Physics-Informed Metaheuristics for Fast RIS Codebook Compilation

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***Abstract*—Reconfigurable Intelligent Surfaces (RIS) can actively manipulate the wave propagation within a space, even in unconventional ways, enabling the software-defined wireless propagation. Enabling real-time RIS operation requires a codebook, i.e., a set of pre-calculated states of the RIS constituent elements that yield any of the supported macroscopic RIS functionalities, such as anomalous steering, splitting and wave absorption. The codebook compilation process occurs offline, and requires the time consuming optimization of either an EM simulator, or an automated RIS measurement system. The process is especially resource-demanding in the case of RIS designs with no known analytical performance model, such as metasurfaces in the general sense. This paper studies the synergy between metaheuristic optimizers and the RIS codebook compilation process. Specifically, well-known and widely efficient metaheuristic optimizers are imbued with attributes of the RIS physics, yielding considerable gains in the codebook compilation time. This process leverages correlations between microscopic configurations and macroscopic RIS responses, geometric optics, and EM simulators. The evaluation outcomes indicate a significant potential in the design of high-performing and resource-effective metaheuristics for RIS.**

***Index Terms*—RIS, Metamaterials, Metasurfaces, Codebook, Heuristics, Design.**

I. Introduction

Evolving B5G/6G technologies allow for objects between transmitters and receivers to actively participate in the communication process. This paradigm shift, known as Programmable Wireless Environment (PWE) [1], enables the software-defined wireless propagation within a complex region in 3D space, for example allowing waves to steer around objects or avoid eavesdroppers, among many interesting new capabilities.

The enabler of PWEs is the Reconfigurable Intelligent Surface (RIS) technology, stemming from the physics of metamaterials [1]. Macroscopically, RISs are thin, planar and rectangular devices that resemble tiles, and have the ability to interact with impinging electromagnetic (EM) waves in a software-configurable manner in real-time. Examples are beam steering, beam splitting, perfect absorption, wavefront phase, amplitude and/or polarization modulation, and even wavefront sensing [2], collectively denoted as EM functionalities. Microscopically, an RIS is a hardware platform that allows for the software-defined transformation of surface current distributions induced by impinging waves. Forming a desired surface current distribution on the RIS, by properly tuning embedded active elements such as PIN diodes or MEMS, produces the corresponding macroscopic EM functionality.

It is noted that the general RIS concept, i.e., a programmable surface current transformer, does not come with a generalized analytical model describing its operation [2]. As such, the proper tuning of the states of all RIS elements for each supported macroscopic EM functionality is a computationally-demanding optimization task. Exceptions are simplified RIS designs, such as the reflectarrays, which come with an analytical model of operation, albeit with performance trade-offs (e.g., narrow-band operation and partial/coarse control over the impinging-to-scattered wavefront transformation) [2].

At the system level, a PWE is formed by coating all major planar surfaces in an environment with RISs that collaborate to simultaneously serve multiple users and diverse functionalities. The real-time PWE operation relies on the existence of a *codebook* [3], [4], i.e., a data structure that maps macroscopic RIS functionalities to corresponding microscopic states of active elements, i.e, the RIS configuration. The compilation of such codebooks needs to account for: i) a large set of supported EM functionalities and ii) a high degree of efficiency per single functionality.

Presently, there is a lack of exploration into optimization algorithms specifically aligned with the compilation of such RIS codebooks. Despite the existence of very efficient algorithms in the general field of metaheuristics [5], it remains unclear: i) how these algorithms can be imbued with knowledge of the RIS physics and ii) what is the improvement margin in RIS codebook compilation time that comes from the utilization of efficient algorithms over existing alternatives. Finally, the study of RIS-specific metaheuristics must encompass both the generic metasurfaces and the RISs for which analytical models exist (e.g., simple reflectarrays). The former typically need full-wave simulations while the latter exploit analytical tools to speed up the compilation process.

In this context, the contributions of this work are as follows:

- We introduce the Physics Informed Codebook Compilation Software (PICCS), which is applicable to any EM functionality and frequency band, as well as to any RIS design. The software integrates RIS physics insights, em-

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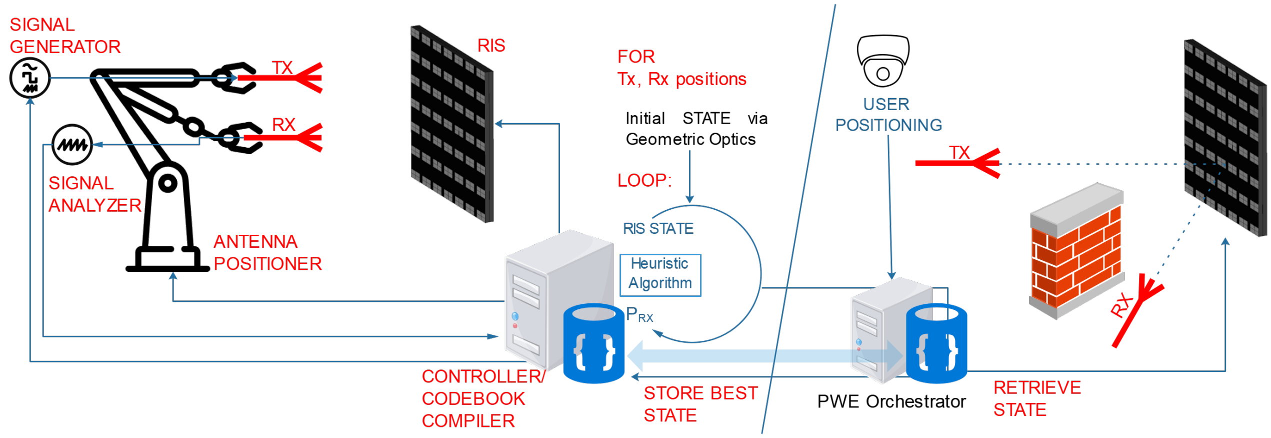

Fig. 1: Illustration of the codebook compilation workflow during the RIS manufacturing (left), and its use during the RIS operation (right).

ploying geometric optics in the case of RISs that do not come with an analytical performance model. Moreover, attributes of the RIS geometry are taken into account in order to reduce the solution space, exploiting periodicity and statistical correlations between specific active RIS elements and the efficiency of EM functionalities.

- We study the integration of such physics insights into a wide set of popular metaheuristic algorithms and quantify their performance benefits over existing solutions in the RIS codebook compilation task.
- We evaluate the compilation software and the specially adapted metaheuristics via full-wave simulations over an RIS design that represents a controllable departure from the RIS-reflectarray model. Specifically, for the scope of the software evaluation, we incorporate elements of metasurfaces in terms of allowing for electrical interconnectivity among the constituent RIS elements.

The rest of this paper is organized as follows: Section II presents the related studies. In Section III, we introduce PICCS and describe its components. The evaluation takes place in Section IV. Research challenges are outlined in Section V and the paper is concluded in Section VI.

II. Related Work

Several proposals within the bibliography focus on defining a codebook for real-time RIS operation [3], [6]. The challenge lies in minimizing the time required for codebook compilation. To tackle this, the studies lean towards employing analytical models for specific RIS designs [3], [7]. Generalized codebook compilation for any RIS design poses issues of high computational demands [7]. However, achieving an accurate codebook compilation necessitates incorporating insights from the physical layer [8]. Furthermore, examining the RIS behavior through full-wave EM simulations, even if limited to specific scenarios rather than encompassing the entire codebook, can yield valuable insights that can favor the codebook compilation time.

Regardless of the RIS design in study, several simple approaches seek to improve the codebook compilation time. One such approach is the continuous relaxation of the active/tunable element values during the RIS configuration optimization process. Once the optimization has concluded, the produced values are mapped to the closest discrete ones that are actually supported by the RIS design [8]. Another popular assumption is the exploitation of symmetry and/or patterns in the RIS design and in the required EM functionality [2]. First, if the desired EM functionality RIS exhibits some obvious symmetry in the state of the RIS elements, it can be directly exploited to reduce the solution space. Second, if the RIS design is periodic, i.e., it comprises a repeating element (also known as "unit cell"), one or more elements can be grouped together, forming a "supercell". The optimization process can then focus only on optimizing just the combined supercell states. The macroscopic EM response of the RIS is then derived under the assumption of periodically repeating supercells, each with the same, optimized configuration of states.

The above approaches target the reduction of the solution space in the RIS codebook compilation. In terms of algorithms employed for the optimization task, the related studies are at present very limited. The Genetic Algorithm (GA), paired with an EM solver, constitutes a popular choice mainly due to its simplicity and adaptability, despite its known major drawbacks in computational requirements and optimization efficiency [2]. Iterative optimizers constitute another popular choice due to their simple operation [9]. Iterative optimizers treat multi-parametric objective functions by optimizing each single parameter in isolation, and in a serial manner until convergence. It is a well-known fact, however, that convergence may not be attained, while the algorithm can also be trapped around a local optimum solution [5]. Moreover, iterative optimization is not known to favor optimization speed as a general algorithmic trait. Finally, the advent of machine learning has also produced related applications in the RIS field [10]. Extensive data produced via measurements or full-wave simulations was collected and employed to train an early classifier of RIS configurations [11]. Non-promising data can be skipped during the RIS configuration optimization subprocess. Nonetheless, this process acts as an add-on to any optimization process, and is not an optimizer on its own accord.

Finally, there are suggestions advocating for a fully-connected RIS structure over the RIS-reflectarray model, showing improved ability in the manipulation of the impinged signals [3], [6]. This further accentuates the need for the study of RIS-specific codebook optimization algorithms, thoroughly assessed via full-wave EM simulators [12] or physical measurements [13]. Furthermore, more sophisticated and promising prototype suggestions for the RIS unit [12], [13] can seamlessly integrate into the fully-connected RIS concept. The only differentiating factor lies in the placement location of the tunable mechanism and no additional effort or complexity is imposed during this procedure.

III. The Proposed Physics Informed Codebook Compilation Software for RIS

We begin by defining the codebook compilation process within the PWE operation, as shown in Fig. 1. The RIS lifecycle is considered to have two phases: the manufacturing and the operating phase [1]. The codebook compilation occurs during the manufacturing phase as follows: An RIS prototype and a set of receivers and transmitters are placed within an automated positioning and evaluation setup, which can be either actually manufactured or precisely simulated. (For the remainder, the term simulation will refer to full-wave EM simulation). For every functionality of interest (i.e., those declared as 'supported' by the manufacturer) an optimization loop for the RIS configuration takes place, and the optimal value is placed in a database, namely, in the RIS codebook. During the operating phase, a server/orchestrator invokes the codebook and deploys the proper configuration to each RIS unit, employing information from user positioning systems [1].

As already mentioned, the definition of the RIS configuration that yields a specific macroscopic response in a given topology constitutes a complex optimization problem. The proposed PICCS software integrates three concepts, i.e, the definition of initial compilation solutions via geometric optics (GO), statistical insights from the RIS physics that can speed up the subsequent optimization around the initial solution, and the integration to metaheuristic algorithms (MA) toward the end-objective. These components are described below.

A. Defining Initial Compilation Solutions via Geometrical Optics and Applicability to Generalized Metasurfaces

GO, also known as ray tracing, is a well-established framework for simulating the propagation of EM waves in domains that are larger than the wavelength. Despite its widespread use, it is characterized by lower accuracy in comparison with EM simulations. Taking into account that the effectiveness of most optimizers heavily relies on its initial starting point, we utilize GO only as a preliminary RIS configuration. This approach aims to initialize the process closer to the optimal solution rather than starting from default or random points.

In the following, we focus on the beam steering case, as it constitutes the building block for more complex functionalities, such as beam splitting and multi-directional steering [14]. In other words, complex functionalities can be decomposed to a set of simple beam steerings. The configuration of each steering is considered to be present in the codebook. Then, the process of [14] can merge them into a single configuration that yields the required complex functionality.

In the beam steering functionality, GO can be used to interpret or implement the generalized Snell's laws. In the case of a homogeneously configured RIS, the angles of incidence and reflection are always equal. However, when the RIS is configured with a phase-gradient along its surface, via the proper tuning of the elements embedded in each subwavelength cell, the reflection angle can be different, allowing for controllable anomalous steering of the incident wavefront.

In the context of point-to-point communications, GO offers insights into wavefront (ray) pathways between each RIS tunable element and the transmitter (Tx) and receiver (Rx) antennas, by considering their relative distances and angles. It progressively computes the incident and necessary reflected angles, in accordance with the tunable element values in each cell of the RIS, assuming they are decoupled. These values serve as the initial estimation of the optimization process. Employing GO reveals that the symmetry in an RIS configuration pattern is solely based on the symmetry between the Tx and Rx with respect to the RIS.

The departure from the simple RIS-reflectarray model is associated with the adoption of the overlapping phase-shifter model. The interconnection of the adjacent unit-cells results in the dual contribution of each RIS element in the introduction of the required phases. However, the applicability of GO is not constrained by the specific phase-shifter model, as it only relies on the relative distances and angles from the Tx to the Rx via each RIS element. An example is shown in Fig. 2 (bottom right), where overlapping phase shifters are defined to expedite the GO process. The same concept can be employed for any metasurface type, considering, e.g., one such virtual phase shifter at the position of each active element (e.g., PIN diode).

B. Detecting Statistical Insights from the RIS Physics

PICCS is designed to be physics-informed, i.e., to rely on knowledge gained from observing the physical layer, which can be fed into the optimization process to pinpoint the factors that govern RIS response. PICCS exploits correlations between specific groups of tunable elements and the macroscopic RIS response, as quantified by the path loss in the $Tx \rightarrow \text{RIS} \rightarrow Rx$ link.

There are two groups of tunable elements that are expected to have such a strong correlation with the path loss. The first group consists of elements positioned in close proximity to the receiver and the transmitter, especially those aligned closely in a vertical direction relative to them. Meanwhile, the second group comprises peripheral elements situated at the

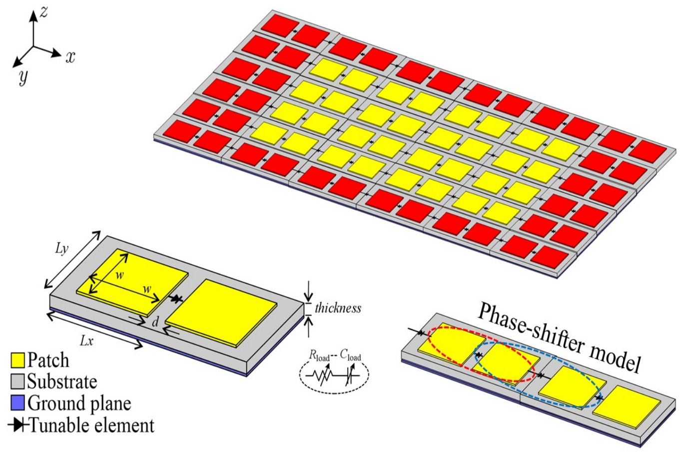

Fig. 2: Schematic of the RIS used in this work, where the horizontally adjacent metal patches are interconnected with tunable lumped loads. The peripheral phase-shifters (red) and the central ones (yellow). Despite the lack of strict periodicity per element, virtual phase shifters can be defined to expedite GO (bottom right).

edges of the RIS. These peripheral elements operate in a non-homogeneous environment due to their placement, potentially influenced by surrounding structures or interactions with the edges. Such abrupt variations in the surface current distribution strongly impact the scattering of the RIS by means of diffraction. The simulations have confirmed these correlations, with the peripheral elements having the strongest impact.

In light of the above insights, PICCS uses GO to compute the values of the central elements (for which GO is acceptably accurate) and to initiate the peripheral element values. Moving to the optimization procedure, MA concentrate solely on updating the peripheral values, in a range also determined by the GO analysis. This focused approach streamlines the optimization process, allowing for targeted adjustments and significant compilation speed-up, regardless of whether the compilation is based on a manufactured or simulated setup.

C. Integration of RIS Physics Insights with Metaheuristics Algorithms

In MA, different metrics for the RIS scattering performance can serve as optimization targets, allowing us to introduce custom-tailored trade-offs. However, it is not generally straightforward how to integrate insights from physics. (E.g., and example of such an integration is to apply larger 'weights' to the elements that have the larger effect on the RIS response). Here, we study the case of the following popular MAs [5]:

1) **The Gradient Descent Algorithm (GDA)** is a deterministic mathematical approach used for optimization. It begins from an arbitrary value and progressively adjusts it based on the slope of the optimization function, seeking the point where the maximum/minimum value exists. Within the context of RIS configuration optimization, GDA starts from the initial values determined by GO. The lower and upper bounds for the space solution is set to be $\pm 10\%$ of the mean of all initial tunable load values. The number of the optimization variables with the usage of the PICCS is reduced by 77.3%.
2) **Genetic Algorithm (GA)** mirrors the theory of natural evolution and operates as a search heuristic. It imitates natural selection, favoring the reproduction of the most adaptable individuals to generate the next generation of offspring. Within the compilation task, the GA starts with parents, only for peripheral elements, sourced by the GO and configurations within the predefined bounds. The crossover probability governs the likelihood of breeding between parents, yielding to children-configurations. Meanwhile, the mutation probability determines the chance of mutation, with the number of mutants. The mutation rate and step affect the magnitude of the updates, within the predefined bounds, for the next children-configurations.
3) **Non-dominated Sorting Genetic Algorithm II (NSGA-II)** is an evolutionary algorithm used for multi-objective optimization. It is an extension of the traditional GA. In PICCS, the key parameters like crossover probability, mutation rate and step are the same with GA. However, their application differs significantly. NSGA-II utilizes these parameters with a focus on Pareto dominance, crowding distance between the generated configurations, and non-dominated sorting in order to direct the evolution of the children-configurations toward a diverse set of Pareto-optimal configurations.
4) **Strength Pareto Evolutionary Algorithm 2 (SPEA2)** is another evolutionary algorithm designed for multi-objective optimization problems. Like NSGA-II, SPEA2 aims to find a set of solutions that represent the Pareto front. In PICCS, SPEA2 has the same values for the key parameters with NSGA-II and GA. However, it introduces an archive to sustain a diverse set of non-dominated RIS configurations. Special attributes of the SPEA2 are the KNN parameter and the specific genetic operation parameters (gamma for crossover and h for mutation). These features equip SPEA2 for multi-objective optimization, emphasizing the diversity of the generated configurations.

IV. Evaluation of PICCS

For the evaluation of the PICCS, we use a RIS design influenced by our earlier work [8]. This design, depicted in Fig. 2, embodies a controlled departure from simple RIS-reflectarray approach, by interconnecting the horizontally adjacent cells with tunable loads. The RIS unit cells are gaps between square metal patches that are bridged by lumped complex impedance loads. The patches lie on a metal-backed dielectric substrate and a thin metal sheet that acts as a groundplane. Specifically, the substrate is Rogers RT/Duroid 5880, with electric permittivity, ε_r, 2.2 tangent loss, $\tan\delta$, 0.0009 and thickness of 1.016 mm. The groundplane is a perfect conductor, akin to the square patches, and possesses a thickness of 17.5 μm. This cell design negates transmission, provides wide angular and spectral bandwidth, while the value of its embedded load imparts control over the amplitude and phase of reflected wave in the x polarization.

TABLE I: RIS design dimensions.

Parameter	Value
Width of unit-cell substrate (Ly)	11.25 mm ($= 0.15\lambda$)
Length of unit-cell substrate (Lx)	11.25 mm ($= Ly$)
Gap between patches (d)	1 mm
Patch width (w)	10.25 mm
Thickness of patch	17.5 µm
Tunable element width	1 mm

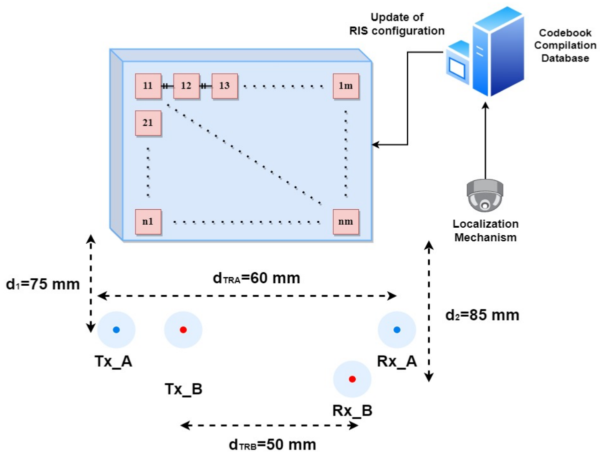

Fig. 3: Overview of the Setup A (blue) and the Setup B (red).

The RIS unit has been designed to operate at 4 GHz, and after the fine-tuning procedure, the dimensions of the patches are presented in Table I. The tunable elements connecting the horizontal adjacent patches can simulate any type of integrated circuit chips that could be used as configuration mechanisms in the RIS. In our approach, the tunable loads assume continuous values in the complex plane, i.e., for both reactance and resistance. Note that the tunable load is strategically placed between each pair of horizontally adjacent patches, thus modifying the surface impedance produced by the combination of gap capacitance and the grounded dielectric inductance.

A. Description of Studied Setups

The two setups we study are depicted in Fig. 3. Fig. 2 provides an illustration of the RIS unit employed for beam steering between the Tx/Rx. The selection of $n_y = 6$ and $m_x = 12$ square patches, resulting in a total of 66 tunable loads. These dimensions represent a trade-off in favor of computation time and resources, for a sufficiently large RIS implementation. The two antennas are x-polarized center-fed half-wave dipoles placed so as to minimize their coupling. Tx antenna emits Gaussian pulses at the central frequency of 4 GHz and the Rx antenna receives the signal after it is scattered off the RIS.

The setups, differentiated by Tx/Rx positions, denoted with A and B. In setup A, Tx/Rx are symmetrically positioned opposite the center of the RIS, while setup B lacks such symmetry; this setup serves the purpose of evaluating PICCS performance in non-trivial conditions where reduction of optimization variables is not possible. Note that in both setups, the antennas are positioned within the near-field of the RIS, to challenge the usage of simplifying far-field assumptions. In a real-world scenario, the accurate antenna and RIS positions can be tracked by standard wireless localization techniques [15].

TABLE II: Transmission between Tx/Rx for different scenarios conducted by full-wave EM simulations.

	Scenario	Transmission Coefficient (dB)	Number of simulation runs
Setup A	Antennas	-25.80	1
	Reflectarray	-21.69	1
	GO	-17.40	1
	NPAO	-15.64	1193
	PICCS	-15.47	25
Setup B	Antennas	-23.07	1
	Reflectarray	-22.88	1
	GO	-19.03	1
	PICCS	-15.32	25

In this work we employed the open simulation platform of [12]. The platform is built upon an open-source Finite-Difference Time-Domain (FDTD) solver, known as openEMS. The simulations take place in a free-space environment, with perfectly matched layers (PML) enveloping the RIS and antennas thereby eliminating all reflections except those off the RIS. In this way, any decrease in the path loss (increase in power transmission coefficient) between static Tx and Rx can be attributed to an improved configuration of the RIS tunable elements. The path loss between the two antennas is quantified by $|S_{21}|$, i.e., the magnitude of the scattering coefficient from Tx to Rx.

B. Step-by-Step PICCS implementation for Setup A

The transmission efficiency between the Tx and Rx antennas, evaluated via the S_{21} coefficient, are calculated via simulations for the first setup across various scenarios to comparatively assess the advantages of PICCS. The results are outlined in Table II. The scenario labeled 'Antennas' corresponds to the coupling between the Tx/Rx (without the RIS) and serves as a reference baseline.

Introducing a static reflectarray marginally improves the link between the antennas, by approximately 4 dB. However, when the RIS is configured using the GO (without any further optimization) there is an additional enhancement of 4.4 dB. This highlights the effectiveness of the GO as an initial estimator for the RIS configuration. So, even without an optimization procedure, the RIS brings a significant increase of 8.4 dB in the $|S_{21}|$.

Moving forward, a non-physics aware optimization (NPAO) procedure was employed to further improve $|S_{21}|$, resulting in an additional increase of approximately 2 dB. On the downside, the NPAO improvement required 1193 simulation iterations.

The large dataset results obtained from the NPAO using simulations can be processed to verify the correlation between the groups of tunable RIS elements and the overall response,

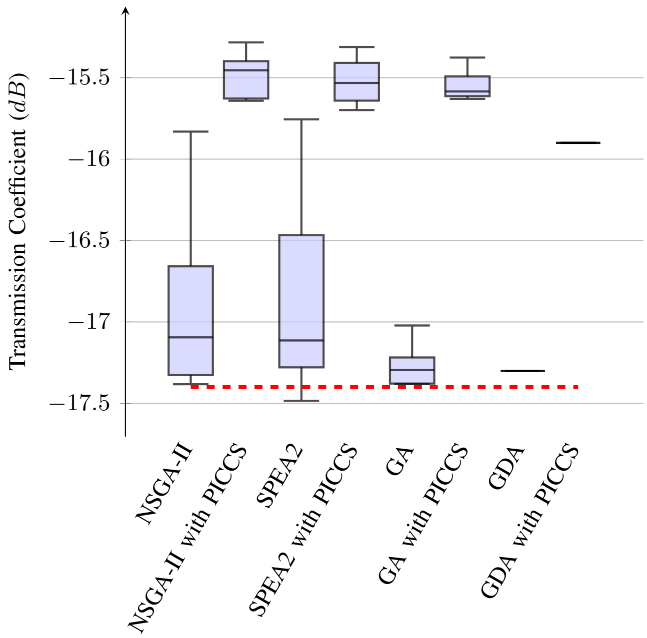

Fig. 4: Statistical box-plots of the $|S_{21}|$ (in dB) for different MA with and without the PICCS usage.

as discussed in Section III-B. The correlation is quantified between the tunable element values and the resulting $|S_{21}|$ value, as acquired in each iteration along the optimization process. The correlation is normalized in the [0,1] range, with the two extremities denoting no impact and direct impact, respectively. As expected, all tunable elements show some correlation with $|S_{21}|$. The average correlation value is 0.24, with a minimum of 0.02 and a maximum of 0.58. For the peripheral elements, the mean correlation is 0.25, while elements closer to normal incidence/reflection with respect to the antennas have a mean correlation of 0.20. The peripheral elements that are also in close proximity to the antennas exhibit the strongest correlation, with a mean value of 0.49.

C. Integration of PICCS with MA

In comparing the performance of PICCS with the various MAs referenced in Section III, we conduct 25 runs for all the algorithms. The summarized outcomes are presented in Fig. 4. Both sets of MAs, with and without PICCS, start from the initial guess determined by the GO. The red line highlights the transmission coefficient calculated from the RIS configuration using GO, emphasizing the optimization benefits within each MA.

According to Fig. 4 integration of PICCS to all MAs yields improved performance as compared to optimization with the same MAs and same iteration count but without using physical insights. Specifically, PICCS with all MAs exhibit an enhancement in $|S_{21}|$ of 2.5 dB.

Referring back to Table II, the performance of PICCS demonstrates a similar improvement in S_{21} compared to NPAO, but this improvement was achieved after only 25 simulator runs (2% of the runs the NPAO required). Employing PICCS resulted in an overall enhancement of approximately 10.3 dB.

Another important observation from Fig. 4 is that employing PICCS leads to a reduced variance around the optimal solution. This ensures that the optimal solution lies within a narrower variable range, allowing the optimization to converge after only a few adjustments. Finally, among the various algorithms tested, NSGA-II emerged as the most effective in consistently finding the optimal solution.

D. Results of PICCS implementation in Setup B

Having demonstrated that the proposed PICCS leads to improved performance with minimized computational resources in a setup with four-fold symmetry, we move to the more complicated setup B: This setup has only two-fold symmetry, so the optimization solution space is doubled in relation to Setup A. The PICCS is integrated only with the NSGA-II that was previously identified as the most promising MA.

Examining the results for Setup B in Table II, we observe that with only 25 measurements using PICCS we achieve an enhancement of over 3.6 dB, as compared to the computation solely from GO. The overall enhancement from using PICCS amounts to 7.65 dB.

V. Open Challenges

The evaluation of the proposed software has demonstrated that leveraging insights from the physical layer can expedite the RIS codebook compilation process. Moreover, the integration of these insights with established MAs, notably NSGA-II and SPEA2, has significantly reduced the required computational resources, highlighting the importance of monitoring advancements in metaheuristics for maximizing their impact on RIS codebook compilation. Additionally, delving deeper into the physical layer holds promise for providing insights into metamaterial physics and engineering, potentially leading to the creation of specialized optimization tools tailored specifically for RIS codebook compilation.

Within the PWE context, an RIS might need to serve several users simultaneously. Furthermore, achieving intricate RIS functionalities, such as beam splitting in multiple directions, can be viewed as a fusion of simpler ones. In such scenarios, firstly, the phase-profiles from multiple simpler individual functions are extracted from the codebook. Then, these are superimposed using dedicated processes like the one described in [14]. Finally, interpolation is used to compute the actual tunable element value from the phase in each cell. PICCS takes up from these initial values, with simulations or measurements, to satisfy the defined multi-parameter objectives.

The RIS design used to evaluate the proposed software shows that the departure from the conventional RIS-reflectarray model can provide a more efficient control over the effective surface current distribution generated by the interaction of an impinging EM wave (at given frequency, direction, polarization) with the tunable unit cells. Exploring the interconnection among cells, also called non-locality, emerges as a new area warranting comprehensive exploration.

VI. Conclusion

This paper studied the role of software optimizers in offline RIS codebook compilation which can subsequently be used to optimize real-time operation. The compilation workflow was defined, denoted as Physics-Informed Codebook Compilation Software (PICCS). PICCS combined a set of metaheuristic optimizers assisted by statistical observations extracted from the RIS physics. Specifically, it was shown that the correlation between the peripheral RIS element states and the overall RIS response outweighs that of other elements. Moreover, during the optimization procedure, PICCS employs principles of geometric optics, in order to: i) pinpoint a promising initial solution to the optimization/compilation process, and ii) prioritize the optimization of the peripheral elements' states, in finite-sized RIS with non-periodic phase profiles. PICCS reduced the computation time required for the RIS codebook compilation by 98%, compared to existing approaches. Notably, among various metaheuristic optimizers tested, NSGA-II stood out as the most efficient in identifying the optimal RIS configuration. The outcomes of the study indicate that the further development of RIS-specific metaheuristic optimizers shows promise in terms of reducing in the RIS codebook compilation time.

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