Future Wireless Communications Empowered by Reconfigurable Intelligent Meta-Materials

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Executive Summary

Deliverable D1.3 of the project Metawireless consists of an intermediate report on the research activities performed within Task 1.3 of WP1.

WP1 is the work package that deals with all the research activities planned by the Metawireless project in order to achieve the technical objectives defined in technical annex of the grant agreement. Specifically, Task 1.3 is concerned with the technical Objective 3, i.e.

The development of new communication schemes, optimization protocols, and algorithms for wireless networks employing reconfigurable intelligent surfaces, coping with the large degrees of freedom and the passive nature of metasurfaces.

According to the technical annex of the grant agreement, the activities of Task 1.3 comprise an initial phase of literature review to learn the latest theoretical tools and results that have emerged for the analysis and design of wireless networks based on the use of reconfigurable intelligent surfaces. Afterwards, the research activities will focus on overcoming the state-of-the-art and developing innovative protocols and algorithms capable of operating in practical wireless networks that make use of reconfigurable intelligent surfaces.

The rest of this document is organized as follows. Section 1 provides the results of the state-of-the-art review performed during the first phase of Task 1.3. Section 2 describes the ongoing research activities and the innovative contributions achieved by the ERSs, also providing specific references that are key to the research activities performed by each ESR. Finally, concluding remarks are provided in Section 3. All references are provided in Section 4.

List of Project Beneficiaries and Partner Organizations

- Consorzio Nazionale Interuniversitario per le Telecomunicazioni (CNIT)

- Centre National de la Recherche Scientifique (CNRS)

- KTH Royal Institute of Technology (KTH)

- NEC Laboratories Europe GmbH (NEC)

ACRONYMS

ESR (s)	Early-Stage researcher(s)
ITN	Innovative Training network
MSCA	Marie Skłodowska-Curie Actions
IPR	Intellectual Property Rights
METAWIRELESS	Future Wireless Communications Empowered by Reconfigurable Intelligent Meta-Materials
WP	Workpackage

1. Introduction

In order to be successfully integrated into future wireless networks, a practical algorithmic and protocol suite must be developed to ensure the automatic reconfiguration of reconfigurable intelligent surfaces, with as little as possible direct human intervention. This is essential in order to reduce the operation costs of large-scale wireless networks, and ensure the plug-and-play deployment of reconfigurable intelligent surfaces. Task 1.3 addresses this issue. The results of the state-of-the-art review concerning Task 1.3 can be grouped into three main categories, i.e. channel estimation and channel-aware design techniques; machine learning techniques for network management and operation; metasurface-aided localization and sensing.

Channel-aware design. Channel estimation is a critical issue in networks employing reconfigurable intelligent surfaces, due to the fact that the passive nature of metasurfaces makes it difficult to employ traditional pilot-based techniques. In [1], the authors propose a method for channel estimation that is based on the parallel factor decomposition algorithm in order to unfold the cascaded channel from the transmitter to the receiver. The proposed method is based on an alternating least squares algorithm that iteratively estimates the channel between the transmitter and the metasurface as well as the channel between the metasurface and the users. Simulation results show that the proposed iterative channel estimation method outperforms the benchmark schemes based on genie-aided information. In [2], the authors propose a compressed-sensing-based channel estimation algorithm in which the angular channel sparsity of large-scale arrays that operate at millimeter wave frequencies is exploited to perform channel estimation at a reduced pilot overhead. The authors design pilot signals based on prior knowledge of the line-of-sight-dominated transmitter-to-metasurface channel as well as prior information on the high-dimensional transmitter-to-receiver and metasurface-to-receiver channels, by using compressed sensing methods. A distributed orthogonal matching pursuit algorithm is exploited in order to capitalize on the channel sparsity. In [3], the authors propose a two-stage channel estimation scheme by using iterative re-weighted methods for estimating the channel parameters in a sequential optimization loop. Simulation results show that the proposed method provides better performance than the two-stage orthogonal matching pursuit approach, in terms of channel estimation error and spectral efficiency gain. In [4], the authors propose two novel channel estimation methods by assuming a structured time-domain pattern of pilots and reconfigurable intelligent surface phase shifts. The authors show that the received signal follows a parallel factor tensor model that can be exploited to estimate the involved communication channels in closed-form or iteratively. Numerical results corroborate the effectiveness of the proposed channel estimation methods and highlight the existing tradeoffs. In [5], the authors propose a two-timescale channel estimation framework. The key idea of the framework is to exploit the property that the transmitter-metasurface channel is high-dimensional but quasi-static, while the metasurface-receiver channel is mobile but low dimensional. To estimate the quasi-static transmitter-metasurface channel, the authors propose a dual-link pilot transmission scheme, in which the transmitter emits downlink pilots and receives uplink pilots reflected by the reconfigurable intelligent surface. The authors propose a coordinate descent-based algorithm to recover the transmitter-metasurface channel. With the aid of numerical results, the authors show that the proposed two-timescale channel estimation framework can achieve accurate channel estimation with low pilot overhead. In [6], the authors introduce a general framework for the estimation of the transmitter-metasurface and metasurface-receiver cascaded channel, by leveraging a combined bilinear spare matrix factorization and matrix completion. In particular, the authors present a two-stage algorithm that includes a generalized bilinear message passing algorithm for matrix factorization and a Riemannian manifold gradient-based algorithm for matrix completion. Simulation results illustrate that the proposed method achieves accurate channel estimation performance for application to metasurface-assisted systems. In [7], the authors present an architecture for reconfigurable intelligent surfaces that comprises an arbitrary number of passive reflecting elements, a simple controller for their adjustable configuration, and a single radio-frequency chain for baseband measurements. By capitalizing on the proposed architecture and by assuming sparse wireless channels in the beamspace domain, the authors introduce an alternating optimization approach for the explicit estimation of the channel gains by relaying on a single radio-frequency chain. Simulation results demonstrate the channel estimation accuracy and achievable performance of the proposed solution as a function of the number of training symbols and the number of reconfigurable intelligent surface reflecting elements.

Machine learning techniques. Machine and especially deep learning have recently emerged as a major technology to enable the automatic operation of wireless networks, without the need of human intervention. Thus, in the context of networks aided by reconfigurable intelligent surfaces, machine learning proves very useful to reduce the complexity of network design, thus coping with the large amount of degrees of freedom that are available if reconfigurable intelligent surfaces are massively employed throughout the network. In [10], the authors put forth the connection between reconfigurable intelligent surfaces and machine learning, arguing that both are needed to realize the vision of smart radio environments. The authors discuss how the use of machine learning is essential to reduce the complexity related to the design of metasurface-based wireless networks, which is anticipated to be higher than in conventional wireless networks. To this end, the authors propose a model-aided deep learning framework, which is further elaborated in [11], which exploits transfer learning to simplify wireless network design by combining together model-based and data-driven methods. The same authors discuss the connection between metasurface-empowered smart radio environments and reinforcement learning in [12]. In [13], the authors introduce a neural-network-based approach for configuring the behavior of tiles in metasurface-based radio environments. The wireless propagation is modeled as a custom, interpretable, back-propagating neural network, in which the reconfigurable intelligent surface elements act as nodes and their cross-interactions as links. After a training phase, the neural network learns how to configure the reconfigurable intelligent surfaces for improving the communication performance. By using a ray tracing simulation environment, the authors show performance gain in agreement with state-of-the-art solutions, but with a distinct gain in reducing the total number of active tiles. In [14], the authors employ deep learning techniques to reduce the design complexity of metasurface-based wireless networks. In particular, the authors propose an unsupervised approach to optimize the reconfigurable intelligent surface phase shifts. In the proposed approach, a customized deep neural network is trained offline by using the objective function to be optimized for training the parameters of the deep neural network. Simulation results show a gain over conventional approaches based on the use of semi-definite relaxation and alternating optimization, even though the considered approach remains heuristic in the sense that no optimality property can be claimed. In [15], the authors propose a joint design of transmit beamforming and phase shifts in a metasurface-assisted multiple-antenna system, by using a deep reinforcement learning framework. The proposed deep reinforcement learning algorithm is shown to be scalable for accommodating various system settings. Instead of utilizing conventional alternating optimization techniques to obtain the transmit beamforming and the reconfigurable intelligent surface phase shifts, the proposed algorithm obtains the joint design simultaneously at the output of a deep neural network whose training is refined in real-time. In [16], the authors propose a deep reinforcement learning framework with reduced training overhead that is able to tune the phase shifts of the reconfigurable intelligent surface elements with reduced training overhead. The proposed approach paves the way to the deployment of distributed reconfigurable intelligent surfaces, which are able of self-configuration and operation without the assistance of base stations or infrastructure nodes. The authors illustrate numerical results that show that the proposed online learning framework is able to approach the same rate as a benchmark system with perfect channel state information. In [17], the authors optimize the design of the phase shifts of a metasurface-aided downlink multiple-input single-output wireless communication system, with the goal of maximizing the received signal-to-noise ratio. Because of the non-convexity of the considered resource allocation problem, the authors employ deep reinforcement learning in order to develop a practical phase shift design algorithm. Numerical results reveal that the developed algorithm can achieve near-optimal signal-to-noise ratio performance with relatively low complexity. In [18], the authors consider the problem of joint system deployment, reconfigurable intelligent surface phase shift control, power allocation, and dynamic decoding order determination in a metasurface-enhanced wireless system, while enforcing individual data rate requirements to the multiple users. To tackle this optimization problem, the authors use machine learning. In particular, the authors propose a novel long short-term memory based echo state network algorithm for predicting the future traffic demands of multiple users based on an empirical dataset. In addition, the authors propose a decaying double deep Q-network based position-acquisition and phase-control algorithm to determine the position and control policy of the reconfigurable intelligent surface. In [19], the authors investigate the use of deep learning for channel estimation in a metasurface-assisted massive multiple-input multiple-output system. In the proposed scheme, each user has an identical convolutional neural network which takes as input the received pilot signals and yields as output an estimate of the direct channel between the transmitter and receiver, and the cascaded channel from the transmitter to the receiver through the reconfigurable intelligent surface. The approach is extended to a multi-user scenario, wherein each user has its own convolutional neural network and estimates its own channel. With the aid of numerical simulations, the approach is compared against state-of-the-art deep learning based techniques and performance gains are shown. In [20], the authors study a metasurface-aided wireless communication system for physical layer security, in which a reconfigurable intelligent surface is deployed to adjust its surface reflecting elements in order to guarantee the secure communication of multiple legitimate users in the presence of multiple eavesdroppers. Aiming at improving the system secrecy rate, a design problem for jointly optimizing the base station beamforming and the reconfigurable intelligent surface beamforming is formulated, under the assumption of different quality of service requirements and time-varying channel condition. As the system is highly dynamic and complex, and it is challenging to address the resulting non-convex optimization problem, the authors propose a deep reinforcement learning secure beamforming approach that approaches the optimal beamforming policy. Furthermore, post-decision state and prioritized experience replay schemes are utilized to enhance the learning efficiency and secrecy performance. Simulation results demonstrate that the proposed secure beamforming approach can significantly improve the system secrecy rate and satisfaction probability.

Metasurface-aided localization and sensing. Future wireless networks will have to support more than just voice and data transfer. Another major service to be provided by future wireless networks is anticipated to be that of sensing the surrounding environment and localizing objects or users of interest. Accordingly, several contributions have emerged that investigate the use of reconfigurable intelligent surfaces to perform sensing and localization tasks. Surveys on this topic have appeared in [21], [22]. In [23], two practical signaling and positioning algorithms, based on an orthogonal frequency division multiplexing downlink system, are proposed along with methods to design the time-varying reflection coefficients of the metasurface. It is shown that by enlarging the size of the metasurface, it is possible to obtain satisfactory performance also in the non-line-of-sight regime. A compressed sensing technique is proposed in [24] to estimate the position of mobile terminals in a network aided by reconfigurable intelligent surfaces. Joint user localization and synchronization is carried out in [25]. Theoretical performance bounds are derived based on the use of the Cramer-Rao bound, also accounting for practical hardware impairments. Similarly, ultimate performance bounds for node localization are derived in [26], by means of the Cramer-Rao bound, for the scenario in which the base station is equipped with multiple antennas. The impact on localization performance of using active reconfigurable intelligent surfaces is investigated in [27]. In [28] it is investigated how to optimize the phase shifts of a reconfigurable intelligent surface to optimize the localization accuracy in indoor scenarios.

2. Description of Activities and Results

2.1 Contribution of CNIT-2 – Overcoming Gap 3.1

The research project of CNIT-2 is meant to address the research Gap 3.1 identified in the technical annex of the grant agreement. Specifically, reconfigurable intelligent surfaces provide a huge amount of degrees of freedom, which enables them to perform sensing and localization tasks with extreme accuracy. However, at present, positioning and sensing based on metasurfaces has never been quantitatively investigated. In order to overcome Gap 3.1, the individual project of CNIT-2 is focused on developing novel localization and tracking that fully exploit the potential of metasurfaces. The adopted approach considers both optimal and sub-optimal algorithms, and the efficiency of the latter ones is to be assessed by the tools of Fisher information and the Cramér-Rao lower-bound. Specific algorithms that account for and harness near-field propagation will be devised, and their impact will be quantified through Fisher information.

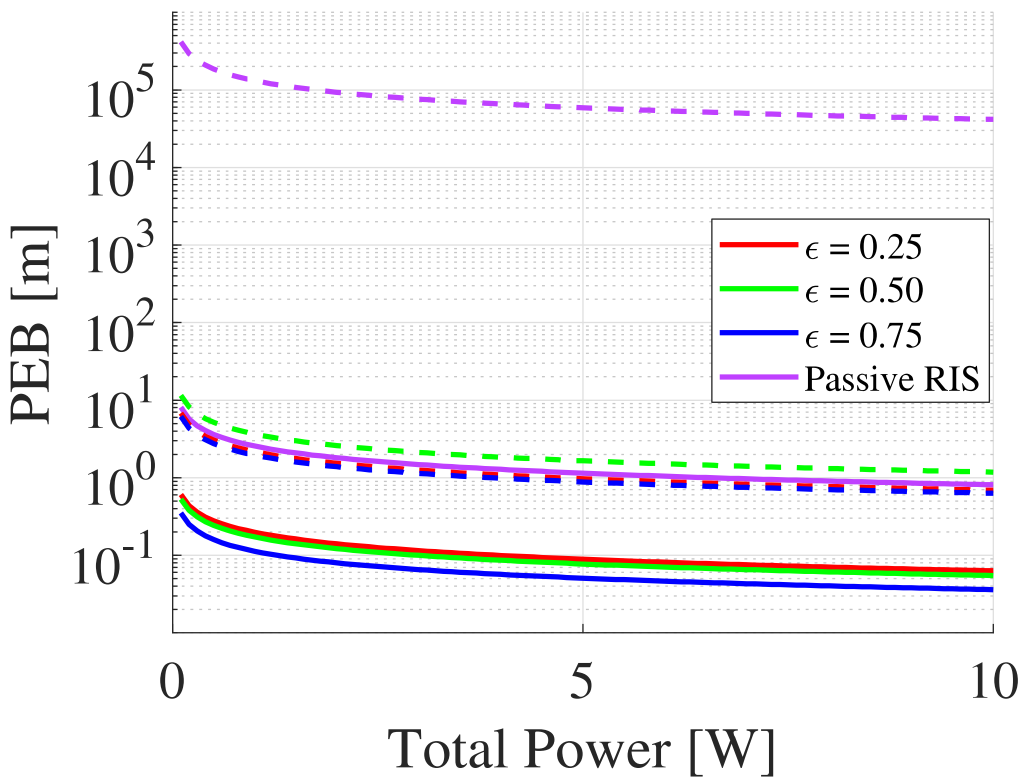
In particular, current research activities have addressed the impact of employing active reconfigurable intelligent surfaces to perform joint communication and localization in wireless networks. Conventionally, reconfigurable intelligent surfaces are considered to be passive or quasi-passive devices consisting of elements that reflect the incoming waves, introducing a controllable phase shift. Although passive metasurfaces are helpful in many applications, they are significantly affected by the multiplicative fading of the reflected signals, limiting their practical applications. In other words, the signal reflected by the metasurface is typically much weaker than the direct signal, which limits the usefulness of passive metasurfaces in scenarios in which a strong line of sight channel is present. To cope with this issue, the use of active reconfigurable intelligent surfaces is considered. Analog amplifiers are deployed at the metasurface, which enables each reflecting unit to apply both a phase rotation and an amplitude scaling to the incoming signal. Similarly to what has been described for the research activity of CNIT-1 (see D2.1), the use of an active reconfigurable intelligent surface is expected to address the issue of the multiplicative fading and thus unlock unprecedented localization accuracies. The presence of active components at the metasurface allows amplifying the incoming signal so that the signal that reaches the destination via the reconfigurable intelligent surface can be of comparable power as that of the direct link. Therefore, traditional geometry-based localization techniques based on angle of arrival (AOA) and time of flight (TOF) estimation are made more robust by the aid of a reconfigurable intelligent surface. On the other hand, considering an active reconfigurable intelligent surface significantly alters the structure of the system model, since the power amplification introduces a noise amplification effect, i.e. the signal reflected by the metasurface contains the noise introduced by the power amplifiers. Therefore, all the mathematical expressions for the performance bounds and the analytical expressions for the estimators differ from those found in the literature

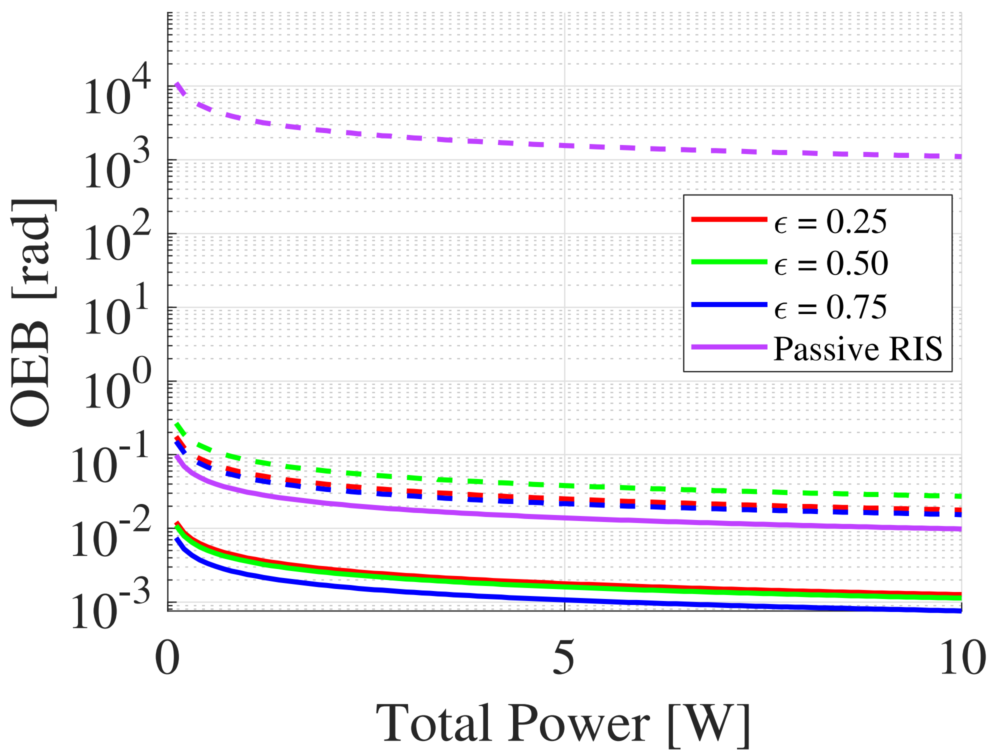
The research activity performed by CNIT-2 has achieved three main results:

1. Provide a realistic model of network enabled by an active reconfigurable intelligent surface and derive the theoretical performance bounds. This has been achieved mainly via the Cramer Rao Lower Bound, which enables to obtain closed-form, mathematically-tractable results.
2. Provide analytical expressions for optimal and sub-optimal estimators, commonly used in estimation problems. This has been achieved by leveraging the classical framework of estimation theory, generalizing its use to account for the presence of the reconfigurable intelligent surface.

3. Derive practical and low-complexity localization algorithms that fully exploit the potentialities of the reconfigurable intelligent surface. All algorithms have been tested by numerical simulation performed in MATLAB, which have shown the good performance of the developed estimators.

The above results have been achieved with reference to a user localization problem in a single-user and single-cell scenario with an active reconfigurable intelligent surface. In this context, the reflection coefficients of the active elements of the reconfigurable intelligent surface have been optimized together with the transmit power of the base station. A location estimator based on multiple signal transmissions and particle filtering is proposed. The developed algorithm fully exploits the additional degrees of freedom provided by the active reconfigurable intelligent surface. Moreover, theoretical performance bounds are derived and extensive numerical simulations show the effectiveness of the developed approach with respect to the use of a more traditional passive reconfigurable intelligent surface. The two figures below show the positioning error bound (PEB) and the orientation error bound (OEB), measured in radiants, achieved by the developed technique versus the total available power. Each figure compares the use of an active and a passive metasurface. The parameter ε measures how much of the total power available is used by the active reconfigurable intelligent surface, while the rest is used by the base station. The limit case ε=1 corresponds to a passive reconfigurable intelligent surface and all the available power is used by the base station. It is seen that, as expected, the use of an active reconfigurable intelligent surface can largely outperform its passive counterpart, at the expense of a larger power consumption





This research activity of CNIT-2 has led to the two following papers:

- G. Mylonopoulos, C. D'Andrea and S. Buzzi, *Active Reconfigurable Intelligent Surfaces for User Localization in mmWave MIMO Systems*, 2022 IEEE 23rd International Workshop on Signal Processing Advances in Wireless Communication (SPAWC), 2022

- G. Mylonopoulos, L. Venturino, S. Buzzi and C. D'Andrea, *Maximum-Likelihood User Localization in Active-RIS Empowered mmWave Wireless Networks*, submitted to 2023 17th European Conference on Antennas and Propagation (EuCAP).

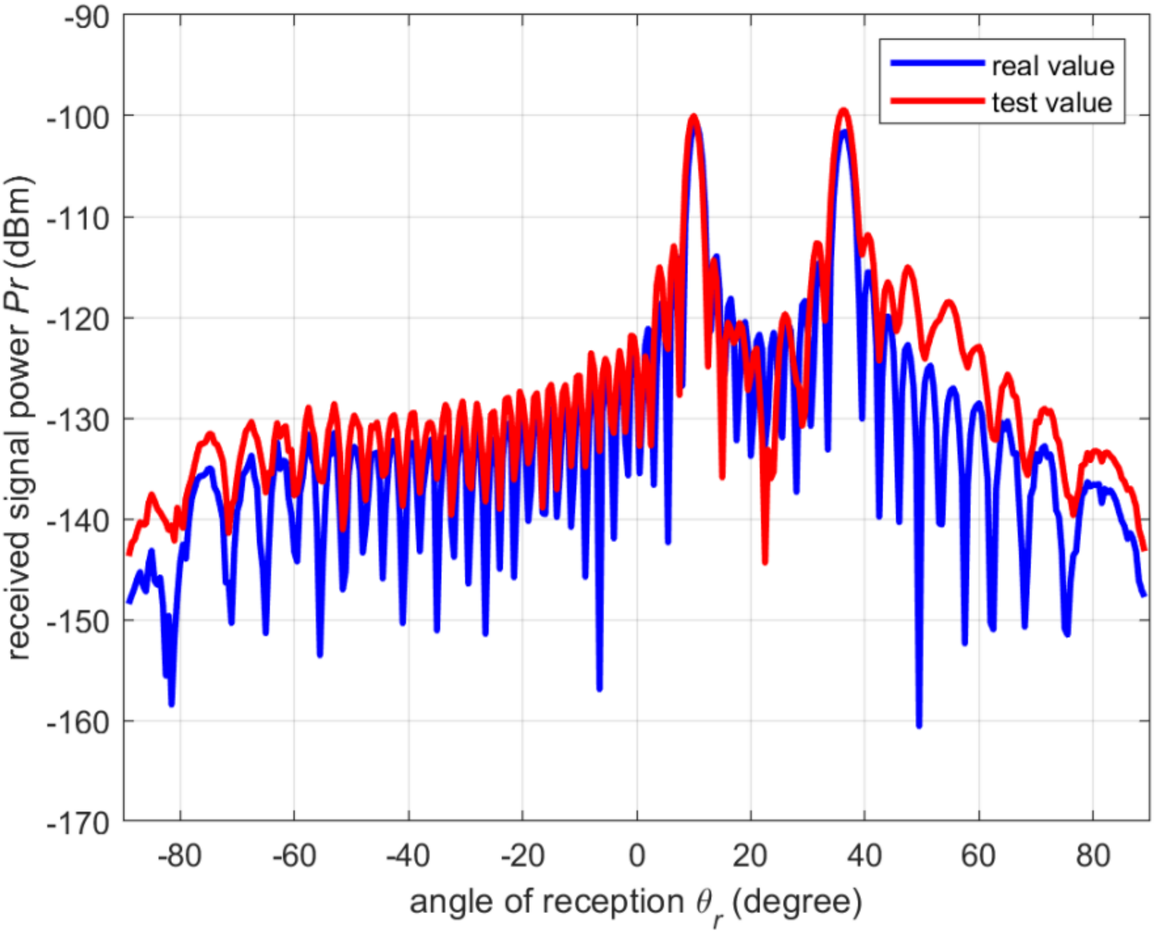
2.2 Contribution of CNRS-2 – Overcoming Gap 3.2

The research project of CNRS-2 is meant to address the research Gap 3.2 identified in the technical annex of the grant agreement. Specifically, system-level analytical studies model the environmental objects as entities that can only attenuate the signals, making the links line-of-sight or non-line-of-sight. As a result, there exist no analytical methodologies to analyze reflections, which are instead of great importance to optimize the operation of wireless networks employing reconfigurable intelligent surfaces. In order to overcome Gap 3.2, the research activities of CNRS-2 are focused on developing a new analytical framework to quantify the system-level performance of wireless networks in the presence of reconfigurable intelligent surfaces. The considered approach is based on modeling metasurface-coated objects by means of spatial shapes whose locations, size, orientation, height are randomly distributed. The analytical tool of random shapes can be used to this end with the objective to formulate key performance indicators (e.g., coverage, spectral efficiency, energy efficiency, delay) in analytically tractable forms, and, to optimize, the interconnected network, e.g., to identify the optimal number of reconfigurable intelligent surfaces per unit area to be deployed. Machine learning tools can be utilized, on the other hand, in order optimize the operation of reconfigurable intelligent surfaces, by first considering link-level network-topologies and by then moving towards system-level studies in the second part of the thesis.

During the reporting period of interest, CNRS-1 has developed deep learning techniques to output the desired reconfigurable intelligent surface configuration matrix after appropriate training. This approach has the advantage of drastically reducing the complexity of traditional design approaches which suffer the huge amount of degrees of freedom to allocate in wireless networks employing reconfigurable intelligent surfaces. Specifically, the proposed approach works as follows. First, given a set of angles of incidence and reflection, the reflection coefficient matrices are generated with the aid of efficient optimization algorithms for metasurface-aided channels. Then, one-shot encoding schemes are used to efficiently encode the angles of reflection and incidence, and to construct the actual input of a neural network to be trained. The corresponding reconfigurable intelligent surface reflection coefficient matrix is the output of the training process.

The proposed approach is shown to provide good results in terms of generating the desired radiation patterns at a low complexity after training. Also, it is shown that using two different loss functions usually results in slightly different but, in any case, good synthesis performance. Recently, the approach is being generalized to the synthesis of dual-beam pattern generated by the reconfigurable intelligent surfaces.

An example of comparison between the desired radiation pattern and the synthesis obtained with machine learning can be found in the figure below



2.3 Contribution of KTH-1 – Overcoming Gap 3.3

The research activity of KTH-1 is meant to address the research Gap 3.1 identified in the technical annex of the grant agreement. Specifically, due to the fact that reconfigurable intelligent surfaces are nearly-passive devices, traditional channel estimation methods are not applicable, since they are based on pilot sequences and thus require the intelligent surface to have transmit/receive modules as well as digital signal processing abilities. Innovative channel estimation algorithms that account for the passive nature of reconfigurable intelligent surfaces are needed. In order to overcome Gap 3.3, the research activity of KTH-1 is focused on developing low-overhead channel estimation algorithms and feedback signaling mechanisms, where end-to-end channel estimation is performed only at the transmitters and receivers without requiring any signal processing and transmission at the metasurface.

The current research activity of KTH-1 has addressed three main lines of work. The first addresses the problem of pilot spacing for channel estimation over aging channels.

The considered setup is that of a fast-fading environment characterized by its exponentially decaying autocorrelation function. In this context, the pilot spacing problem is modeled as a sampling problem to capture the inherent trade-off between the quality of channel state information and the number of symbols available for information carrying data symbols. At first, a quasi-closed form is established for the achievable asymptotic deterministic equivalent signal-to-interference-plus-noise-ratio (SINR) when the channel estimation algorithm utilizes multiple pilot signals. Next, closed-form upper bounds on the achievable SINR and spectral efficiency are derived, as a function of pilot spacing, which helps to find the optimum pilot spacing within a limited search space. The key insight of this research is that in order to maximize the SINR and the spectral efficiency of a multi-user multiple-antenna system, proper pilot spacing must be applied to control the impact of the aging channel and to tune the trade-off between pilot and data symbols.

The results of this research have led to the following research paper.

S. Fodor, G. Fodor, D. Gürgünoğlu, M. Telek, *Optimizing Pilot Spacing in MU-MIMO Systems Operating Over Aging Channels*, submitted, available online at https://arxiv.org/pdf/2204.00213.pdf.

A second direction of investigation has addressed the use of deep reinforcement learning for joint downlink beamforming and optimization of the reconfigurable intelligent surface. The considered system model is that of a multi-user multiple-antenna wireless networks, subject to hardware impairments and in which imperfect channel state information is available for design purposes. The considered approach leverages the framework of deep reinforcement learning to develop a novel beamforming technique. The proposed approach has been compared against a traditional vanilla deep reinforcement learning method under two scenarios:

1) the ideal scenario in which the base station knows the channel and the reflection coefficients applied by the reconfigurable intelligent surface.

2) the more practical scenario in which the BS has imperfect CSI and assumes ideal reconfigurable intelligent surface reflections.

The numerical performance analysis of the developed technique reveals that the introduced framework substantially outperforms the vanilla deep reinforcement learning technique in both the ideal and practical scenarios described above.

The results of this research have led to the following research paper.

B. Saglam, D. Gürgünoğlu, S. S. Kozat, *Deep Reinforcement Learning Based Joint Downlink Beamforming and RIS Configuration in RIS-aided MU-MISO Systems Under Hardware Impairments and Imperfect CSI*, submitted to the 2023 International Communications Conference (ICC), 2023.

Currently, KTH-1 is working on the investigation of a single-cell, two-operator, two-metasurface wireless system, in which the two operators work on non-overlapping frequency bands. Initially it is assumed that there is one user per operator. The uplink channel is considered, and data estimation problems under undesired reflections that cause pilot contamination are examined. In the figure below, blue channels represent frequency band 1 and red channels represent frequency band 2. The base station has a single antenna, and the dashed line channels are the undesired reflections, whose existence the base station ignores.

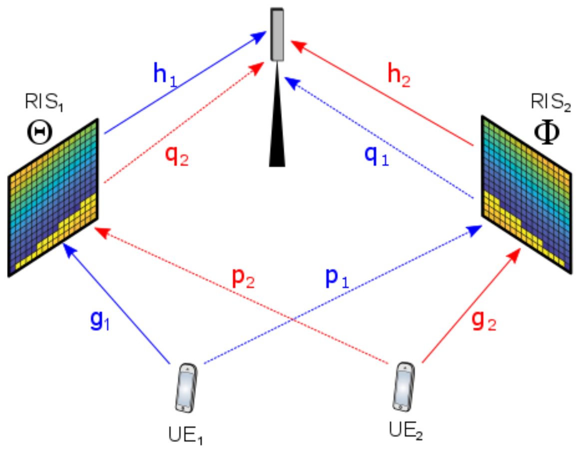


Figure 1: System setup considered in work item 3.

During channel estimation, should metasurface 1 and 2 use the same pilot phase-shift sequence, the undesired reflections will create self-interference and cause pilot contamination, resulting in a biased channel estimate. For this work, it is assumed that channels between the base stations and the reconfigurable intelligent surfaces are known perfectly, while channels between the reconfigurable intelligent surfaces and the mobile user are deterministic quantities to be estimated. In this context, the goal is to improve the system performance as much as possible without the knowledge of undesired reflections. The approach that is being considered at present is based on the Zadoff-Chu method to orthogonalize the pilot sequences used by the two metasurfaces during channel estimation.

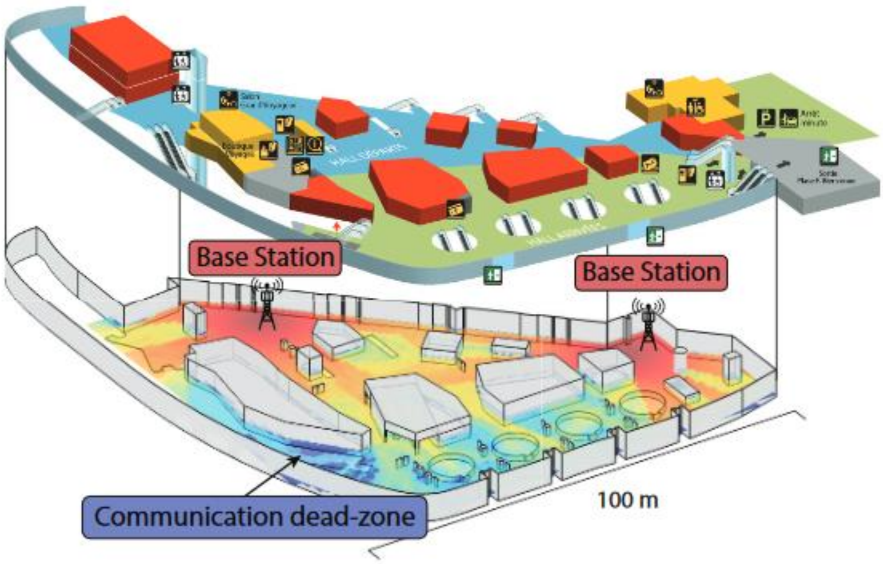
2.4 Contribution of NEC-1 – Overcoming Gap 3.4

The research activity of NEC-1 is meant to address the research Gap 3.4 identified in the technical annex of the grant agreement. Specifically, at present there are no algorithms and protocols for reconfiguring and operating large-scale networks employing reconfigurable intelligent surfaces. Coping with the sudden changes in the propagation environment and with the users' heterogeneous traffic demands, requires embedding the nodes of the network with the intelligence to behave autonomously. Accordingly, the research activity of NEC-1 focuses on developing distributed algorithms for controlling and programming the operation of wireless networks employing reconfigurable intelligent surfaces in a scalable manner. The approach that is being followed is based on leveraging machine learning tools to reduce the amount of data to exchange (low overhead) and devise fast-implementable and performance-guarantee algorithms whose parameters can be optimized by using the data sensed by the metasurfaces.

The current research activity of NEC-1 focuses on the deployment problem of large-scale cellular networks empowered by reconfigurable intelligent surfaces. In particular, it is investigated where should the metasurfaces be placed to provide the best performance. In this context, the research effort has been oriented towards the production of a method to decide where to efficiently deploy a limited number of reconfigurable intelligent surfaces in a wireless environment to assist the pre-existing base stations covering it. The deployment problem is of immediate interest for operators, and has been extensively researched for existing radio access technologies. Well-established solutions exist for traditional wireless networks without reconfigurable intelligent surfaces, e.g. [29], [30]. However, these methods cannot be directly applied when reconfigurable surfaces are present in the network. Indeed, the behavior of metasurfaces is heavily dependent on their configuration, and the deployment needs to consider both the link between the base station and the metasurface and the link between the metasurface and the end device. These new circumstances call for a reformulation of the deployment problem and the search for new ways to solve it. Furthermore, the mutual dependence between deployment location and device configuration can produce a deadlock under some formulations of the problem, if it is not properly taken into account. In [31] the authors study the impact of the installation of reconfigurable intelligent surfaces within an area. To choose the best installation, they assume a set of candidate sites, where they are free to place the devices (both metasurfaces and base stations), with the objective of maximizing the network throughput. In their formulation, while the coordinates of each location are set, the orientation of the device there located is free to be chosen by the deployment method. They assume that metasurfaces can be reconfigured instantaneously, so they can offer the maximum achievable gain for the user they are serving at a given moment. Nevertheless, the reconfigurable intelligent surface can only assist one connection at a time.

Starting from the seminal work [31], NEC-1 has developed a novel solution to the deployment problem, which considers the more realistic case in which the reconfigurable intelligent surface has a limited configuration capability. The minimum Signal to Noise Ratio received by any test point is taken as the objective function to be maximized, which is a suitable metric to improve the coverage while also considering the fairness of the solution. In this context, the problem of joint deployment and device configuration is formulated and tackled by means of the Block Coordinate Ascent method and the Quadratic Transform to handle the non-convexity of the problem.

For performance evaluation purposes, NEC-1 has produced a lightweight ray-tracing simulation tool, able to compute the path loss between the base station and the end device through the reconfigurable intelligent surface. The tool provides a numerical estimation of the properties of the channel using external information about the environment where the radio propagation will happen. This information is shaped as a stereolithography 3D model which accounts for the conductivity and permittivity of the metasurfaces. The developed tool is based on the ray-tracing engine from *Propagation and Channel Models* of the *Communications Toolbox*™ of *MATLAB*®. This engine takes the 3D model, with fixed positions for the emitter and the receiver, and computes a set of geometric paths within the specified limit of reflections. The information of these paths can be obtained as individual rays. The ray-tracing module has also been refined exploiting the model for the behavior of the reconfigurable intelligent surfaces provided in [32], and accounting for the far-field radiation patterns and the direction of the rays. Moreover, a realistic use-case has been obtained thanks to the fact that NEC-1 had access to the architectural details of the Rennes railway station in France, as well as to the technical details of the infrastructure there located, provided by the collaboration with one of the major operators servicing the area. Thanks to this information the simulation routine produced by NEC-1 can provide estimations of a real environment, as shown in the figure below.



Railway station topographic map and related power heatmap showing the dead-zone problem (Rennes, France).

The results of this research have appeared in the work:

A. Albanese, G. Encinas-Lago, V. Sciancalepore, X. Costa-Pérez, D.-T. Phan-Huy, and S. Ros, *RIS-Aware Indoor Network Planning: The Rennes Railway Station Case*, 2022 IEEE International Conference on Communications (ICC), 2022.

The availability of this simulation tool and the possibility of producing a solution evaluation with a small computational cost motivates the current research activity of NEC-1, who is working on an extension of the previous work in a second manuscript, where the same problem is solved using machine learning tools. This new work considers a combination of a test point clusterization phase (to reduce the number of possible associations between the reconfigurable intelligent surfaces and the test points) and a reinforcement learning architecture built using two nested Q-learning agents (to solve the deployment and the association problems). This method exploits the availability of a numerical evaluation metric and feeds it to the training process of the Q-learning agents, which in turn explore the possible solutions for the problem. The obtained results are being compared to those of the previous work, as well as to techniques available in the open literature.

3. Conclusions

The research activities concerning Task 1.3 are progressing as planned. All ESRs have completed the initial literature review phase, which started in M7, and are currently developing innovative designs to tackle the specific challenge of their individual research project and close the corresponding research gap. In particular:

- CNIT-2 has developed novel and practical techniques and algorithms for user localization in wireless networks employing reconfigurable intelligent surfaces. The developed techniques make use of active metasurfaces to boost the localization accuracy, outperforming the use of passive metasurfaces. In the second half of the project, the research activities of CNIT-2 will focus on developing novel detection and tracking techniques to further improve the localization and sensing performance and approach the theoretical bounds.

- CNRS-2 has developed a new analytical framework to quantify the system-level performance of wireless networks in the presence of reconfigurable intelligent surfaces. The framework leverages machine learning methodologies and is able to provide the optimized reflection coefficients of a reconfigurable intelligent surface as the output of a neural network. In the second half of the project, the research activities of CNRS-2 will focus on further refining the prediction performance of the developed framework, exploring the use of additional deep learning techniques, such as deep unfolding and deep reinforcement learning.

- **KTH-1** has developed practical techniques for joint channel estimation and design of wireless networks employing reconfigurable intelligent surfaces. Both traditional channel estimation techniques and methods based on deep reinforcement learning have been developed. All methods are able to work without requiring any signal processing and transmission at the reconfigurable intelligent surfaces. In the second half of the project, the research activities of KTH-1 will focus on further reducing the overhead of the developed methodologies, exploring the use of the tool of bilinear generalized approximate message passing for sparse matrix factorization.

- **NEC-1** has developed deployment techniques for large-scale wireless networks empowered by reconfigurable intelligent surfaces. The developed methodologies have considered both traditional optimization tools and the use of deep reinforcement learning and machine learning techniques. A simulation environment has been produced to emulate the network deployment and operation in a realistic wireless environment. In the second half of the project, the research activities of NEC-1 will focus more closely on the operation of large-scale networks that employ reconfigurable intelligent surfaces. The tool of federated learning will be explored to reduce the overhead related to the huge amount of data to exchange.

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