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Optimal Mobile IRS Deployment for Empowered 6G Networks

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ABSTRACT The development of cellular networks is driving the rapid growth of wireless communications. With the advent of the 5th Generation (5G) towards the future of the 6th Generation (6G) dedicated to achieving strong growth in traffic while reducing energy consumption, there is a need to solve the problems facing leveraging of these networks' advantages and support both operators and mobile users. The main challenges for wireless communications are power consumption, Quality of Service (QoS), and the blind areas of a Non-Line-Of-Sight (NLOS) between mobile users and the Base Station (BS). The Intelligent Reflective Surface (IRS) of a reconfigurable meta material is a promising solution for solving some of the challenges of wireless communications. Additionally, it enhances the QoS of the received signals without the need for a power source to operate. Hence, it does not constitute an additional burden as it consists of passive elements. From the other hand, it provides the perfect solution to cover mobile users in blind areas without the need to deploy extra expensive BSs. In this work, we propose to equip buses by IRS allowing them to act as mobile IRS. These buses will become a relay for the surrounding moving vehicles, represented as taxies in the performance section of this paper. Practically speaking, not all buses have to be IRS equipped. We propose various approaches for selecting the best buses equipped with IRS. In the first optimization approach, we adapt the classical IRS selections methods used in static context to the mobile case. It uses a Multi Integer Linear Programming (MILP) which gives optimal results but with a very long processing time. Thus, we propose a neural-network to learn the result of the MILP. As an alternative solution, another approach is proposed using a Markov decision problem (MDP) relying on Long Short-Term Memory (LSTM) to predict the positions of the surrounding moving vehicles. It is used to solve the optimization problem with the performance criteria targeted for each session. The performance of the proposed approaches are validated based on bus and taxi dataset for the city of Rome in Italy.

INDEX TERMS IRS-Bus, cellular network management, ML, MILP, MDP, LSTM, mobile users, 6G.

I. INTRODUCTION

WIRELESS networks today have more subscribers than wired connections for many features, the most important of which are mobility and ease of use of mobile applications. Mobile users are looking forward to having a high data connection to improve the usage of their applications and browse the Internet easily. Therefore, advanced technologies such as multiple-input-multiple-output (MIMO), millimetre wave (mmWave) and expected new technologies in the future support massive high data rate in 5th generation (5G) and 6th generation (6G). Consequently, there is a need to improve wireless networks performance [1]. This especially occurs in blind areas where there is no line of sight (LOS) between users and the base station (BS). The advent of intelligent reflecting surface (IRS) eliminated the effect of the blind zones.

IRS is considered a revolutionary technology which is able to improve the performance of wireless data transmission systems [2]. IRS consists of meta surface of massive number of reflecting elements of configurable phase shift to serve a terminal device in the far-field and near-field regions [3]. Moreover, reduction of energy consumption in communications which eliminate unnecessary electromagnetic (EM) waves are an incontestable trend today. Hence, some cellular transceivers which could be replaced by IRSs can contribute to support this trend [4]. Comparing IRS to the traditional active antenna arrays, it acts as a passive reflective antenna array that improves the achievable spectral efficiency and hence data rate in a cost-effective. Moreover, it improves the energy-efficient manner and constitutes a self-sustaining energy solution [5].

Several works have studied the performance improvements due to the use of IRS, a little of them studied the impact of the IRS positions which will be mentioned in the next section of related work. As it is known, the main benefit of mobile phones is the mobility while using them. Inspired by this, IRSs positions are expected to be more effective if they follow the same behavior of mobility as mobile phone users. Moreover, in this work, we contribute to have mobile IRSs selected based on its positions. As has been suggested in all work to date, the IRS used to be of a fixed position and its selection is based on various criteria based on the proposals of the authors of previously published works. The goal itself is to improve the signal-to-noise ratio (SNR) to support wireless communications for high data rates and to provide coverage for blind areas.

In contrast to all previous published contributions, this work contributes to the selection of the best buses that can be equipped by an IRS to serve as a relay between the BS and other surrounding moving vehicles in a given blind area and to improve cellular coverage. This is what represents the idea of the IRS mobile position selection. To our knowledge, no study or model has yet been performed to propose a mobile IRS and to select the best IRS buses based on their dynamic locations (routes). In addition, we are targeting a less costly and effective solution in terms of processing time and high quality of results. Now to the end of the article, we will use an acronym IRS-bus for select buses equipped by the IRS.

In this work, we propose different approaches to address the problem of selecting the best IRS-bus serving moving vehicles for each study period.

In the first approach, we adapt the dynamic case which is a widely used static method: at each instant time (t) is selected, an IRS is selected using Multi Integer Linear Programming (MILP), the goal of which is to reduce the distance between taxis and a limited number of IRSs. In this case, the dynamic characteristic of vehicular traffic is taken into account by the new locations of mobile phones (taxis) and buses at each instant time (t). Unfortunately, this approach, which is classic in the static scenario, has a high computational complexity and there is a need to speed it up. Therefore, instead of running MILP continuously, we propose to learn its results by a neural network encoder decoder combining two Long Short Term Memory (LSTM) blocks. LSTM is a well established category of recurrent neural networks (RNN), used for timeseries prediction and has proven its excellent performance.

Since this resulting neural network architecture is not really used for time series prediction but to predict future positions of IRSs, and since it is using what is generally called tabular data (contrarily to timeseries), we call it in the rest of the paper as our decision neural network (DNN).

Optimizing performance parameters for a dynamic scenario, such as the number of handovers per mobile session or how long a mobile phone does not change its IRS is very complex with this approach. Of course, it can be adapted but this will add one more dimension which is time. Instead of optimizing every time (t) and independently of each other, the time dimension must be considered globally in the optimization problem. Thus, we propose another approach based on the Markovian Decision Process (MDP). Each instant time (t), the IRS is selected based on predictions of future bus and taxi locations. The prediction of buses depends on their scheduling, while a taxi depends on another neural network predictor based on Long Short-Term Memory (LSTM). We evaluate the impact of the quality of a vehicle predictor by comparing this approach with an ideal predictor given the efficient future positions of taxis. To be noted, this perfect prediction is not only in theory because practically, taxis can really inform the control center about their planned rides.

We validate our approaches with evaluations using the traces of real taxis and public transport buses in the city of Rome (Italy): cf. [6] and [7].

The organization of the rest of the paper as follows; Section II reviews the state of the art. Section III presents the problem statement. Section IV, presents MILP and the proposed decision learning approach is described. MDP optimization approach is presented in Section V. The performance evaluation of MDP and DNN models are presented in Section VI. Finally, Section VII contains the conclusion and future work, which includes contributions and results of the work.

II. RELATED WORK

Authors of [8] studied the effect of distributing IRSs on the system throughput. They considered a system of one cell with a uniform randomly distributed IRSs. They concluded from that study that the system throughput increases but with varying user's rate when a fewer IRSs deployed of each has more reflective elements instead of deploying large numbers of IRSs. Moreover, they conclude the need for a solution for optimizing the IRS positions.

In the work of [9], cellular network is proposed to use IRS for the aerial users and improve the air-ground communication network performance as well. Moreover, the optimal IRS position is studied to support the proposed air-ground communication. Authors proposed the chose of the IRS positions based on the maximizing the spatial signal-to-interference-plus-noise ratio (SINR) and also to reduce the inter-cell interference. Signal interference as cleared in this work is based on the elevation angle. The authors concluded that the interference increases proportionally with the IRS distance of a low IRS elevation angle even though a wider covered area in this case. They calculated the mean SINR of the area covered by the BSs and IRSs to get the optimal distance of the IRSs maximizes the SINR. This work results are based on numerical analysis with a simple use case. In addition to that, there is no mathematical model, or comparison with other previous models.

The work of [10] studied the effect on the positioning and communication performance due to the use of IRS and multiple sub-carriers at mmWave frequency bands. Authors relayed on using hierarchical analog codebooks and a feedback from mobile stations to design IRS analog phase shifts. By this model, they achieved performance improvement for positioning accuracy and system data rate. They depended on adapting the IRS elements phase shift without proposing a model for selecting best positions for the IRS which will provide high SNR by alleviating the interference and hence support high data rate.

This work [11] proposed a two-step optimization scheme based on Fisher Information analysis. The proposed schema selects the best IRS position to be activated and hence controls its elements' phases for improving the IRS position performance. This work shows a performance improvement with predetermined users locations which is not a practical scenario in addition to the fixed positions of the IRSs.

Authors of [12] proposed a three-dimensional relaying by mounting IRSs on aerial platform like a balloon or airship. This is to provide better LOS than terrestrial IRS and a full angle reflection for the worst scenarios of minimum signal-to-noise ratio (SNR). This solution could be suitable for very special cases as authors mentioned but, there are another parameters should have been taken into account. These parameters are the cost of the aerial platform, stability, control, and the maximum altitude of the aerial platform which make it hard to implement.

Another work [13] proposed an iterative IRS positioning algorithm. Authors built their solution based on deploying IRSs then perform a random beam forming and maximum likelihood estimation of the angle of arrival and the angle of departure of the LOS between the IRS and a mobile terminal. The position of the IRS is centimeter-level adopted based the listed measures. This work is based on achieving IRS positions by using beam training schema and measuring the performance gain of each location. Therefore, it may needs site survey to select best locations which needs more efforts and cost in real life scenario. Also, this work proposed fixed IRSs positions.

In [14], authors proposed a multi-IRS ring based position scheme for an access point cell. They proposed a searching algorithm to obtain a close to optimal solution of arbitrary IRSs. This solution considers the IRS to increase the coverage of the access point and not to alleviate obstacles. IRSs position proposed to be fixed and deployed in a ring model.

The contribution of [15] is to propose the use of IRSs to assist mobile localization at next generation node-B (gNB) to enhance the system communications. Authors relay on reconfigure the IRS phases to maximize the SNR towards users stations and hence enhance the communications and localization of them. This work is useful as a physical layer but does not provide a model for identifying the best IRS placements that would therefore provide enhanced user station communications.

The work of [16] studied the effect of the IRS position on the data rate in case of single and multiple antennas. Authors concluded that the best position of the IRS to be as close to either the transmitter or the receiver. IRS position is affected also by the propagation environment. Authors studied the factors affecting the IRS position but didn't propose a model of selecting it.

Finally, as an alternative solution to using IRS at all, different approaches propose vehicle to vehicle routing or device to device relaying. A comparative study of such adhoc non centralized solutions can be found in [17] and [18]. Decision Neural Network (DNN), adhoc or D2D solution stems from the lack of cellular operators willing to deploy additional base stations, however IRS based DNN suffers much less delay than adhoc or D2D due to the necessity to add a large amount of signalling for both concurrent solutions to work correctly (communication delay that will result from all the necessary routing and discovery procedures).

III. PROBLEM STATEMENT

Classically, when choosing the best IRS in a static scenario, the goal is typically to minimize the distance between the chosen IRSs and the wireless clients. If there is a set of clients S, if d_{ij} is the distance between a client i and an IRS j, if x_{ij} is equal to 1 if a client i is covered by j and 0 otherwise, if ρ is the maximum coverage radius, if B is the set of possible IRSs and $B_i = \{j \in B; d_{ij} < \rho\}$ is the list of potential IRSs under the coverage of client i, the problem is minimizing (1) under constraints (2) and (3):

$$\min_{x_{ij}} \; D = \sum_{i \in S} \sum_{j \in B_i} d_{ij} x_{ij} \tag{1}$$

Sub.const.:

$$x_{ij} = \begin{cases} 1 \text{ if client } i \text{ is covered by IRS } j \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

$$\sum_{j} x_{ij} = 1 \tag{3}$$

In our case, the clients are the taxis, the potential IRSs are the buses. We consider the time as discrete. Since the scenario is mobile, the location of the clients and the buses changes with time and the problem must be adapted the following way, at each time instant n, to find the best set of IRSs for each time instant n (minimizing (4) under constraints (5) and (6):

$$\forall n, \min_{x_{ij,n}} \; D_n = \sum_{i \in S} \sum_{j \in B_{i,n}} d_{ij,n} x_{ij,n} \tag{4}$$

Sub.const.:

$$x_{ij,n} = \begin{cases} 1 \text{ if client } i \text{is covered by IRS} j \text{ at } n \\ 0 \text{ otherwise} \end{cases} \quad (5)$$

$$\sum_j x_{ij,n} = 1 \quad (6)$$

where each variable becomes a function of time n.

The part IV develops this approach. We observe that this approach, although efficient in terms of network performance is very slow to execute because it is computationally expensive. That is why we complement it with a new method based on neural networks to get the result of the MILP directly. The idea is to run the MILP on a large number of data to be learned with the result of the MILP in many different situations by a complex encoder decoder recurrent neural network. Then, instead of executing the MILP each time, the neural network is executed for the taxi and bus configuration to get the result expected by the MILP. This approach is proved to be very efficient in terms of computation while given good performance results.

Although this approach gives optimal choices of IRS in terms of link quality at each time instant n, it is difficult to take into account temporal performance criteria like the average number of handovers in a session or the average time a mobile does not change of IRS. For instance, minimizing the average number of handovers per session, and assuming that each taxi trajectory has constant length and each taxi out of the coverage of any bus keeps formally its previous IRS for sake of simplicity, would lead to the following optimization problem (minimizing (7) under constraints (8) and (9)):

$$\min_{x_{ij,n}} \ NbH = \sum_{i \in S} \sum_{j \in B_{i,n}} \sum_{k=t_b(i)}^{t_e(i)} \mathbb{1}_{\{x_{ij,k} \neq x_{ij,k+1}\}} \quad (7)$$

Sub.const.:

$$x_{ij,n} = \begin{cases} 1 \text{ if client } i \text{ is covered by IRS } j \text{ at } n \\ 0 \text{ otherwise} \end{cases} \quad (8)$$

$$\sum_j x_{ij,n} = 1 \quad (9)$$

where $t_b(i)$ is the time of the beginning of the ride of taxi i and $t_e(i)$ its end. Although this problem is theoretically solvable, at least in brute force, it is heavily complex because a new dimension is added: the time axis. That is why we prefer a radically new approach, based on MDP.

Adopting an MDP approach relaxes the necessity to keep the memory of the past while searching the optimum IRS, simplifying the complexity of the calculations. But we need to integrate the time dimension for estimating the performance criterion of interest like the average number of handovers per session. To this goal, we include in the decision process a predictor of the future positions of the mobiles, essentially the taxies since the buses are scheduled according to a planning. We choose a neural network predictor, based on LSTM (cf. [19]). The choice of LSTM is based on extensive comparisons led in several previous contributions involving timeseries prediction. Results show that LSTM has better prediction results than GRU, RNN and other neural network architectures. Since the election process takes into account a prediction of the future positions of the taxies and buses, a taxi can choose the best IRS for the near future, for instance the one minimizing its number of handovers. Of course, the efficiency of this approach depends on the quality of the prediction. To evaluate its impact, we test two predictors: a neural network (LSTM) based one and what we call a perfect predictor which is the actual future positions of the taxies. Note that this perfect predictor could be implemented by requiring each taxi to send its ride details to know where it plans to go and how.

The MDP algorithm consists at each time n and for each taxi i to elect its best bus $x_{i,n}$ as IRS. Four strategies are evaluated for the election process by the taxies, which are detailed in Section V. Depending on the strategy, a taxy i at n tries to optimize an objective function $U_{i,n}(j)$ for each bus j under its coverage:

$$x_{i,n} = \arg\max_j U_{i,n}(j) \quad (10)$$

Then, the IRS actually elected $z_{l,n}$ at n for the blind zone l is the one which has the highest number of votes:

$$z_{l,n} = \arg\max_{j \in B^Z_{l,n}} \sum_{k \in C_{l,n}} \mathbb{1}_{\{x_{k,n}=j\}} \quad (11)$$

where $B^Z_{l,n}$ is the set of buses in the zone l and $C_{l,n}$ is the set of taxies in the zone l, at n. This approach based on a MDP is presented in Section V.

IV. MILP AND DECISION LEARNING APPROACH

This section describes the DNN proposed method. The various components of general mobile deployment are described. Furthermore, IRS positions for mobility clients are investigated. Finally, the effect of the reinforcement learning is studied.

A. THE MILP OPTIMIZATION MODEL

Figure 1 illustrates the use case architecture we consider in this work. Connectivity through gNodeB (gNb) exists for mobile users' equipment in the cell. Public transit buses are equipped with IRSs on the upper exterior deck to form mobile IRSs. We'll use the term IRS-bus along the rest of the paper referring to the IRS-equipped bus. The IRS is deployed in this way to provide cellular coverage to mobile users in blind zones and thus improve the quality of communication with the BS. These mobile users are considered taxis in our use case.

MILP is used to optimize the selection of buses equipped by IRSs. The model has to be solved too frequently and an alternative must be found. The optimization problem of the MILP [20] is formulated as follows in this subsection.

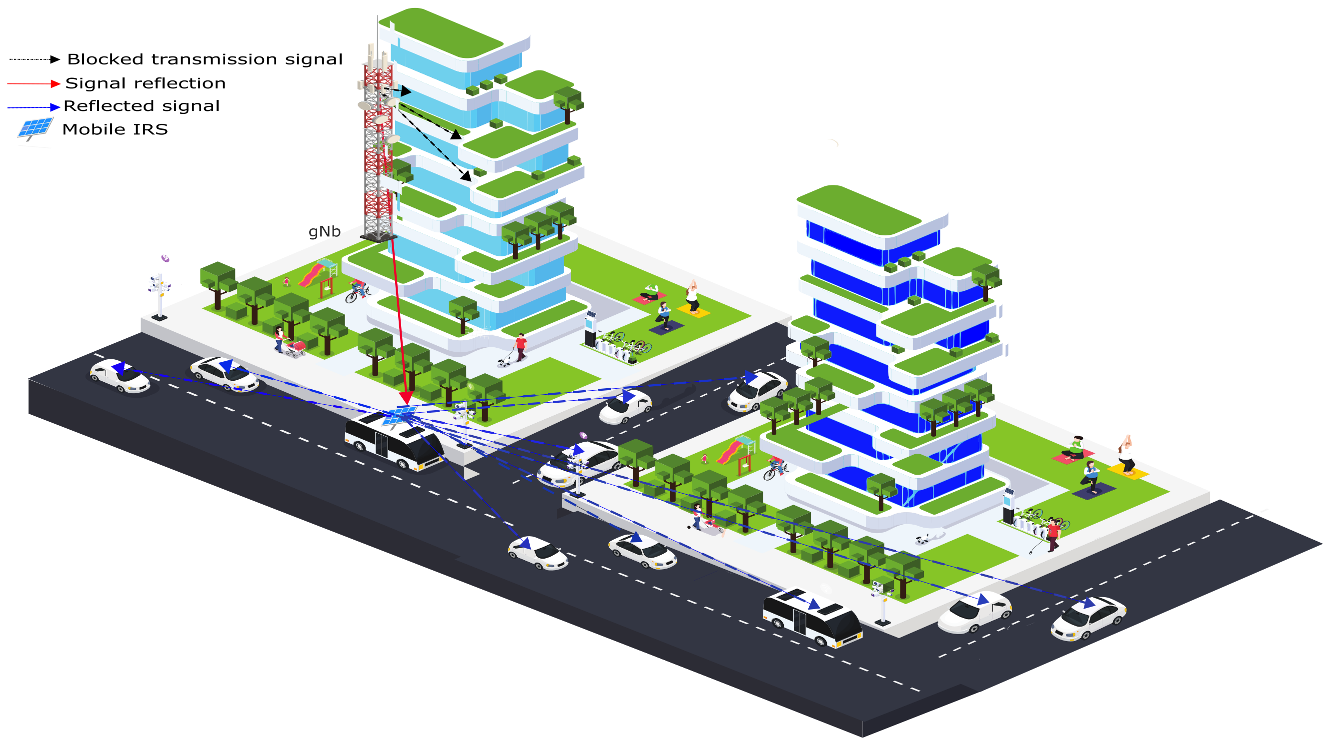

FIGURE 1. Proposed IRS-assisted cellular network architecture.

TABLE 1. Table of notations.

Notation	Description
i	Index of taxis; $i = 1$ to n
j	Index of buses; $j = 1$ to m
n	Time index
$B_{j,n}$	Bus position at n
$d_{ij,n}$	$taxi_i$ and bus_j distance at $time(n)$
D_n	Total bus taxi coverage sum to minimize at n
I_n	The set of taxis at time n
$B_{i,n}$	The set of IRS-buses that can cover taxi i at n
$x_{ij,n}$	equal to 1 if j is IRS of i

Table 1 lists and defines the variables used in this problem formulation solution.

$$\forall n \in (6am, 18pm),$$

$$\min_{x_{ij,n}} D_n = \sum_{i \in S} \sum_{j \in B_{i,n}} d_{ij,n} x_{ij,n} \tag{12}$$

Sub.const.:

$$x_{ij,n} = \begin{cases} 1 \text{ if client } i \text{ is covered by bus } j \text{ at } n \\ 0 \text{ otherwise} \end{cases} \tag{13}$$

$$\sum_j x_{ij,n} = 1 \tag{14}$$

The solution of this optimization problem belongs to the K *median* solutions problem. Our goal is to reduce the distance between the IRS-bus and covered vehicles at time n. To achieve this goal, we need to make a constrain where to minimize D_n which is denoted by the sum of the distance between each taxi i and each IRS-bus j in time n. This is on a condition, only when there is a connection between the taxi i and the IRS-bus j at that time n which is denoted by $x_{ij,n}$. The value of $x_{ij,n}$ is binary equals to 1 except of disconnection as mentioned in constraint 13. Constraint 14 requires only one IRS-bus to be located because we suppose that a taxi should be connected to only one IRS. In the double sum to be minimized, j is taken in $B_{i,n}$ since the list of IRS-buses includes only bus j that have a connection with taxi i at time n. In case where we would have an adaptive coverage radius, a possible solution to reduce the time for resolution, is to force the program code (CPLEX in our case), to stop after a certain time (Anytime solution).

Dealing With Mobility: The idea is that, in an interval of time, we fix the number of potential IRSs, we enumerate all mobile node positions, and that we solve the model. If we want less or more IRS, we need to evaluate the model at our convenience. The more IRS number used, the less the coverage distance will be. The time interval is chosen considering a real deployment such as vehicles relaying inside a crowded urban tunnel, or crossroads in a city with tall buildings. Typically, we use an interval of one to several minutes.

To better understand the real scenario of how IRS buses and taxis interact within the cellular network, consider Fig. 2, where IRS-bus acts as a relay for moving vehicles in its coverage area. Suppose there is an IRS-bus moving from left to right as shown in the figure. There are three different cases that can be described in this figure. The first case,

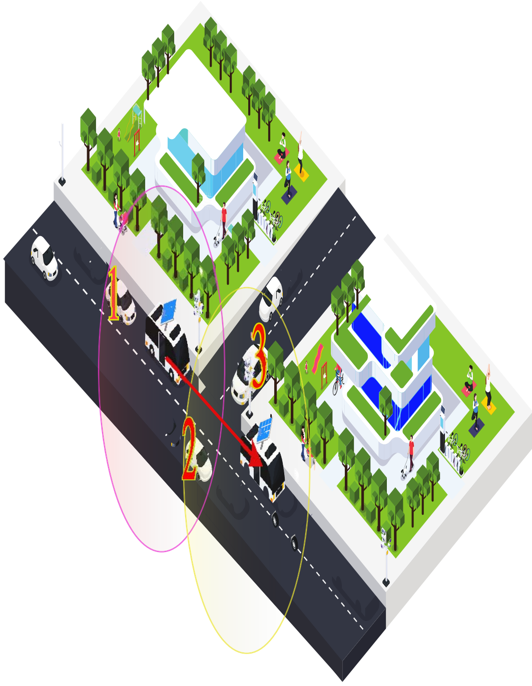

FIGURE 2. Moving coverage zone.

taxi number 1 covered by the IRS-bus when it was on the left side and when the IRS-bus moved to the right, the taxi followed its way away from it and thus is out of IRS-bus coverage area and it maybe connected (handover) to another IRS-bus.

The second case, taxi number 2 connected to an IRS-bus when it was on the left hand side. This taxi is still connected to the same IRS-bus after moving to the right side because it is still in its coverage area.

The third case, taxi number 3 was not covered by the IRS-bus when it was on the left side, and became covered when the IRS-bus moved to the right side. All of these situations reflect real situations that occur throughout the day.

B. DNN: DECISION NEURAL NETWORK

There are different learning approaches that can be used to solve the problem of selecting the best IRS-buses. MILP and MDP can be used and both have their own benefits. If MILP is used to solve the problem, the performance will be optimal but at the cost of the long time it takes to run the model each time which any change of the input parameters. In addition, it is intended to solve linear problems, and therefore cannot solve complex quadratic problems. On the other hand, DNN approach gives sub optimal results but with great benefit of significantly reducing the time needed to learn the optimization solutions. Therefore, we propose to formulate the case solution in a classical optimization model to have many iterations of runs and hence finds out and learn the optimal results. This approach has been validated in [21]. MILP will be used to get out the optimal results and then DNN will be used to learn these obtained results.

The MILP process is shown in the first part of Fig. 3, it is based on the positions databases of buses and taxis in the city of Rome, the output is the selected IRS-bus dataset. This output data set will be fed to DNN for learning as will be described later in the performance evaluation section.

C. ENCODER & DECODER RECURRENT NEURAL NETWORK (LSTM)

The DNN consists of an encoder and a decoder network as shown in Fig. 3. This approach is intended for natural language processing, but we have adapted its inputs to match our MILP results as validated in a previous work [22]. These two LSTM networks work in symbiosis to compress the input data and to extend the output again. The encoder has the same MILP input which is the positions (latitude and longitude) of taxis and buses. The encoder output is fed to the decoder along with the shifted labelled data. The output corresponds to the optimally computed IRS-bus list for MILP shifted by one. The final labels consist of the IRS-bus's list. The training process uses MILP inputs and MILP results. Here numbers of optimal IRSs results from MILP vary each timestep and hence we need a more sophisticated LSTM architecture using the encoder decoder one.

The use of an LSTM-based encoder and decoder has hence an advantage over normal LSTM, as normal LSTM cannot differentiate between the input and output sizes.

V. MARKOV DECISION PROCESS-BASED OPTIMIZATION APPROACH

In this section, we present the approach based on a Markov Decision Process. The idea consists in letting each taxi in a blind zone choosing its *preferred IRS-bus*, among all the IRS-buses present in the zone. Then, the choices of the taxis of the blind zone are gathered and the most preferred one (which has the most votes) is elected as the *actual IRS* of the zone. This algorithm is run each minute. For the election process, the taxis may use predictions of their locations together with the bus schedule in the near future. Thus, they can anticipate the set of IRS-buses under their coverage at the next time slots. In this study, the future time window is 4 slots plus the current one, a slot being equal to 1 minute. Four policies are considered:

- *Strategy Q:* A taxi chooses as a preferred IRS-bus randomly among the set of IRS-buses covering its zone;
- *Strategy Q'A:* A taxi chooses as a preferred IRS-bus among the set of the IRS-buses covering its zone the one which is expected to appear the highest number of times in the near future, considering the vehicular and bus location predictions;
- *Strategy Q'B:* The same as strategy Q'A except that if a taxi chose already a preferred IRS-bus the slot just before, and if this preferred IRS-bus is still under its coverage during the current slot, the taxi keeps this preferred choice instead of running the whole algorithm again;

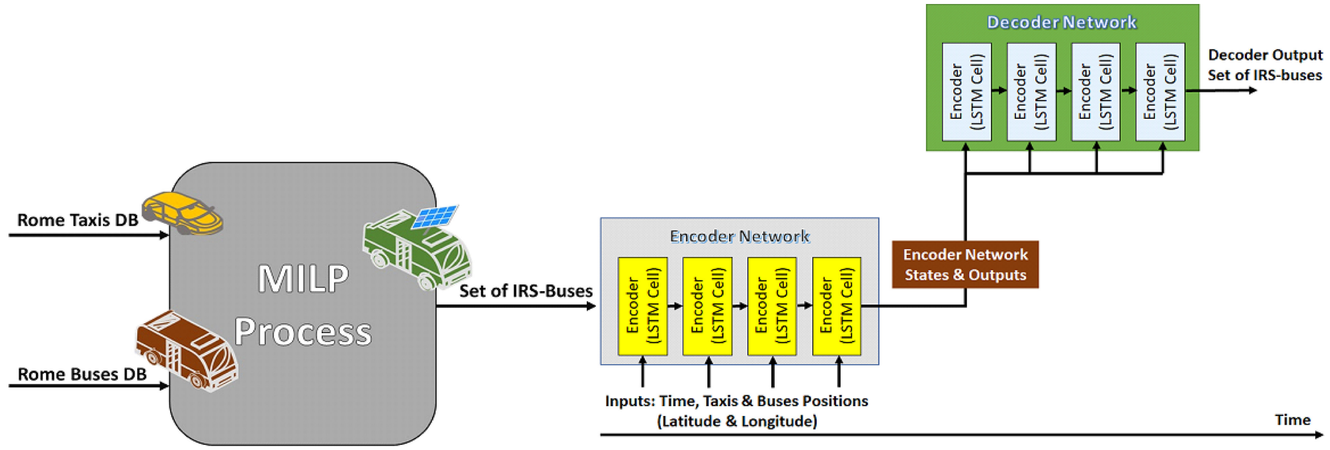

FIGURE 3. MILP resolution process & LSTM based encoder and decoder architecture.

- *Strategy Q":* The same as strategy Q'A except that when a taxi considers the predicted presence of a IRS-bus in the near future, it does not consider potential IRSs for which the taxi will have disconnected communications with the IRS.

In other words, when a taxi expects an IRS-bus B to be under its coverage at times t, $t+1$, $t+2$ and $t+4$, it attributes a weight of 4 in the case of strategy Q'A or Q'B because the taxi is expected to be under its coverage 4 times at t, $t+1$, $t+2$ and $t+4$ and of 3 in the case of strategy Q" because it does not consider the bus after a disconnection (which occurs at time $t+3$). The goal of strategy Q" is to force taxis choosing as IRS-buses which minimize the number of disconnection and thus of handovers. Two kinds of predictions are considered: perfect predictions, exactly corresponding to what will happen to the taxi, and approximated ones based on neural networks predictors [19]. Perfect predictors are for the case where taxies enter their trajectory in the information system before driving. It is also a best case, or an upper bound. The strategy Q does not rely on prediction. It is thus a worst case, or a lower bound. The reason for being of strategy Q'B is to add a continuity element in the process of preferred IRS election, thus decreasing the number of handovers.

We assume that a map partitioned in N zones, buses and taxis drive though this map, the time is discretized in time units (or "slots") chosen equal to 1 minute and at the beginning of each time slot n, a bus is elected as IRS for its zone, and for the duration of slot n. We recall that $d_{i,n}(j)$ is the distance between the vehicle i and the IRS-bus j at n (in km), ρ is the coverage radius of IRS-buses or vehicles (in km) and we denote:

- $K(n)$: total number of vehicles (taxis) driving at time n;
- $X_n = (x_{1,n}, \ldots, x_{K(n),n})$ where $x_{i,n}$ is the id of the IRS-bus elected by the vehicle i for slot n;
- $Z_n = (z_{1,n}, \ldots, z_{N,n})$ where $z_{i,n}$ is the *id* of the elected IRS-bus for the zone i for slot n;
- $B^Z_{l,n}$: set of the IRS-buses at n in the zone l;
- $C_{l,n}$: set of the vehicles at n in the zone l;
- $q_{i,n}(j)$: expected measure of the quality of the connection between vehicle i and IRS-bus j at n, equal to 1 if they are in direct visibility and 0 otherwise;
- $q'_{i,n}(j)$: expected measure of the quality of the connection between vehicle i and IRS-bus j from slot n to slot $n+\tau$ (i.e., including a future time horizon, not only slot n, τ being chosen equal to 4 minutes), equal to the number of slots during which they are in direct visibility;
- $q''_{i,n}(j)$: expected measure of the quality of the connection between vehicle i and IRS-bus j from slot n but without discontinuity.

Thus, we have

$$q_{i,n}(j) = \begin{cases} 0 \text{ if } d_{i,n}(j) > \rho \\ 1 \text{ otherwise} \end{cases} \tag{15}$$

$$q'_{i,n}(j) = \sum_{k=0}^{T} \mathbb{1}_{\{d_{i,n+k}(j)<\rho\}} \tag{16}$$

$$q''_{i,n}(j) = \sum_{k=0}^{T} \prod_{l=0}^{k} \mathbb{1}_{\{d_{i,n+l}(j)<\rho\}} \tag{17}$$

Let S be the set of the possible states for X_n, Z_n.

Let $\alpha_{i,j}$ the action taken by taxi i to elect j as preferred IRS for its zone. $\alpha_{i,j}$ returns

- $x_{i,n}$ with equal probability from the set of IRS-buses $\{j; q_{i,n}(j) = 1\}$ in case of strategy Q;
- $x_{i,n} = \arg\max_j q'_{i,n}(j)$ in case of strategy Q'A;
- $x_{i,n-1}$ if $d_{i,n}(x_{i,n-1}) < \rho$ or $x_{i,n} = \arg\max_j q'_{i,n}(j)$ otherwise in case of strategy Q'B;
- $x_{i,n} = \arg\max_j q''_{i,n}(j)$ in case of strategy Q".

Let $\beta_{l,j}$ the action taken by the zone l to elect IRS-bus j as IRS. $\beta_{l,j}$ returns

$$z_{l,n} = \arg\max_{j \in B^z_{l,n}} \sum_{k \in C_{l,n}} \mathbb{1}_{\{x_{k,n}=j\}} \tag{18}$$

In other words, the IRS chosen by zone i is the one which is chosen by the highest number of taxies in this zone.

$\{S, \{\alpha\}_{i,j}, \{\beta\}_{l,j}, \Pi, R\}$ is a Markov decision process, the transition probabilities Π being given in the description of α and β (either uniformly distributed or deterministic depending on the different cases described above). We observe the average effective number of handovers per trajectory, and the average number of consecutive slots with the same IRS in a trajectory. We consider the *effective* number of handovers by opposition to the *expected* number of handovers partially estimated by the predictions. We call *platoon* a set of consecutive slots with a same IRS, per trajectory. Note that of course a taxi may be connected to the same IRS even if it changes of zone if the corresponding bus follows the same path and is elected all along the path by the zones its crosses. The rewards R are the performance criteria of interests. For example, it is $+1$ if a taxi is still covered and by the same IRS and 0 otherwise in case where the performance criterion of interest is the average number of consecutive slots or $+1$ if there is a change of IRS and 0 otherwise in case where it is the number handovers. Note that a taxi may be covered by an IRS j, at slot n, it may be under the coverage of no bus at all at slot $n+1$ and it may be covered by IRS j again at slot $n+2$. In this case, it does not correspond to a platoon since the taxi is not covered by the IRS j at $n+1$ but there is no handover since there is no change of IRS. That is why these two performance criteria, average platoon size and average number of handovers, are complementary.

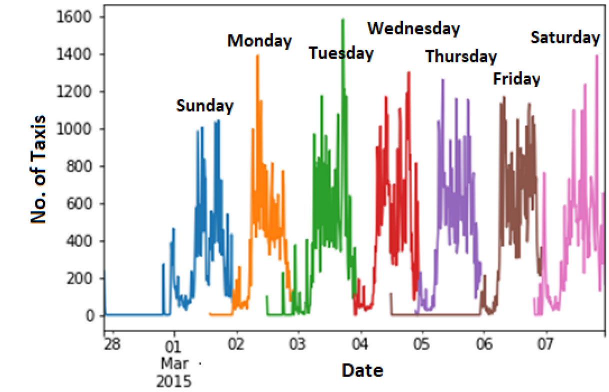

FIGURE 4. Daily vehicle activities in Rome area.

FIGURE 5. IRS-Bus position (red) serving several taxis (blue) after MILP optimization (one run).

VI. PERFORMANCE EVALUATION

A. DNN WITH LSTM EVALUATION

In this subsection, the performance of the DNN according to its architecture of Fig. 3 will be validated. As mentioned before, the input of the DNN is the taxis and buses positions and the output is the optimal IRS-buses positions dataset.

The encoders and decoders family has the ability to handle inputs and outputs of different sizes and with different semantics as well as handle complex tasks. Therefore, it is proposed to be used in the learning process over normal LSTM as it gives higher learning speed and performance. It should be noted that, in our case, the output is completely decorrelated from the input (taxi positions versus IRS ones). Additionally, the input size is different from the output size.

The performance of the DNN architecture is studied for different sizes of neural networks and meta parameters. The learning time and mean square error (MSE) are also studied based on using the LSTM and gated recurrent unit (GRU). The simulation code is built on Python (3.8) and two PCs of CPUs i7-10700 CPU @ 2.90GHz and 64GB RAM and i7-10750H CPU @ 2.60GHz and 32GB RAM.

Dataset used of mobile taxis and public transit buses of Rome city (Italy) [6] and [7] are used for validating the performance of the proposed models. These traces are constrained to the city center without losing the generality of the proposed models. The duration of taxi dataset is 60 days with GPS latitude and longitude coordinates recorded along with time. We have a large number of records for each taxi with a time-varying accuracy starting from one second time period.

According to the taxi data set, taxi activity throughout the day was studied to determine the best time period for the simulation. Figure 4 shows a sample of daily taxi activity on 1 March 2015 for a week in the city of Rome on workdays and weekends. As shown in the figure, the pattern of taxis activity is characterized by the type of workday or weekend and the time of day. In our case, the area of simulation is focused on Rome for time calculation issues.

For the simulation runtime, we determined 12-hour study time period between 6:00 AM and 6:00 PM with an interval of 5 minutes time shift. This time period is concluded based on the taxis daily activity presented in Fig. 4. The number of IRSs is limited to 100 and 200. The list of taxis is also limited to 100 out of every 5 minutes time shift.

The output of python code is the IRS-bus positions which is presented geographically as shown in Fig. 5. The blue signs are taxis, the red signs are the proposed IRS buses, and the red line is between a group of taxis and the IRS-bus they serve. The performance of DNN is studied in terms of Mean Square Error (MSE). The batch size changes in steps 3, 6, 9 and 12 which corresponds to number of samples. In

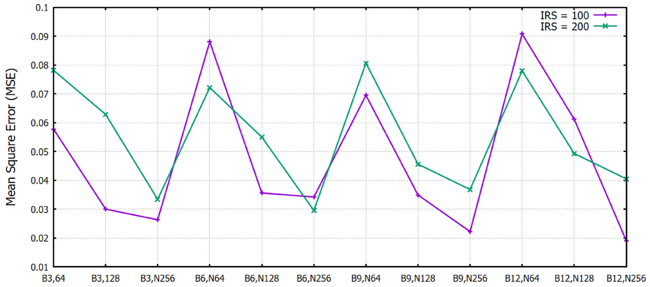

FIGURE 6. Mean square error (MSE) of 4 days for number of samples (batch size): 3, 6, 9, and 12, number of neurons: 64, 128 and 256, number of IRS:100 and 200.

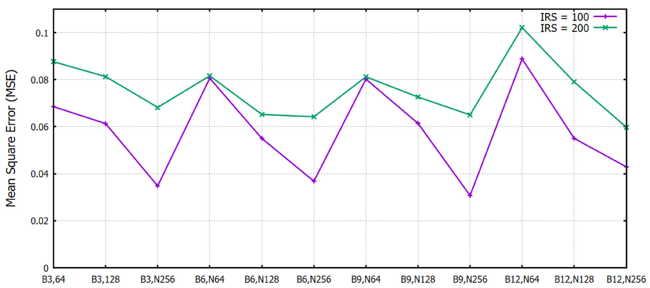

FIGURE 7. Mean square error (MSE) of 10 days for number of samples (batch size): 3, 6, 9, and 12, number of neurons: 64, 128 and 256, number of IRS:100 and 200.

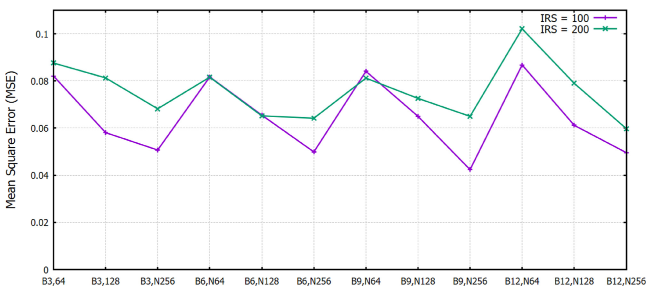

FIGURE 8. Mean square error (MSE) of 16 days for number of samples (batch size): 3, 6, 9, and 12, number of neurons: 64, 128 and 256, number of IRS:100 and 200.

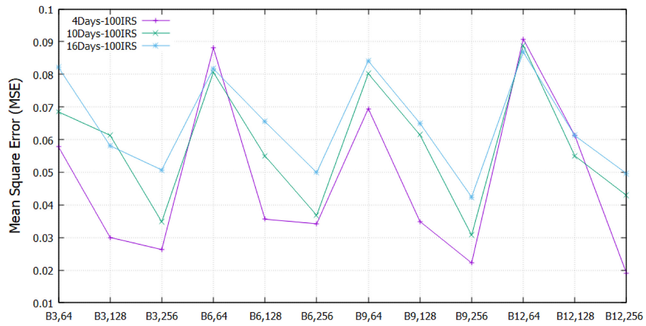

FIGURE 9. Mean square error (MSE) of 4, 10, and 16 days for 100 IRSs.

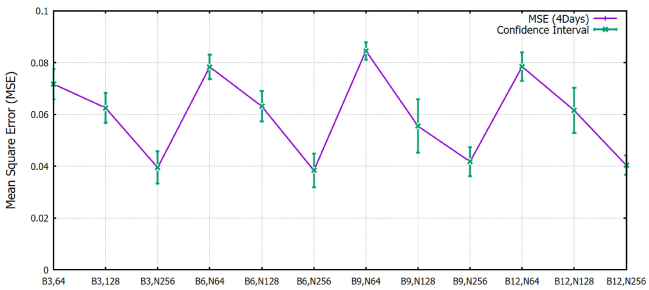

FIGURE 10. Mean square error (MSE) and confidence interval of 4 days for 200 IRS.

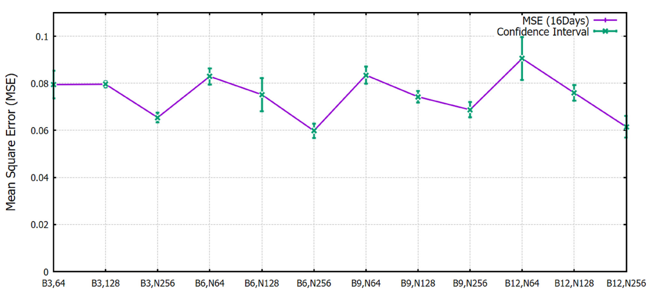

FIGURE 11. Mean square error (MSE) and confidence interval of 16 days for 200 IRS.

addition, since a DNN can consist of a different number of neurons, we studied its performance based on changing the number of DNN used neurons in steps 64, 128, and 256. As shown in Fig. 6, Fig. 7, and Fig. 8, the MSE changes with the change in the number of neurons. It is obvious that MSE decreases as neurons of the same batch size increase. Furthermore, the effect on MSE is shown for both 100 and 200 IRS for better a conclusion.

In order to compare the effect of the training dataset length on the MSE, Fig. 9 shows that 4, 10, and 16 days dataset are not enough to determine the effect of the training dataset. Therefore, there is a need to train the model using several larger datasets to determine its effect but with a penalty of very long processing time that can last for days/weeks and requires superior server hardware specifications.

On the other hand, in order to check the reliability of the DNN model performance, the MSE of 200 IRS is studied of 4 and 16 days datasets with 90% confidence interval and 3 different runs with a 2-day time shift. The MSE for DNN and the confidence interval are shown in Fig. 10 and Fig. 11.

In order to determine the effect of the input sample size on the performance of the DNN model. We studied the impact on the MSE with batch sizes of 3, 6, 9 and 12. Additionally, the effect of batch size was studied for different numbers of 64, 128, and 256 neurons and this study was repeated for different dataset size of 4, 10, and 16 days. As shown in Fig. 12, it consists of three columns and three rows. Row 1 of subfigures a, b, and c shows the effect on MSE for the 4-, 10-, and 16-days dataset size for a fixed number of neurons of 64 for both 100 and 200 IRS. Row 2 of subfigures d,e, and f shows the effect on MSE for 128 neurons. Finally, row 3 of subfigures g, h, and i shows the same effect on the MSE of 256 neurons. As shown in these horizontal line subfigures, for the same number of neurons, the MSE changes without a specific pattern. Therefore, we can conclude that there is no obvious impact on the MSE due to batch size change. Conversely, when looking at the subfigures vertically of the

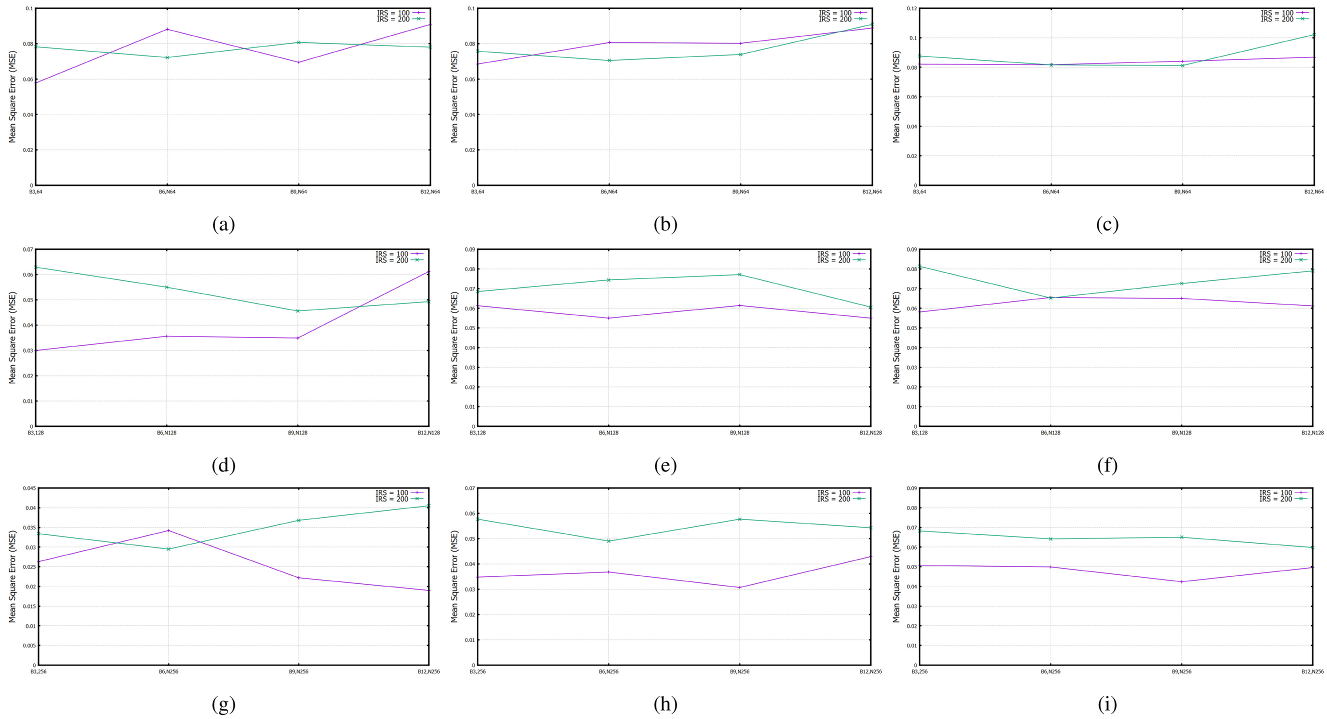

FIGURE 12. **Effect of batch size on the MSE. (a) 4 Days-64 Neurons. (b) 10 Days-64 Neurons. (c) 16 Days-64 Neurons. (d) 4 Days-128 Neurons. (e) 10 Days-128 Neurons. (f) 16 Days-128 Neurons. (g) 4 Days-256 Neurons. (h) 10 Days-256 Neurons. (i) 16 Days-256 Neurons.**

TABLE 2. **Simulation processing time and precision.**

Code	Simulation Time	Precision
$CPLEX$	$420 Hours$	100%
DNN	$18.33 Minutes$	71%

three columns (a, d, g), (b, e, h), and (c, f, i) the MSE improves as the number of neurons increases.

CPLEX evaluation time is a very critical parameter. Table 2 shows the difference simulation times of 10 days dataset for using both CPLEX and DNN. As shown in the table, the time taken by DNN is much less than the time taken by the CPLEX. As it can be seen, MILP optimization of 10 days dataset takes simulation run time of several days on the mentioned computer. Thus, this is a main repressive issue to use MILP for such dynamic problems. According to the high processing time difference between both methods, DNN is preferred. In addition, with every small change we need to rerun the MILP algorithm from scratch, which consumes a very long processing time in each rerun. Note that error percentage is less than 28%.

B. MARKOV DECISION PROCESS-BASED MODEL EVALUATION

To validate our MDP algorithm, we tested it on the same real vehicles mobility dataset [6] and buses dataset provided by Rome city [7] as in the previous section. Before beginning the discussion of model evaluation, let us recall that the term platoon will be used to refer to continuity of contact with the IRS-bus.

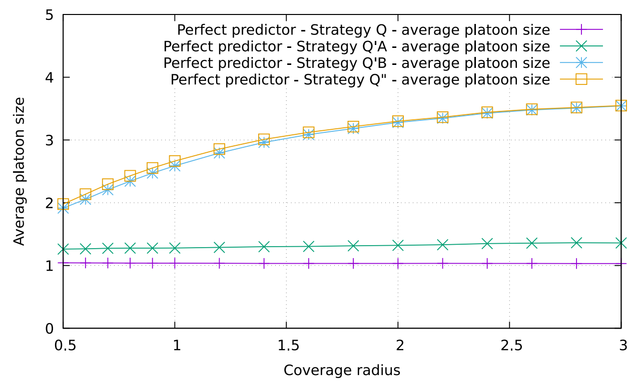

FIGURE 13. **Average platoon duration, for a perfect predictor.**

Figures 13 and 14 show the average platoon duration in function of the coverage radius ρ, with a perfect predictor and with the neural network based one. As expected, the strategy Q is the worst one: the taxis have the IRS they are connected to which change almost all the time. Strategy Q'A is better but still bad, although it is of course better in the case of the perfect predictor compared to the neural one. It is interesting to observe that both strategies Q'B and Q" behave more or less the same. As expected, fostering the choice of IRS which are expected to give longer platoon duration (strategy Q") must lead to higher platoon durations. But, keeping the preferred IRS if it is possible introduces a stability element which leads to the same result. Naturally, the perfect predictions gives better results than the imperfect

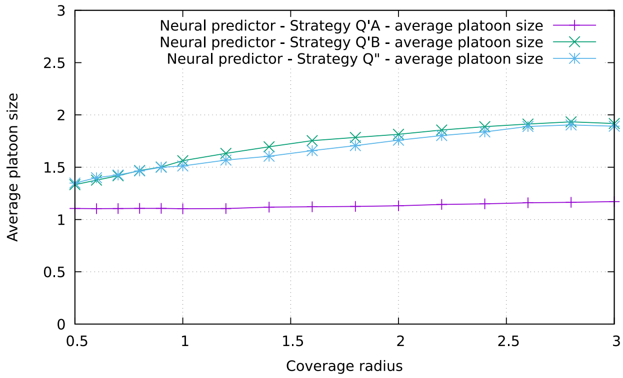

FIGURE 14. **Average platoon duration, for the neural network predictor.**

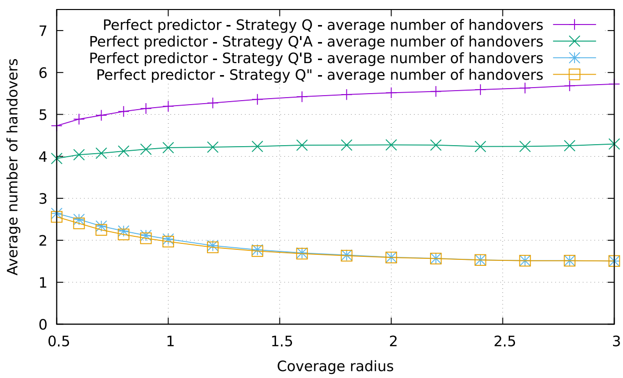

FIGURE 15. **Average number of handovers, for a perfect predictor.**

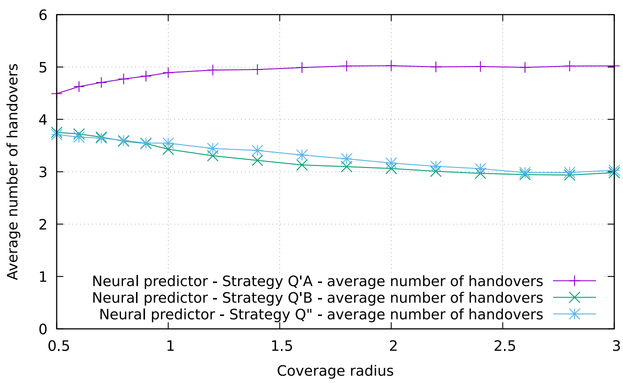

FIGURE 16. **Average number of handovers, for the neural network predictor.**

one. Note that the strategy Q does not depend on the predictor, but we copy it on both figures for comparison purposes.

Figure 15 and 16 show the average number of handovers for all the strategies, in function of the coverage radius ρ. Interestingly, it decreases in function of ρ for strategies Q" and Q'B, which is expected since the platoon duration increases, but it increases for the two other strategies. When the coverage radius increases, there are more buses in a zone which can acts as IRSs, thus more chance to have a IRS change, leading to more handovers. If the IRS election strategy is not sufficiently strong to foster the choice of stable IRSs, increasing the coverage radius becomes dominating, thus increasing the number of handovers.

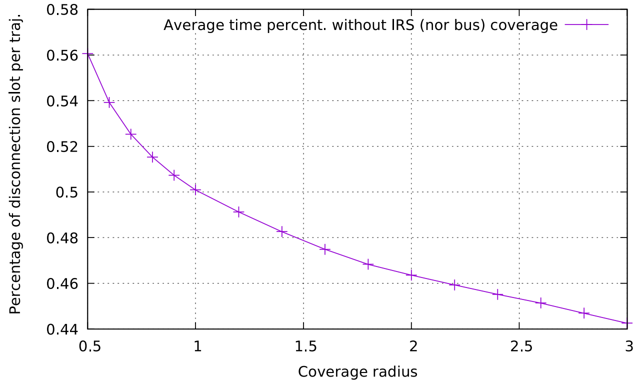

FIGURE 17. **Percentage of disconnection slots per trajectory.**

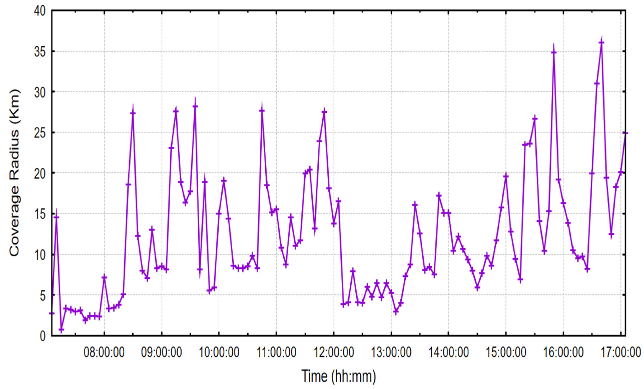

FIGURE 18. **Average weekday continuous connectivity coverage radius.**

Figure 17 present the proportion of disconnection slots per trajectory. Of course, it does not depend neither on the strategy nor on the predictor. We present it just to understand that their may be handovers due to IRS change but also to lack of coverage. Of course, it depends on the bus frequency but in any cases, the bus traffic is usually less dense than the vehicular car traffic.

In the same context as calculating the probability of disconnection, but on the contrary, this time we study the size of the coverage radius that maintains the continuity of the connection between taxis and the nearest IRS-bus. Figure 18 demonstrates the required average coverage radius in kilometer to maintain the connectivity between taxis and IRS-bus, in function of the time. As shown in the figure, the size of the coverage radius changes all the time of the day. This is due to the change in the density of the number of buses with respect to the time of day. Moreover, the coverage radius at some times throughout the day reaches several kilometers which is impractical, and this happens for two reasons. First, this is due to the low bus density at that time. Secondly, when there is a taxi far from the bus, due to the calculations in the simulation program, the radius of coverage is enlarged to integrate that taxi into the connected area.

VII. CONCLUSION AND FUTURE WORK

This work provided the IRS mobility contribution by equipping specific buses designated by the IRS to provide a communication relay with the BS for surrounding moving vehicles. In addition, this work provides the optimization framework for selecting the best IRS-bus. The performance of the proposed models and strategies has been validated based on the bus and taxi dataset in the city of Rome (Italy). There are two proposed approaches to solve this optimization problem.

Using MILP gives optimal results but with a very long processing time costs. That is why, an important contribution of this paper is the use of a LSTM-based encoder and decoder to approximate the behaviour of the MILP. The use of a LSTM-based encoder and decoder enhanced the taxi location detection behavior on a regular LSTM. Although its does not give the optimum, our approximation is very good while extremely efficient in terms of execution speed. LSTM processing time takes hours for the training but a few seconds for the execution once trained, while MILP takes several days to go through the same input dataset to optimize an area like downtown of Rome. The only drawback to the LSTM is that it gets suboptimal results from MILP but it is acceptable when we hit the MSE of 0.019. So, with our approach, we radically change the order of magnitude of the time needed to solve the IRS selection problem.

Another novelty in this work is an MDP approach for IRS selection, which gives high result accuracy and low processing time for IRS bus prediction while allowing easily targeting session-level performance criteria. This method complement the first one by allowing to easily consider, e.g., the average number of handovers per mobile session. Additionally, this MDP process is based on an LSTM neural network which is used to predict the positions of the moving vehicles. Here, we take advantage of the news prediction possibilities of the neural networks for the movement of the vehicles while keeping the computational efficiency of the MDPs. Four MDP policy strategies are considered. The moving vehicle uses the first strategy (Q) to randomly select an IRS bus from all buses which can be connected to it. In the second strategy (Q'A), the moving vehicle selects the IRS bus from the buses that it can be connected to based on the expectation of the bus with the highest present. The moving vehicle in the third strategy (Q'B) selects the same IRS bus it was connected to in the immediate previous time if this bus can still cover it, otherwise it comes back to strategy (Q'A). This is to minimize number of handovers. In the last strategy (Q"), the moving vehicle selects the bus based on the same criteria (Q'A) except for the prediction of the next IRS-bus to handover directly to it without disturbing the connection. The performance of the (Q'B) and (Q") strategies yielded better results with respect to the considered performance criteria which are the average number of handovers or the average time without handover during a session.

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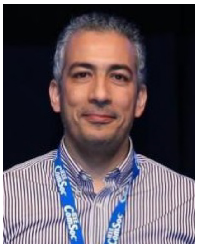

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