Two Hops IRS Optimization in Urban Mobile Environment

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ABSTRACT

The intelligent reflective surface (IRS) is a new technology that can reduce the number of base stations and improve signal quality. Whereas in the literature, IRS is often considered in one-hop scenarios, we propose to address two-hop IRS in a vehicular context. On the one hand, two-hop IRS should improve connectivity by enabling blind devices in blind areas to be connected to the network, and on the other, connections may be more volatile due to a higher number of intermediate devices. In this work, their impact on network performance is investigated through different performance criteria. Our approach is validated using real vehicular traces in the city of Roma, Italy.

CCS CONCEPTS

• **Networks → Network performance analysis**; *Network simulations.*

KEYWORDS

Intelligent Reflective Surface, IRS, Multi-hop IRS, Mobile user

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1 INTRODUCTION

Mobile communications have the attractive benefits of being wireless and providing a high-speed internet connection. Therefore, it is a boom era for the rapid development of wireless communications. Moreover, mobile operators, through developers, are looking for new technologies to increase bit rates and reduce power consumption beyond 5G networks.

One technology for solving this problem is Intelligent Reflective Surface (IRS). IRS supports wireless infrastructure reduction by reducing the number of required base stations (BSs)/gNodeB to mitigate non-line-of-sight (NLoS) areas with the base station. It is also a great asset in a constant bit rate connection, as it increases the strength of the signal received.

Most of the research assumes that the IRS has a fixed location and that signals pass through a single reflection stage on the surface of the IRS, which is made of a reconfigurable meta-material.

In our previous work [14], we proposed two optimization models for the IRS location to improve network performance. As a complement, we present, in this work, the use of IRS devices that collaboratively reflect signals in a multi-hop fashion to regions suffering from NLoS up to the base station. Additionally, we propose IRS positions are mobile and equipped in buses. We thus present different approaches that contribute to the best selection of buses that the IRS can equip to work collaboratively to form multi-hop reflectors for mobile vehicles and users in certain blind spots to improve wireless network coverage and performance. These approaches are used to select the active-passive and passive-passive network reflectors combination. These approaches are based on future knowledge of bus and cab positions using trajectory predictions. The idea behind these approaches is to guarantee good quality of service by optimizing the number of handovers. In particular, these strategies are based on the number of times a bus will occur in the future, to select the IRS.

The performance of the proposed approaches is evaluated based on the traces of taxis and the public transportation of buses [1], [12] in the city of Rome.

The rest of the paper is organized as follows: Section 2 introduces the related work. Then, in section 3, we define and describe our approach, before presenting the results obtained in part 4. The fifth section concludes the article with an outlook for future work.

2 RELATED WORK

Most studies propose fixed IRS positioning or using active relays for mobility, such as mobile relays. In [7], for example, a comparison is made between a mobile relay and IRS systems in an indoor environment to support NLoS for mmWave networks. Another

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article looks at the positioning of the IRS to optimize throughput. It proposes a ring architecture with an access point at the center. The IRS is then alternately placed close to the AP and at the end to assess signal quality. Finally, the number of IRS and rings is varied to evaluate throughput. The results are compared with approaches without IRS or other power control policies.

In [13], a review of articles on the IRS is proposed, from the design of the IRS to their use in wireless networks. Some difficulties linked to the IRS are also exposed, for example, the acquisition of the channel state to know when to transmit and avoid collisions, the lack of implementation and real experimentation on the subject, etc. Finally, the authors close the article with a list of research directions.

As with most technologies, more and more studies are combining the use of IRS with other technologies for better performance. This is the case of [15], where sensors installed on IRS are used for target detection. In the field of security, models against eavesdropping are presented. This is the case of [18], which aims to secure communications against eavesdropping. They also rely on machine learning, more precisely on Deep Reinforcement Learning, to guarantee optimal QoS by searching for optimal reflection matrices that maximize the system's achievable throughput. Deep RL is also used in [4], which proposes joint optimization of UAV trajectories and phase changes of IRS elements in communications between UAVs and mobile users.

Several contributions have suggested using a fixed-site single IRS in wireless communications as in [2] and [5]. Furthermore, the work of [14] has suggested the dynamic placement of the IRS. About multi-hop wireless signal reflections using multiple IRS deployments, this is a recent contribution as there are few papers on this topic. One of these articles was published in 2020, and the others in 2022.

The work of [8] has proposed using multiple-IRS deployment to support wireless communication between BS and mobile users. First, the authors suggested selecting the IRS group based on maximizing the signal strength received by the cell phone user. Secondly, the derivation is introduced to calculate the trade-off between the optimal path of the base station and the mobile user and the beamforming gain to minimize the path loss. In addition, this trade-off is optimized based on graph theory.

In the work of [16], the use of drones to transmit radio signals to another drone or to a ground station to form a multi-hop transmission is proposed. In addition, the work examined the impact of using an IRS between the drone and the ground station to improve quality of service (QoS). To achieve this, a heuristic graph-based power consumption model is proposed to reduce the power consumption of drones.

In [9], the main contribution of this work is to use multiple-IRSs with a multiple-input multiple-output antenna. The IRS selection criteria are improved using a graph model based on the maximum signal power of the received signal. Moreover, an efficient routing model based on an iterative solution has been proposed.

The work of [11] used two IRSs to propose a new design for phase shifting and precoding in a MIMO network. The aim is to maximize the weighted sum rate, whose model is non-convex. Since non-convex models cannot be solved using standard tools, two methods are applied to solve the optimization problem: majorization-minimization and block coordinates descent.

In the paper [10], an overview of the use of single, double, and multiple IRSs deployment. Also, the objective function of this work is to improve both IRS passive reflection and channel utilization.

Moreover, in the work of [6], an optimization model for multiple-IRSs deployment of several hops is proposed. The objective function seeks to optimize two parameters that maximize the transmission rate and achieve non-interference transmission for several IRSs and graph network topology.

3 TWO HOPS IRS

The idea here is to extend the signal based on multi-hop approaches and thus achieve better coverage. To achieve this, we assume the existence of areas inaccessible to antennas, known as blind zones, in our study region. Any IRS bus in these areas will need a second IRS to extend its signal to the base station. And so, a second IRS will be chosen.

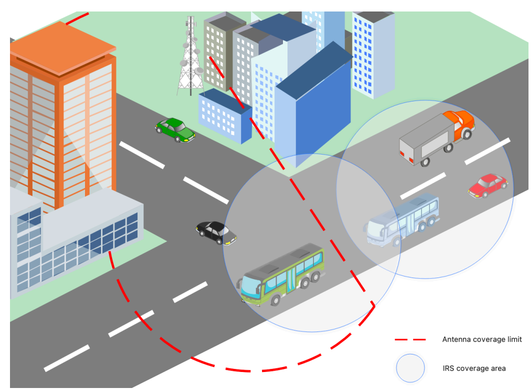

Figure 1: Usage scenario

Multi-hop approaches are widely used in wireless networks: IoT networks, VANeT, etc. They enable network coverage to be extended beyond the reach of individual nodes. They are often implemented at the routing level. Figure 1 describes a multi-hop IRS scenario for extending an antenna's signal using two IRSs. Assuming that a cab or a mobile user is not in sight of the antenna, IRS technology enables these objects to be covered passively. However, if the IRS visible to the antenna is out of range of the user, it can call on another IRS to extend the signal back to the user.

The choice of an IRS is made by election. Each mobile will elect an IRS called IRS1. If the IRS1 is in a blind zone, it will hold an election to choose its potential IRS, called IRS2. Figure 2 shows the IRS election process for a cab in a blind zone. Initially, we looked for all the buses that could cover the cab. If at least one bus covers the cab, a bus is chosen according to the strategy: Q, Q'A, Q'B, or Q". For each selected bus, one is elected per zone. The bus with the most votes becomes the IRS for a zone. Next, we check whether the chosen IRS is in Line-of-Sight(LoS) with the antenna or whether it, too, is in a blind area. If the former, the election is over. However, in the second case, the process continues with the search for buses in LoS that can cover the level 1 IRS or IRS1. If there are any, as in the case of the taxi, one bus is chosen according to the strategy, and then one bus is elected from among those selected in the zone to reduce the number of buses used. This is the IRS level 2 or IRS2 bus. This work aims to show the difference between one and two hops,

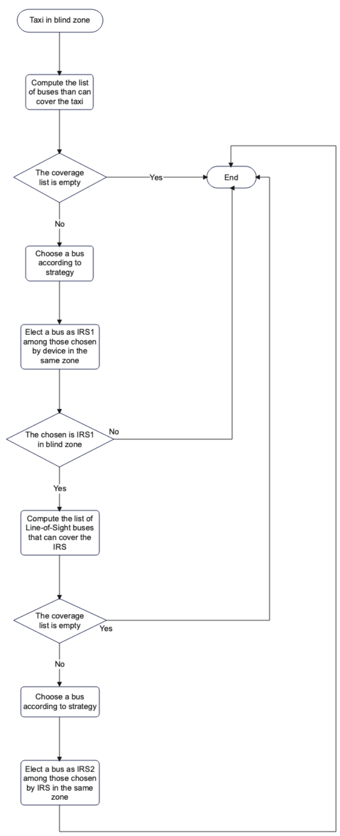

Figure 2: Flowchart of IRS election algorithm

so the management of reflection angles is just as present in a single hop as in two hops. Given this, we have assumed that the IRSs are randomly configured, which, according to [17], offers better performance than without the IRS.

3.1 Settings

This work exploits taxis and bus records from Rome's public transport system. Bus information includes line numbers, stops, and timetables (schedules). We also use taxi traces for one day, between 10 a.m. and 11 p.m., with around 1,535 trajectories in the historic center of Rome. Each trajectory contains ten positions. We then use the results of trajectory prediction obtained in [3] for that day. This prediction model is based on LSTM (Long Short Term Memory) and predicts at each time t, a taxi's position at times t+1, t+2, t+3, and t+4. The coverage area is restricted to the following coordinates: latitude 41.8 - 42.0 and longitude 12.4 - 12.6, representing an approximate area of 22.239 km x 16.576 km. This area is divided into small zones of around 250 x 200 meters, with randomly distributed blind zones. The blind zone percentage is set at 40%. In the next section, we set the coverage radius between 100 and 600 meters.

3.2 Strategies

First, a taxi in a blind area will elect its IRS bus, and then each zone - note that here, a zone represents the subdivision of the study area into smaller zones - will elect an IRS1 for the zone according to each strategy. If the chosen IRS1 is in a non-blind area, the election stops. Otherwise, the blind IRS1 will repeat the election process to select a non-blind IRS in its vicinity.

Four strategies are studied based on IRS selection:

- `Q`: A taxi is randomly elected from the list of available buses.
- `Q'A`: The bus most likely to appear most often in the future is chosen as the IRS.
- `Q'B`: Similar to the `Q'A` strategy, except that the cab retains its previous IRS if it is still under its coverage.
- `Q"`: Identical to `Q'A` except that the previous IRS is not considered.

The following equations define the different strategies Q, Q', and Q" with :

- i: a taxi identifier
- n: a time slot, set at one minute considering the dynamic nature of vehicular networks.
- j: an IRS j
- $d_{i,n}(j)$: distance between taxi i and IRS bus j
- ρ : the coverage radius

$$q_{i,n}(j) = \begin{cases} 0 & \text{if } d_{i,n}(j) > \rho \\ 1 & \text{otherwise.} \end{cases} \tag{1}$$

$$q'_{i,n}(j) = \sum_{k=0}^{T} 1_{\{d_{i,n+k}(j)<\rho\}} \tag{2}$$

$$q"_{i,n}(j) = \sum_{k=0}^{T} \prod_{l=0}^{k} 1_{\{d_{i,n+k}(j)<\rho\}} \tag{3}$$

The last three strategies are based on predictions of taxis and bus positions, while the Q strategy is without predictions.

The following criteria are used to evaluate the different strategies:

- `Disconnectivity`: It represents the number of times a mobile is not covered (no IRS) or covered by an IRS1 in a blind zone without an IRS2.
- `Number of handovers`: This is the average number of times a device changes IRS. Changing one of the IRS in the case of a multi-hop is considered a handover.
- `Average connection duration`: This is the average period for which a cab retains the same IRS. Changing one of the IRS (if applicable) is a change of connection.

4 RESULTS

Results are collected for each criterion: disconnectivity, number of handovers, and connection duration. For each strategy, we compare the 2-hop results with the single-hop results. Figure 3 shows the coverage, i.e., the average number of buses present as a function of the coverage radius. It is strategy-independent and thus identical to all strategies. It shows that just over half the cabs are covered for a radius of R=100m and that almost all cabs are covered for R=600m, indicating good coverage.

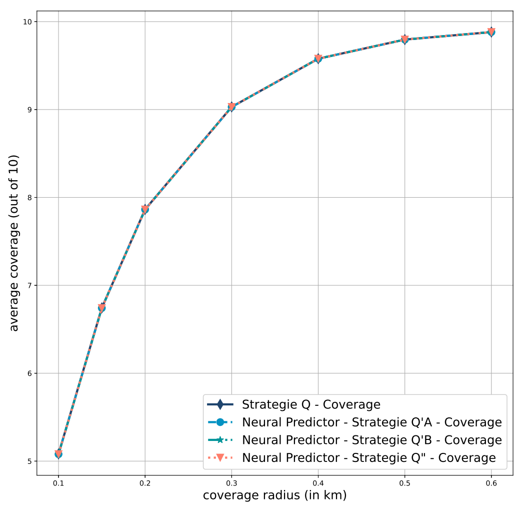

Figure 3: Taxis coverage by coverage radius

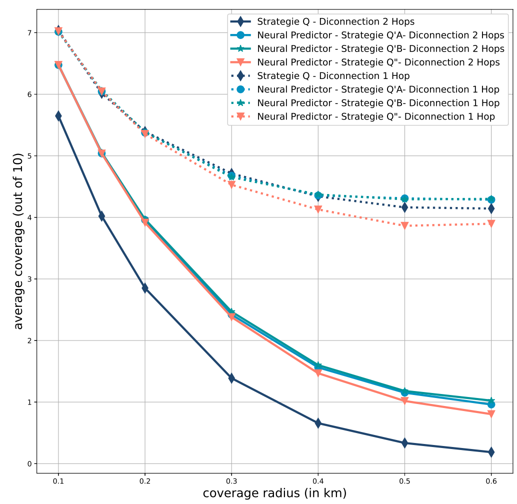

Figure 4: Taxis disconnection 1-2 Hops by coverage radius

4.1 Disconnectivity

Figure 4 shows the average number of disconnections for strategies Q, Q'A, Q'B, and Q". First, we note that disconnections decrease as the coverage radius increases. It goes from around 70% disconnections to less than 10%. This makes sense because increasing the radius increases the number of IRS candidates with the cab under their coverage. Then we see that between 100 and 230m radius, the three strategies Q' and Q" are almost similar. At around 300m, the Q" strategy performs slightly better than the Q'A and Q'B strategies. The Q strategy performs better than the Q' and Q" strategies. These results can be explained by the fact that within a 200m radius, there are few buses to cover cabs: 1 out of 2 cabs without a bus (see figure 3). Since the strategies only make sense when there are several candidates, i.e., for small lists, they produce practically the same result. The Q' and Q" strategies aim to retain the bus with the highest future occurrence. In other words, the bus chosen as IRS1 may be in a blind zone and have no IRS2, or the cab may leave its coverage for some time before returning. The dotted lines represent the disconnection of strategies for a single hop. We can see that there are more single-hop disconnections, whatever the value of the coverage radius R. From 400 meters upwards, the difference is more than 30%. This shows the usefulness of multi-hop for more effective coverage.

4.2 Numbers of handovers

The notion of handover here refers to a change in the IRS. In the case of two hops, a handover occurs when one of the two IRS changes. Figure 5 represents, on average, the number of handovers as a function of the coverage radius for the strategies for one and two hops. The number of handovers is similar for a small coverage radius and generally lower between 100 and 150 meters. The reasons for this are low coverage, with few IRS available, and, as a result, no change. Then, this number increases for strategy Q and increases and decreases for strategies Q' and Q" as the radius increases. As the radius increases, the number of candidate buses and connections increases, and the handover phenomenon becomes more apparent. But at a certain point, for strategies such as Q", Q'B, and even Q'A, which aim to keep the same bus for as long as possible, increasing the radius enables it to continue a little longer with the same IRS bus, even if the trajectories start to diverge, hence the decrease after a certain threshold. This is not the case with the Q strategy, which chooses blindly.

The dotted curves represent one-hop strategies. For the Q' and Q" strategies, there are fewer handovers with the single hop than with two, as there are half as many IRS in some cases. Finally, we note that for the Q strategy, the number of hops has no impact on the number of handovers. This means that the IRS changes as much in one jump as it does in two due to the random draw. Another aspect is the behavior of the strategies. The Q'B and Q" strategies are relatively similar in one and two jumps. In addition, there are always fewer handovers for these two-hop strategies, up to a coverage radius of 400 meters, than for the single-hop Q'A strategy.

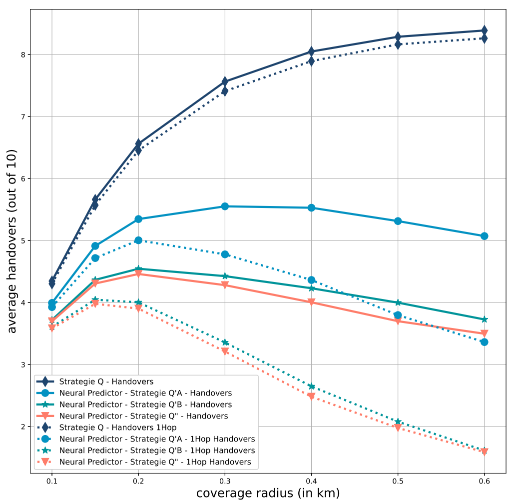

Figure 5: Average number of handovers by coverage radius

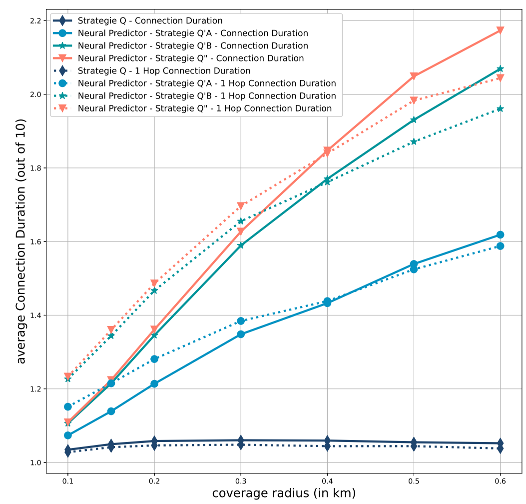

Figure 6: Average connection duration by coverage radius

4.3 Connection duration

The trend is the opposite for connection duration, as shown in figure 6, which illustrates the average length of time a cab stays with the same IRS or IRS pair in the case of a double hop. The connection duration is almost equal to 1 for the Q strategy. This makes sense, given the number of handovers close to 100%. It's important to note that in addition to this separation of strategies, which confirms the previous findings, connection duration is higher with one hop than with two up to a radius of 400 meters and vice versa beyond that. It's easier to retain one IRS than two or more, especially when coverage is low. The duration for how long a cab can stay with the same pair of IRS also increases as the coverage radius increases.

As for connectivity, the connection/disconnection curve increases/decreases with the coverage radius. This is logical because as the coverage area increases, a cab or bus is more likely to find an IRS bus to cover it, depending on whether it's a Level 1 or Level 2 election. The number of handovers decreases with radius because the better the radius, the greater the chance of always being covered by the same IRS, even when moving. There is an exception for the Q strategy, which gives a better connection rate and the same number of handovers and connection duration for single-hop and double-hop. It is also important to mention that a temporary loss of connectivity is not considered a handover, so there is no strict relationship between the connection duration and handover criteria. However, connectivity also influences the connection duration. Then there's a classification of strategies, with the Q" and Q'B strategies giving better results than the Q'A strategy regarding the number of disconnections, handovers, and connection duration. Finally, and most importantly, the impact of the double hop in increasing coverage capacity should be noted.

4.4 Prediction quality

In this section, we compare the results obtained with the LSTM-based Neural Predictor, which for each time slot predicts four positions for the cab corresponding to t+1, t+2, t+3, and t+4 with the Perfect Predictor. The Perfect Predictor uses the actual positions of the cabins as a prediction, allowing us to verify our model. The LSTM predictor we use here [3] is not perfect and has an RMSE of around 0.04 for testing. We, therefore, seek to determine how sensitive our results are to prediction accuracy. The curves show the results for each strategy Q'A, Q'B, and Q" in Perfect and Neural predictor for the number of handovers (figure 7) and average connection duration (figure 8). The results show similar results between the two Predictors. This can be explained by the fact that the neural predictor used also has relatively good accuracy and that we are considering short-term predictions.

4.5 Max First vs. SINR First

In wireless networks, some metrics are used to estimate signal quality, such as RSSI (Received Signal Strength Indicator), SNR (Signal-to-Noise Ratio), SINR (Singal-to-Interference plus Noise Ratio), etc. In this section, we propose integrating SINR into the IRS bus election. We propose to elect the bus with the best SINR as IRS while always based on predictions and strategies. The SINR is, therefore, calculated for each prediction, and the device with the highest SINR is chosen as the IRS. However, optimizing the SINR contradicts most of the performance criteria selected, for instance, optimizing the number of handovers and connection time, as choosing the candidate IRS with the best SINR at each stage does not guarantee that the same IRS will be maintained. We therefore tested two cases:

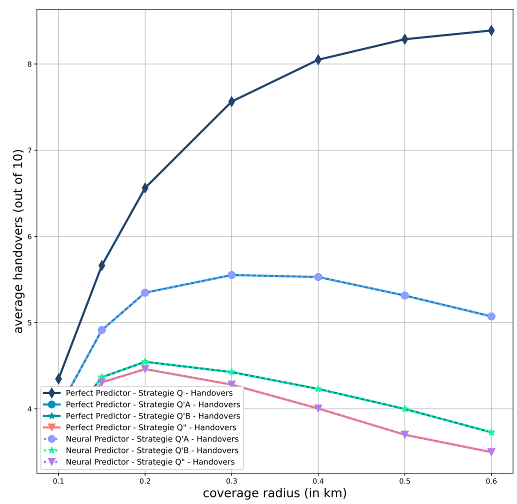

Figure 7: Average number of handovers for Perfect and Neural predictors for the three strategies

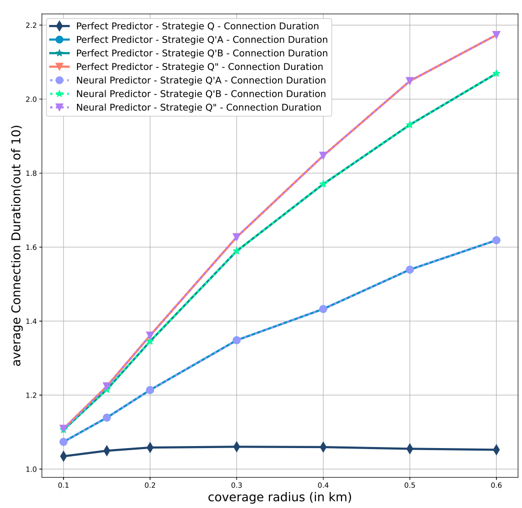

Figure 8: Average connection duration for Perfect and Neural predictors for the three strategies

- `Max First`: First, we look at the bus most likely to appear according to the prediction. Then, in the event of a tie, the bus with the best SINR is chosen. This is the MaxFirst mechanism.
- `Sinr First`: In the second case, it's the other way around. The bus with the best current and future SINR is chosen, and in the event of a tie, the number of occurrences of the bus is used to determine the final result. This is the SinrFirst mechanism.

We have tested these mechanisms for each strategy.

Figures 9, 10, and 11 show respectively the number of disconnections, the number of handovers, and the average connection time, with little difference between the two mechanisms for both single and double hops. This may be due to the way the SINR is calculated. In this section, we have aggregated the SINRs, taking predictions into account. The bus with the most occurrences is more likely to be chosen if the SinrFirst strategy is also used.

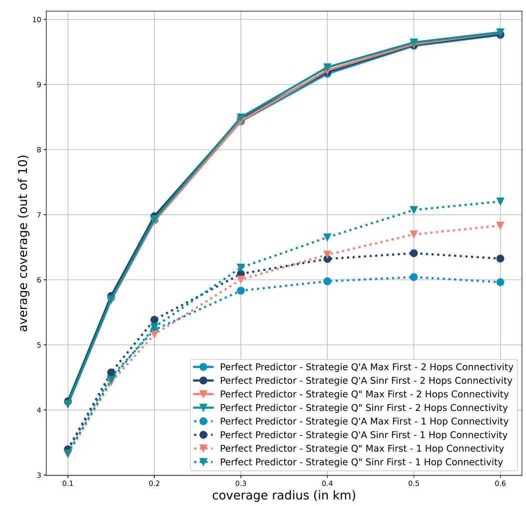

Figure 9: Average connectivity for MaxFirst and SinrFirst election for strategies Q'A and Q"

4.6 Impact of N

Another parameter impacting these results is granularity. In other words, the number of zones in the study area. If N is small, the zones are large, while the zones are small if N is large. A blind zone corresponds to a rectangle of size L/N x l/N where l and L are the dimensions of the study area.

Figures 12 and 13 show the average disconnection number for a coverage radius of 100 and 600 meters, respectively. This number decreases as a function of N. This means that there are fewer disconnections when the zones are small. This can be explained by a higher probability of encountering an IRS in a non-blind zone. So in the case of a larger blind-tagged area, all nearby buses are susceptible to be blind IRS1 and may not have IRS2. Meanwhile, if the zones are small, some of these buses may be in non-blind zones, and the probability of having an IRS2 is higher.

The number of handovers increases as a function of N, especially for a small radius (fig 14). A small radius and small area mean that the coverage is small, and with alternating blind and grey spots, there's scope for changing IRS on level 2 IRS if there is any. As the

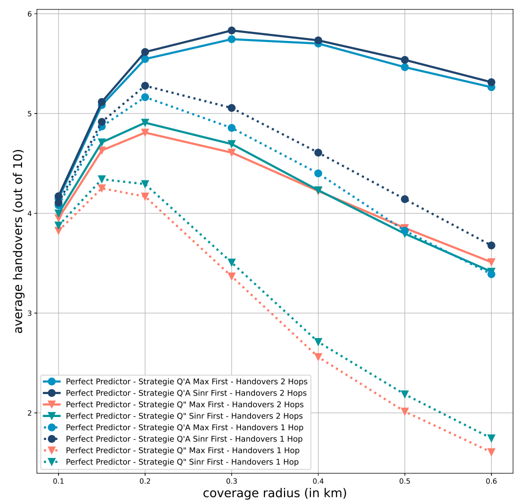

Figure 10: Average numbers of handovers for MaxFirst and SinrFirst election for strategies Q'A and Q"

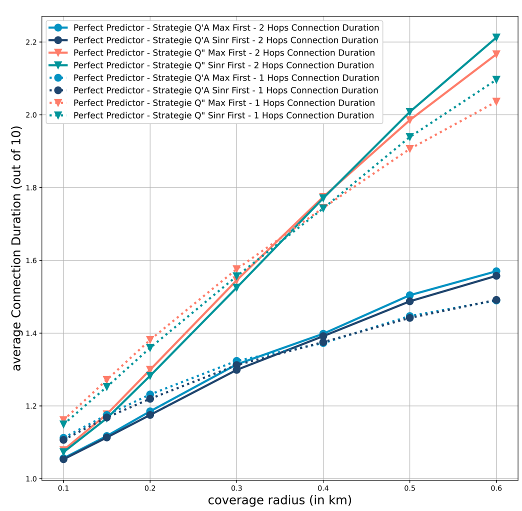

Figure 11: Average connection duration for MaxFirst and SinrFirst election for strategies Q'A and Q"

radius increases (fig 15), the effect of granularity is less noticeable, and results tend to stabilize but with more handovers generally for a small radius. This may be due to the large number of handovers from extended coverage.

All tests were performed with a maximum confidence interval of approximately 10%.

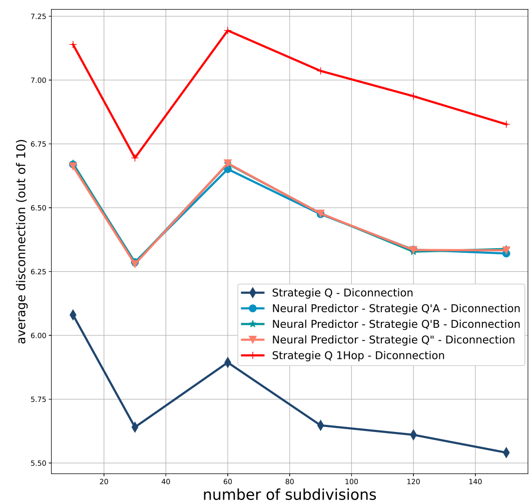

Figure 12: Taxis disconnection for R=100m by N

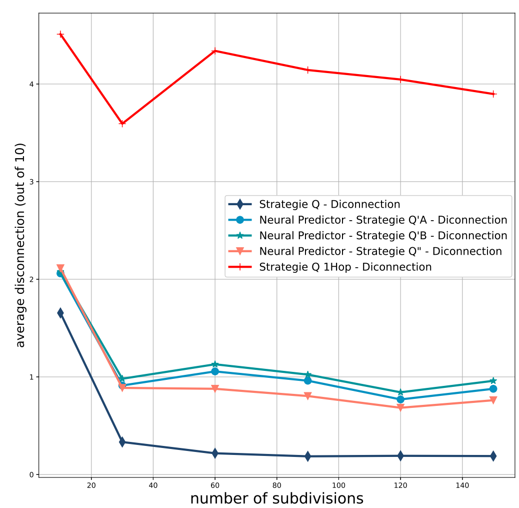

Figure 13: Taxis disconnection for R=600m by N

5 CONCLUSION

In this paper, we proposed an approach combining mobile IRS and multi-hop. We assumed the presence of blind zones to validate our scenario and demonstrated the benefits of multi-hop to increase network coverage. We then compared different IRS election strategies based on the number of handovers and connection duration. The results show the advantages of the multi-hop strategies we propose to guarantee low numbers of disconnections. We also looked at

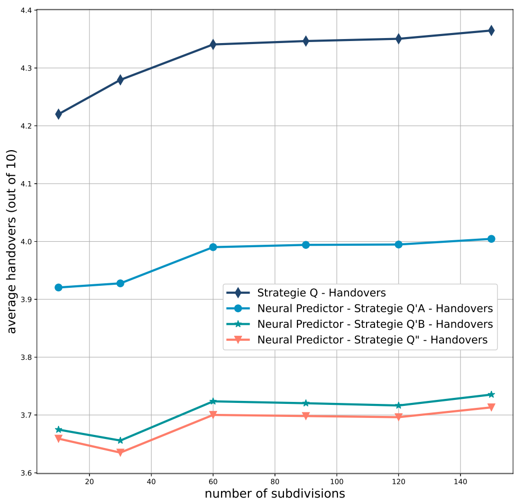

Figure 14: Average number of handovers for R=100m by N

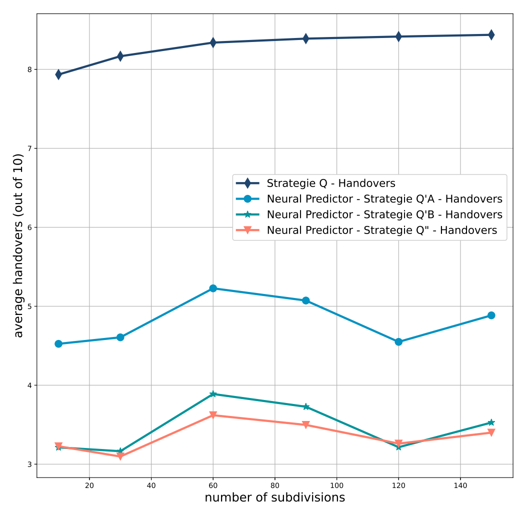

Figure 15: Average number of handovers for R=600m by N

the evolution of different performance criteria as a function of the coverage radius and zone size. Finally, we studied the effect of the introduction of SINR on the choice of IRS.

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