01 Jan 2022

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Recommended Citation

P. Chatterjee et al., "Distributed Decision Making for V2v Charge Sharing in Intelligent Transportation Systems," *Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks workshops*, pp. 506 - 514, Institute of Electrical and Electronics Engineers, Jan 2022.
The definitive version is available at https://doi.org/10.1109/SECON55815.2022.9918576

2022 19th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON) | 978-1-6654-8643-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/SECON55815.2022.9918576

Distributed Decision Making for V2V Charge Sharing in Intelligent Transportation Systems

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***Abstract*—Electric vehicles (EVs) have emerged in the intelligent transportation system (ITS) to meet the increasing environmental concerns. To facilitate on-demand requirement of EV charging, vehicle-to-vehicle (V2V) charge transfer can be employed. However, most of the existing approaches to V2V charge sharing are centralized or semi-centralized, incurring huge message overhead, long waiting time, and infrastructural cost. In this paper, we propose novel distributed heuristic algorithms for V2V charge sharing based on the multi-criteria decision-making policy. The problem is mapped to an alias classical problem (i.e., optimum matching in weighted bipartite graphs), where the goal is to maximize the matching cardinality while minimizing the matching cost. An integer linear programming (ILP)-based problem formulation can not achieve optimum matching because the global network topology is not available with the EVs due to their limited communication range. Our proposed heuristics can yield an almost stable matching with lesser computational and message overhead compared to other existing distributed approaches. An average case matching probability is also calculated. Simulation experiments are conducted to measure the performance of our heuristics in terms of message overhead, matching percentage, and matching preference. The proposed solution outperforms the existing distributed approaches and shows comparable result with respect to standard centralized stable matching algorithm.**

***Index Terms*—Intelligent Transportation System (ITS); Electric Vehicles (EVs); V2V charge sharing; multi-criteria decision making; distributed algorithm; matching.**

I. Introduction

In a smart city environment, intelligent sensing and actuation (control) techniques help improve the quality of living [1]. Among many technologies, Intelligent Transportation Systems (ITS) form a significant part of a smart city. Specifically, ITS deals with traffic safety, accident caution, lane changing guidance, improved navigation support, and danger discretion [2]. In an ITS scenario, as depicted in Figure 1, there exist mainly three types of communications – Vehicle to Vehicle (V2V), Vehicle to Roadside unit (V2R), and Roadside unit to Roadside unit (R2R).

In recent years, there has been an emergent importance of Electric Vehicles (EVs) in the context of ITS. The deployment and scaling up of EVs in urban areas greatly depend on the quality and access of charging infrastructure. Charging infrastructure includes low speed charging stations at homes and workplaces as well as fast charging points in public areas, such as shopping malls, petrol pumps, public parking, and mass transit stations. High infiltration of EVs will lead to incremental demand of excess charging which in turn will eventually lead to significant challenges, namely how fast, from where and when the charging can take place, or what is the cost of charging. The Idaho National Laboratory published a report "Plugged In: How Americans Charge Their Electric Vehicles", claiming that around 85% of the EV drivers refuel their vehicles by electricity at home [3]. This is primarily because of the inaccessibility and non-ubiquity of charging stations at other places. With optimal placements of new charging stations, the total return on investment (ROI) might be increased [4] [5] [6].

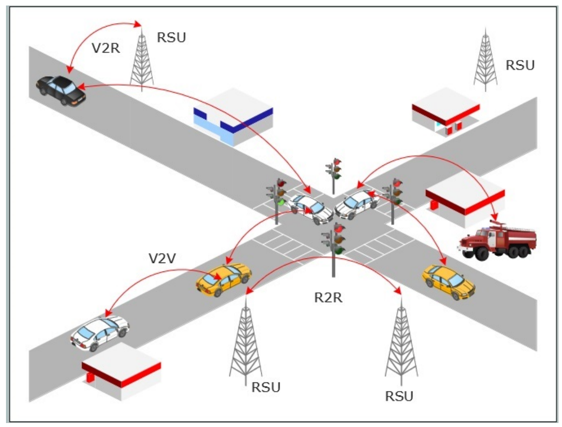

Fig. 1: An Intelligent Transportation System (ITS) Scenario

A direct V2V charging scheme supplies flexible and fast energy exchange for EVs without the support of charging stations [7]. It provides mutual benefits to the buyers as well as sellers while traveling, without worrying about the presence of any pre-existing dedicated charging station.

A. Motivation

While a number of approaches have been proposed recently to address the charge sharing phenomenon in V2V networks, they are mostly centralized [8], [9] or semi-centralized [7], [10]. These are not suitable for energy constraint EVs in a dynamic vehicular environment due to high message communication overhead and long response time of the aggregators [11]. There exist a few distributed solutions [12], [13] which consider only Euclidean distance between the EVs as a metric for matching. However, in real applications, there can be several criteria such as charging cost, waiting time, reliability, etc. In [14], a consumer-provider allocation strategy is proposed based on multiple criteria, involving additional cars acting as multi-point relays (MPRs). However, the consumer selects a provider based on only the charging cost. The convergence time and message overhead of the algorithms are high. Moreover, these schemes assume homogeneous communication ranges for all EVs, which is unrealistic. Finally, none of the works focus on how to maximize the matching cardinality while preserving the preference of EVs, which is one of the criteria for optimum matching [15].

B. Our Contributions

This paper proposes a novel distributed matching-based approach to V2V charge sharing through a multi-criteria decision-making policy. The EV offering charge is called a *donor* while the EV accepting charge is called an *acceptor*.

The contributions of this paper are summarized as follows.

1) An Integer Linear Programming (ILP)-based multi-criteria decision-making problem is first formulated for *acceptor-donor* matching for charge sharing. The goal is to maximize the matching cardinality while assigning a preferable *donor* to an *acceptor*. The problem is then mapped into an optimum matching in weighted bipartite graphs [15].
2) A distributed heuristic approach for **V2V Dis**tributed **C**harge **S**haring) (*V2VDisCS*) is proposed for *acceptor-donor* pairing. It has smaller computational and message complexities with respect to the existing distributed approaches [12], [13], [14].
3) An average case probabilistic analysis establishes a theoretical result on the matching percentage. Simulation studies demonstrate that *V2VDisCS* outperforms existing distributed approaches [13], [14] with respect to the matching percentage and message overhead. For matching preference, *V2VDisCS* shows comparable result with respect to the centralized Gale-Shapley [16] algorithm, and ensures an *almost stable matching* [17].

The rest of the paper is organized as follows. Section II summarizes related work and Section III introduces the system model. Section IV formulates the problem while Section V describes our proposed two distributed algorithms – one for the *acceptor* and another for the *donor*. Section VI analyzes the experimental results and Section VII concludes the paper.

II. RELATED WORK

In this section, we will describe the existing state-of-the-art strategies on V2V charge sharing for electric vehicles.

A. Centralized Approaches

In [8], authors introduce a centralized charging system where charging stations are selected by considering their respective charging costs. In [9], authors propose two algorithms for matching the demander and supplier EVs, where all the EV drivers are connected to a central server via a mobile application. Server does the matching at regular predefined intervals based on several parameters i.e. location, availability, energy consumption. In [18], a data control center connects all the EVs, smart houses, charging stations, power/communication infrastructures for real-time information collection, while an aggregator coordinates the grouping of consumer EVs and provider EVs. In [19], V2V charging strategy is modelled as an optimization problem by taking care of parking place reservations. In [20], a centralized aggregator collects charging requests and calculates charging/discharging schedule to minimize charging cost. In [21], gridable electric vehicles take optimal charging/discharging decisions through the aggregator, which is used to balance the demand and supply of power by updating the price at a specific interval.

In [22], based on matching theory, enough suppliers are provided according to demand. All charging stations are controlled by one local aggregator, which performs all necessary information sharing and decision-making. In [23], authors propose two matching algorithms where the benefits of both demander and supplier are considered. Based on the collected information, the data control center chooses the best parking lot for charge transfer between EV pairs. Authors in [24] formulate a new concept of V2V Wireless Power Transfer. A dynamic programming solution is applied to propose the energy-feasible path for the recipient vehicle from the origin to the destination. In [25], a multi-objective mobile charging vehicles (MCV) scheduling problem is investigated. By optimizing the charging sequence and the actual amount of energy being charged, the proposed framework aims to minimize the EV waiting time while maximizing the charging benefits of all EVs. To solve the multi-objective optimization problem, a deep reinforcement learning (DRL) based framework is further explored.

B. Semi-centralized Approaches

In [7], authors propose an Mobile Edge Computing(MEC) based V2V navigation framework. Authors deduce three charging models for local charging : Long Short-Term Memory based travel time prediction, charging time estimation and charging comfortable degree. They have designed a Q-learning based adaptive route selection algorithm for choosing optimal moving path. Finally, a global charging navigation mechanism is proposed on the basis of weighted bipartite graph which increases the amount of energy transfer between EVs while decreasing the waiting time. In [10], the Oligopoly game and Lagrange duality optimization techniques are exploited, where an online coordinator makes the charging/discharging decision depending on real time information.

C. Distributed Approaches

In [12], the authors propose a distributed matching algorithm for charge sharing using Bichromatic Mutual Nearest Neighbor (BMNN) assignments to preserve the privacy of the users while providing a satisfactory assignment. The algorithm works in rounds. In case of highly dense networks, the algorithm takes more time to converge, but still cannot ensure 100% matching due to the unavailability of all suppliers within the limited communication range of a demander. In [13], a partially homomorphic encryption based algorithm is proposed for privacy preservation of the suppliers by hiding their locations until matched. Based on the preference of the demander, although a supplier is assigned, no matching decision is carried out at the supplier end. Both of the above works consider only distance metric for demander-supplier matching. However, there can be several criteria in real applications to select a supplier.

The authors in [14] propose a Multi-Point Relay (MPR)-based approach, where the providers' announcements are done through MPRs by using quality of service-optimized Link State Routing (LSR) protocol. Next, the consumers send offers to the providers with minimum payment and the providers select the appropriate consumer based on the maximum payoff, considering multiple criteria. However, the consumer may have different criteria such as travel time, charge transfer rate, reliablity, etc, to select a provider. One of the important criteria during the interaction between EVs can be *trust*, which is not considered here. The computational and message complexities are high in the above approaches. Moreover, the authors consider homogeneous communication range for EVs, which is unrealistic.

Table I shows the comparison of the existing works.

III. System Model

This section defines the relevant concepts followed by the introduction of the system model and underlying assumptions.

Definition 1 (*Acceptor*)**.** *An EV requesting for charge or accepting charge, is called an acceptor.*
Definition 2 (*Donor*)**.** *An EV ready to share its excess charge is called donor.*
Definition 3 (*Reachable donor set*)**.** *This is the set of donors within the communication range of an acceptor.*
Definition 4 (*Reachable acceptor set*)**.** *This is the set of acceptors within the communication range of a donor.*

A. Assumptions

The proposed system model makes the following assumptions. Each EV has a unique ID and can track its own (absolute) location, speed and travel direction. The EVs can have heterogeneous communication ranges, but follow a unit-disc model. An EV can directly communicate with another EV through wireless communication, if they reside within their communication range.

The *donors* maintain a set of criteria required for the charge-sharing purpose: (i) the cost per unit charge, Cu; (ii) the trust value or reliability with respect to a particular *acceptor*, R; (iii) the amount of available charge to be shared, $charge$; (iv) the estimated travel time to reach an *acceptor*, T; and (v) the charge transfer rate, $rate$.

B. Trust Model

For V2V message communications, this paper follows a Data-oriented Trust Model (DTM) [26], which is a well-known model used in VANETs. Let a charge request message be received at a vehicle EV_d from a vehicle EV_a. Then the overall trust $R_{(d,a)}$ at the EV_d at time (t) is calculated as:

$$R_{(d,a)}(t) = \sqrt{R_{(d,a)}(t-1) \times \sqrt{T_{dir} \times T_{ind}}}$$

Here, T_{dir} relies on the quality of the received message; and T_{ind} is the rating given by an *acceptor* to a *donor* after the completion of the charge sharing phenomenon. We assume that the value of T_{ind} ranges from 1 to 5 with an initial value of 0.5 [27]. The initial value of $R_{(d,a)}$=1, and T_{dir} is always assumed to be 1.

C. Travel Time Estimation

For travel time prediction model, we follow the method suggested in [7]. The derivation is as follows:

$$T_k(e_i) = TM_k(e_i) + TW(e_i)$$
$$= \frac{L(e_i)}{v_k(e_i)} + \nu(e_i) \cdot p(e_i) \cdot \delta(e_i)$$

where $T_k(e_i)$, $TM_k(e_i)$, $TW(e_i)$ and $v_k(e_i)$ respectively denote the average traveling time, moving time, waiting time and velocity of an EV k going through the road segment e_i having length $L(e_i)$. Now $\nu(e_i)$ = {0, 1} indicates whether there is a traffic light located in the road segment e_i, where 1 implies the traffic light is available. The notation $p(e_i)$ signifies the probability that an EV suffers from the red traffic light in e_i; whereas $\delta(e_i)$ implies the average waiting time for the red traffic light in e_i, The average velocity $v_k(e_i)$ is derived as:

$$v_k(e_i) = \frac{Tf_k(e_i)}{Td_k(ei_)}$$

where $Tf_k(e_i)$ and $Td_k(e_i)$ denote the predicted traffic flow and traffic density of the road segment e_i, respectively.

IV. Problem Formulation

Steps required for problem formulation are described below:

1) Weight allocation : Suppose there are m number of EVs $\{EV_1, EV_2, ..., EV_m\}$ in *reachable donor set* of an *acceptor*. Each *donor* has five criteria $\{Cu$, R, $charge$, T, $rate\}$. Each *acceptor* assigns different weights $\{w_1, w_2, w_3, w_4, w_5\}$ to each of the criteria by point allocation method [28] at any particular time. These weights reflect the importance of each criterion to make a decision i.e. to select a *donor*. Weight assigned to each criterion may vary from one *acceptor* to another *acceptor* at any time instant.

2) Score and Rank generation: An *acceptor* wants to minimize (T, Cu) and maximize $(rate, charge, R)$. *Acceptor* calculates the *Score* of a *donor* based on equation 1.

$$Score = \frac{\frac{Cu}{Cu_{max}} \times w_1 + \frac{T}{T_{max}} \times w_4}{\frac{R}{R_{max}} \times w_2 + \frac{rate}{rate_{max}} \times w_3 + \frac{charge}{charge_{max}} \times w_5} \quad (1)$$

TABLE I: Comparison of Existing Works

Approach	Paper Ref.	Merits	Demerits
Centralized	[8]	Hybrid algorithm of particle swarm optimization and genetic algorithm	Not scalable; communication bottlenecks, bandwidth limitations, and costly expansion of the supporting infrastructure to handle the explosive increase of data from rapid EV uptake; EVs need to communicate complete charging information to central aggregator hence cannot take decision in self-organized manner [11]
	[9]	Trip-based probabilistic EV charging behavior model	
	[18]	Max-weight V2V matching based on weighted bipartite graph	
	[19]	Data transmissions between parking service center and mobile EVs in real-time, optimization problem	
	[20]	Renewable energy sources, mixed integer programming problem	
	[21]	Mobility aware V2V energy swapping based on price control	
	[22]	Mixed-integer optimization problem based on matching theory	
	[23]	Two V2V matching algorithms proposed	
	[24]	V2V wireless power transfer, dynamic programming solution	
	[25]	multi-objective MCV scheduling, DRL based framework	
Semi-centralized	[7]	MEC based charging navigation, Q-learning based algorithm	Power loss at swapping stations, charging cost increased
	[10]	(Dis)charging strategy is modelled as Oligopoly game and Lagrange duality optimization techniques	
Distributed	[12]	Dynamic environment, privacy preservation, bichromatic mutual nearest neighbor (BMNN)	Long convergence time [log D rounds, where D: # acceptors/donors]; high message complexity; only distance as metric, homogeneous communication range
	[13]	Partially homomorphic encryption based distance calculations	Increased computational and message complexities; decision taken by demander only; only distance as metric, homogeneous communication range
	[14]	Multi-criteria decision making, Provider announcement by MPRs and QoS-OLSR	Additional cars used as MPRs; Increased computational and message complexity; Some of important criteria not considered, Homogeneous fixed communication range

where $Cu_{max}, T_{max}, rate_{max}, charge_{max}$ and R_{max} are the maximum possible values of the criteria. A higher *Score* value means a lower preference and a lower *Score* value means a higher preference. An *acceptor* tries to select a *donor* with minimum *Score* value such that:

(i) Cost per unit charge is within *acceptor's* budget (Cu_{accept}).
(ii) Travel time should be less than or equal to the admissible time(T_{accept}), by which the *acceptor*, with its residual charge, can reach to a respective *donor*.
(iii) Charge transfer rate should be less than or equal to the acceptable rate ($rate_{accept}$) of the *acceptor*.
(iv) A *donor* is able to provide the required charge ($charge_{req}$) to the *acceptor*.
(v) Reliability of a *donor* should be greater than or equal to a minimum threshold value (R_{min}).

The *Score* generation can be formulated as an optimization problem:

$$\begin{aligned} \text{Minimize} \quad & Score \\ \text{subject to} \quad & Cu \leq Cu_{accept} \\ & T \leq T_{accept} \\ & rate \leq rate_{accept} \\ & charge \geq charge_{req} \\ & R \geq R_{min} \end{aligned}$$

Now, an *acceptor* sorts the *Scores* of different *donors* in its *reachable donor set* and assigns *Rank*. The *donor* with minimum *Score* is ranked as 1.

3) Matching: To decrease the matching cost, an *acceptor* always tries to match with the *donor* with minimum *Rank*. On the other side, if we want to increase the matching cardinality, it may not be always possible to assign the most preferable *donor* to an *acceptor*. This is an alias problem of finding the *Optimum Matching* in a *Weighted Bipartite Graph* [15]. A matching of maximum cardinality and minimum weight is called optimum matching.

Definition 5 (*Acceptor-Donor* weighted bipartite graph)**.** *An Acceptor-Donor weighted bipartite graph $G = (A \cup D, E)$ is a graph whose vertices can be divided into two disjoint sets A and D such that each edge $e_{ij} \in E$ connects a vertex $a_i \in A$ and a vertex $d_j \in D$ and has weight as $Rank_{ij}$, where $Rank_{ij}$ is the rank of donor d_j assigned by the acceptor a_i.*

Our objective is to find an optimum matching on the *Acceptor-Donor weighted bipartite graph.*

The symbols used in the paper are listed in Table II.

V. Proposed Distributed Algorithms

To construct the *Acceptor-Donor weighted bipartite graph* for the whole vehicular network, global knowledge of the entire network is required. But, due to the limited communication ranges of EVs, an EV cannot possess information about the whole network. In that case, with the partial view of the entire network, it can construct a subgraph of the global *Acceptor-Donor weighted bipartite graph* and can try to find a matching solution, where matching cardinality is maximized and matching cost is minimized.

It is alias to the problem of *Distributed Stable Matching with Incomplete preference list (DisSMI)* [29]. In [29], authors propose a solution where nodes are distributed among some agent nodes, such that each agent owns some nodes and every node

TABLE II: Symbol Table

Symbol	Meaning
R	Reliability
T	Travel time
Cu	Cost per unit charge
rate	charge transfer rate
charge	available charge
T_{dir}	Direct Trust
T_{ind}	Indirect Trust
Tf_k	predicted traffic flow
Td_k	traffic density
w	Weight of criteria
$charge_{max}$	maximum value of available charge
Cu_{max}	maximum value of cost / unit charge
R_{max}	maximum value of reliability
$rate_{max}$	Maximum value of charge transfer rate
T_{max}	Maximum value of travel time
$Score$	Score of *donor*
$Rank$	Rank of *donor*
m	Number of reachable *donors*
G	*Acceptor-Donor weighted bipartite graph*
E	Edge set in G
EV_{rd}	*Reachable donor set*
EV_{ra}	*Reachable acceptor set*
T_s	Threshold time
m_{ij}	Decision matrix
EV_{ranked}	Rank list of reachable donors
N_{ij}	Weighted decision matrix

is owned by a single agent. An agent can access and modify all the information of the owned nodes, but it cannot access the information of nodes owned by other agents [30]. The limitation of the above solution with respect to our problem is that, we need to incorporate extra cars/infrastructure serving as agents which is cost-intensive. The solution converges after multiple iterations, which is computationally intensive.

Hence, we have proposed **Dis**tributed heuristics for **V2V** **C**harge **S**haring (*V2VDisCS*), without involving any agents, rather relying on only V2V communication and local computation at EV. The algorithm completes in one run.

A. Description of the algorithms

In this section, we shall illustrate the algorithms which are executed parallelly at *acceptor* and *donor* end.

a) Acceptor side: Algorithm 1 performs the *donor* selection procedure. To decrease the matching cost, an *acceptor* always tries to match with the *donor* with minimum *Rank*. The steps involved are described as follows:

Step 1: An *acceptor* broadcasts *REQ* message containing the location and velocity information and waits for *REPLY* message. If it does not receive any *REPLY* within a predefined time (T_S), it goes for static charging stations. [Static charging point allocation through RSU is beyond the scope of this paper.]

Step 2: If an *acceptor* EV_a receives *REPLY*s from *donors* e.g. EV_1, EV_2, EV_3, EV_4, it prepares the *Reachable donor set* $\{EV_1, EV_2, EV_3, EV_4\}$ and a *decision matrix* as shown in Table III, containing different criteria of the *donors*.

Step 3: An *acceptor* assigns weights to each criterion and calculates *Scores* by following eqn 1. Let us assume that, 20%,

Algorithm 1 *Acceptor* EV_a selects a *donor*

Input : T_s:threshold time
Output: $Matched\_Donor$: Selected *Donor*
Initialize: EV_{rd}=null, //*Reachable donor set*
    $Rank = \infty$,//*Rank* of selected *donor*
    $Matched\_Donor = null$;
EV_a sends *REQ*;
while $time < T_s$ **do**
    if EV_a *receives REPLY*($Cu, R, T, rate, charge$) *from* EV_b **then**
        $EV_{rd} = EV_{rd} \cup EV_b$; //Put all replying EVs in *reachable donor set*
        $m \leftarrow \{Cu, R, T, rate, charge\}$ //Put criteria in decision matrix m
    end
end
if $EV_{rd} == null$ **then**
    Goes for static charging point allocation;
else
    EV_{ranked}=*Rank_Donor*(EV_{rd}, m) ; // call procedure to calculate *Ranks* of *donors* in EV_{rd}
    Sends *REGISTER*(EV_{ranked}) to all *donors*$\in EV_{rd}$;
    while $time < T_s$ **do**
        if *receives CONFIRM from* $EV_d \in EV_{rd}$ **then**
            if *Rank of* $EV_d < Rank$ **then**
                $Rank$=*Rank* of EV_d;
                $Matched\_Donor = EV_d$;
            end
        end
    end
    if $Matched\_Donor == null$ **then**
        Goes for static charging point allocation;// Not receive any *CONFIRM*
    else
        Sends *MATCHED* to $Matched\_Donor$;
        Return ($Matched\_Donor$);
    end
end

Algorithm 2 *Rank_Donor*(EV_{rd}, m)

Output: EV_{ranked} : *Rank* list of *donors* in EV_{rd}
Initialize w_i(weights);

Weighted decision matrix N_{ij} = $m_{ij} \times w_i$;
Calculate $Score_j$ $\forall EV_j \in EV_{rd}$;
Sort EV_{rd} according to *Scores*;
Assign *Rank* to each $EV_j \in EV_{rd}$, based on their position in the sorted EV_{rd} list and store in vector EV_{ranked};
Return(EV_{ranked});

20%, 10%, 30% and 20% weightages are assigned to T, R, Cu, *charge* and *rate* respectively and {30, 10, 5, 20, 40} are the values for T_{max}, Cu_{max}, R_{max}, $charge_{max}$ and $rate_{max}$ respectively. Then,

Score of EV_1 = $\frac{0.20\times\frac{5}{30}+0.10\times\frac{4}{10}}{0.20\times\frac{5}{5}+0.30\times\frac{5}{20}+0.20\times\frac{4}{40}}$ = 0.25

Score of EV_2 = $\frac{0.20\times\frac{9}{30}+0.10\times\frac{10}{10}}{0.20\times\frac{3}{5}+0.30\times\frac{10}{20}+0.20\times\frac{7}{40}}$ = 0.52

Score of EV_3 = $\frac{0.20\times\frac{7}{30}+0.10\times\frac{3}{10}}{0.20\times\frac{2}{5}+0.30\times\frac{15}{20}+0.20\times\frac{7}{40}}$ = 0.23

Score of EV_4 = $\frac{0.20\times\frac{12}{30}+0.10\times\frac{8}{10}}{0.20\times\frac{1}{5}+0.30\times\frac{20}{20}+0.20\times\frac{40}{40}}$ = 0.3

Hence *Ranks* of EV_1, EV_2, EV_3 and EV_4 are 2, 4, 1, 3 respectively.

Step 4: An *acceptor* multicasts *REGISTER* message containing the *Rank* list (EV_{ranked}) to all *donors* in *reachable donor set* and waits for *CONFIRM* message. If it receives *CONFIRM* within T_S from multiple *donors*, then it chooses one with minimum *Rank* and sends *MATCHED* message to the selected *donor*. If it does not receive any *CONFIRM*, it goes for static charging point finding with the help of RSU.

b) Donor side: Algorithm 3 illustrates the steps executed at *donor* side. To increase the matching cardinality, a

TABLE III: Decision Matrix of EV_a

	EV_1	EV_2	EV_3	EV_4
T(in minutes)	5	9	7	12
R	5	3	2	1
Cu(in $ per kWh)	4	10	3	8
$charge$(in kWh)	5	10	15	20
$rate$(in kWh per hour) [31]	4	7	7	40

donor selects a particular requesting *acceptor* with minimum $|EV_{ranked}|$. The description of the algorithm is as follows:

Step 1: If a *donor* receives *REQ*, it sends *REPLY* to that particular *acceptor*.

Step 2: If a *donor* receives multiple *REGISTERs* within time T_S, it puts all the responses in a priority queue. *Donor* chooses an *acceptor* as per priority (Higher priority is assigned to $|EV_{ranked}|$ and lower priority for *Rank*) and sends *CONFIRM* to the selected *acceptor*. It empties the queue.

Suppose for a network having six *acceptors*, $\{EV_a, EV_b, EV_c, EV_d, EV_e, EV_f\}$, the priority queues of the four *donors* $\{EV_1, EV_3, EV_2, EV_4\}$ at any time instant are shown in Table IV. Here, EV_1 selects EV_a; EV_2 selects EV_c; EV_3 selects EV_f; EV_4 selects EV_f.

TABLE IV: Priority Queues of *donors*

(a) Priority Queue of EV_1

$\|EV_{ranked}\|$	*Rank*	*Acceptor*
1	1	EV_a
2	1	EV_b
2	2	EV_c
3	3	EV_d

(b) Priority Queue of EV_2

$\|EV_{ranked}\|$	*Rank*	*Acceptor*
2	1	EV_c
2	2	EV_b
3	2	EV_d
3	3	EV_e

(c) Priority Queue of EV_3

$\|EV_{ranked}\|$	*Rank*	*Acceptor*
2	2	EV_f
3	1	EV_d
3	2	EV_e

(d) Priority Queue of EV_4

$\|EV_{ranked}\|$	*Rank*	*Acceptor*
2	1	EV_f
3	1	EV_e

Step 3: If *donor* does not receive any *MATCHED* within T_S, it resets itself;

The message communication between *acceptor* and *donor* is shown in diagram 2. In the *Discovery* phase, EVs exchange *REQ* and *REPLY* messages to find out the *reachable donors* and *reachable acceptors*. In the *Pairing* phase, the matching has been performed. Here, a *donor* sends *CONFIRM* message to a particular *acceptor* and an *acceptor* sends *MATCHED* message to a particular *donor*. So, an *acceptor* got matched with a single *donor* and vice-versa. Finally, the charge sharing is conducted in the last phase.

Algorithm 3 *Donor* EV_d confirms an *acceptor*

Input : $\{Cu, R, T, rate, charge\}$: criteria of *donor*
Output: EV_a: Selected *acceptor*
Initialize: Q = null;//Priority Queue
if *donor* EV_d *receives REQ from* EV_a **then**
  Sends *REPLY*$\{Cu, R, T, rate, charge\}$ to EV_a ;
end
while $time < T_S$ **do**
  if *Receives REGISTER(*EV_{ranked}*) from* EV_a **then**
    Inserts EV_a in Q based on $|EV_{ranked}|$ and $Rank$ of EV_d (assigned by EV_a);
  end
end
Deletes EV_a from Q and sends *CONFIRM* to EV_a;
Empties Q;
if *not receives MATCHED within* T_S **then**
  Reset;
end

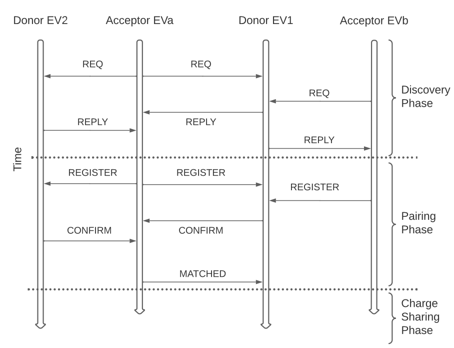

Fig. 2: Message Communication between *acceptor* and *donor*

B. Complexity Analysis

The comparison of message complexities with the existing distributed approaches are depicted in Table V. Here, n is the number of *reachable acceptors*, m is number of *reachable donors* of an *acceptor*. For homogeneous transmission range and uniform distribution of *acceptors* and *donors*, $m^4 >> n$. k is the number of reachable MPRs and providers of an MPR. For [13], we have considered message complexity in one round.

TABLE V: Comparison of Message Complexities

	V2VDisCS	Ref [13]	Ref [12]	Ref [14]
Acceptor or Demander or Consumer	$O(1)$	$O(m)$	$O(m)$	$O(m^4)$
Donor or Supplier or Provider	$O(n)$	$O(n)$	$O(n)$	$O(1)$
MPR	NA	NA	NA	$O(k^4)$

The comparison of computational complexities with the existing distributed approaches are depicted in Table VI. Here, $n = |EV_{ra}|$, $m = |EV_{rd}|$, TTL(Time to Live): 4 hop(provider announcement phase), D: No. of demanders.

TABLE VI: Comparison of Computational Complexities

	V2VDisCS	Ref [13]	Ref [12]	Ref [14]
Acceptor or Demander or Consumer	$O(m\ log\ m)$+$2T_S$	$O(m\, log\, m)$+$(m+1)T_S$	$logD$ rounds, where each round takes $m\ log\ m + (m+1)T_S$	$O(m^4\ log\ m^4)+$ $T_S m^4$
Donor or Supplier or Provider	$O(1)$	$O(n)$	$logD$ rounds, where each round takes $(n\ log\ n + n)$	TTL+T_S + $O(n^4\ log\ n^4)$

C. Calculating Matching Probability of an Acceptor

Let, N_d be the arrival rate of *donors* and N_a be the arrival rate of *acceptors* in a deployment area B at any time instant *t*.

Probability that a *donor* EV_d sends *CONFIRM* message to any one of the *acceptors* EV_a among its *reachable acceptor set* at time *t* is

$$P_{confirm_d} = \frac{1}{|EV_{ra}(t)|\ of\ EV_d}$$

Hence, probability that an *acceptor* EV_a do not get any *CONFIRM* is

$$P_{not\_confirm} = (1-P_{confirm_1})(1-P_{confirm_2})...(1-P_{confirm_m})$$

where $m = |EV_{rd}(t)|$ of EV_a.

Probability that an *acceptor* EV_a got matched is

$$P_{matched} = 1 - P_{not\_confirm}$$

Now, for constant arrival rates of *acceptors* and *donors*, homogeneous communication ranges r_a and r_d for *acceptors* and *donors* respectively,

$$P_{confirm_1} = P_{confirm_2} = ... = P_{confirm_m} = P$$

Therefore,

$$P_{matched} = 1 - \left(1 - \frac{B}{\pi r_d^2 N_a}\right)^{\frac{\pi r_a^2 N_d}{B}}$$

VI. Simulation Results

A. Simulation Environment

In this section, we have presented our simulation results as a performance index of our proposed algorithms. For the simulation, we use a system with following specifications: 1.8 GHz Dual-Core Intel Core i5, 8 GB 1600 MHz DDR3 RAM. Octave tool [32] is used for programming. Among the three existing distributed works, discussed in Section II-C, we have compared our simulation results with Distributed Stable Matching [13] and MPR-based Method [14]. The other work [12] is not considered, as the algorithm proposed in that paper works in rounds, hence takes more time to converge. For every result in this section, we took the average of 20 different runs for statistical significance. The simulation parameters are listed in Table VII.

TABLE VII: Simulation Parameters

Parameter	Value
Region($\mathcal{R} \times \mathcal{R}$)	1 km×1 km
Number of *donors*	20-50
Number of *acceptors*	20-50
Communication range of EV	100 m to 500 m
EV Deployment	Uniform random distribution
Vehicle speed	10 - 25 km/hr
Cu_{max}	10 $ per kWh
T_{max}	30 mins
$rate_{max}$	50 kWh per hour
$charge_{max}$	20 kWh
R_{max}	10

B. Performance Metrics

Performance of our proposed algorithms is analyzed based on the following metrics:

1) **Successful matching percentage:** It is the percentage of *acceptors* got matched with the respective *donors*.
2) **Matching preference:** It is denoted by the *Rank* associated with the matched edge between an *acceptor* and *donor*. It signifies that whether an *acceptor* is matched with its preferable *donor* or not.
3) **Message overhead:** This is the number of messages exchanged between the *acceptors* and *donors* during the entire matching process.

C. Performance Analysis

1) Successful Matching Percentage: In Figure 3, we have compared the matching percentage of *V2VDisCS* with respect to [13] and [14] varying number of *donors*. *V2VDisCS*(simulation) and *V2VDisCS* (Theoretical) indicate the results that we get from simulation and from theoretical matching probability calculation (Sec V-C) respectively. We achieve 100% matching, when $\frac{no.of donors}{no.of acceptors} = 2.25$, while the communication range is $0.2\mathcal{R}$. *V2VDisCS* outperforms the existing Distributed Stable Matching algorithm [13] significantly with atmost 80% increase in matching % and with [14] atmost 3 times improvement. *V2VDisCS* (simulation) is also very close to *V2VDisCS* (Theoretical).

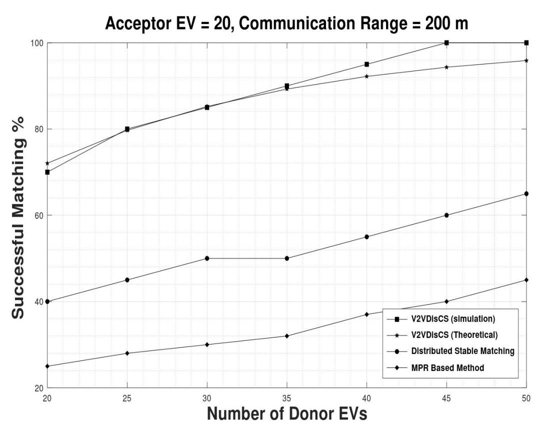

Fig. 3: Successful matching % vs Number of *donors*

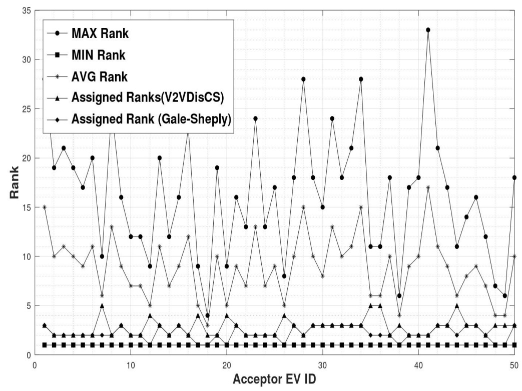

Fig. 4: *Ranks* of *reachable donors* for each *acceptor*

2) Matching Preference: In Figure 4, for a particular 100% matching scenario with 50 *acceptors* and 50 *donors*, the *Ranks* of the *reachable donors* for each *acceptor* are plotted. Here, *MIN Rank* and *MAX Rank* denote the minimum and maximum *Ranks* of *reachable donors* respectively. *AVG Rank* denotes the average of minimum and maximum *Ranks* and the *Assigned Rank(V2VDisCS)* denotes the *Rank* of the matched *donor*, found by *V2VDisCS*.

We can see in the figure that, for 100% *acceptors*, the assigned *Ranks* are below the average *Rank*, 10% *acceptors* get their first preference and none of the *acceptors* get the worst choice. Hence, we can conclude that, most of the *acceptors* get their favorable *donors*.

In this figure, we also plotted the *Rank* of the matched *donor* for each *acceptor*, found by the Gale-Shapley algorithm [16], which is a standard centralized stable matching algorithm. We can see that, for almost 76% *acceptors*, assigned *ranks* by *V2VDisCS* are less than or similar to the results of [16]. Hence, there are 24% unstable edges [17]. In spite of being a distributed heuristic approach with partial view of the network, *V2VDisCS* performs well compared with centralized matching.

Remark. An edge $\{a \in A, d \in D\} \in E \backslash M$ in an *Acceptor-Donor bipartite graph* $G = (A \cup D, E)$ is unstable relative to matching M if a is unmatched or prefers d over its current match in M [17].

In Table VIII, we have listed percentage of unstable edges(ϵ) considering different scenarios, by varying number of *acceptors* and *donors*. Here, we can see that $\epsilon \leq 0.38$, which is a fraction of the number of matched edges. Hence we can claim that, we have achieved almost stable matching [33].

3) Message Overhead: In Figure 5, the number of different types of messages, communicated in *V2VDisCS* is shown for a particular scenario with 100% matching.

Fig. 6 compares the message overhead of *V2VDisCS* with [13] varying communication range. In Fig 7 we have compared the message overhead of *V2VDisCS* with [13] and [14] varying number of *donors*. In both the cases, the message overhead of *V2VDisCS* is lesser than the existing approaches.

TABLE VIII: % of Unstable Edges

#Acceptors	*#Donors*	% of unstable edges (ϵ)
30	30	38
30	40	34
30	50	31
40	30	33
40	40	28
40	50	26
50	30	29
50	40	26
50	50	22

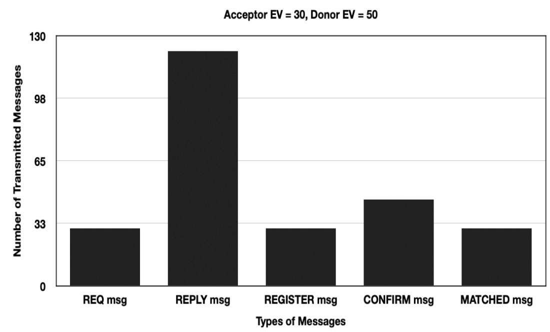

Fig. 5: Different types of Message Communication

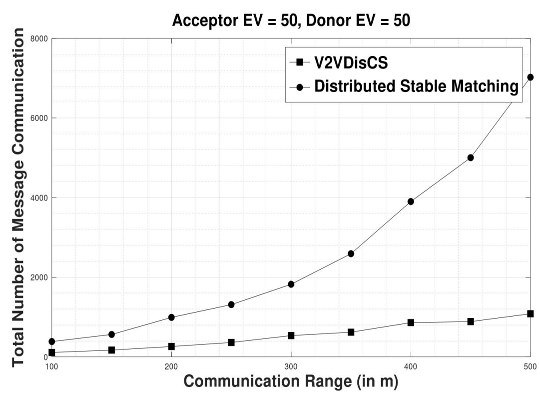

Fig. 6: Total Number of Message Communication vs. Communication Range

VII. Conclusions

V2V charge transfer is an emerging technology for EVs nowadays, which can reduce the congestion in the static charging points. In this paper, we have proposed distributed heuristics *V2VDisCS* for V2V matching for charge sharing by solving a multi-criteria decision-making problem, where we can maximize matching cardinality and minimize matching cost. An average case matching probability analysis is performed. Simulation results show that the proposed solution outperforms the existing distributed state-of-the-art with respect to matching percentage and message communication overhead. It shows comparable result for matching preference with respect to standard centralized stable matching algorithm

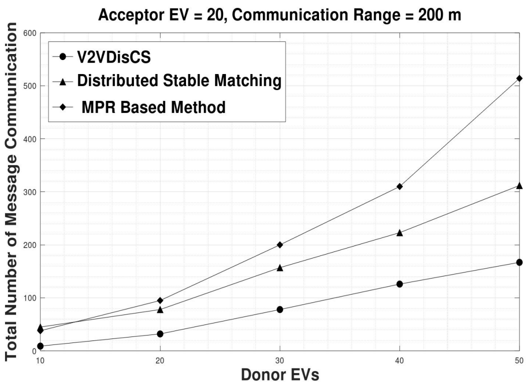

Fig. 7: Comparison of Message Overhead

and ensures almost stable matching. In future we will consider more real simulation scenarios, such as increased number of EVs in a larger deployment area and will check the performance, if an *acceptor* is allowed to reach a *donor* beyond its communication range. How close the proposed solution is to the optimal one also need to be proved.

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