technique [57]<br>• [Mixed] [Integer] Linear Programming [62,68,82]<br>• Game theory [81]<br>• Heuristic algorithms [49,68]<br>• Queueing Theory [66,67] |
| Mobile Social Networks (MSN) | • Optimal Energy Usage [100–104,106]<br>• Energy Distribution for Balancing [18,107–114]<br>• Energy Sharing for Content Delivery [120–126] | • Markov models and variants [100,101,120,123,124]<br>• Dynamic Programming [102–104,125]<br>• Distributed computing [18,107–110]<br>• Game Theory [121,122]<br>• Matching theory [101,102] |
| Vehicular Networks (VANET) | • Charging Price Control [136–140,144,145]<br>• Supplier/Demander Matching [9,142,145–148]<br>• Security and Privacy management [143,150–153] | • Blockchains [150,151], payment networks [152], homomorphic encryption [143]<br>• Lagrange duality [144,145]<br>• Mixed Integer Linear Programming [136,138,144,145]<br>• Matching theory [9,143,145,146,148]<br>• Game theory [144,145] |
| Unmanned Aerial Vehicle (UAV) Networks | • Network energy replenishment [17,159,164–169]<br>• Wirelessly-powered communication [170–174]<br>• Wirelessly-powered mobile edge computing [175–177] | • Traveling Salesman Problem [166]<br>• Knapsack Problem [167]<br>• Lagrange duality [17,159,173,175–177]<br>• [Integer] Linear Programming [171]<br>• Game theory [174] |

addressed. Some of these potential research directions are discussed below.

*Coordinated multi-UAV charging*: In a recent study [160], coordination between a UAV and a wireless charging vehicle (WCV) is introduced in order to prolong the network lifetime. This collaboration is indeed used to reassign charging tasks from busy chargers to its neighbouring chargers. However, a collaborative approach with peer-to-peer energy sharing (i.e., *C2C*) has not been studied yet. UAVs and other chargers could collaborate on charging sensor nodes as well as charging themselves to further improve the lifetime of the network.

*UAV-assisted charging of mobile networks*: Current research trend for UAV-assisted charging has mostly been studied for static IoT devices or wireless sensor networks (WSN). To the best of our knowledge, no study has addressed the potential usage of UAV-assisted charging for mobile networks with moving agents. The current algorithms might not perform well when the nodes are mobile themselves. Therefore, new algorithms and protocols need to be developed specifically for the UAV-assisted charging of mobile networks.

## 4. Concluding remarks

In this study, we have provided a comprehensive survey on the use of peer-to-peer energy sharing in four different applications of mobile networks, namely, wireless sensor networks (WSN), mobile social networks (MSN), vehicular ad hoc networks (VANET) and UAV networks. For each application, we have explored how the energy sharing is utilized and what kinds of problems are solved, and which technical approaches and mathematical tools are adopted. Table 5 provides an overview of major research problems and common technical approaches used in the literature reviewed in this study.

Utilization of energy sharing has been extensively studied in wireless sensor networks domain, however, it is a very active research area in the other applications. We have also highlighted some of the open problems that are waiting to be addressed by the research community at the end of each application's section. We believe that this study will bring the research community working on the adoption of energy sharing towards solving the energy optimization problems in different mobile networking applications together and let them benefit from each other's findings.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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