Towards Machine Learning-Enabled Context Adaption for Reliable Aerial Mesh Routing

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Abstract—In this paper, we present Context-Adaptive PARRoT (CA-PARRoT) as an extension of our previous work Predictive Ad-hoc Routing fueled by Reinforcement learning and Trajectory knowledge (PARRoT). Short-term effects, as occurring in urban surroundings, have shown to have a negative impact on the Reinforcement Learning (RL)-based routing process. Therefore, we add a timer-based compensation mechanism to the update process and introduce a hybrid Machine Learning (ML) approach to classify Radio Environment Prototypes (REPs) with a dedicated ML component and enable the protocol for autonomous context adaption. The performance of the novel protocol is evaluated in comprehensive network simulations considering different REPs and is compared to well-known established routing protocols for Mobile Ad-hoc Networks (MANETs). The results show, that CA-PARRoT is capable to compensate the challenges confronted with in different REPs and to improve its Key Performance Indicators (KPIs) up to 23 % compared to PARRoT, and outperform established routing protocols by up to 50 %.
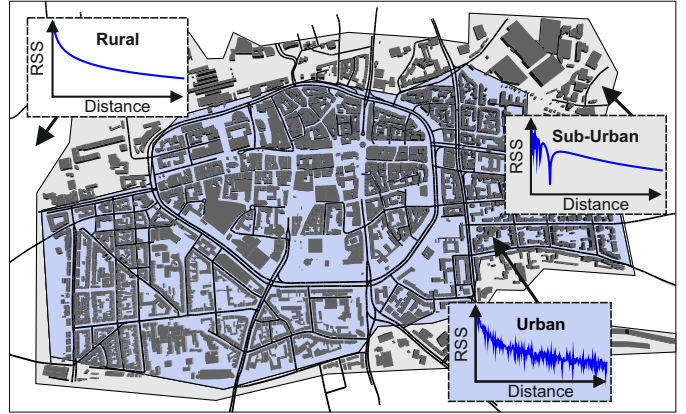

Fig. 1. Example of an application scenario, consisting of multiple radio environment prototypes (Map data: © OpenStreetMap Contributors, CC BY-SA).

I. INTRODUCTION

Aerial mesh networks offer the ability to be deployed spontaneously for events or by emergency personnel to manage desaster situations. Although this enables wide application ranges, certain challenges arise throughout these scenarios.

Besides high agent's mobilities and hybrid vehicle types participating in the network, the agents must also be able to operate in different REPs. Multi-REP scenarios (see Fig. 1) are considerably the most challenging situations for autonomous aerial mesh networks, as the mission cannot be interrupted to reconfigure the drones to fit a new REP, especially if they have a high mobility and REP changes are frequent. However, even if the application is limited to a single-REP area, an autonomous context adaption is neccessary to enable a quick network deployment without pre-evaluation.

Our previous work [1] has shown, that mobility-predictive routing protocols, such as our proposed PARRoT, and B.A.T.Mobile [2] outperform the considered well-known protocols in terms of robustness and reliability within different stress tests, channel conditions, and agent mobilities. Although, the reinforcement learning-based PARRoT widely performed best, a high impact of short-term channel variations on the Packet Delivery Ratio (PDR) has been observed and motivated further enhancement. Thus, we present CA-PARRoT, extending PARRoT with a compensation mechanism and introducing a hybrid ML approach.

The contributions are summarized as follows:

- Presentation of the enhanced **CA-PARRoT** protocol and extension of our open-source C++ simulation framework for Objective Modular Testbed in C++ (OMNeT++) [3].[1]
- Parameterization study for different REPs and proposal on a **machine learning-based parameter selection**.
- **Performance analysis** of CA-PARRoT in comparison to well-established routing protocols, as well to our mobility-predictive representatives B.A.T.Mobile and PARRoT.

The remainder of the paper is structured as follows. After discussing the related work in Sec. II, we present the extensions made to the CA-PARRoT protocol, and an approach to auto-adaptive parameterization in Sec. III. Afterwards, an overview about the methodological aspects is given in Sec. IV. Finally, detailed results are provided and discussed in Sec. V.

II. RELATED WORK

Unmanned Aerial Vehicle (UAV) mesh networks are deployed in recent, diverse applications, such as modern logistics, to provide contactless delivery systems or disinfect larger areas during COVID-19 pandemic [4]. Furthermore, the air-assisted traffic control in Intelligent Transportation Systems (ITSs) allows the exchange of safety-critical messages, but,

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[1]The simulation framework is available under: https://www.github.com/cedrikschueler/PARRoT
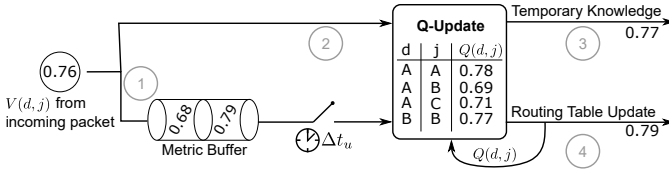
Fig. 2. Architecture of the timer-based knowledge management in PARRoT.

also infotainment related data among and across hybrid vehicular types, to enable autonomous driving and better traffic efficiency in smart cities [5][6].

The empirical analysis of Cavalcanti et al. [7] points out the popularity of routing protocols, channel models, and simulation methods for vehicular communication research. A summary of MANET routing protocols is given in [8]. A common distinction is the classification into *reactive* protocols –e.g. Ad-hoc On-demand Distance Vector (AODV) and Dynamic MANET On Demand Routing Protocol (DYMO)–, that build up routes on demand, and *proactive* protocols, which maintain routes by periodically broadcasting their information. Well-known representatives of the latter are Optimized Link State Routing (OLSR), Destination-Sequenced Distance Vector (DSDV), and Better Approach To Mobile Ad-hoc Networking (B.A.T.M.A.N.).

Further approaches, like Greedy Perimeter Stateless Routing in Wireless Networks (GPSR), include *geo-based* knowledge, like position and velocity, into the routing process, to respect the impact of mobility on communication capabilities. PARRoT [1] and B.A.T.Mobile [2] are considered *geo-predictive*, as they utilize cross-layer mobility knowledge to predict agent's positions and make their routing decisions. Thus, they follow the anticipatory mobile networking [9] paradigm, which describes the information aggregation to predict the network situation and not being forced to react, but to be prepared for upcoming changes. Besides mobility prediction, to assess topology changes, context-classification is an important part of anticipatory networking. Machine learning techniques have attracted a keen interest of the wireless research community due to their inherent of solving prediction and optimization problems in complex environments [10]. As a result, they are expected to be an essential part of upcoming network generations [11]. In this paper, we utilize ML methods to compete the challenging task of channel classification [12], by learning from channel parameters [13].

III. PROPOSED EXTENSIONS TO THE PARRoT ROUTING PROTOCOL

In this section, we present the proposed adaptions made to CA-PARRoT, after briefly discussing the fundamentals of the underlying PARRoT routing protocol, which we refer to our previous work [1]. Afterwards, we introduce additional parameters to the RL and present a ML-based component, dedicated to classify the conditions and select appropiate parameters to enable a zero-touch deployment.

A. PARRoT Fundamentals

PARRoT joins the core ideas of integrating mobility domain knowledge to predict agent trajectories, and derive autonomous routing decisions, based on agents' relations and link availabilities. PARRoT inherits the mobility prediction from B.A.T.Mobile [2]. Every agent approaches to predict its position $\tilde{\mathbf{p}}(t+\tau)$ for a future timestep with a prediction width τ. For this purpose, τ is divided into equidistant timesteps on which an iterative process is applied. Based on the temporary predicted position, the trajectory is moved towards the next target, if available. If no more target points can be retrieved from the mobility domain, remaining prediction steps are extrapolated from the position history.

All agents periodically broadcast routing messages, which wrap identification data, metrics, and position information in a total of 40 Bytes. As originator, the contained reward metric is set to a value of 1. Upon a received message, neighbor information is extracted and the agent invokes the reinforcement learning update process, and an update of its routing table. If the agent can contribute to the route building process, it emplaces its mobility information and updates the reward metric to its own best estimation for a route to the originator. The message is then forwarded and propagates through the network. By this procedure, every agent generates a Q-table with possibly multiple entries to reach a destination node. By default, the routing behaves always greedy and the next hop with the best metric score is selected. Neighbors can be considered as forwarders for the time scope of the predicted link availability or a maximum of τ.

Aforementioned link availability is calculated based on the position $\mathbf{p}(t)$ and the predicted position $\tilde{\mathbf{p}}(t+\tau)$ of the current node i, and a candidating neighbor node j, respectively. The relative trajectories are compared with respect to the maximum communication range r_{TX}, which is derived from a freespace model. As an output, the time where i and j can communicate is further processed into the RL metric $\Phi_{\text{LET}}(i,j)$ and is also used to track the validity time of entries.

B. Variance-compensating Update Process

Radio signals propagate via multiple paths in urban environments, causing constructive or destructive interference at the receiver. The wireless channel is therefore affected by influences that may only be valid for a short period of time. Especially in the routing context, this leads to incorrect assessments of the current situation and can be a main reason for performance losses. To overcome this issue, a measure is neccessary, to prevent occasionally occuring input from foreign agents from having too much impact on the reinforcement learning-based routing process and the stored knowledge. On the other side, missed out messages from neighboring nodes need to be handled.

Within our previous B.A.T.Mobile [2] protocol, a timer-based approach was introduced addressing the described problem. Incoming routing packages only update a current score candidate S_C, which is shifted to a *neighbor score buffer* after
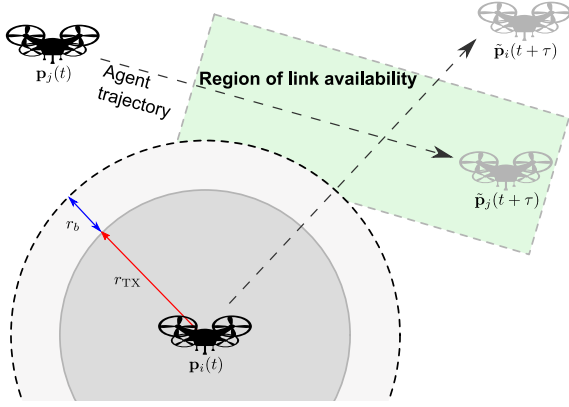
Fig. 3. CA-PARRoT's approach to assess link availabilities between two agents i and j by utilizing agent trajectories to predicted positions $\tilde{\mathbf{p}}(t+\tau)$.

Fig. 4. Concept of the ML-based, context-adaptive parameter selection.

an elapsed update interval t_u. Concerning the update process in CA-PARRoT, a small adaption has to be made:

Incoming chirps contain the best effort estimation $V(d, j)$ of the last forwarder of the message j, to reach a target destination d. The forwarding process utilizes the most recent metric by calculating the quality indicator $Q(d, j)$, and, then decides to forward the chirp or not. In PARRoT, this metric was stored upon every reception of a chirp. Because the Q-learning is implemented as an online learning process, this behaviour leads to an very unstable Q-table, that is easily affectable by incoming packets.

CA-PARRoT stores route information depending on the freshness (*is the sequence number higher?*), and its worth (*is V higher than the stored one?*). This means, that only the *best candidates* are stored and other information is discarded. To reduce the variance of stored knowledge, we supply CA-PARRoT with a timer-based update as shown in Fig. 2.

The new update routine is divided into four parts and works as follows:

1) Neighbor-related information is always stored (i.e. position, velocity, $\Phi_{\text{Coh}}(j)$), but route information is only stored in the metric buffer if
   - The information is more recent
   - The received metric is higher
2) The recently buffered value triggers a calculation of the Q-value, for which, the currently stored value $Q(d, j)$ is queried. This leads to,
3) A temporary valid knowledge, with which the further processing of the chirp is determined.
4) Triggered by a periodic timer, the buffered knowledge is overwritten with the most recent route candidate. Also, this timer incorporates an update of the routing tables.

C. Machine Learning-enabled Estimation of the Channel Properties

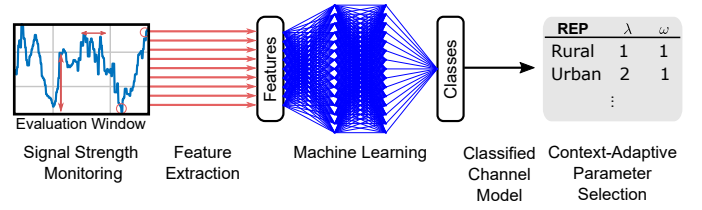Routing protocols need to handle different circumstances, which cannot be fulfilled with a fixed parameterization. In order to make CA-PARRoT more adoptable for disjunct REPs, we consider the range budget r_b as a REP specific parameter. As described in Sec. III-A a assumed communication range r_{TX} is derived from a freespace channel model, and is used in the calculation of the partial metric Φ_{LET}. The range budget r_b is added to this value, leading the edge condition for the relative agent trajectories $\Delta\tilde{\mathbf{p}} = \Delta\mathbf{p} + t \cdot \Delta\mathbf{v}$, with the relative agent position $\Delta\mathbf{p}$, and velocity $\Delta\mathbf{v}$ to be

$$r_{\text{TX}} + r_b = \sqrt{\Delta\tilde{\mathbf{p}}_x^2 + \Delta\tilde{\mathbf{p}}_y^2 + \Delta\tilde{\mathbf{p}}_z^2}. \tag{1}$$

This then resolves to the metric $\Phi_{\text{LET}}(i, j)$ between the current agent i and a neighbor agent j in accordance with [1]. Fig. 3 illustrates the impact of r_b on the Link Expiry Time (LET) calculation.

Additionally, the partial metrics can be of different importance in other REPs. To address this, we modify the Q-learning formula, and add a link weighting λ for $\Phi_{\text{LET}}(i, j)$ and a cohesion weighting ω for $\Phi_{\text{Coh}}(j)$ respectively. The basic discount factor γ_0 still guarantees a path degradation for $\gamma_0 \in [0, 1)$. Thus, the Q-learning update formula defines as

$$Q(d, j) = Q(d, j) + \alpha[\gamma(j) \cdot V(d, j) - Q(d, j)]$$
$$\text{with: } \gamma(j) = \gamma_0 \cdot \Phi_{\text{LET}}^\lambda(i, j) \cdot \Phi_{\text{Coh}}^\omega(j). \tag{2}$$

The proposed extensions lead to a parameterization tuple of $(r_b, \alpha, \gamma_0, \lambda, \omega)$ which is pre-evaluated for different REPs and is stored in a database. As shown in Fig. 4, each agent monitors the Received Signal Strength (RSS) and distance pairs for incoming routing messages, from which features are extracted and used to classify a REP by a ML component. Based on the result, a parameter set is selected.

To reduce the amount of re-calculations in stable environments, a backoff counter is implemented. Environment checks always take place before the Q-table update as described in Sec. III-B. The backoff counter is initially set to the length of the backoff window w_b and decreases with every timer event. The environment check is performed, if the counter reaches a value of 0 and skipped otherwise. Fig. 5 indicates the following condition: If the REP changed, w_b is reset to 1 to ensure a fast validation of the new estimation. If the previous classification is confirmed, w_b grows exponentially and, therefore, increases the trust in the current prototype classification. Regardless of how w_b changes, the backoff counter needs to be reset to the new value afterwards.
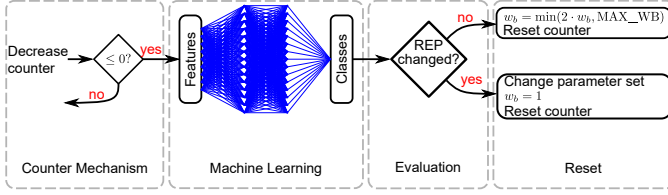
Fig. 5. Workflow of the backoff counter and the modification of the backoff window w_b.

Fig. 6. Cross validation accuracy of different ML classification approaches.

IV. METHODOLOGY

In this section, we present the methodological aspects of the performance evaluation in Sec. V. All simulations are carried out with the OMNeT++ [3] simulator, using MANET protocol implementations from the *INETMANET* framework. A UDP Constant Bitrate (CBR) video stream between two hosts is established to gather the PDR and latency as end-to-end KPIs. The agents move within a three-dimensional playground, following a controlled waypoint pattern.This is a variation of the well-known random waypoint mobility, with the extension, that future waypoints are pre-calculated and, thus, can be exploited by mobility prediction.

Radio Environment Prototypes (REPs): To evaluate the proposed context-aware self adaption, we consider three REPs, MANETs are possibly deployed in.

- **Rural** environments provide fairly simple radio conditions, where pathloss is primarily caused by signal attenuation over distance.
- **Sub-urban** environments contain scattered objects, that cause an additional reflecting path to the line-of-sight component in near-field situations.
- **Urban** areas are characterized by complex surroundings, leading to multipath propagations, interfering with the Line-of-Sight (LOS) path, and, thus, creating a highly challenging radio prototype.

TABLE I
DEFAULT PARAMETERS OF THE EVALUATION SETUP

Parameter	Value
OMNeT++ version	5.6.1
INETMANET version	4.x
MAC	802.11g
Rural channel model	Friis ($\eta = 2.75$)
Sub-urban channel model	Two-Ray Ground
Urban channel model	Nakagami ($\eta = 2.75$, $m = 2$)
Playground size	500 m x 500 m x 250 m
Number of runs per configuration	25
Simulation time	900 s
Number of routing hosts	10
Transmission power	20 dBm
Receiver sensitivity	-85 dBm
Mobility model	Controlled waypoint
Speed	50 km/h
Traffic load per video stream	2 Mbit/s
Chirp interval Δt_{Chirp}	0.5 s

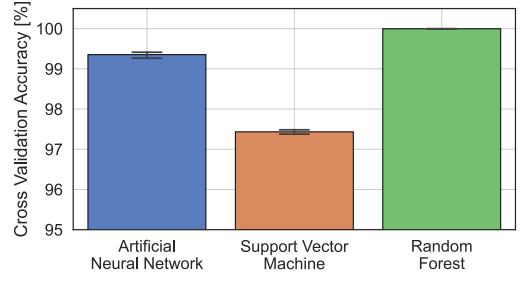Tab. I summarizes the simulation parameters. The respective

channel models were chosen due to their popularity in vehicular research according to [7]. As well, due to their popularity, we consider

- **AODV** as a *reactive* distance vector routing protocol,
- **OLSR** as a *proactive* link state approach,
- **GPSR** as a *geo-based* distance minimization protocol,
- **B.A.T.Mobile** and **PARRoT** as our *geo-predictive* previous works,

as references for the performance evaluation.

The training and evaluation of the REP classification are performed with the *LIMITS* [14] framework. For the REP classification task, we consider the following machine learning models whereas the parameters are chosen based on an initial grid search optimization:

- **Artificial Neural Network (ANN)** [15] with two hidden layers, 10 neurons per hidden layer, learning rate $\eta = 0.1$, momentum $\alpha = 0.01$, sigmoid activation function, and 500 training epochs.
- **Random Forest (RF)** [16] using 100 random trees and a maximum depth of 15.
- Linear **Support Vector Machine (SVM)** [17] trained via Sequential Minimal Optimization (SMO).

In the later result analysis, we analyze the 10-fold cross validation accuracy of each model. The best performing classification model is then embedded into CA-PARRoT for performing the online classifications during the simulation runs.

V. RESULTS

In this section, we present the evaluation of our proposal CA-PARRoT. First, the ML-based REP classification is elaborated with *LIMITS*, which also offers the capability to export the models. In parallel, we carry out a parameter study for each REP, where we investigate the adjustment of the range estimation through the range budget r_b.

The results are then merged in the new routing protocol CA-PARRoT, whose end-to-end performance is evaluated and compared with other protocols in a live setup, where CA-PARRoT is deployed without pre-parameterization and needs to prove its self adaptability.

A. Configuration of Context-Adaptive PARRoT

Fig. 6 shows the cross validation accuracy for the considered ML models ANN, linear SVM, and RF. All models show a
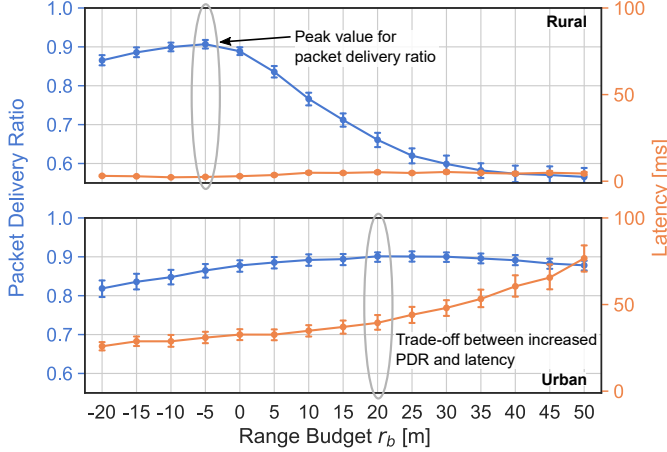
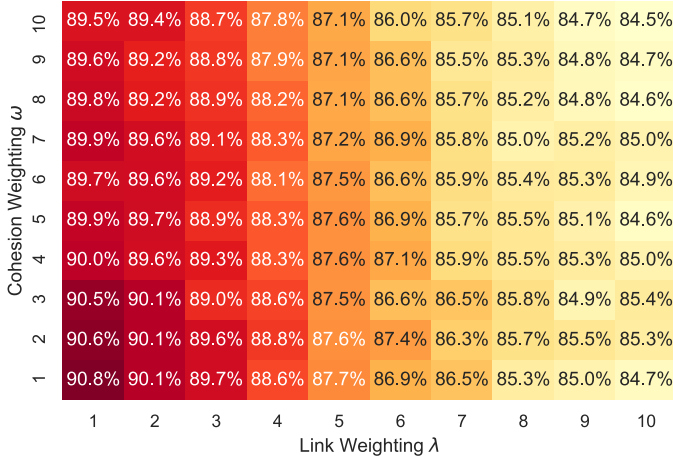Fig. 7. Range budgets r_b for rural and urban radio prototypes.

Fig. 8. Parameter evaluation for a rural REP.

high accuracy and provide a reliable REP classification from signal strength and distance pairs. Random Forest shows to be the most accurate model and, thus, is chosen to be integrated into CA-PARRoT.

The range budget r_b is an important parameter, as it does not only impact the Q-learning, but also limits the expiration timeframe for all knowledge entries through the estimated LET. Fig. 7 shows the achieved KPIs for r_b variations in urban and rural scenarios. The rural prototype shows a massive performance degradation for positive range budgets, which correspond to an overestimation of the communication radius. In turn, a peak value for a slight underestimation can be observed, and, thus, a default of $-5\,\mathrm{m}$ for rural prototypes is determined. Contrary, the urban prototypes shows an increasing latency for higher r_b, but also a higher PDR. As a tradeoff conception, $20\,\mathrm{m}$ are selected as default, as the PDR begins to plateau here, and the latency is lowest for this PDR level. The used two-ray ground model for sub-urban areas, is based

on a smaller attenuation coefficient, which leads to a higher communication range. Thus, $r_b = 600\,\mathrm{m}$ is set, to cover the biggest possible distance within the scenario playground.

Parameter	Rural	Sub-urban	Urban
Range Budget r_b	$-5\,\mathrm{m}$	$600\,\mathrm{m}$	$20\,\mathrm{m}$
Learning Rate α	0.5	0.2	0.6
Basic Discount γ_0	0.8	0.2	0.3
Link Weighting λ	1	3	1
Cohesion Weighting ω	1	2	2

The metric weightings λ and ω are evaluated for intervals of $[1, 10]$ each, which result in a heatmap as shown in Fig. 8 for a rural REP. The parameter optimization for the RL parameters is carried out according to [1]. Tab. II compromises the resulting parameterizations of PARRoT for rural, sub-urban, and urban REPs.

B. Performance Evaluation in a Three-Dimensional Random Waypoint Scenario

Fig. 9 shows the results of the performance evaluation across different REPs for the considered reference protocols and the ML-based CA-PARRoT. In the shown scenarios, CA-PARRoT was deployed without manual configuration so that the ML component was responsible to classify the REP and select the appropriate parameter set.

For a rural REP, a performance gain of $3\,\%$ compared to PARRoT can be observed and, thus, only a gap of $5\,\%$ remains to the theoretical upper bound, which expresses the mobility-constrained availability of routes. B.A.T.Mobile is outperformed by $19\,\%$, and AODV, as best performing established reference protocol, can be exceeded by $48\,\%$. Also, considering the latency, CA-PARRoT's latency is $10\,\%$ lower than PARRoT's, and $21\,\%$ lower than OLSR's.

As described before, the channel model for the sub-urban REP considers a higher communication range. Therefore, Fig. 9 (b) shows a high availability of one-hop connections across all protocols. B.A.T.Mobile and PARRoT both use range estimations in their routing process, derived from a freespace model with higher attenuation, and, thus, being too low for this REP. This causes both protocols to plan multi-hop routes although one-hop connections would be available. Here, the better fitting parameter set of CA-PARRoT with a higher range budget r_b prevents the protocol from being too pessimistic, thus, also deciding to route packets directly to their destination.

Fig. 9 (c) and Fig. 10 (c) show the achieved KPIs for the urban REP, characterized by the highest channel variance of the considered REPs. As shown, the proposed timer-based compensation technique and ML-based classification component enable CA-PARRoT to overcome the challenges, posed by the urban REP, and raise the PDR by $11\,\%$, while reducing latency by $23\,\%$ compared to our previous protocol PARRoT.

Compared to B.A.T.Mobile, the former best performing protocol in [1], CA-PARRoT achieves a $5\,\%$ higher PDR and
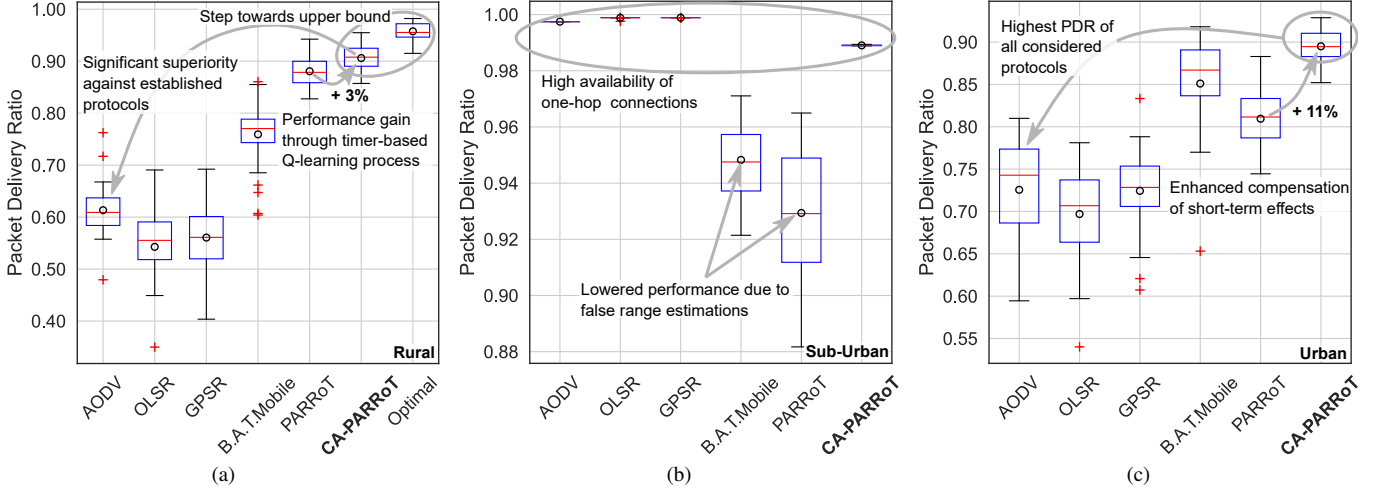
Fig. 9. Comparison of the PDR of different routing protocols across the rural (a), sub-urban (b), and urban (c) REPs.
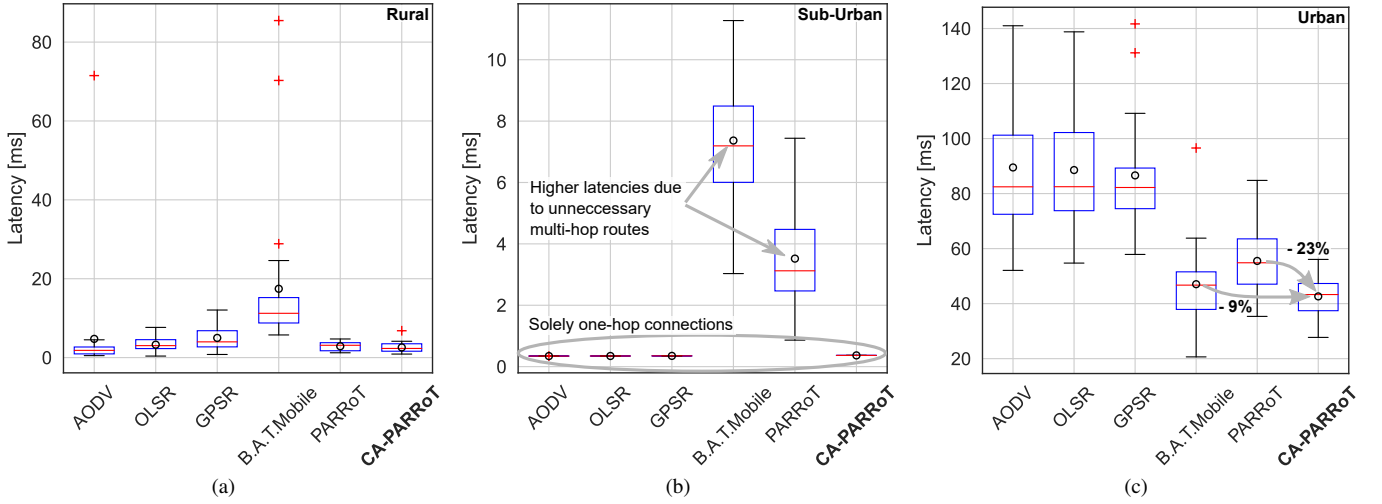

Fig. 10. Comparison of the latency of different routing protocols across the rural (a), sub-urban (b), and urban (c) REPs.

a $9\,\%$ lower latency. The established reference protocols are outperformed by up to a $23\,\%$ better PDR and $50\,\%$ lower latency.

VI. CONCLUSION

In this paper, we presented CA-PARRoT as an extension of PARRoT, that uses a timer-based update process to compensate short-term effects in challenging surroundings. The dedicated machine learning component for predicting the current REP enables CA-PARRoT to choose the best known parameter set and, thus, being able to operate autonomously in different REPs. As shown in comprehensive simulations, CA-PARRoT achieves a significant gain compared to PARRoT and outperforms the considered other protocols.

In future work, we will consider more radio prototypes and evaluate type-dependent optimization techniques to be applied depending on the predicted REP.

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