Ubiquitous Wireless Power Transfer for Multiple Mobile Devices

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Abstract. *We propose two new computational problems associated with the charging of mobile devices using wireless power transfer via magnetic induction. Algorithms for these problems may enable ubiquitous charging, meaning the user is no longer required to be aware of the devices charging processes. We prove both problems as being NP-Hard and propose three dynamic-programming algorithms to solve them in linear time regarding the size of the time-horizon. We also propose three greedy algorithms for the problems. Experiments indicate that the best dynamic-programming algorithm among those proposed reaches between 89% and 97% of effectiveness, while the best greedy reaches between 74% and 92%, depending on the considered scenario.*

1. Introduction

The global market of wireless charging devices was valued at $ 6,514.2 million in 2018 and is projected to reach $ 49,304.1 million by 2027 [Patil 2020]. Most of these devices use *Inductive Power Transfer* (IPT) protocols as physical layer. Nevertheless, most wireless charging solutions in the literature do not address the charging process in their modeling, often focusing purely on *Wireless Power Transfer* (WPT) [Jadidian and Katabi 2014, Shi et al. 2015]. In theory, maximizing the power transfer is equivalent to minimize the charging time and maximize the life-time of the devices around if the system features a single power receiver or a single transmitter. However, the problems became quite different for multiple transmitters and receivers, especially for heterogeneous networks.

The two problems proposed by this work start filling a gap between the aforementioned works and the charging processes of the powered devices. The *Minimum-Time MIMO Charging Problem* applies to cases where a *Multiple-Input-Multiple-Output* (MIMO) IPT transmitting station must charge a set of nodes as soon as possible. Use cases include the automated charging of wireless nodes and the power distribution among *unmanned aerial vehicles* (UAVs) in *Flying Ad hoc Networks* (FANETS).The automated charging of wireless nodes is often implemented using a wireless transmitting vehicle that runs within the network area and meanwhile provides the power for charging the nodes. Thus, charging the nodes in a sub-area as fast as possible is fundamental for the vehicle to attend other sub-areas without disconnections due to energy issues. For the power distribution among FANETs, in turn, the nodes must approach each other for the power transmission to occur, so the main purposes of the network may be temporally prejudiced and, therefore, it is required for the charging to be agile. Besides that, UAVs face landing inaccuracies that might lead to conditions of poor coupling with the transmitter. Thus, a MIMO setup can improve tolerance to misalignment and distance.

The *No-Starvation MIMO Charging Problem*, in turn, is related to *ubiquitous wireless power charging*. The term refers to the paradigm where users of mobile devices remain oblivious to battery charging due to the ubiquity of transmitters and the management of the charges. The *Ubiquitous WPT* has already some glimpses since a few years ago. *Huang et al.* [Huang et al. 2012], for instance, describes a power transmitter based on flexible sheets and solar panels, which is simple enough to allow extensive implantation and have its own power supply, avoiding issues towards energy distribution. Assuming that mobile receivers are always close enough to the populations of transmitting devices, the priority is no longer to minimize charging time. Indeed, if the devices are not expected to stay out-of-reach for long periods, the transmitting controller might just manage the available resources in a way to fulfill all energy requirements of the receivers around.

The main contributions of this dissertation are: **(i)** the definition of two new computational problems involving the process of charging multiple devices using *MIMO inductive power transfer systems*, **(ii)** the proof that both proposed problems belong to NP-Hard complexity class, **(iii)** the proof that the charging approach used by the previous work is sub-optimal regarding network lifetime and charging time, **(iv)** the proposition of a *dynamic-programming* method to solve both problems in linear time regarding the duration of the considered time horizon, **(v)** three algorithms for solving each proposed problem using the *dynamic-programming* method, **(vi)** three other algorithms for each proposed problem using greedy approaches, and **(vii)** an algorithm for generating random instances of the proposed problems which have guaranteed solution.

2. Related Work

Runtime Optimization of WPT. Systems with more than one IPT transmitting device may follow the *beam-forming* approach, which roughly enables the transmitting range and misalignment-tolerance to be improved [Jadidian and Katabi 2014, Shi et al. 2015]. Unlike the previous work, ours addresses the optimization of the whole charging process, instead of the simple power transfer. **Charging Optimization.** As far as we know, all works which address the optimization of the wireless charging instead of simply optimizing the power transference focus on scheduling of wireless nodes in wireless sensor networks. In short, such works address the optimization of the battery charges by selecting sub-networks to be prioritized by a single power-transmitter at each time-interval [Zhao et al. 2020, Lin et al. 2019]. Unlike these works, we consider a MIMO setup, which allows beam-forming and enables the transmitting-voltages to be used as decision variables. Indeed, maximizing the transferred power with a single transmitter is a polynomial-time problem and might be solved by the exploration method described on page 40 of the dissertation text. **Wireless Energy Distribution.** Some works focused on the distribution of energy across populations of power transceiver devices. Most works abstracted the WPT method and focused on optimizing the scheduling of the devices to be charged [Nikoletseas et al. 2017, Madhja et al. 2018]. As a wireless energy distribution technology, this work differs from its predecessors for (i) admitting charge limits within each battery can operate, (ii) considering bases dedicated to power transmission, and (iii) aiming, under ideal conditions, that users do not have to worry about the explicit charging of their devices and, therefore, the power sourcing of their devices be truly ubiquitous.

3. Primer

For a better understanding of the rest of this text, we provide some definitions. We consider a wireless charging setup as being a population of n_a IPT transmitting devices spread across an environment together with a population of n_p receiving devices. The transmitting devices have a centralized control which can determine the input voltage of each active circuit as long as the maximum power and the maximum current constraints are respected. Each receiving device is composed of a passive circuit which receives the power, a chargeable battery and a consumer device such as a cellphone or a electric vehicle. The charging vector of a given time-slot express the state of the system and consists of the instantaneous charge of every battery. Analogously, the input-voltage vector consists of the input-voltage of each active circuit at a given time-slot. Although Section 5.7 of the dissertation discuss the parameter acquisition, we often abstract sensing aspects and focus on the computational problems themselves. We consider a finite time-horizon with t time-slots of equal and known duration. The transmitting voltages and charges are discretized considering intervals of s_a volts and s_p coulombs respectively.

4. Theoretical Contributions

This dissertation proposes two new computational problems regarding the prolonging of the battery autonomy of wireless devices using WPT. The **No-Starvation MIMO Charging Problem** consists of finding the input-voltage time-series of each transmitting device in order to provide all needed power to every receiving device within a given time-horizon. The input-voltage set of each time-slot of the horizon must be chosen in a way that the maximum power constraint is respected. Moreover, each electric current must respect the maximum allowed for each device and all devices batteries must end the charging process with more than a minimal charge. The **Minimum-Time MIMO Charging Problem**, in turn, consists of finding the input-voltage time-series which minimizes the charging-time. Analogously, the maximum power and maximum current constraints must be respected at each time-slot and all devices batteries must end with more than a minimal charge.

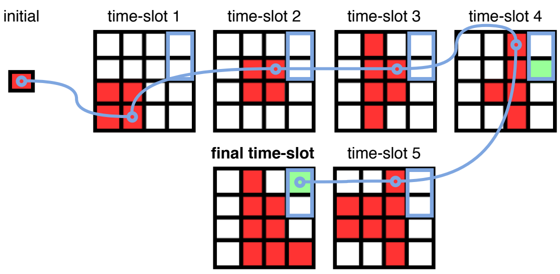

Figure 1. The *No-Starvation MIMO Charging Problem* aims at finding a path to any valid final charge-vector within the last time-slot.

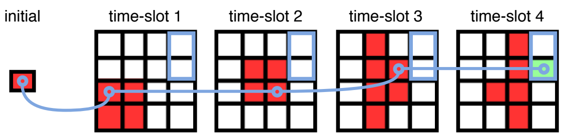

Figure 2. The *Minimum-Time MIMO Charging Problem* aims at finding the fastest path to any valid final charge-vector.

We demonstrate that the approach of the previous work, that is, always maximizing the immediately received power, is sub-optimal and may lead to very unfavorable scenarios, although the average case has good results. We prove that both proposed problems belong to the NP-Hard complexity class by providing polynomial-time reductions from the well known NP-Hard *0-1 Knapsack Problem.* We propose a dynamic-programming method to solve both problems in linear-time regarding the number of time-slots in the time-horizon. Thereunto, we discretize the time and battery-charge vectors and define a hash-based memory structure which contains one set of charge-vectors for each time-slot. One charge vector q_t is considered to be "reachable" from a charge vector q_{t-1} from the previous time-slot if and only if there is at least one input-voltage vector which transitions q_{t-1} to q_t while respecting all constraints. Thus, the method to find a solution for an instance of the *No-Starvation MIMO Charging Problem* is as illustrated by Figure 1. Starting from a single initial charge-vector, we first populate the memory structure of the first time-slot with charge-vectors reachable from the initial one. Then, we populate the next time-slot using charge-vectors reachable from the previous set and so on. If there is at least a valid charge-vector in the last set, we walk the way back and build the solution. The method for an instance of the *Minimum-Time MIMO Charging Problem* is similar, as illustrated by Figure 2, but whatever the found valid last state, we stop populating the next sets and build the solution.

We propose three algorithms based on the dynamic programming approach, which are as follows. **(i) Simple Algorithm**: consists of the literal application of the method and uses double-precision variables to store the memory structure. **(ii) Pareto Algorithm**: for each slot, it stores a set of charge-vectors in such a way that no vector is a multiple of another. The multiple is chosen so that the transferred power is maximized. **(iii) Fly-Weight Algorithm**: consists of an adaptation of the Simple Algorithm designed to improve space-efficiency. Indeed, it requires only about 20% of the memory space used by the Simple one. Such algorithms run in $O\left(t \cdot exp(log(s_a) \cdot n_a) + t \cdot exp(log(s_p) \cdot n_p)\right)$ time, which is exponential regarding the number of devices but linear regarding the number of time-slots. A naive brute-force algorithm, in turn, would run in $O\left(exp\left(log(s_a) \cdot n_a \cdot t\right)\right)$ time.

Finally, we propose three greedy algorithms. These are **(i) Max-Sum-Of-Currents Algorithm**: maximizes the sum of the charging currents of all batteries at each time-slot, **(ii) Max-Sum Algorithm**: maximizes the sum of the charges of all batteries at each time-slot, and **(iii) Max-Min Algorithm**: maximizes the life-time of the receiving device with weaker state-of-charge at each time-slot. Such algorithms run in $O\left(t \cdot exp\left(log(s_a) \cdot n_a\right)\right)$ time.

5. Experimental Results

We evaluate the proposed algorithms via a large set of simulations. We run the simulations via MATLAB using the mathematical modeling described in Chapter 3 of the dissertation. We employ the random instance generator proposed in Section 6.1 to create instances with a guaranteed and known solution to both problems. For the *No-Starvation MIMO Charging Problem*, the simulations aim on estimating the success probability of each algorithm when solving an random instance. For the *Minimum-Time MIMO Charging Problem*, in turn, the main evaluated response-variable is the *Normalized Charging Time*, that is, the ratio between the charging-time of the found solution and the charging-time of the solution generated as a byproduct of the random instance. We employ different parameters to generate a total of 450 instances of different difficulties.

Since the computational problems are proposed in this dissertation, there is no algorithm designed specifically for solving those. Thus, we choose the WPT optimization algorithm *MultiSpot* to be the baseline, given its notoriety in recent literature. For justice sake, we abstract the parameter acquisition phase of the algorithm and provide the exact value of each necessary parameter. The other baseline is the *Max Power Algorithm*, which uses brute-force to find the voltage input for each transmitter that maximizes the transferred power, which is the most common objective-function in WPT literature.

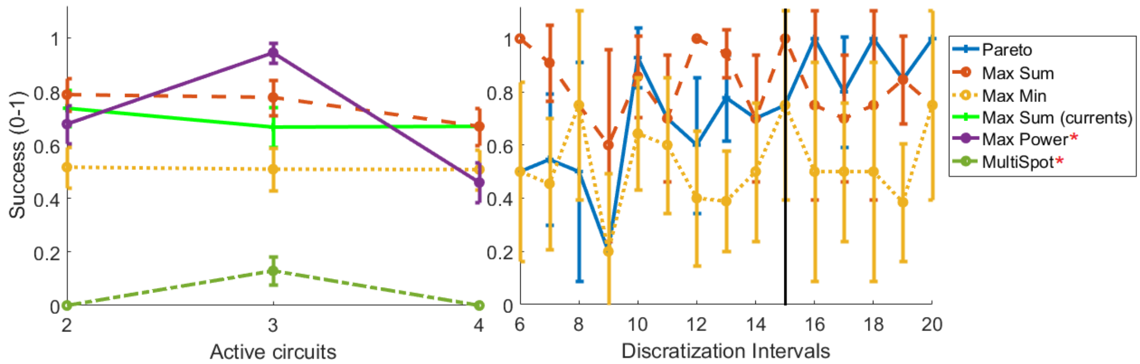

Figure 3. Comparison between the solutions generated by the proposed algorithms and the baseline (*) for instances of the No-Starvation MIMO Charging Problem. Over 15 charge discretization intervals (black vertical line), the dynamic-programming algorithms (represented here by Pareto) achieve better performance than greedy ones.

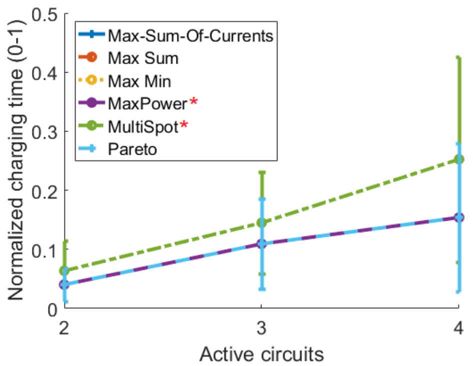

Figure 4. Comparison between the solutions generated by the proposed algorithms and the baseline (*) for instances of the Minimum-Time MIMO Charging Problem.

Figure 3 shows some experimental results for the *No-Starvation MIMO Charging Problem*. The most effective dynamic-programming algorithm is *Pareto* with at least 15 discretization intervals for the charge variables, whose success ratio varied between 89% and 97% for the tested scenarios. The most effective greedy algorithm is *Max Sum*, with success ratio between 74% and 92%. The null hypothesis of these two algorithms reaching the same effectiveness can be rejected with 10% significance level using binomial test (p-value $= 0.09968$). Finally, the most effective baseline is *Max Power*, which surpassed 70% in all scenarios. However, the null hypothesis of *Max Power* be equivalent to *Max Sum* is also rejected with 10% significance level against the hypothesis that *Max Sum* is superior (p-value $= 0.08873$). Figure 4 shows some experimental results for the *Minimum-Time MIMO Charging Problem*. There is no evidence of improvements when comparing to the *Max Power Algorithm*, although *MultiSpot* is beaten by far by all other considered algorithms, since it does not include most constraints in their mathematical modeling.

6. Publications

1. de Sousa, Alexander; Vieira, Luiz ; Vieira, Marcos. Optimal transmission range and charging time for Qi-Compliant systems. IEEE Transactions on Power Electronics, pages 12765-12772, v.35, 2020. (Qualis A1) doi:10.1109/TPEL.2020.2996999

2. de Sousa, Alexander; Vieira, Luiz ; Vieira, Marcos. Ubiquitous Wireless Power Transfer for Multiple Mobile Devices with no-starvation. IEEE Transactions on Mobile Computing, pages 1–12. (Qualis A1). In preparation.

3. de Sousa, Alexander; Vieira, Luiz ; Vieira, Marcos. Minimum-Time MIMO Charging Problem. IEEE Communications Magazine (Qualis A1). In preparation.

4. de Sousa, Alexander; Vieira, Luiz ; Vieira, Marcos. Communication Using Magnetic Induction. In: Fei Hu. (Org.). Magnetic Communications: From Theory to Practice. 1st ed., CRC Press, 2018, p.53-71, ISBN 9781498799782, .

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