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Enhancing Device-to-Device Direct Discovery Based on Predicted User Density Patterns

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Abstract

Device-to-Device (D2D) direct discovery service is a key component for Proximity Services (ProSe) and D2D communications. Depending on the type of the studied network (pedestrian, vehicular, residential, industrial), large spatio-temporal fluctuation in mobile users' density may occur inducing several patterns throughout the day. The current standards only account for fixed configurations of this service, and currently, the research into adaptive algorithms is done using analytical models and synthetic scenarios and configurations, which makes such solutions perform poorly on real systems. We propose an adaptive D2D discovery algorithm that, building upon existing work on user density prediction analytical models of the discovery process, uses historic network traces to update its operational parameters dynamically. We test the proposed algorithm and compare it to the discovery mechanism, defined in the Third Generation Partnership Project (3GPP) standards, in order to analyze the feasibility of these types of solutions. The simulation results show that the proposed algorithm strikes a balance between network utilization and time required for discovery, which is a very promising starting point for further research on this type of solutions.

Keywords: Wireless Communications, Device-to-Device (D2D), Proximity Services (ProSe), Device Discovery, Prediction, User Density.

1. Introduction

Device-to-Device (D2D) communications, as introduced by the Third Generation Partnership Project (3GPP) in Release 12, are based on geographical proximity. User Equipments (UEs) are able to detect and communicate with other UEs in their vicinity [1].

D2D communications are applied in different environments for both commercial and public safety use. It is already expected to bring up some advantages like spectrum utilization optimization and improvement in overall throughput and latency. 3GPP has already defined public safety use cases. It should maintain communications in environments where we have little or no coverage like on trains or underground. It would be also used for a partial or complete network shutdown occurring due to large scale natural disaster or power cuts. Extra capacity must be provided when needed, especially in large metropolitan areas [2].

D2D direct discovery is one of the defined proximity services along with D2D communication and D2D synchronization. Direct discovery allows UEs to identify users and applications within reach. D2D discovery can be either used to broadcast information (called announcement) or targeted at the detection of a specific device/application in a request/response manner, used for specific use cases (e.g. D2D relay discovery).

The evolved Node B (eNB) can be part of D2D direct discovery either for resource pool broadcast or resource allocation [3]. This approach is called mode 1 or "Scheduled" mode, and it is used for "in-coverage" scenarios where D2D users are

connected to the eNB. For "out-of-coverage" scenarios, the discovery resource pool parameters are pre-configured in the D2D-enabled devices and mode 2 (also referred to as "UE-Selected" mode) is applied. The UEs autonomously and independently select resources in order to perform D2D discovery in discrete time intervals of a fixed duration ("discovery period"). Mode 2 can also be used for in-coverage cases where UEs use their connectivity to the eNB only to get the resource pool configuration and rely on themselves for resource selection [2].

For D2D discovery (and like any other communication service), the number of users is important and its variation affects the network performance, since mobile users tend to consume resources in significantly different ways, depending on the time at which they use network services and the location where they do. This results in large variations of network usage profiles or even different daily users' density profiles according to each location.

In this paper, we have two main contributions. First, we propose an online prediction framework, based on Support Vector Regression (SVR) [4] and trained with real network traces, able to predict these instantaneous density. SVR is known to be more efficient for large dataset processing since it uses only few samples (support vectors) from the training dataset, which reduces notably the processing time. In addition, it only requires minimal computational resources, unlike other regression tools, such as artificial neural networks (ANN) which consumes more processing time, needs more complex configuration, and suffers from lack of generality causing probably under/over fitting

issues. So, we look at base station load profiles extracted from a real dataset of call detail records (CDRs), analyze and then classify into three groups based on the users' density fluctuation pattern throughout the day. Each profile represent a specific resource usage. We integrate a set of these load patterns, in the ns-3 simulator to implement a realistic network traffic generator tool.

For our second contribution, we take advantage of those predicted user density patterns that allow the anticipation of the potential number users for different types of areas and traffic classes, and based on that and a state-of-the-art analytical model for D2D discovery in mode 2 [5], we propose an adaptive algorithm that enhances the discovery process performance for dynamic environments. The main challenge for D2D discovery is increasing messages sending during announcing and monitoring procedures. In particular, announcing UEs would consume a lot of energy for permanent periodic transmission of discovery messages. This paper proposes an efficient direct D2D discovery procedure enabling energy saving. We validate our model with real traces of spatio-temporal UEs density patterns, which allow us to see how feasible such an approach is.

The rest of the paper is organized as follows. In Section 2, we discuss the related work in D2D discovery and existent user density models. In Section 3, UEs density prediction using mobile phone traces is introduced, and in Section refsec:discovery, an optimization of the UE transmission probability for D2D direct discovery is described. Based on the two previous sections, we propose, in Section 5, a proactive transmission algorithm for direct discovery that takes into account the user density patterns. Then, Section 6 shows the evaluation performance of the algorithm and results analysis for two scenarios with different user traffic patterns. Finally, we conclude and discuss future works direction in Section 7.

2. Related Work

Device discovery is not a new concept. WiFi and Bluetooth already use discovery protocols. However, the communication range and the frequencies occupied vary from one technology to another and the choice of one over the other highly depends on the use case and the need. Over the years, many research studies had been conducted in order to improve both WiFi and Bluetooth device discovery performances [6][7][8][9][10] and [11].

In this paper, we focus on cellular-based discovery. D2D discovery, as defined by 3GPP in their standards for Proximity Services (ProSe) [2][3][12], is a periodic unacknowledged broadcast of announcements (i.e. discovery messages). Each terminal transmits the discovery message based on a throttling process using a pre-defined Transmission Probability (which could be either 0.25, 0.5, 0.75, or 1). A UE sends a discovery message to all nearby devices to announce its presence and/or an application it supports. Out of reach UEs would not be able to receive the discovery message.

Although literature work related to D2D communications started a while ago, existing research on D2D has focused on the direct communication and how to mitigate interference and

to control power[13, 14, 15]. In [16] and [17], radio resources were simultaneously used by cellular as well as D2D links, thereby saving bandwidth. In [18] and [19], new interference management and interference cancellation strategies were proposed to enhance the overall capacity of cellular networks and D2D systems. In [20], the authors proposed a new network model for a D2D underlaid cellular system. In this system, both centralized and decentralized power control algorithms were defined and trade-off between supporting reliable communication for the uplink cellular user and improving the cellular network throughput.

Most papers on D2D discovery have mainly focused on evaluating and enhancing the performance of network-assisted discovery. For example, throughput of network-assisted discovery was evaluated in [21] and power control strategies were investigated in [22]. In [23] and [24], the eNBs were used to improve the discovery process in order to allocate resources and prevent contention. Authors from [25] took advantage of the network availability as well to speed up the discovery process. Therefore, for scenarios with infrastructure failures, such work can not be considered. Discovery needs to be independent of the network core.

For D2D discovery in mode 2, few contributions were made. Griffith and Lyons [5] developed an analytical model which calculates the optimal value of the discovery message transmission probability that minimizes the mean number of periods required for a successful discovery message transmission. The computation of this value requires a prior knowledge of the topology and the number of devices performing discovery, which is not always the case in real life. Furthermore, this model is static, and assumes there are no population changes in the network.

End-user communications devices (also known as "User Equipment", or UEs) are carried by subscribers that commute between different places throughout the day (from home to work, for example), which induce a specific time-dependent patterns of daily UE density within each base station. Few recent works investigate the impact of users' density on the process of D2D discovery. In [26], the authors propose a performance analysis for D2D discovery for multiple periods and show the impact of both high and small transmitting users density cases. The analysis showed that the discovery retransmission scheme behaves better with low transmit UE density while probability-based transmission scheme behaves better with high density. In [27], Chour et al. exploit the Road Side Units (RSUs) of the Vehicle Ad hoc Network (VANET) to propose a VANET-aided discovery protocol. The authors test different traffic volumes (vehicle per hour per lane), only in highways. The results show a low discovery latency. In [28], an analytical study of the number of UEs in a network-assisted D2D discovery group was provided. The authors analyze the statistical behavior of the distance between two D2D peers using the core network knowledge, assuming that the base stations follow a Poisson distribution. Based on that, they identify conditions to maximize the D2D discovery probability.

Even for D2D communication services, few works address the issue of studying D2D adaptation for different users' density patterns. In [29], an evaluation of the UEs density and traf-

fic load impact on a proposed transmission scheduling scheme is made. The model is evaluated in a static network by using different levels of users' density, then it is evaluated in a dynamic networks use-case by introducing a realistic human mobility model (SLAW). In the context of prediction-based D2D discovery algorithms, the authors in [30] investigate the optimal beacon probing and wakeup schedule under the condition that D2D contact intervals among mobile nodes following a power-law distribution discovered by network science. Simulations show that the proposed approach reduces the energy consumption while keeping the same performance. Although the authors claim to use real mobile mobility trace, the corresponding study is old (2006) and accounts only for traces of Bluetooth sightings by groups of users carrying small devices in office environments, conference environments, and city environments.

The main shortcoming of the previous works evaluating D2D discovery performance is that they use either simulated users' density pattern or theoretical models which may deviate from the real-world users' density behavior and ignore the daily fluctuation of UEs numbers. In our work, we validate our model with several real load profiles and this allows us to evaluate the reactivity of the model in different environments, and enhance an algorithm derived from analytical models with predictions based on actual traffic. The advantage of using real traces is that it guarantees the model reliability and enhances its efficiency. To the best of our knowledge, no previous contributions propose an adaptive D2D direct discovery algorithm based on realistic UEs' density traces and take advantage from a learning-based UEs' density prediction model to anticipate and optimize the discovery process.

3. Online User Density Prediction

3.1. SVR description

We propose a model based on Support Vector Regression (SVR) algorithm [4] for cell users' density prediction. Let $(x_{i,t}, y_{i,t})^N$ be a time-series training sample, where $x_{i,t}$ stands for the features vector that describes our data at timestamp t ($t \in 1, \dots, N$) and for base station i , $y_{i,t}$ stands for the label of each features vector or, in our case, the instant users' density at timestamp t and N_i stands for the number of timestamps of data collected from the base station i used for training (These parameters are more explained at section 3.2). The SVR model aims to find a linear function (or hyperplane) f which maps $x_{i,t}$ with $y_{i,t}$ in a feature space \mathbf{F} (usually with higher dimension) that provides a linear projection of the data. Hence, the linear function f will be the solution of the optimization problem into the \mathbf{F} . The function is formulated as follows:

$$f(x) = \langle W^T \cdot \phi(x) \rangle + b. \quad (1)$$

W is a weighting vector in \mathbf{F} space, b is a bias and ϕ is the mapping function corresponding to \mathbf{F} . To find this function, the following risk function should be minimized as stated in by this primal problem formulation:

$$\min_{W,b} \frac{1}{2} \|W\|^2 + C \sum_{i=1}^N (\xi_i + \xi_i^*). \quad (2)$$

$$\begin{aligned} \text{s.t. } & (\langle W \cdot x_i \rangle + b) - y_i \leq \varepsilon + \xi_i, i = 1, 2, \dots, N \\ & y_i - (\langle W \cdot x_i \rangle + b) \leq \varepsilon + \xi_i, i = 1, 2, \dots, N \\ & \xi_i^* \geq 0, i = 1, 2, \dots, N, \end{aligned}$$

where ξ_i and ξ_i^* are slack variables introduced to deal with prediction errors higher than the insensitive loss parameter ε and C is the penalty parameter.

To solve the quadratic programming of the primal formulation, Lagrange multipliers, (α_i) , are introduced and problem formulation become as follows:

$$\begin{aligned} \min_{\alpha, \alpha^*} & \frac{1}{2} \sum_i^N \sum_j^N K(x_i, x_j) (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) \\ & + \varepsilon \sum_i^N (\alpha_i + \alpha_i^*) - \sum_i^N y_i (\alpha_i - \alpha_i^*) \end{aligned} \quad (3)$$

$$\text{s.t. } \sum_{i=1}^N (\alpha_i - \alpha_i^*) = 0,$$

$$0 \leq \alpha_i, \alpha_i^* \leq \frac{C}{N}, i = 1, 2, \dots, N$$

The optimal prediction function obtained after resolving the previous optimization problem is as follows:

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x_i, x) + b, \quad (4)$$

where $K(x_i, x_j)$ is the Kernel function and its equation is as follows:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

3.2. Online users' density prediction model description

The SVR prediction constitutes a local load forecasting, i.e. each base station load is trained apart. Thus, the SVR is trained under in-cell normal load. Otherwise, the in-cell load includes also the D2D load since, D2D communications are made for nearby devices within the same cell. So that, the training process take in consideration implicitly the D2D load. We are making the hypothesis on this paper that the D2D load constitutes almost 30% of the total normal load. Furthermore, our model is general for D2D communications and is able to cover different types of D2D applications.

In this section, we describe the details of our users' density prediction model. In our contribution, we use the radial basis function (RBF), $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ as kernel function because it is more efficient with non-linear time-series (as our case) due to its generalization ability and non-linear mapping ability into a infinite feature space.

The prediction is performed in two steps: training, in which we use the history of users' density, and testing steps, in which model parameters are optimized. We model the training data with a set of four pertinent features for each base station. Each training vectors $X_{i,t} \in \mathbb{R}$ is described as follows, $X_{i,t} = \{x_{i,t}^1, x_{i,t}^2, x_{i,t}^3, x_{i,t}^4\}$, where:

- $x_{i,t}^1 \in \{1, 2 \dots 144\}$ stands for the chronological order of the ten-minute time interval within a day.
- $x_{i,t}^2 \in \{1, 2 \dots 24\}$ indicates the hour of the corresponding training sample. The choice of this feature is based on the daily cycles inferred from the data.
- $x_{i,t}^3 \in \{1, 2 \dots 7\}$ indicates the weekday standing for the training data. We choose this feature because we noticed that the data has weekly cycles.
- $x_{i,t}^4 \in \{1, 2 \dots 52\}$ represents the chronological order of training data week. We choose this feature because some yearly behavior can occurred like holidays or seasonal periods, etc.
- t stands for the timestamp into the whole time-series, i.e., $t \in N$ as defined earlier.
- i stands for the index of the base station concerned by the prediction.

The choice of these features formulation is made based on the periodicity analysis. To perform the periodicity analysis on users' density time-series, we adopt in our study the Welch's method [31] that consists on estimating the power spectral density (PSD) of the signal (In our case the signal is the training time-series of users' density). It is an improvement on the standard periodogram spectrum estimation method and it reduces the noise in the estimated power spectrum density. The normalized PSD Welch's estimation is represented in Fig. 1. From this figure, we observe some frequencies with high amplitude values, such as a peak at 10^0 (1 cycle/day) which describes a daily periodicity, another peak at $10^{0.3}$ (2 cycle/day) corresponding to a 12h-periodicity and the peak near to 10^{-1} (0.14 cycles/day) which corresponds to a weekly cycle.

Then, for the training step, each vector $X_{i,t}$ must be trained with its corresponding label $y_{i,t}$ which stands for the base station UEs' density at the time interval $x_{i,t}^1$. We use here a training dataset of eleven weeks, as history time-series.

To find the optimal value of the model parameters C , ϵ and γ (the latter parameters belongs to the RBF kernel function), we used the cross-validation technique and we fix the optimal parameter which minimize the error as depicted in Fig. 2.

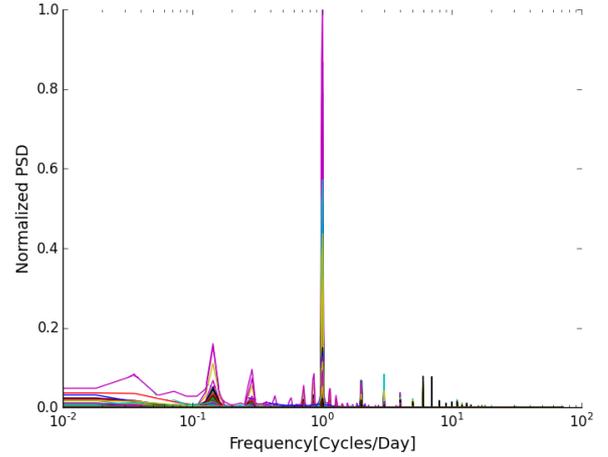


Figure 1: Welch's periodogram: Time-series periodicity analysis

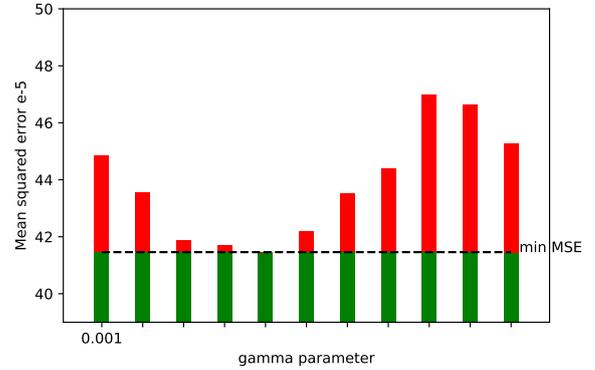


Figure 2: Performance measurement of the SVR-based load prediction

SVR prediction efficiency is validating by using testing data extracted also from Dakar dataset, which corresponds to the data of the week just after the data window used for the training step. Fig. 3 shows a comparison between a predicted and real base station data and we can see that the prediction is very close to the real load.

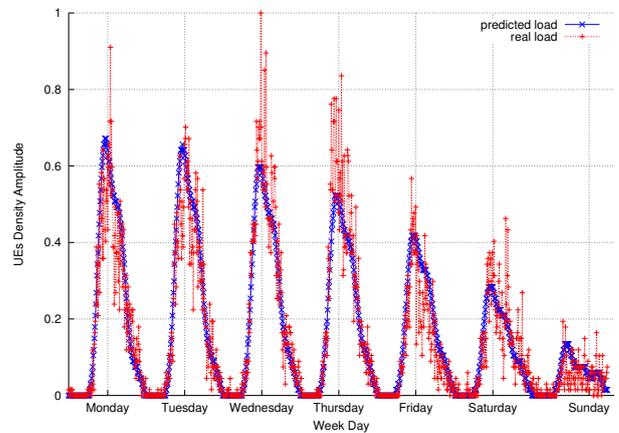


Figure 3: Predicted versus real traffic profiles

The accuracy of the load SVR-based prediction is evaluated by two major indicators: The Mean Squared Error (MSE) measurement and the squared correlation coefficient. MSE gives an overall idea of the errors which occurred during forecasting and measures the average squared deviation of predicted values from the real data. Its mathematical expression is as follows:

$$MSE = 1/n \sum_{1 \leq k \leq n} (y_k - f_k)^2 \quad (5)$$

where y_k corresponds to the real load value at time k , f_k represents the predicted value and n is the total number of points constituting the load (real and predicted) time series.

The model MSE average reaches a minimal value of 4.3×10^{-4} with large testing history data and this value is very acceptable for long time-series forecasting. On the other hand, the squared correlation coefficient (or the coefficient of determination R^2) is a statistical measurement of how close the real data are to the prediction. For our model, this performance measurement reaches a value equal to 0.91. Thus, these metrics prove that our prediction model has a good accuracy.

In this contribution, we integrate a set of users' density time-series profiles, extracted from a realistic dataset of mobile traces provided by Orange Senegal, in ns-3 to implement a realistic traffic generator. The trained dataset of the prediction model is issued from this traffic generator. The code source of the ns-3 traffic generator and the realistic traces are published¹ to be used as an open source mobile traces.

The users' density profiles inferred and classified into three profile classes of base stations UEs' density in reference [32].

Each base station profile belongs to a specific pattern of network usage and load fluctuation, which depend on the nature of its location. Fig. 4 depicts a simple illustration of these load profile shapes:

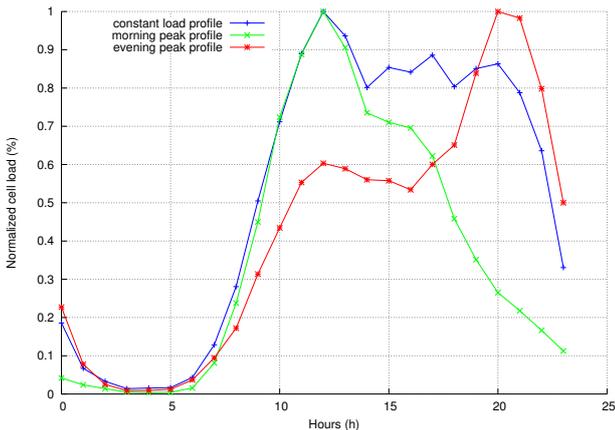


Figure 4: Base station load profile illustration

The red curve belongs to the “Night peak profile” and represents residential areas, green curve corresponds to areas with “Day peak profile” where most of business areas and activities

are located, and the blue curve with a “constant load profile” corresponds to mixed areas. [32] presented a general approach and demonstrated the ability and the potential of using machine learning tools to optimize networks. The work was essentially focused to propose classification algorithms for very wide networks and global prediction. Based on the aforementioned results, the following section will describe an adaptive and real time UEs discovery to optimize the D2D resources network.

4. Discovery Optimization

In the operational mode described in the paper, the discovery message is broadcasted and no acknowledgement is expected. There is no requirement in the 3GPP standards for how many UEs need to discover which other UEs, as that will depend on the requirements of the application being announced. In this paper we took the conservative approach of using the worst case, i.e. we consider the discovery process complete when all UEs have discovered all other UEs in the same group. A discovery message is considered successfully received between two specific UEs if the first UE succeeds to transmit a discovery message and the second UE succeeds to receive this message (i.e. the receiver is not transmitting at the same time slot, and other UEs are not creating interference by sending their discovery message at the same time and frequency).

If a UE transmits a message and the message does not experience any collision, that UE will be discovered by all the other UEs as long as they are within reception range, not transmitting during that time slot, and authorized to receive discovery messages.

In Table 1, we provide a list of symbols we use in this section.

Table 1: List of Symbols

Symbol	Definition
N_f	Number of resource block pairs available for discovery
N_t	Number of subframes available for discovery
N_r	Total number of resources in discovery pool
N_u	Total number of UEs in the scenario
θ	Transmission probability in the discovery pool
θ^*	Optimal transmission probability computed

4.1. Discovery Characteristics

For our work, we consider D2D discovery as performed by the UEs without any network intervention. We assume having out-of-coverage UEs operating in mode 2 and picking resources from a discovery resource pool composed of pre-defined numbers of resource block pairs (RB), noted N_f , and subframes (SF), noted N_t . The total number of discovery resources is defined by Eq. (6).

$$N_r = N_t \times N_f. \quad (6)$$

In Fig. 5, we show a 3D representation of how these parameters operate with each other. Each tile corresponds to a pair of RB and one subframe. Discovery resources are not necessarily contiguous. This configuration follows a periodic repetition in time (not shown in the figure).

¹<https://github.com/SHM91/NS3-RealisticTrafficGen1>

An extensive study has been conducted in our team [33]. The study shows the benefits that D2D can take advantage of, when Frequency Hopping (FH) is used. Yet, as explained in the work many practical details about the distance between devices may prohibit FH from achieving the targeted improvement. Nonetheless, FH or other multiplexing techniques will have an impact on the device discovery. The abstract result is an increase in the number of subframes and hence is equivalent to adding more resource blocks for the discovery in our work. The Fig. 5 shows an abstraction of the benefits of additional multiplexing techniques such as FH. We can see that it is equivalent to adding a new dimension that represents extra subframes that are available during the hopping sequence.

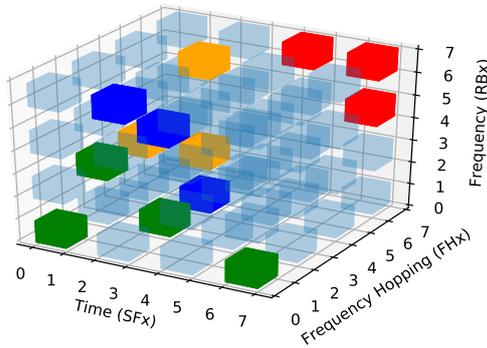


Figure 5: 3D representation of the discovery resource pool when introducing Frequency Hopping

D2D discovery transmissions happen using a uniform probability called “transmission probability” which can be any of the following four values: 0.25, 0.5, 0.75, 1. Each UE uses this same pre-configured value to autonomously choose resources from this grid, and the discovery message is sent in the corresponding tile (i.e. resource blocks and subframe combination, represented in blue).

By default, the channel used for D2D communications is half-duplex. It means that UEs are unable of simultaneously transmitting and receiving discovery messages [2]. So, a UE which sends a discovery message at a specific subframe, automatically misses all other discovery messages sent by all other UEs at the same subframe (i.e. the times in the same column).

4.2. Optimized Transmission Probability

D2D direct discovery in mode 2 lacks adaptivity to the changing communication environments, because it relies on fixed pre-defined parameters, including the transmission probability. In our proposal, using the daily load predicted by the SVR model makes the D2D discovery more dynamic, and aims to adapt instantly the transmission probability according to the predicted users density.

We assume that we have N_u UEs in a discovery group. A discovery message is successfully received between two specific UEs when several conditions are satisfied:

- the transmitter is allowed to announce in the current period after checking its threshold: θ .
- the receiver should not be announcing at the same time slot (i.e. subframe): $1 - \frac{\theta}{N_r}$, otherwise it would miss the transmitter’s discovery message, because the discovery messages are sent over a half-duplex channel, which prevents the UEs from sending and receiving data in the same time slot.
- none of the other UEs pick the same resource in the same time slot as the transmitter: $(1 - \frac{\theta}{N_r})^{N_u-2}$, in order to avoid any collisions.

Accounting for those requirements, the final expression of success probability is determined by Eq. (7).

$$P_{success} = \theta \left(1 - \frac{\theta}{N_t}\right) \left(1 - \frac{\theta}{N_r}\right)^{N_u-2}. \quad (7)$$

The value of θ that maximizes the success probability is determined by differentiating Eq. (7). Therefore, taking into account the half-duplex nature of UE transmissions and assuming that the number of users interested in discovery is equal to N_u , the optimal value of the transmission probability θ is defined by Eq. 8 and Eq. 9 below [5].

Knowing that the SVR algorithm provides the user density in a network. The maximum number of users is pre-determined (an input) and that allows the computation of the fluctuation of the number of users throughout the day. The prediction provides information about the user density for every hour of the day. That’s why the discovery session is set to one hour and the optimal transmission probability varies every hour.

Additionally, the proposed solution would work similarly with more frequent inputs (e.g. every 30, 10, or 5 minutes), as the optimal transmission probability value would be calculated accordingly. The algorithm is adaptable and dynamic. So, finer granularity allows more accuracy of the number of users in the network, which means better algorithm precision.

First step is to check the number of subframes N_t defined in the discovery resource pool. If $N_t = 1$, UEs will never get to discover each others because of the half duplex constraint. That’s why that case is specifically checked for, and if met, we know that discovery would not happen. Then, we examine if the number of devices performing discovery are way smaller than the numbers of subframes and resources (N_t and N_r respectively). For this case (represented by Eq. 8), the UEs choose to announce all the time because of the low probability of collisions.

$$\theta^* = 1, \quad \text{if } N_u < \frac{N_r \times (N_t - 2) + N_t}{N_t - 1} \quad \text{and } N_t > 1. \quad (8)$$

If the previous checks fail, we compute the optimal value of the transmission probability θ based on Eq. 9.

$$\theta^* = \frac{2N_r + N_r \times (N_u - 1) - \sqrt{4N_r \times (N_r - N_t) + N_t^2 \times (N_u - 1)^2}}{2N_u}. \quad (9)$$

The authors from [5] show that there is a small impact to performance when quantizing θ to multiples of $1/4$ ($0 < \theta \leq 1$), as allowed by the 3GPP standard. The model presented in [5] assumes an ideal environment with minimalistic propagation errors. It also considers a pessimistic approach of discovery messages handling: all colliding discovery messages are dropped and their respective applications and UEs are not discovered. However, in [34], Ben Mosbah et al. use simulations to prove that adding interference and retrieving discovery message with the strongest signal don't affect the quantized value of the transmission probability (i.e. the discovery performance is better using that specific value).

5. Proposed Algorithm

Our proposed algorithm makes use of the predicted user density patterns (section 3) and the discovery analytical model (section 4) in order to determine the transmission probability value providing the best discovery performance. We make the hypothesis here that the D2D users amount represents 30% of the global predicted users amount within the cell [35]. The algorithm is executed every hour, matching the fluctuation of the number of users determined by the user density prediction. It takes into consideration the number of predicted users for that area during that time of the day and computes the optimal value of the discovery transmission probability accordingly (i.e. based on the number of resources and the number of users as shown by Eq. 8 and Eq. 9). Therefore, at the beginning of each hour, the algorithm takes into account the geographical area to determine the traffic type. It checks its saved real database of similar traffic, calculates the average and gets the number of predicted users in the area for that hour and for that specific traffic. The user density patterns utilized during this process are extracted from real network traces. Therefore, it gives a close idea of the actual number of UEs present in the network. Based on this information, the optimal transmission probability θ is calculated in order to get the best discovery performance. This value will be used throughout the whole hour, until the next period of time where the predicted number of UEs may change.

Data: Total number of discovery resources (N_r) and number of subframes dedicated to discovery (N_t)
Result: Probability of transmission to be used (θ)
for each hour of the day do
 get the total number of predicted users in the area for that hour based on the predicted user density pattern (N_u);
 for any given UE performing D2D discovery do
 compute θ (using Eq. (8) and Eq. 9);
 round θ to the nearest multiple of 0.25;
 use the resulting value of θ for the rest of the hour;
 end
end
Algorithm 1: Hourly Adjusted Transmission Probability

6. Performance Evaluation

In this section, we present the test and evaluation of our algorithm based on ns-3 simulations [36]. We use a scenario extracted from Orange Senegal traces study [32] and integrate it in ns-3 as realistic UEs' density patterns, to study the efficiency of the proposed algorithm.

It will be shown that combining machine learning approach with a D2D algorithm optimizes and speeds up the time discovery by predicting in advance the D2D users density. Moreover, realistic trace data-sets of mobile networks, which adds dynamicity to the model. Compared to [29], the D2D algorithm has been tested on different traces including the city of Milan.

6.1. General Assumptions

Table 2 summarizes the list of network parameters and their values used for our simulations.

Table 2: Simulation Parameters and Values

Parameters	Values
UE transmission power	23 dBm
Propagation model	Cost231 ([37])
Available bandwidth	50 RBs
Carrier frequency	700 MHz
Discovery period	0.32 s
Number of retransmission	0
Number of repetition	1
Number of resource block pairs	4
Number of subframes	5
Total number of resources	20
Total number of eNBs	3
Discovery start	2 s
Total simulations per scenario	100

We don't include a measure of interference as a parameter because in [34] it was already shown that the results obtained with simpler air propagation models still hold, and this simplifies the analysis, allowing us to focus on the elements that actually have a significant impact on the discovery performance.

Sets of UEs density patterns are extracted from Dakar data to be integrated in ns-3 to implement a realistic traffic generator tool. The tool is then used to generate realistic pattern to train SVR model in order to make a prediction of the UEs density evolution within each area and then use the predicted values for the D2D Direct discovery algorithm.

In our scenarios, we are interested in comparing the performance (in terms of time required to complete discovery, and messages sent) of our discovery algorithm with that of the discovery mechanism defined in the 3GPP standard (with different operational parameters). The number of messages sent will let us know how much spectrum is being used for the discovery operations, and the time to discovery will provide an indication of the impact on the user experience. In order to provide an upper boundary to the time metric, the discovery process can only run for 60 seconds, giving up on discovering more UEs after that amount of time.

The results shown are the outcome of running the scenario 100 times in the simulator. For each metric we show the average value and 95 % confidence interval. In each simulation, every UE is able to send announcements using a randomly chosen discovery resource. A UE uses discovery resources to send discovery but there is no guarantee that its discovery message would make it to the receivers because of potential collisions with other UEs choosing the same resources, or the fact that the receiver is transmitting too (i.e. the half-duplex constrain of the D2D channel prevents the UE from receiving the message).

6.2. Morning Traffic with Low User Density

6.2.1. Scenario Description

We consider a morning users' density profile scenario in an area characterized by user fluctuation due to the presence of high education institutions. As a consequence, a morning traffic profile is considered. Under normal conditions the area would be served by 3 eNBs, but in this scenario they have been rendered unusable (e.g., due to backhaul connectivity losses). The UEs are randomly deployed, as represented in Fig. 6. The maximum number of users at peak hours are 50, 75, and 100.

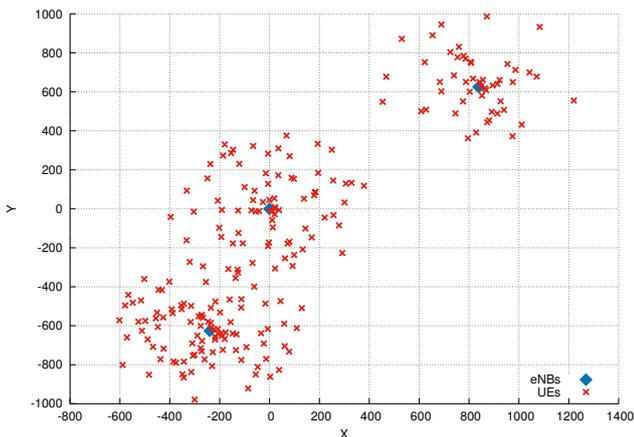


Figure 6: Example of nodes position for the morning traffic scenario with low user density

6.2.2. Results

Simulation results are illustrated in Fig. 8, 9 and 10. Each one of them shows the number of messages and time (measured in periods) until all the UEs in the area were discovered (or until the 60 second discovery period expired).

For the 3GPP algorithm, the transmission probability is invariable throughout the simulation and can be either 0.25, 0.5, 0.75 or 1. However, our algorithm uses the information about the predicted number of users to adjust the correspondent transmission probability dynamically. UEs are able to compute their own transmission probability over time. A significant energy savings and packets loss avoidance can be ensured using the considered discovery mechanism, which is the immediate consequence of reduced number of transmitted messages as shown in Fig. 8a, 9a and 10a.

The discovery performance is very similar among all areas. We can observe an increase in the network activity which

reaches a peak around noon. The curves validate the fact that we are simulating a morning-based traffic. We can also notice that during the hours with low number of UEs, there is a direct trade-off between the time required to complete discovery and the number of messages sent. We can see how our proposed algorithm strikes a balance between both metrics. For the number of messages, only the configuration with a transmission probability of 0.25 provides better performance at certain times, and at those points the time metric shows better results for our algorithm. What may be more important, our algorithm shows a more predictable behavior (with more consistent values for number of messages and time required) than the 3GPP algorithms.

The proposed algorithm uses the optimal transmission probability based on the user density prediction. Although each value of the transmission probability is optimal for a range of users, moving from one value to the next one is very delicate. At certain transition points, small variations in the number of users may switch the optimal value of the transmission probability.

For our scenarios, we consider 5 subframes and 4 resources block pairs. In Figure 7, we plot the optimal transmission probability for different number of users based on Equation 9, after rounding θ^* to the nearest multiple of $\frac{1}{4}$. We observe that for a number of users varying between 29 and 49, the optimal transmission probability is equal to 0.5. However, if the network traces predict 50 UEs, the computed optimal transmission probability value will be 0.5. If, in reality, we have 52 UEs, the actual optimal transmission probability should be 0.25. Prediction errors like that double the number of messages sent, and are the most significant factor on the cases where the proposed algorithm behaves worse than the 3GPP one. This may be avoided with finer granularity in the input and more accurate predictions.

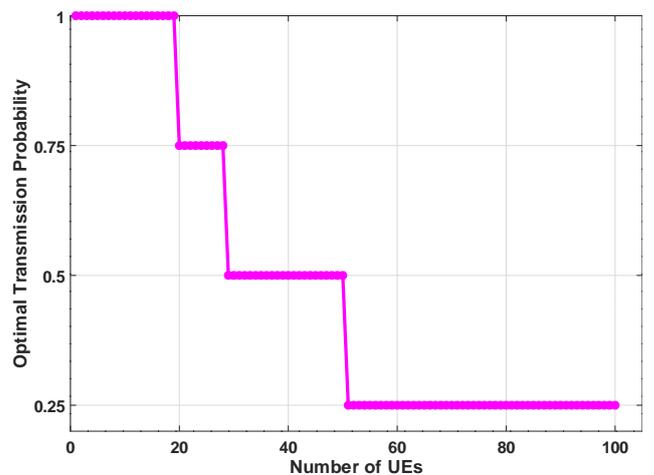
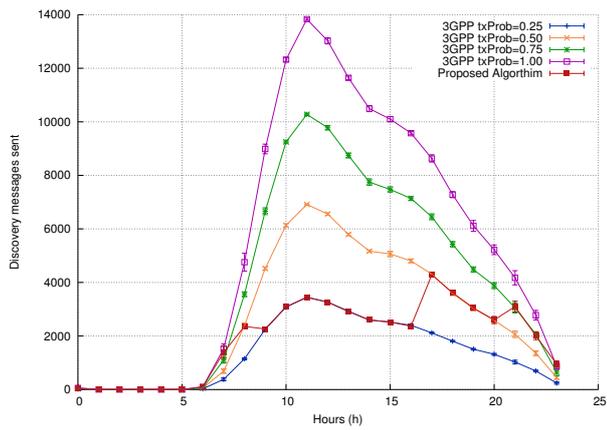
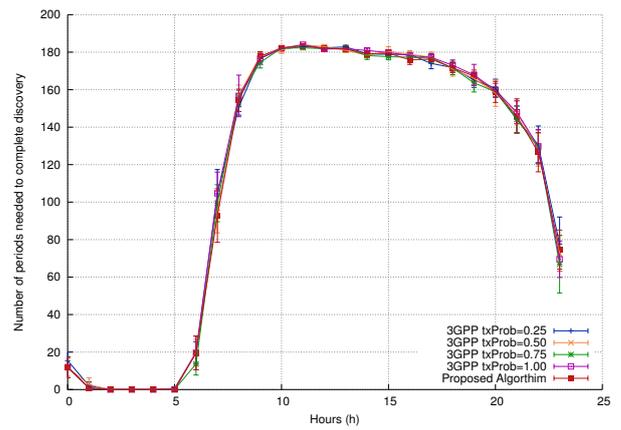


Figure 7: Optimal transmission probability associated to the number of UEs for 5 subframes and 4 resources block pairs

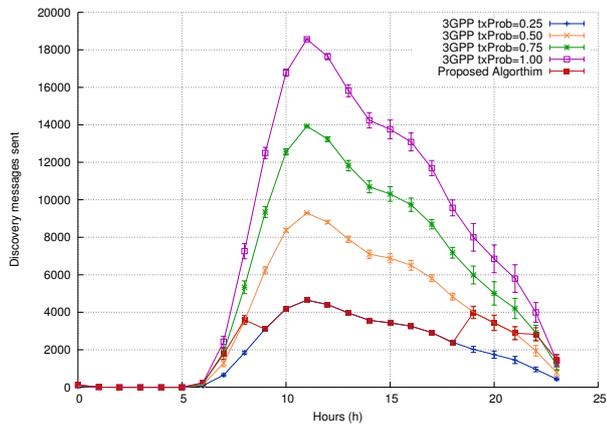


(a) Number of discovery message sent

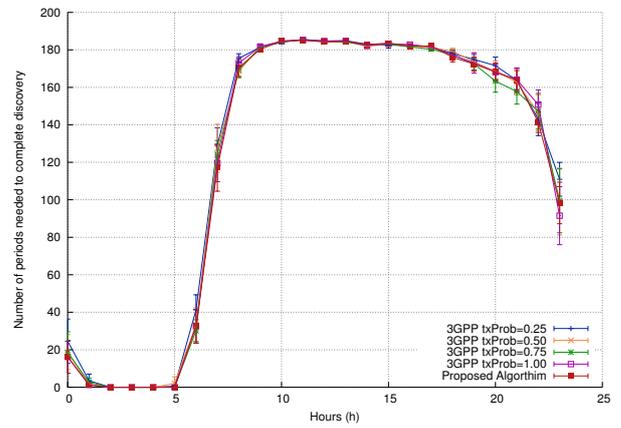


(b) Number of periods needed to complete discovery

Figure 8: Morning Traffic (Low User Density): Area 1

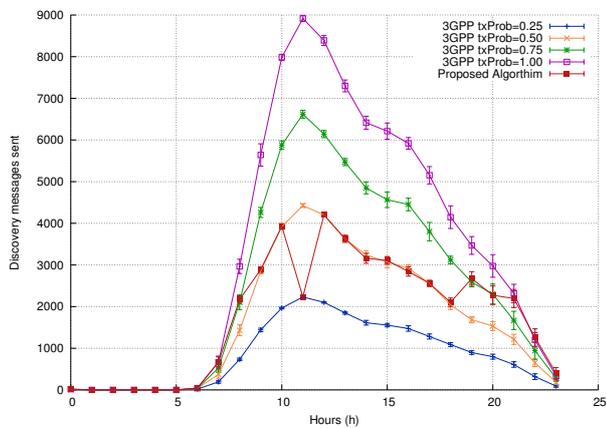


(a) Number of discovery message sent

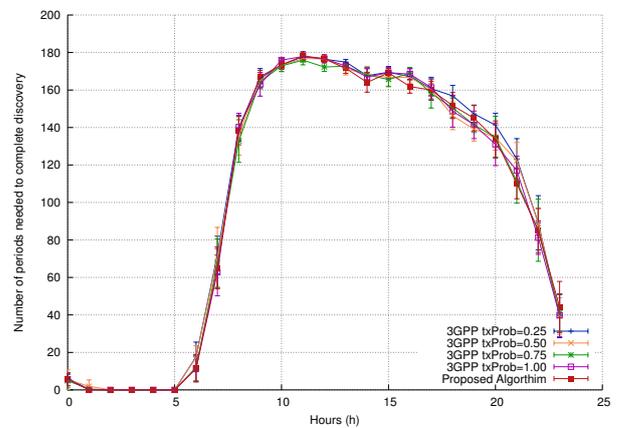


(b) Number of periods needed to complete discovery

Figure 9: Morning Traffic (Low User Density): Area 2



(a) Number of discovery message sent



(b) Number of periods needed to complete discovery

Figure 10: Morning Traffic (Low User Density): Area 3

6.3. Morning Traffic with High User Density

6.3.1. Scenario Description

Unlike the scenario described in 6.2, in this subsection, we consider a business district covered by 13 eNBs as shown in Fig. 11. The area is also predicted to accommodate a morning traffic profile, but in this case, with higher concentration of deployed UEs.

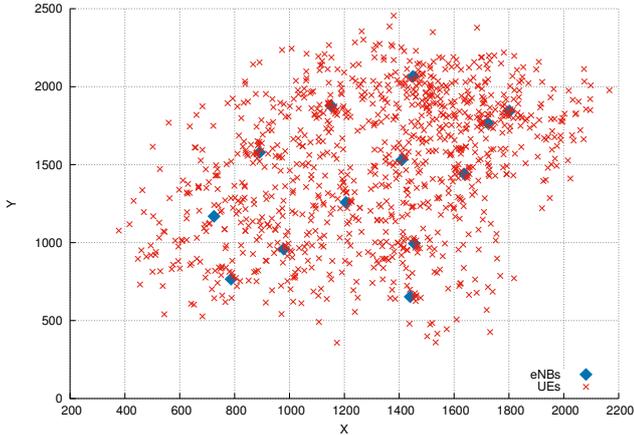


Figure 11: Example of nodes position for the morning traffic scenario with high user density

6.3.2. Results

Simulation results are represented in Fig. 14, 15, 16, 17, 18, and 19 we show the results obtained for the first 6 eNBs in the topology. The remaining eNBs show performance results similar to these ones, and those figures have been omitted for simplicity.

As we can see, while the specific values are different, the trends obtained are similar to those from the scenario with lower user density. The most significant difference is that, with more UEs to detect in each area, the 60 second high bound is in this case a hard bound to the amount of UEs detected, with all the versions of 3GPP and the algorithm using all that time, and still failing to discover all the UEs in the area. Looking at Fig. 20 we see how for all these eNBs the high user density prevented discovering all the UEs, except in the case of extremely low predicted density. During the rest of the day, the percentage of discovered users became almost a constant, as during the times with higher number of users sending messages that translated as higher interference, and in the periods with lower amount of UEs, message collisions and lower received signal strength (due to the greater distance to some UEs), kept the ratio of discovered UEs almost constant.

Apart from that major difference, we can observe how the number of messages sent during discovery follows a similar pattern to those obtained for the lower density scenario. This means that the predicted user densities worked equally well regardless of the saturation of the network, with consistent results across all the eNBs in the area.

Additionally, it is possible to use Eq. 7 to theoretically compute the time required for one random UE to discover another

UE in its vicinity, according to a defined confidence (i.e. success criteria) [38]. As an example, we consider a success criteria value of 99 % and we integrate the prediction traces to anticipate the number of devices throughout the day. For two different densities, we draw the number of periods needed for one UE to discover another UE, then deduce the consumed energy percentage, when using our proposed algorithm (adaptive dynamic transmission probability) and other static transmission probabilities values. In Fig. 12, we can see how, regardless of the fluctuation of UEs connected to the network, and therefore, the different values of the optimal Transmission Probability during the day, with our proposed algorithm the UEs always finish discovery as quickly as possible. In turn, this means that as a result of that, the total energy consumed by the UEs that use our proposed algorithm is lower (as shown in Fig. 13).

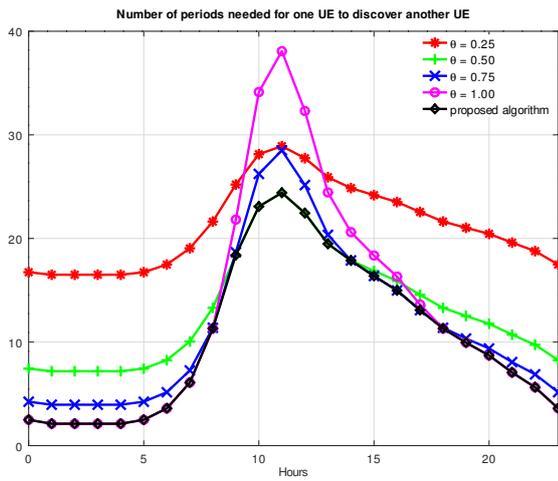
6.4. Discussion

In this Section we have presented the results obtained with our simulations of a morning traffic pattern. Similar results were obtained with the simulation of scenarios following the evening traffic pattern, with the results obtained being comparable to the ones in this paper. In all the cases, the discovery algorithm using predictions from the traces performed close to the version of the 3GPP algorithm with the optimal transmission probability. A detailed analysis of the reasons for why the proposed algorithm was not performing optimally showed that this behavior is similar to what was observed in [34], where a discovery algorithm based on the same concept performed in each case slightly worse than the optimal version of the 3GPP algorithm, but better than every other version. Furthermore, also similarly to the results in [34], we observe how a fixed transmission probability provides optimal performance in the scenarios where that happens to be the optimal choice, but in the rest of cases that fixed value significantly slows the whole discovery process.

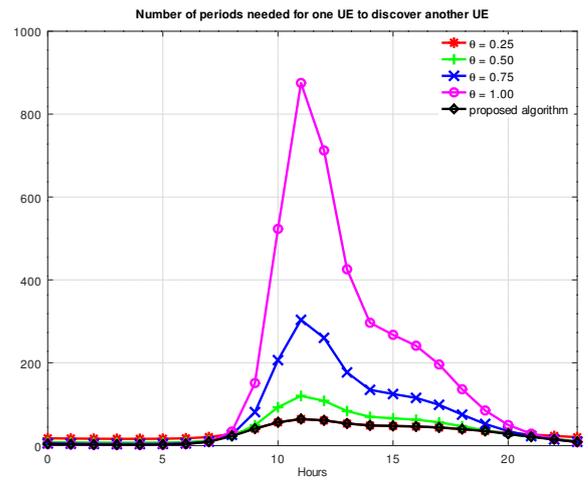
In our case we observe a similar behavior, where the 3GPP algorithm with the optimal transmission probability for each hour behaves better than our proposed algorithm. However, when the user count changes and a different version of the 3GPP algorithm becomes the optimal, our algorithm's performance stays close to that optimal value.

We have also observed that there is a strong correlation between the accuracy of the predictions used by the algorithm, and its performance. If the predictions are not accurate, or if the 95 % confidence interval is too ample, it is likely than in a given scenario the algorithm will choose a transmission probability that is not the optimal for the number of UEs actually deployed in the area.

Finally, we should highlight the value of being able to predict the user density in the network, as it can be used by the devices to adjust their operational parameters depending on the situation (for example, aim for a faster discovery process at the expense of spectrum utilization when minimizing the delay is the top priority, but switch to a longer process that requires sending less messages when the batteries are low).

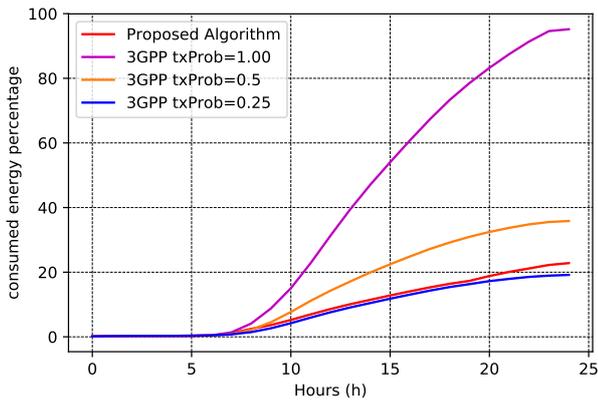


(a) Low density case

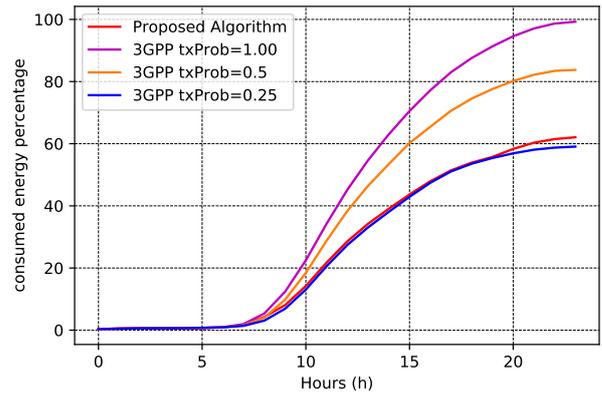


(b) High density case

Figure 12: Number of periods needed to finish the discovery

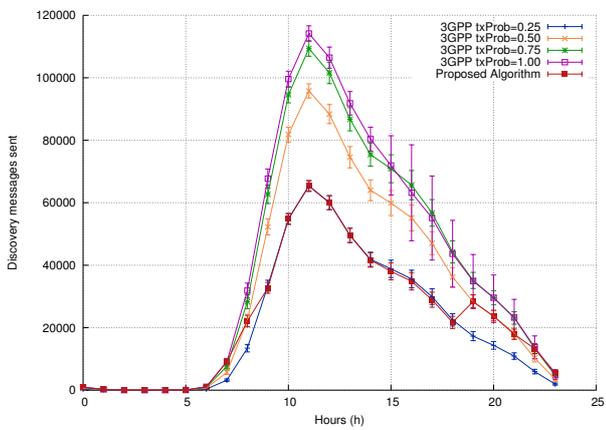


(a) Low density case

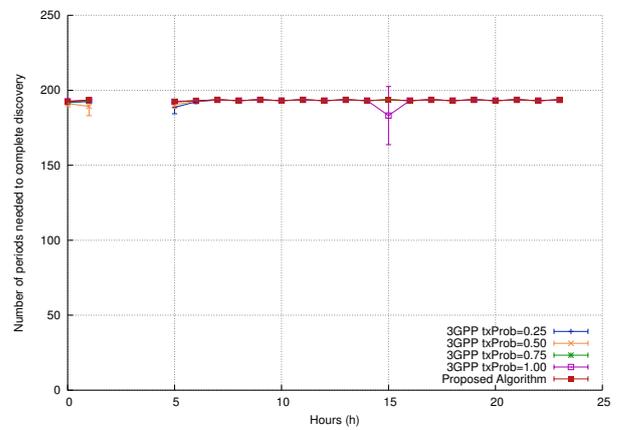


(b) High density case

Figure 13: Consumed Energy Percentage

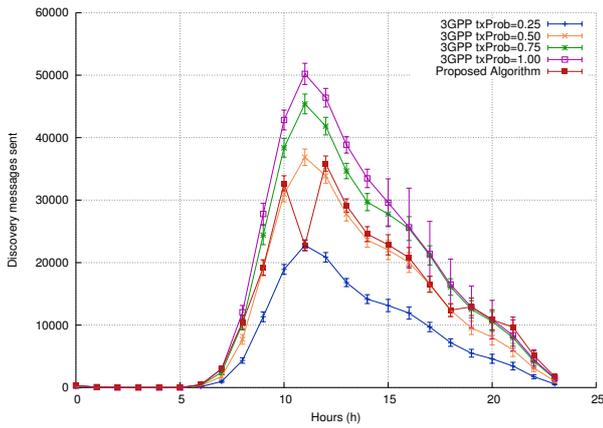


(a) Number of discovery message sent

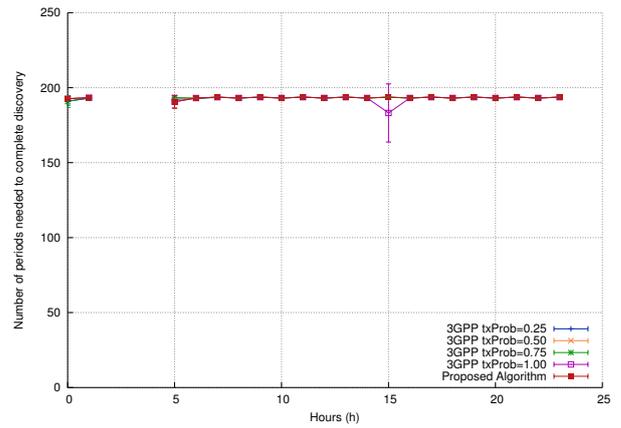


(b) Number of periods needed to complete discovery

Figure 14: Morning Traffic (High User Density): Area 1

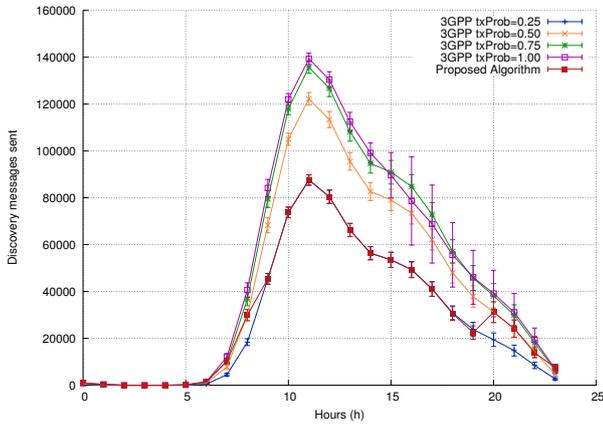


(a) Number of discovery message sent

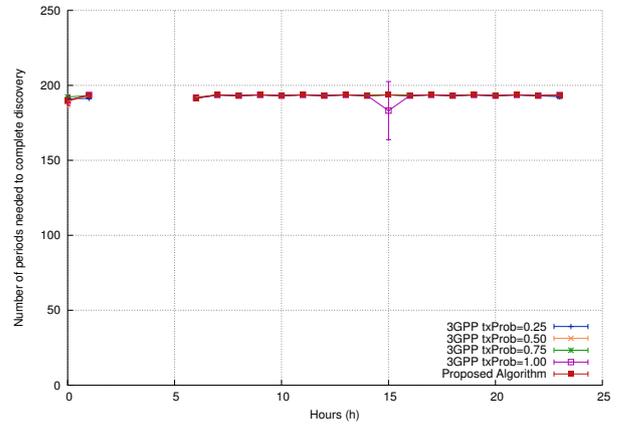


(b) Number of periods needed to complete discovery

Figure 15: Morning Traffic (High User Density): Area 2

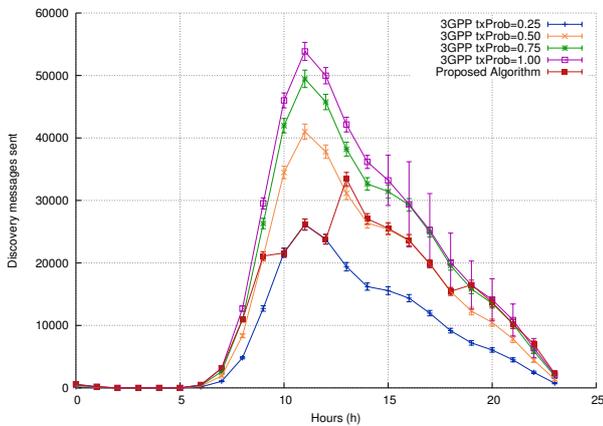


(a) Number of discovery message sent

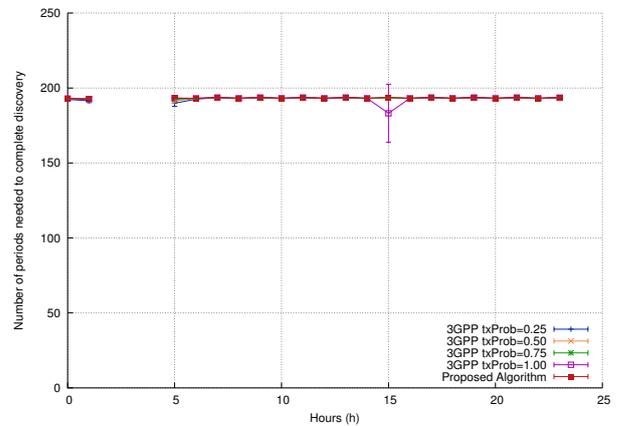


(b) Number of periods needed to complete discovery

Figure 16: Morning Traffic (High User Density): Area 3

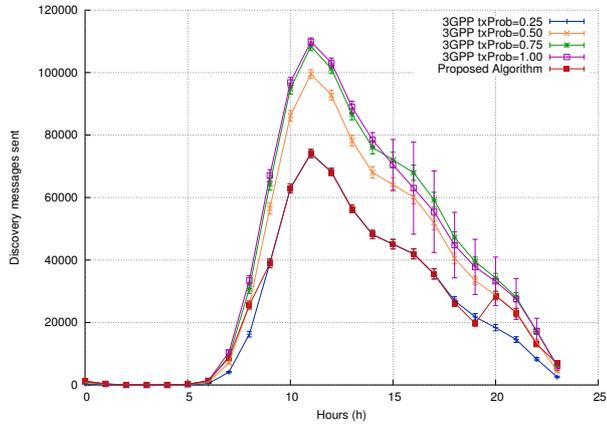


(a) Number of discovery message sent

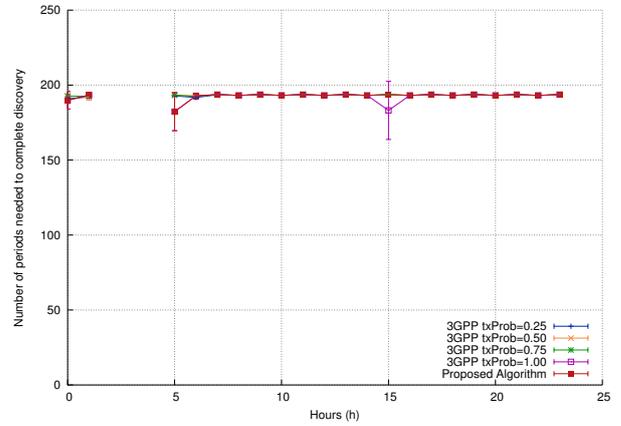


(b) Number of periods needed to complete discovery

Figure 17: Morning Traffic (High User Density): Area 4

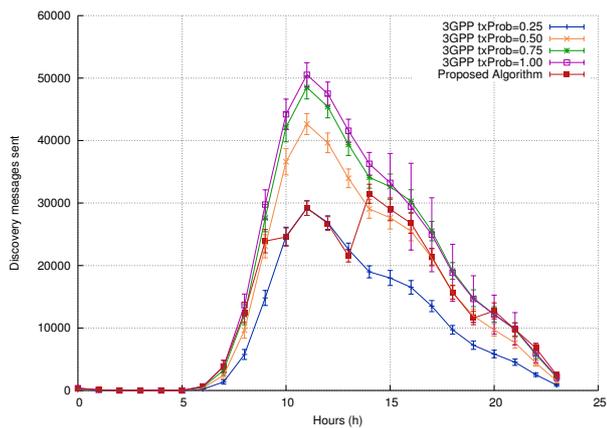


(a) Number of discovery message sent

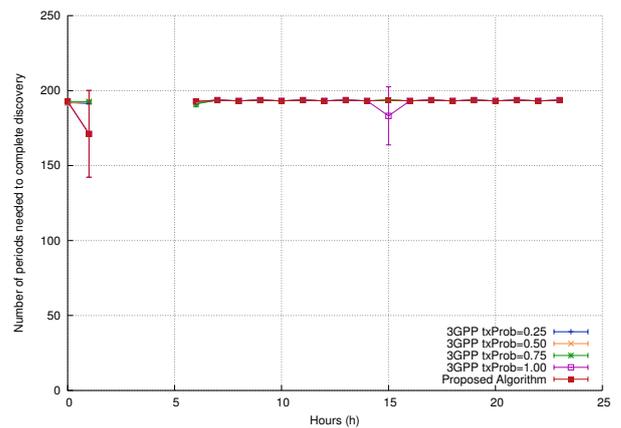


(b) Number of periods needed to complete discovery

Figure 18: Morning Traffic (High User Density): Area 5

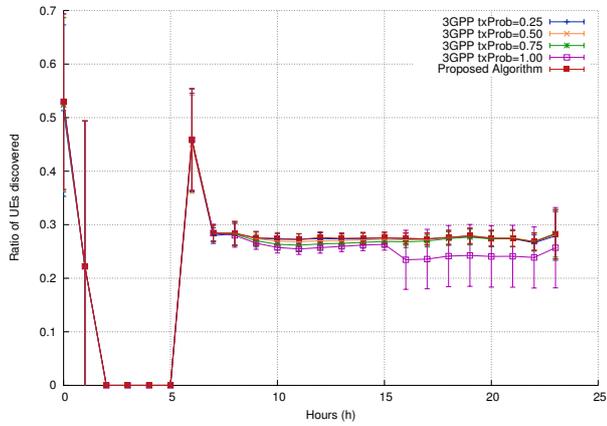


(a) Number of discovery message sent

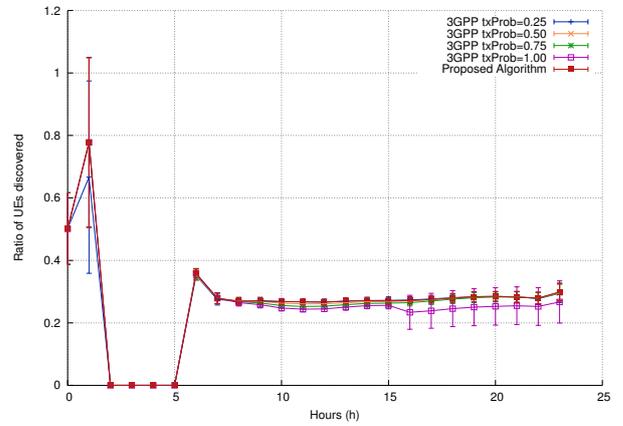


(b) Number of periods needed to complete discovery

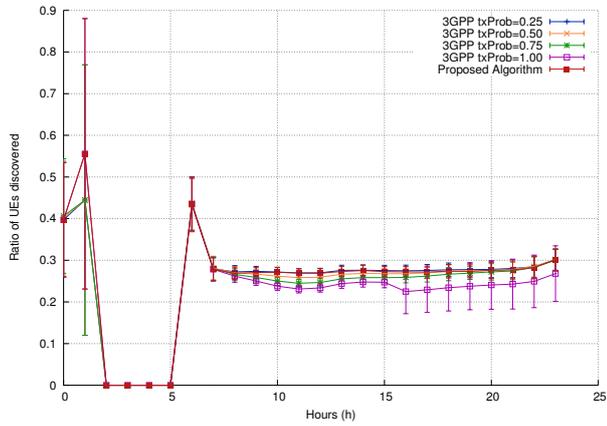
Figure 19: Morning Traffic (High User Density): Area 6



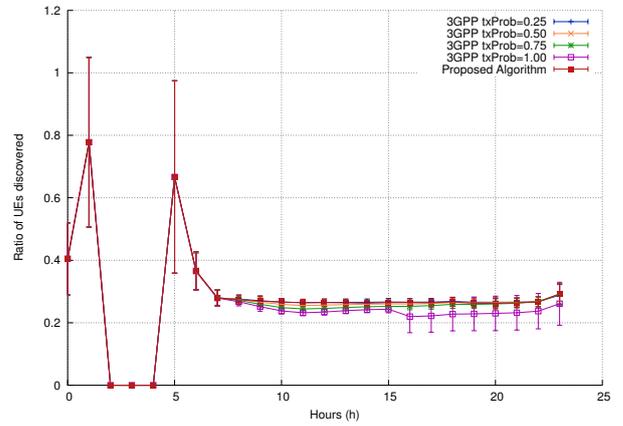
(a) Ratio of UEs discovered - Area 1



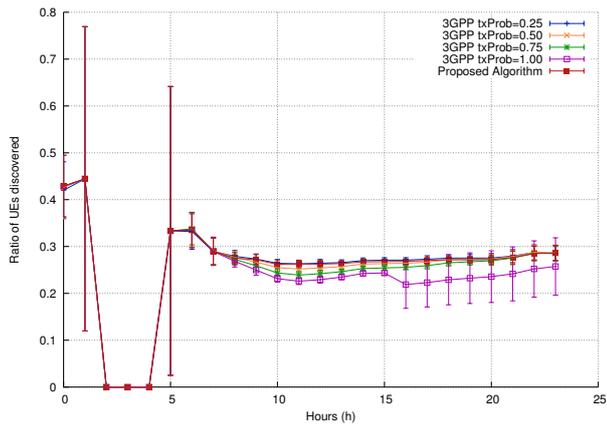
(b) Ratio of UEs discovered - Area 2



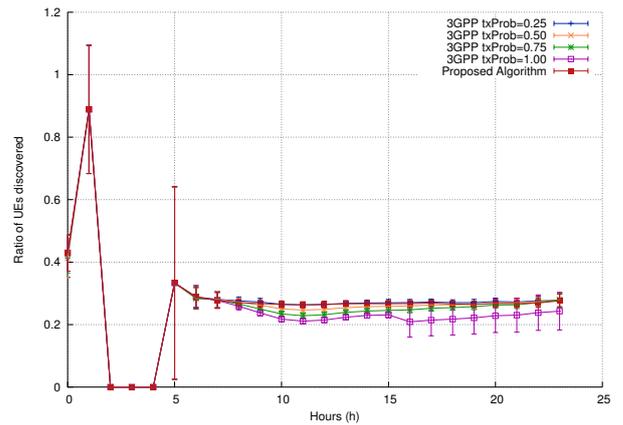
(c) Ratio of UEs discovered - Area 3



(d) Ratio of UEs discovered - Area 4



(e) Ratio of UEs discovered - Area 5



(f) Ratio of UEs discovered - Area 6

Figure 20: Ratio of UEs Discovered with Morning Traffic - High User Density

7. Conclusions

In this paper, we proposed the use of predicted user density values to build an adaptive discovery algorithm that improves the performance of D2D discovery. This algorithm is novel compared to other proposals in that it can use historic information of users in the network to dynamically adjust its operating parameters and provide always optimal performance.

We show how adaptive algorithms that use the predicted values as their baseline and account for deviations from that expected value can significantly improve the overall performance, not just in a specific subset of scenarios. We also show how an algorithm derived from an analytical model, without further tuning, can strike a balance between channel utilization and time required for discovery. So that a significant energy consumption savings can be achieved by reducing overall discovery messages signaling in the network, and further optimize network resource utilization for the discovery procedure.

From the work presented here, there are several lines of future work to enhance and expand these contributions: Further testing and evaluation of different scenarios should be carried out, to further consolidate the users' behaviors and the conclusions drawn in this work. This work should become the foundation of a process so that the discovery algorithm can feedback on the predicted user patterns, in order to maintain the accuracy of the predictions over time. Furthermore, the design of context-aware algorithms that change their operational parameters based on the environment (e.g. number of users expected to be in the same area) and its internal state and priorities (e.g. battery level, and user delay expectations) emerges not only as a feasible line of research, but one that, based on the results shown in this paper, can deliver significant results in the short and mid-term. Finally, further research into the discovery process and its limits, to better understand the effect that caps like the 60 second maximum time that we used in this paper have on the overall performance, and to dynamically set limits (defined either in terms of number of messages or amount of periods) for each topology and deployment, depending on the required confidence, minimum or required number of UEs that need to be discovered, need for optimization of the amount of messages sent, and so on.

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