Available *online* at: http://ajeeet.ft.unand.ac.id/

Andalas Journal of Electrical and Electronic Engineering Technology

ISSN 2777-0079

Review Article

A Comprehensive Review of Intelligent Reflecting Surfaces from Hardware to Industrial Integration and Future Directions

Anne N. Munira, Joseph Muguro, Waweru Njeri

Department of Electrical and Electronic Engineering, Dedan Kimathi University of Technology, Private Bag 10143, Nyeri, Kenya.

ARTICLE INFORMATION

Received: April 23, 2024
Revised: May 25, 2024
Accepted: May 28, 2024
Available online: July 23, 2024

KEYWORDS

IRS, Hardware, Architecture, Channel estimation, Optimization

CORRESPONDENCE

Phone: +254(0)717826486

E-mail: anne.njeri@dkut.ac.ke

A B S T R A C T

An Intelligent Reflecting Surface (IRS) has emerged as a key solution to performance bottlenecks in wireless communication. Its ability to combat multipath fading and improve signal and energy efficiencies has made it relevant to various industry applications, including the Internet of Things (IoT), smart manufacturing, cognitive radio, radar, and Multiple-Input Multiple-Output (MIMO) systems. This paper presents a comprehensive review of the IRS's structure and hardware requirements, channel estimation, optimization methods, and key applications to enable readers to understand how the IRS operates, its benefits, and some of the challenges involved in its application. The structure and hardware requirements are important to understand as they dictate the material composition, number, and arrangement of reflecting elements, and their reconfigurability. Channel State Information (CSI) plays a crucial role in optimized transmission as it gives information on the channel conditions, enabling users to tailor their transmission accordingly. In this work, all scholarly papers related to the IRS published between 2010-2024 were considered, sampled, and categorized based on the key themes. An analysis of the hardware and architecture reveals that transceiver hardware imperfections significantly affect IRS optimization and should be considered. While several channel estimation techniques offer comparable benefits, accuracy turns out to be the most important factor to consider. Further, results show that flexibility and inference accuracy make machine learning techniques superior to other optimization methods. Still, challenges remain in relation to IRS standardization, privacy concerns, and handover techniques that ought to be addressed for future industrial integration.

INTRODUCTION

Over the years, significant technological advances have been made to improve the QoS of communication systems. From developing advanced modulation schemes, optimizing wireless network protocols, and implementing error correction codes, the focus has been on increased efficiency to meet the rising demands for fast, secure, and reliable communication. However, such techniques have little control over random and unpredictable wireless communication systems. An IRS presents a revolutionary technology with enormous potential to transform communication systems [1]. The use of IRS introduces a paradigm shift in how one designs, deploys, and optimizes wireless systems, offering substantial improvements in capacity, coverage, energy efficiency, and overall system performance.

The IRS has gained the attention of researchers and industry experts as it provides a potential solution to performance bottlenecks in wireless communication. An IRS is an artificial structure comprising many sub-wavelength-sized elements, such as passive reflecting elements or electronically controlled phase shifters [2]. These elements are strategically deployed to alter signal propagation. By intelligently configuring these elements' phase shifts or reflection coefficients, an IRS effectively shapes the direction, controls amplitude, and changes the signal's phase, enabling various desirable signal processing functionalities [3]. Depending on the application of these metasurfaces, several terminologies have emerged, including IRS [4], Reconfigurable Intelligent Surfaces (RIS) [5], Large Intelligent Surface Antennas (LISA) [6], and Large Intelligent Metasurface (LIM) [7]. For reasons of consistency, the IRS is adopted in this review.

Among the merits of the IRS is that it overcomes the limitations imposed by traditional wireless communication systems, such as multipath fading, limited bandwidth, and unreliability caused by random interference. By carefully manipulating the wireless channel characteristics, IRS effectively improves the strength of signals, mitigates co-channel and inter-user interference, and by so doing, improves the quality of communication [8]. This technology offers the potential for significant improvements in coverage extension, capacity enhancement, and energy efficiency, which are critical considerations in today's wireless networks.

https://doi.org/10.25077/ajeeet.v4i1.100

The advantages of the IRS are not limited to a specific domain or industry. It can impact various sectors, including telecommunications, smart cities, healthcare, Internet of Things (IoT), and autonomous systems. In telecommunications, IRS can help overcome signal attenuation and path loss challenges, enabling reliable and high-quality wireless connectivity in urban environments, indoor spaces, and rural areas [8]. In the IoT domain, IRS can enhance the connectivity and energy efficiency of massive IoT deployments, facilitating the seamless integration of large number of devices [9]. Moreover, in the context of 5G and beyond, IRS can enable intelligent beamforming, spatial multiplexing, and efficient spectrum utilization, facilitating ultra-fast and reliable communication [4].

While the potential benefits of the IRS are compelling, it is essential to acknowledge the challenges and disadvantages associated with this technology. The deployment of IRS introduces new complexities in terms of hardware design, channel estimation, synchronization, and optimization [10]. The massive number of elements and the need for real-time control and coordination require sophisticated algorithms and efficient signaling protocols. Additionally, the cost, power consumption, and integration of the IRS into existing infrastructure pose practical challenges that need to be addressed. Further, [11] shows that in the presence of hardware imperfections, the IRS becomes less beneficial due to the trade-off between capacity improvement and the number of reflecting elements. Nonetheless, extensive research efforts are underway to tackle these issues and unlock the full potential of IRS technology.

In reviews [1] - [4], the authors provide surveys and overviews of the IRS design and performance in communication systems. Authors in [1] go into detail on the hardware components, design, and some applications of the IRS. The focus in [2] is on theory and design, use cases, and practical challenges associated with IRS implementation. Authors in [8] present a contemporary survey of the reconfigurability of the IRS regarding its phase shift design for the application in wireless communication alongside some practical applications of metasurfaces. An overview of IRS hardware and functionality, deployment, performance evaluation, and brief details on channel estimation protocols are presented in [3]. Various channel estimation techniques have been presented in [8] - [33] with an evaluation of their implication on IRS performance. Research has shown that channel estimation is key in informing optimization processes and related outcomes, which are presented herein.

The research community has shown significant interest in IRS, resulting in many publications in recent years. While the IRS is still in the early stages of deployment, several experimental testbeds and proof-of-concept demonstrations have showcased its feasibility and potential. Researchers and industry experts are actively exploring various aspects of IRS, including theoretical foundations, hardware design, channel modelling, signal processing algorithms, deployment strategies, and performance evaluation. With an emphasis on system-level optimizations, standardization efforts, and integration with current communication technologies, developing trends show a move from theoretical investigations to actual implementations and field trials.

This review paper presents a comprehensive summary of all works related to the IRS in current research while showing how they are related and connected to improved communication. The synthesis of existing knowledge and identification of research challenges will contribute to the maturation of IRS technology and its successful integration into next-generation communication systems.

In essence, the emergence of IRS technology has generated significant excitement and interest in the communication industry. Its ability to reshape wireless propagation and overcome traditional limitations opening up new possibilities for enhanced connectivity, improved system performance, and efficient spectrum utilization. While the IRS is still in the research and development phase, its potential impact spans various sectors and industries. This review paper thus provides an in-depth evaluation of current progress in IRS research, its advantages, disadvantages, and future trends. Understanding the capabilities and challenges of the IRS can guarantee its optimal deployment and integration into future communication networks.

While authors in [1] - [4] address key aspects of the IRS and its place in future wireless communication, the main challenge- channel estimation is only presented in brief while it significantly affects the extent to which the capabilities of the IRS can be realized. This paper presents an overview of the IRS design and architecture from available literature, followed by details about various channel estimation protocols, algorithms, and techniques, providing a better understanding of current challenges and solutions offered in the literature. This review presents an in-depth evaluation of the IRS application, focusing on various optimization problems, parameters considered, and the gaps that remain unaddressed. Finally, a conclusion is given on open problems for future research based on evaluating current studies.

METHOD

This section details the process followed in selecting journal papers for inclusion in this review and how they were categorized.

Inclusion Criteria

Research articles were gathered from scholarly journals and databases published between 2010 and 2023 for inclusion in this review. Since this review encompasses all works related to the performance, design, and future applications of the IRS in diverse fields, all relevant peer-reviewed articles on this subject were considered for evaluation. Using the IEE explore, Google Scholar, and Research.com, over 100 articles on IRS were discovered and filtered by relevance for inclusion in this work. The distribution of the 70 papers by themes is shown in Figure (1) below.

Organization

This review is organized into sections and subsections containing closely related articles for easy comparison and evaluation. In Chapter 3, we address IRS design and hardware considerations. In Chapter 4, channel estimation approaches are considered. Chapter 5 addresses optimization methods and Chapter 6 highlights other uses of the IRS, including upcoming technologies. Chapter 7 presents a discussion of all the sections highlighted to compare the available techniques to reveal the best options and prevailing challenges and recommendations derived from the discussion. Finally, chapter 8 concludes the review, after which the references used are listed.

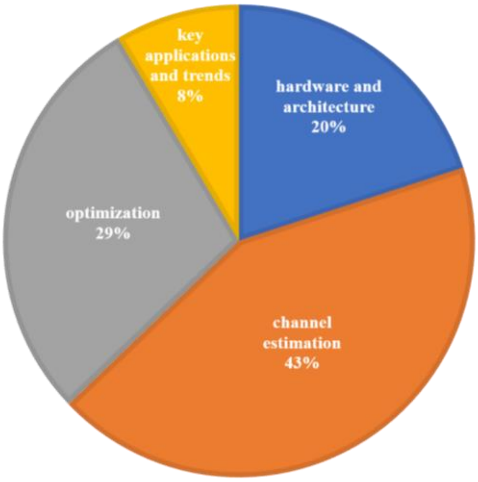

Figure 1: Distribution of research paper by thematic areas

Hardware Design and IRS Architecture

An IRS is a planar or 2-D array of meta-atoms/metasurfaces having subwavelength thickness whose passive beamforming enhances SE and EE. The IRS has proved beneficial in reconfiguring the wireless environment through passive beam shaping [1]. In [1], the authors present an overview of IRSs and their place in the wireless communication environment, showing how the random and unpredictable wireless communication environment presents a significant performance bottleneck necessitating the use of IRSs, which helps to achieve the desired energy and spectral efficiencies. The work in [2], offers an overview of IRS design, configuration, and applications in communication systems. The arrangement and structure of the reflecting elements determine the degree of phase shift of the incident wave, dictating the various applications of the IRS [2].

The IRS consists of three layers; the first consists of the passive tunable patches that are etched into a dielectric material, and the second is made up of a copper plate whose role is to prevent the signal from leaking out [12]. The third layer comprises a controlling circuit board for the real-time manipulation of the signal phase to direct the beam in the desired direction, as shown in Figure (2) below.

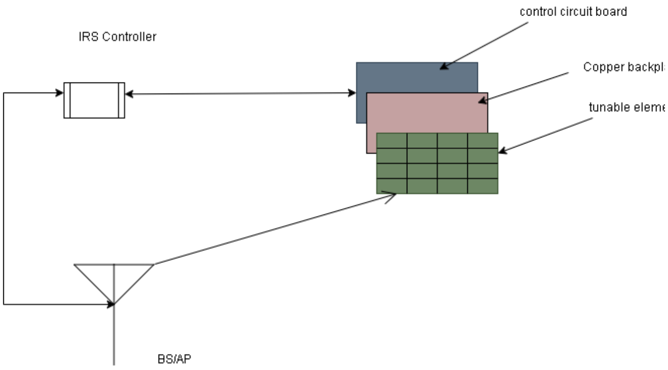

Figure 2: IRS structure

The IRS controller plays an essential role in phase shift optimization by receiving the set reconfiguration points and sending the decisions on phase/amplitude shifts to all the reflecting elements. The controller's power consumption has been shown to depend on the circuit implementation. In [12], a Field-Programmable Gate Array (FPGA), implemented to control a varactor-diode-based IRS, was shown to consume 0.72W, which is significantly below that of an active beamforming relay.

The unique characteristics of IRSs are highlighted in [4], including passive reflection. Further, they do not introduce additional noise, offering a significantly energy-efficient solution. Authors in [4] also show that the IRSs apply full-band operation, implying that they operate in any frequency while achieving a full-duplex transmission. IRSs are designed for use in LoS and non-LoS systems. In LoS systems, the IRS replicates the direct path, leading to improved diversity. In non-LoS, the IRS provides an alternative path for the signals. However, for the IRS to significantly improve the system's performance [13], optimal hardware design is crucial. In their work, authors in [13] design the graphene-based reflecting surface to obtain a phase response of 306.82 degrees, noting that amplitude and phase response depend on IRS hardware design, affecting the achievable data rate.

The question of IRS deployment is also important in this case since it determines the signal received and the data rate achieved. Authors in [14] delve into the deployment challenges, showing that a hybrid deployment structure would be more beneficial while the IRS should be placed closer to users or the BS. The hybrid IRS deployment structure requires decentralized IRS allocation where the IRS elements are distributed at the receiver and transmitter ends [14]. This is important as it results in a significantly higher minimum rate than the BS-side and user-side deployment schemes. In addition, authors in [11] show that because of path loss, the IRS placement determines energy efficiency and must be carefully considered.

In addition to IRS hardware design and reconfiguration, the transceiver hardware is shown to affect the performance of IRS-aided communication systems significantly. Transceivers may be characterized by imperfections, as shown in Figure (3) below. These impairments determine the system capacity and have attracted the attention of various researchers, as described herein. In [15], the authors assess the impact of hardware impairments on the ergodic capacity and outage probability. Their results indicate that the ergodic capacity is significantly affected by hardware impairments in the transmitter or receiver.

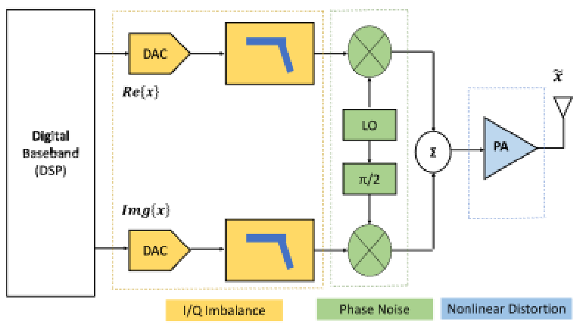

Figure 3: Various transceiver imperfections [18]

Similarly, [16] considers hardware impairments in a Multiple-Input Single Output (MISO) system and shows that in addition to outage probability and ergodic capacity, symbol error rate and diversity order in such a system are independent of IRS elements. This indicates that hardware impairments should be carefully considered in practical transmission systems. Further, authors in [17]-[18] show that the system's spectral efficiency saturates after a particular SNR and no improvement in reflecting elements can enhance it.

Understanding the system requirements informs the choice of IRS design and architecture and transceiver hardware. This results in varying outcomes of channel estimation methods and subsequent optimization techniques, as highlighted in sections 4 and 5 below.

Channel Estimation

For the IRS's capabilities to be fully exploited, accurate channel estimation is required. This section summarizes recent works on CSI estimation in the context of the IRS. Estimating the Access Point -IRS (AP-IRS) and IRS-user channels separately would be challenging and impractical for a completely passive IRS. Therefore, researchers focus on estimating the cascaded AP-IRS-user channel. The IRS can be equipped with RF chains for signal processing capabilities, enabling it to acquire some crucial channel characteristics. In such a case, the IRS is said to be active or semi-passive, depending on the activation pattern. Authors choose whether to use fully passive IRS without signal processing abilities or incorporate active elements depending on the needs and complexity level required. In this section on channel estimation, research works are categorized into various subsections comprising common techniques for ease of comparison.

The Least Square (LS) method has found its application in channel estimation, proving effective, straightforward, and less complex compared to the Minimum Mean Squared Error (MMSE) method and other channel estimation techniques. However, varying results are obtained depending on the number and active/passive nature of the IRS elements, as discussed in this section. The LS method estimates the channel response between transmitters and receivers, indicating signal distortion, gain, and attenuation. Due to its computational efficiency, the LS has been applied in many channel estimation approaches, including the ON/Off technique, element grouping, and as an input to machine learning networks, as described below.

The On/Off Approach

The On/Off method is founded on turning the IRS off for direct channel estimation and turning it on for estimating the cascaded channel. In [6], the authors adopted an On/Off method for CSI estimation. The first phase entails turning off the LISA to estimate the direct channel using uplink pilots. In the second stage, the reflective elements are turned on each at a time and pilot transmission in each time slot. The cascaded AP-IRS-user channel is estimated by exploiting the estimated BS-user channel [6]. Although this method proved straightforward, the pilot overhead becomes extremely prohibitive in cases involving large numbers of reflective elements.

Considering a MISO point-to-point system, channel reciprocity and Time-division Duplex (TDD are adopted in [19] to estimate the channel coefficients. A binary LS method is proposed that enables the estimation of the M+1 channel vectors for all N elements of the IRS. With an On/Off approach similar to that adopted by [6], the authors in [19] show that the IRS elements required increases by 8% when using LSEs than when assuming perfect CSI for optimization. In addition, they show that it is challenging to achieve perfect On/Off modes due to practical hardware limitations. Therefore, there is a need to incorporate the errors when computing the cascaded channel matrix, as shown in [20], where the authors discuss the importance of including the error when modeling the activation states of the IRS. The On/Off method is also applied in[21] and [22] utilizing LS and Bayesian MMSE estimations, respectively.

Moving from a random activation pattern, authors in [23] propose an efficient channel estimation scheme to lower the Cramer-Rao lower bound (CRLB). It is shown that channel estimation efficiency significantly depends on the activation pattern. Contrary to the On/Off method adopted by [6]., authors in [23] design an IRS activation pattern following a series of Discrete Fourier Transforms (DFTs). Compared with the On/Off method, the authors find that the proposed training scheme has a variance of one order less, implying that it significantly reduces the training period.

Element Grouping

Since training overhead is a major characteristic of the IRS elements, several authors sought to solve this limitation by grouping the IRS into several groups, each composed of adjacent elements. Similarly, this approach has been used in [24], where the authors subdivided the IRS into N sub-surfaces comprising neighboring reflecting elements to reduce the computational complexity, as shown in Figure (4) below. Using a predefined reflection pattern, the superimposed CFR of the system is derived. This system shows a 14dB power gain over the On/Off CSI estimation technique.

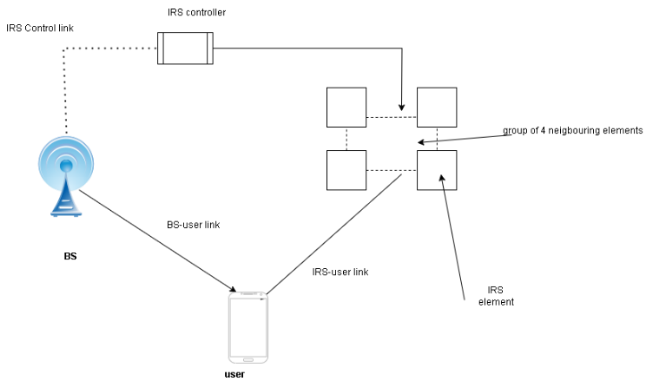

Figure 4: IRS element grouping

Considering the constraint of discrete phase shifts, authors in [25] propose an effective channel estimation scheme that follows a progressive estimation of the channels for all IRS elements. In this case, the intra-group channels are estimated from the per-group estimates. In this case, the hierarchical design primarily entails IRS channel estimates following partitions and groupings of IRS elements.

 https://doi.org/10.25077/ajeeet.v4i1.100

Similarly, authors in [26] design a channel estimation scheme by applying sparse and grouping techniques to lower the channel estimation complexity in millimeter wave (mmWave) channels. The design is shown in Figure (6) below. Here, elements with the same color are given the same reflection coefficients, through which the authors showed that complexity is significantly reduced while enhancing the channel estimation accuracy.

Machine Learning Techniques

Machine learning channel estimation approaches work by establishing a channel-signal relationship by referring to the initial channel estimate provided. The LS or MMSE methods provide the initial CSI used in neural networks for improved accuracy, reliability, and reduced complexity. A Deep Learning (DL) channel estimation approach is adopted in [20], where the authors use the Convolution Neural Network (CNN) shown in Figure (7) below to enable each user to access the CNNS and accurately estimate its channel. The twin CNN structure takes in LS estimates from which a non-linear relationship is constructed between the channel and the received signals. One of the most significant outcomes of this work is that the proposed DL method does not require to be retrained after a change in user locations for up to 4 degrees. Similarly, deep learning methods are applied in [27], [28], and [29].

Authors in [27] apply the LS method in the terahertz (THz) system, enabling them to estimate the individual channel components, which are shown to be independent. The LS estimates are used as the starting point in the machine learning approach. In [28], the LS estimates are used considering no prior knowledge of the channel characteristics, providing inputs to the CNN-based Deep Residual Network (CDRN) framework. Results indicate that this approach provides a better estimate of the channel with reduced complexity.

In a Self-Supervised Learning (SSL) method, authors in [29] apply the LS estimates as input for the inference phase of their channel estimation architecture to give out the refined channel estimates. The SSL approach eliminates the need for ground truth labels and provides better results than the CDRN network implemented by [28].

In [30], the authors apply the concept of sparsity in the Terahertz (THz) range and incorporate deep learning for efficient channel estimation. First, the problem is turned to a sparse recovery problem from a channel estimation issue. The sparse matrix is solved by a two-stage neural network that aids in the design and reconstruction of the signal. Simulation results indicate that the proposed method leads to significantly good results regarding the average error rate and NMSE, with the error rate being approximately 0.16 [30].

To lower the channel estimation complexity, authors in [31] propose a DL approach that decouples the problem into three main phases. First, the direct channel is estimated. The reflected channel communication and reflected sensing channels are estimated in the next two phases. Two CNN architectures are presented for offline and online training. One CNN is applied in the direct channel estimation (DE-CNN), while the second CNN is used for reflection estimation (RE-CNN). Simulation results indicate that the proposed DL scheme ensures better performance than the LS estimator.

In [32], the authors argue that the errors associated with phase 1 in the approach presented by [31] will be passed on to the second and third phases, limiting the estimation accuracy and reliability. To solve this challenge, a single CNN is applied in [32] to estimate the cascaded channel and then use it to extract individual channels. This technique mitigates the error propagation effect while reducing the channel estimation complexity. Applying offline and online training similar to [31], the authors in [32]compare the performance of the CNN-based channel estimation process to LS and On/Off methods. In this case, the database obtained in offline training serves as the input during the online phase.

While [31] and [32] are based on limited sizes of IRS structures, the authors in [33] propose a scalable and flexible unsupervised learning model that solves the size limitation. In this case, multi-carrier waveforms, discrete and continuous phase shifts, and large-size IRSs are considered. Further, the authors in [33] show that clustering may serve to reduce the execution time, adding to the merits associated with the proposed scalable unsupervised learning model

Considering a semi-passive IRS, authors in [34] develop an effective channel estimation technique that relies on a probabilistic method for antenna selection to select the optimal positions of the active IRS elements. This design for selecting the active antennas adopts extrapolation to optimize the channel extraction process and the activation pattern. Specifically, two deep-learning schemes are utilized. First, a CNN network is used for channel extrapolation to obtain full channels from the estimated channels. Second, an FNN network is applied for beam-searching approaches, mapping the channel estimates to the beamforming vector.

Compressive Channel Estimation

In [35], a compressive channel estimation technique is presented for millimeter wave (mmWave) systems. The inherent sparsity associated with mmWave systems is utilized to minimize training overhead significantly. The authors model the BS-1RS and IRS-UE channels as narrowband geometric channel models and then apply Khatri-Rao and Kronecker products to estimate the cascaded channel matrix. Essentially, the authors in [35] shift from channel estimation to sparse signal recovery, and estimation of the sparse signal is done following two methods: the Orthogonal Matching Pursuit (OMP) and Gaussian-Mixture Approximate Message Passing (GAMP). Compared to the conventional LS estimator and Oracle LS method, the proposed compressed sensing method has a higher computational efficiency than the conventional LS method while achieving a performance close to that of the Oracle LS estimator.

Considering a broadband mmWave system, authors in [36] propose a downlink transmission framework that relies on compressive sensing to estimate the BS-UE and IRS-UE channels, assuming knowledge of the BS-IRS channel. The pilot signals are decomposed into two for separately estimating the BS-IRS and IRS-UE channels. An efficient Distributed Orthogonal Matching Pursuit (DiOMP) algorithm is presented, which outperforms the conventional OMP algorithm. Further, the authors propose a redundant dictionary to mitigate the leakage power associated with transformation matrices.

Considering a single SiSo communication system, authors in [37] develop a two-phase channel estimation technique for a double-IRS system. The main focus here is to estimate the individual channel gains for the UE-IRS1, IRS-IRS2, and BS-IRS2 links instead of estimating the cascaded channel gains. In phase 1, the authors estimate the BS-IRS2 and IRS2—IRS1 channels simultaneously to reduce the complexity and save time. In phase 2, the UE-IRS1 is modeled as a 2-dimensional Markov process. The Dynamic Turbo Orthogonal Approximate Message Passing (D-TOAMP) and Dynamic Compressive Sensing AMP (DCS-AMP) algorithms are used to estimate the channel gain. While applying the Kalman-like filter (KLF) and the Kalman filter (KF) to track the UE-IRS1 channels, the authors show that this method reduces computation and significantly lowers the estimation error.

In [38], the authors acknowledge that channel estimation in an LIS-aided system is characterized by high training overhead (for passive LIS) or high power consumption (for active LIS). The authors propose two approaches to address these limitations: compressive sensing and deep learning. In the first approach, a LIS with few active elements is used. The LIS elements' channels are constructed using retrieved channels from the active elements. In the second approach, the LIS learns the optimal interaction with the incident signals following a deep learning approach. The authors show that with less than 1% of elements of the LIS being active and with negligible training overhead, the two solutions are close to the upper bound of a system adopting perfect CSI.

In [7], the authors propose a Joint Bilinear Factorization and Matrix Completion (JBF-MC) algorithm that approaches the sparse matrix problem from a different perspective. In their work, [13] presents two crucial stages. In stage 1, sparse matrix factorization is done following the Bilinear Generalized Approximate Message Passing (BiG-AMP) algorithm. In STAGE 2, matrix completion is done using the Riemannian Gradient (RGrad) algorithm. Evaluating the performance regarding Normalized Mean-Square-Error (NMSE), this approach shows superior performance compared to K-Singular Value Decomposition (K-SVD) and Sparse Modelling Software (SPAMS) techniques of sparse matrix factorization. Simulation outcomes also revealed that the matrix completion method achieves better Iterative Soft Thresholding (IST) than Iterative Hard Thresholding (IHT).

As the size of the sparse matrix increases complexity, authors in [39] presented a low-complexity Iterative Atom Pruning Based Subspace Pursuit (IAP-SP) scheme that enabled the simultaneous estimation of the BS-IRS and IRS-UE channels. The approach performed better than that presented in [35] by removing redundant columns in the generated sensing matrix iteratively.

In [40], the authors show that channel overhead and complexity in mmWave channel estimation can be significantly reduced by incorporating super-resolution and partial on-off schemes. In this scheme, a subset of the reflecting elements is turned on instead of turning on each element simultaneously. By switching on the elements in the subset, the channel estimate H_{LS} estimate obtained can be seen as a low-resolution image. This is then converted to a high-resolution image via linear interpolation. This interpolated channel estimate is used as input to the super-resolution network, which has three convolution layers that are now adopted for higher channel estimation accuracy. Simulation outcomes revealed that this scheme achieves better NMSE than the LS, OMP, and DNN-based methods.

In [41], the authors propose to address the challenges associated with channel estimation in the mmWave channels by developing a hybrid multi-objective evolutionary paradigm. Contrary to the sparse signal recovery solutions, which lead to a suboptimal solution, authors in [41] use Iterative Hard Thresholding (IHT), a gradient-based method, to achieve a multi-objective optimal solution. Simulation outcomes showed that the scheme used outperforms the OMP, oracle-LS, and Two-stage channel estimation techniques in NMSE and spectral efficiency.

Utilizing a block-sparse processing technique to estimate the equivalent angles, authors in [42] consider the effect of beam squint in estimating the cascaded BS-IRS-User channels. A twin-stage orthogonal matching pursuit method (TS-OMP) is proposed to effectively estimate the cascaded channel's delays, gains, and equivalent angles. In the second stage, an OMP method is proposed to estimate the path delays and gains following the estimated equivalent angles. Simulation results show that even in a very high number of pilots, the proposed TS-OMP method approaches an ideal solution with known path delays and channel gains.

Other Methods

Considering a multiuser MIMO system, the authors in [43] utilize the fact that the IRS reflects the channels from all the users to the BS via the same channel to reduce the channel estimation time. A three-phase channel estimation protocol is presented, which relies on the highly correlated user-IRS-BS channels to reduce the pilot sequence. In phase 1, the BS estimates the direct BS-Users channels with the IRS turned off. In phase 2, the IRS is turned on with only one user allowed to transmit pilot symbols to enable the BS to estimate the user-IRS channel. In phase 3, the other users are allowed to transmit their pilot symbols. However, instead of estimating the entire channel vectors, the authors in [43] note that only the scaling factors need to be estimated because these channels are just scaled versions of the single user's estimated channel. Evaluating this channel estimation technique, the authors show that the minimum pilot sequence length is significantly reduced for cases with and without receiver compared to a MIMO system without IRS.

In [44], the authors build on the 3phase channel estimation scheme proposed by authors in [43] to develop a more effective 2phase channel estimation, which shows a significant reduction in error propagation. In the first phase, the authors estimate the direct and reflected links associated with a typical user. In the second phase, the CSI associated with the other users is estimated. By altering the IRS's reflection patterns, the errors associated with the direct channel do not affect the reflected channel estimate. Comparing this technique with the one proposed in [43], it is shown that the proposed 2phase channel estimation scheme accurately estimated all the channel coefficients with a reduced pilot sequence and outperformed the 3phase scheme in the presence of noise at the AP.

 https://doi.org/10.25077/ajeeet.v4i1.100

In [45], a two-stage channel estimation protocol was proposed to further reduce the training overhead by using a semi-passive IRS. Here, the authors leverage the channel coherence differences between BS-IRS and the IRS-UE channels to reduce pilot overhead by introducing semi-passive elements. The two channels are estimated separately. First, the BS-IRS channel is estimated following a super-resolution algorithm that seeks to move the estimated AoA and AoDs to values much closer to the real values via gradient descent. An accurate estimate of the BS-IRS channel is obtained by solving the optimization problem via a closed-form solution. Second, the RIS-UE channel estimate is obtained by a parallel factor (PARAFAC) decomposition technique that leads to a more robust LS estimate of the channel. Simulation results indicate that the two-stage channel estimation protocol achieves higher accuracy and a 10% higher spectral efficiency than LS, MMSE, and compressed sensing.

While all the channel estimation techniques above address the entire composite channels, authors in [46] developed a scalable CSI estimation scheme that only estimates the end-to-end composite channels followed by transmit power allocation. The authors sought to address the challenge of increased computational complexity and pilot overhead by developing a scheme that relies on known overhead to strike a flexible trade-off between pilot overhead, complexity, and achievable rate. Instead of estimating the direct and reflected channels separately, the authors in [46] estimate only the composite channel comprising the direct link and M reflected channels considering the Q^{th} training slot. This way, the problem is simplified into a search for the optimal q =1,…Q, that maximizes the achievable rate. It is shown that the proposed system is independent of the reflecting elements, enabling it to be adjusted dynamically for preferred trade-offs between performance and pilot overhead.

Table 1: A summary of research on channel estimation

Subcategory	References	Approach	IRS Active/ Passive
On/Off method	[6]	On/Off method for reflective radio	Passive
	[19]	On/Off with LS estimation	Passive
	[21]	On/Off activation pattern for IRS grouping	Passive
	[22]	MMSE-On/Off estimation	Passive
	[23]	DFT-based IRS activation pattern	Passive
IRS element grouping techniques	[24]	IRS grouping for CSI estimation and reflection optimization	passive
	[25]	Grouping for per-group and intra-group channel estimation	Passive
	[26]	Grouping and Sparse patterns	Passive
Machine learning techniques	[27]	LS method for 2-stage channel estimation	
	[28]	LS for CDRN channel estimation framework	Passive
	[29]	LS for self-supervised channel estimation	Passive
Compressive channel estimation approaches	[30]	Deep learning with a 2-stage neural network	Passive
	[31]	A 3-stage approach utilizing two different CNN networks	Passive
	[32]	A single CNN network for the cascaded channel estimation process	Passive
	[33]	A flexible and scalable unsupervised learning model	
	[34]	CNN and FNN	Semi-passive
	[35]	OMP and GAMP	passive
	[36]	DiOMP	Passive
	[37]	D-TOAMP and DCS-AMP	Semi-passive
	[38]	OMP and deep learning	Semi-passive
	[7]	Big-AMP and R-grad	Passive
	[39]	IAP-SP	Passive
	[40]	Super-resolution and LS	Passive
	[41]	A hybrid multiobjective evolutionary paradigm	Passive
	[42]	Block-sparse processing and TS-OMP	Passive
	[45]	PARAFAC and LS	Semi-passive
	[43]	MMSE	passive

Subcategory	References	Approach	IRS Active/ Passive
Other methods	[44]	Twin-stage LSE	Passive
	[46]	Scalable LSE	Passive

Optimization

The benefits derived from IRS applications in wireless communication systems arise from the ability to alter the phases of each IRS element for beam steering. Various authors have approached the phase shift optimization problem differently, some focusing on data rate maximization, others hoping to achieve maximum SINR, and many other aspects of the wireless communication system. This section presents a review of current works on IRS reflection optimization.

Iterative Optimization Methods

To minimize transmit power, authors in [47] present an optimization technique focusing on three aspects: the phase shift matrix, power allocation, and the transmit beamforming vector. Since these three factors are highly coupled, making the problem non-convex, an iterative algorithm is employed to establish feasible starting points and solve the two subproblems formed for phase shift and beamforming optimization**.** Simulation results indicate that transmit power decreases as the number of reflective elements and the IRS-user distance increase.

Addressing the same problem as in [47], transmit power in the AP is the main focus in [48], whereby the authors use transmit precoding and IRS discrete phase shifts with the constraint of a set minimum value of SINR. Ignoring hardware imperfections and assuming perfect CSI, the authors present two algorithms to solve the problem for a single-user system. The branch-and-bound method provides an optimal solution while the successive refinement algorithm is applied to give a sub-optimal solution to the optimization problem. The authors advance the problem from a single-user to a multiple-user setup and show that discrete phase shift gives the same power gain as would be obtained from a continuous phase shift problem.

Similarly, discrete phase shifts are considered by the author in [49], whereby an Alternating Optimization (AO) algorithm is adopted to optimize the SINR relying on the Gradient Extrapolated Majorization-Minimization (GEMM) technique. In this case, transmit beamformer, IRS phase shifts, and receive beamformer are the optimization variables, unlike the approach adopted in [48], where only the transmitter precoding and IRS phase shifts are used. Results in [48] show that applying the GEMM technique to solve the power minimization problem performs better than the semidefinite relaxation approach, as it nearly reaches the upper bound scheme. Further, the GEMM algorithm has low complexity and only 20 iterations are required for convergence.

Moving from single-IRS to multi-IRS systems, the authors in [50] maximize the sum rate by jointly optimizing the IRSs' passive reflection and user association. An intractable non-convex problem is formulated and effectively solved by an AO algorithm. Specifically, fractional programming handles the IRS beamforming while network optimization addresses the user association issue. Simulation results indicate that the proposed algorithm leads to a 200% increase in energy efficiency and at least a 400% gain in sum rate for all users.

In [21], the achievable rate is maximized following joint transmit power and passive IRS beamforming vector to solve the problem sub-optimally. First, the authors design a transmission protocol for channel estimation where only the group channels are estimated, thereby reducing channel estimation complexity. A customized initialization scheme is proposed for the iterative optimization algorithm that leads to a locally optimal solution. The research done in [21] leads to the understanding that the trade-off between estimation complexity and flexibility of the passive beamformer can be addressed by having an optimal size for the IRS groups.

Machine Learning Optimization Approaches

In [52], the concept of SINR constraint in a cognitive radio (CR) communication system is addressed. In this case, the main aim is to jointly optimize the transmit power at the Secondary User (SU) and passive beamforming at the IRS. Successive convex approximation and AO techniques are applied to provide a suboptimal solution to the problem. The research done by [52] shows that in the high-interference situations that mainly characterize cognitive radio systems, an IRS helps to minimize interference from other users at minimal cost due to reflection optimization.

In [53], the authors focus on improving the system's secrecy rate by suppressing interference from an eavesdropper, as shown in Figure (5) below. In this case, semidefinite relaxation and AO approaches are used to lead to a suboptimal solution to the problem. The authors adopt joint optimization of the transmit beamforming vector and IRS reflection matrix by destructively combining signals at the eavesdropper and constructively adding the signal s from the direct and reflected paths. Simulation results reveal a high performance approaching the upper bound, and outperforming the heuristic approach.

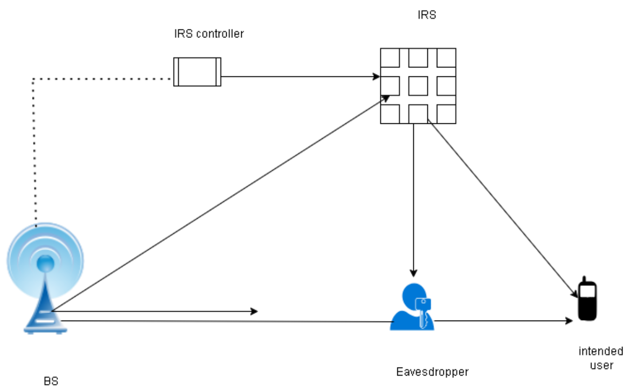

Figure 5: IRS application in a single eavesdropper scenario

Moving from one to multiple eavesdroppers, authors in [51] advance the issue of secrecy addressed in [52], [53], and [54]. In this case, the main goal is to find the optimal BSs and IRS's reflection beamformers subject to the desired QOSs of intended users. Utilizing Markov decision processes, a Deep Reinforcement Learning (DRL) approach is adopted for optimal joint beamforming. Further, the authors propose modified Post-Decision State (PDS) learning and Prioritized Experience Replay

(PER) techniques to trace the dynamic vs. uncertainty of the channel and enhance the learning. The outcomes show that the approaches in [59] and [55] lead to 17.21% and 8.67% improvements in the secrecy rate, respectively.

Following SINR consideration, the authors in [55] address the secrecy issue by using an IRS equipped with Intelligent Spectrum Learning (ISL) abilities to extract interfering signals from the incident signals. A Convolutional Neural Network (CNN) scheme enhances the IRS reflection optimization. In this case, the IRSs' On/Off states are dynamically adjusted so that the IRS can decide whether or not to reflect incident signals relying on capabilities provided by the ISL technique. The optimization problem in [55] is modelled as a mixed-integer non-linear program (MINLP). Simulation results show that the proposed method has a more than 95% inference accuracy and leads to higher SINR than always-ON and always-OFF IRS designs.

Similarly, the benefits of deep learning are applied by [56] to jointly optimize the BS beamforming and IRS passive beamforming. In this case, the authors rely on a system objective to which they parameterize the mapping from the received pilots. A permutation invariant/equivariant Graph Neural Network (GNN) architecture captures the interactions arising from the different cellular network users. This work shows that by considering user interactions, the proposed GNN-based structure leads to more generalizable and scalable solutions to the minimum-rate and sum-rate maximization problems.

While still utilizing deep neural networks, authors in [57] adopt an unsupervised learning method to achieve real-time prediction for passive beamforming in a 3-node system. The neural network is labeled "RISBFNN," comprising five fully connected (FC) layers. Using an Adam optimizer set to an initial learning rate of 0.001, the authors show that this scheme leads to a near-optimal solution compared to SNR optimization, whose result is suboptimal.

Hybrid Methods

Iterative optimization is similarly adopted in [58], where the authors seek to establish the fundamental capacity limit by optimizing the transmit covariance and IRS phase shift matrices. An iterative algorithm is used for the narrowband transmission scenario to derive a locally optimal solution for a flat-fading system. Further, frequency-selective channels are considered where convex relaxation is applied alternately for a suboptimal solution to the capacity maximization problem under OFDM transmission. Simulation results show that condition number, channel power, and rank can be adjusted for improved capacity.

Alternative optimization is applied in [59] to optimally solve the non-convex problem formulated for an IRS-assisted UAV system. In this case, the optimization variables are the UAV hovering location, the active and passive beamforming variables, and the computation task scheduling. The AO algorithm is accompanied by a genetic algorithm that helps decouple the problem's various elements for alternate optimization until convergence is attained. In every iteration, a feasible solution is found at an acceptable cost regarding time and space. Following this investigation, computation task delay can be effectively minimized, improving the UE performance.

Focusing on a MISO system, authors in [60] develop two algorithms to optimize the AP beamformer and the IRS phase shifts. The main goal in [60] is to maximize the system's spectral efficiency, subject to the phase shifts and constrained by the transmit power. The problem, in this case, is modelled as a non-convex optimization problem, which is solved by fixed-point iteration and manifold optimization. Results indicate optimal local solutions by effectively tracking the unit modulus constraints.

For the UAV condition investigated in [59], the authors in [61] delve into the possibility of jointly optimizing the IRS reflections, BS selection, and BS beamformers in a multi-BS communication system with an aerial IRS. With the IRS mounted on the UAV, the authors seek to maximize energy efficiency based on IRS coefficients, power, QoS, and capacity constraints. A Branch-Reduce-and-Bound (BRnB) algorithm applying SDR and monotonic optimization is used to show how the multi-BS joint beamforming increases energy efficiency by at least 50%.

While [52] and [53] work under the assumption that the eavesdropper's CSI is known, [54] looks into the converse scenario where transmit power is optimized alongside a jamming technique for the more practical scenario lacking the eavesdropper's CSI. In [54], the authors seek to minimize the power required for optimum QoS at the intended user while allocating the residual power to artificial noise to jam the eavesdropper's signal. The non-convex optimization problem, in this case, is solved using oblique manifold and minimization-maximization algorithms whose performances are compared. It is shown that secrecy is significantly improved by optimizing the transmit power and number of IRS elements.

Considering a single AP with several antennas and multiple users with one antenna each, authors in [62] propose a joint active and beamforming optimization scheme. Two methods are presented: Semidefinite Relaxation (SDR) and an AO scheme that was solved iteratively. Results show a significant reduction in transmit power and an increase in achievable rate with the number of IRS elements in single-user and multiuser cases.

Other Optimization Approaches

The impact of phase shift optimization on the system's ergodic capacity is given priority in [63]. In this case, the ergodic capacity's upper bound is solved by considering a Rician fading system. The authors in [63] show that in extreme Rician fading, the phase shifts should be optimally designed. Considering statistical CSI and hardware impairments, the ergodic capacity approximation technique shows that the ergodic capacity increases with the number of reflecting elements and is significantly enhanced in 2-bit quantization approaches.

While focusing on the achievable rate, authors in [24] concentrate on the upper bound of the achievable rate and propose an effective method founded on the channel impulse response (CIR). They develop a strongest-CIR maximization (SCM) method that seeks to utilize the time domain of the signals to provide a sub-optimal solution that is less complex than the SDR approach. In [24], the phase shifts are aligned to the strongest CIR.

While most of the researchers cited above majored in IRS reflection optimization based on the phase shift only, the authors in [64] assessed the impact of amplitude control in a joint BS beamforming and IRS reflection optimization scheme. The problem, in this case, is constructed as a MINLP problem, for which a penalized Dinkelbach-BSUM algorithm maximizes the achievable rate. Simulation outcomes reveal that additional benefits regarding the achievable rate are obtained when the amplitude is optimized alongside the phase shift compared to phase shift control only. Amplitude control increases performance gains in cases with serious CSI errors compared to the SDR approach.

Table 2: IRS optimization techniques

Category	References	Optimization technique	Achievements
Iterative methods	[47]	Iterative initial points search followed by joint optimization	Decrease in transmit power with the number of IRS elements and the distance between IRS the cell-edge users
	[48]	Successive refinement for iterative optimization and the branch-and-bound method	Significant transmit power saving derived from using IRS with discrete phase shifts
	[49]	AO using the GEMM algorithm	A better solution to the power minimization problem and low complexity
	[50]	Iterative optimization via fractional programming	up to 200% increase in energy efficiency and at least 400% gains in sum rate
Machine learning optimization approaches	[51]	Deep reinforcement learning (DRL)	Improvements in the secrecy rate while tracing the uncertainty of the channel
	[55]	Intelligent Spectrum Learning (ISL) through CNN	More than 95% inference accuracy and higher SINR compared to the always-ON IRS design
	[56]	A permutation invariant/equivariant graph neural network (GNN)	Sum-rate maximization with a minimal number of pilots
	[57]	Unsupervised learning with a RISBFNN deep neural network	The realization of a near-optimal solution with real-time prediction
Hybrid methods	[59]	AO algorithm combined with the genetic algorithm	Results in decreased computation task delay and improved performance of UE
	[60]	Fixed-point iteration and manifold optimization	A local optimal solution is obtained by tracking the unit modulus constraints.
	[21]	Iterative optimization	Optimal IRS grouping
	[52]	Successive convex approximation and AO	Minimized interference
	[53]	semidefinite relaxation and AO	Increased secrecy rates close to the upper bound
	[61]	monotonic optimization and SDR	Energy efficiency increased by at least 50%.
	[54]	Oblique manifold (OM) and minimization maximization (MM) algorithms	Improved user security in the absence of eavesdroppers' CSIs
	[62]	SDR and iterative optimization	An increase in achievable rate with the

Category	References	Optimization technique	Achievements
			number of IRS elements
	[51]	Deep reinforcement learning (DRL)	Improvements in the secrecy rate while tracing the uncertainty of the channel
Other optimization techniques	[24]	A strongest-CIR maximization (SCM) method	A suboptimal solution that is less complex compared to the SDR approach
	[64]	A penalized Dinkelbach-BSUM algorithm	Higher achievable rates compared to the SDR approach
	[63]	Ergodic capacity approximation technique	Increase in ergodic capacity with the number of elements

Industry Applications of the IRS

Focusing on the industry, an IRS has found its application in IoT, where IRSs mounted on UAVs facilitate power transfer or information control. In [65], the authors adopt a harvest-then-transmit approach where the IRS aids downlink power transfer and Energy Harvesting in the uplink. In this case, the authors optimize the reflection matrix and the EH schedule. A deep deterministic policy gradient is applied in line with the proximal policy optimization algorithm to solve the network throughput maximization problem. The research outcomes show that the proposed methods lead to a higher expected sum rate than UAV communication systems lacking an IRS.

Similarly, the IRS's role in simultaneous power and information transfer has been applied in [66]. The authors' focus is IRS's sum rate maximization the by jointly optimizing the transmit precoding and the IRS's phase shift matrix. In this case, the BS is considered to have a constant power supply as it transfers information to a set of users. Having the non-convex unit modulus constraints in simultaneous wireless information and power transfer, the authors adopt a classic block coordinate descent algorithm for iteratively solving the transmit precoding matrices and phase shift optimization problems. Deploying an IRS is thus shown to significantly enhance the sum rate while increasing the operating range of the Energy Receivers.

In cognitive radio, [67] considers the role of IRSs in energy detection for spectrum sensing, where the IRS-based system is shown to have a higher probability of detection than systems without the IRS. Further applications of the IRS are in smart manufacturing, whereby authors in [68] show that in Industry 5.0, ultra-reliability and low latency communications can be achieved by deploying IRSs to facilitate better interaction between machines and humans in the industrial setup, which numerous blockages from machines can characterize. In addition, [69] and [70] show that the IRS can potentially increase radar performance by improving target parameter estimation and target sensing.

RESULTS AND DISCUSSION

The IRS has shown the potential to revolutionize communication systems through its applications in various sectors. This section presents a discussion of the various subsections with recommendations on the best approaches as informed by the literature reviewed herein.

Hardware Design and IRS Architecture

It has been shown that IRS design is an important factor to consider for optimum performance. From the resources evaluated herein, it is evident that consideration should be given to the optimum number of IRS elements, appropriate deployment of the structure, and hardware imperfections since these aspects considerably affect the EE, SE, and ergodic capacity. The best technique entails a distributed deployment pattern with elements at the BS and the users [14].

Channel Estimation

Channel estimation is vital for optimum performance in IRS-aided communication systems. Several estimation methods have been discussed herein. The LS method has been used for channel estimation in various application scenarios. According to the results shown in each source evaluated, the LS channel estimation technique is mostly applicable in relatively smaller IRS elements to reduce the channel estimation time and complexity. However, since it has been shown in [19] that relying on the LS estimates alone requires at least 8% more IRS elements, the deep learning techniques presented by [27],[28], and [29] would be more appropriate.

The On/Off method is shown to be straightforward and applicable for slowly varying channels [6], [19], [20], 20, and 21]. However, it is limited by long training times since, for an N-element IRS structure, the estimation phases are N+1. The DFT-based activation pattern proposed by [23] is the best since it results in a one-order less computational complexity.

This problem has been solved by grouping the IRS elements to reduce the training overhead, as shown in references[24]-[26]. The grouping pattern proposed by [26] outperforms the other techniques due to the distributed nature shown in the 2-D lattice array and the additional benefits derived from sparse grouping. However, this method suffers from one major disadvantage: reduced freedom concerning IRS refection since the same reflection coefficient is given to every element in a particular group, which may not always be optimum.

Machine learning approaches have reduced training time and provided more accurate channel estimates. As shown in [20] and

[27]-[34]. These approaches enable the system to learn a mapping between received signals and channel characteristics. However, they require high computational resources and are dependent on initial training data from other offline channel estimation techniques, such as LS methods, which may lead to the propagation of errors. The antenna selection approach used in [34] proves to be the best method as it significantly reduces training time by incorporating a few active elements while eliminating the need for clustering.

Focusing on the mmWave channels, several approaches have been proposed for channel estimation as described in section v. above. While [35] - [39] show significant improvements in channel estimation accuracy, [40] - [42] reveal the importance of hybrid techniques that further minimize the complexity and improve the estimation accuracy. The method proposed by [40] is the best technique since it leads to the lowest NMSE compared to the LS, OMP, and DNN-based methods.

Since the accuracy of CSI estimation remains crucial for performance improvement in SE and EE, authors in [43] - [46] present other channel estimation methods following multi-stages and scalability. Among the methods, the technique proposed by [45] shows a 10% higher spectral efficiency than LS, MMSE, and compressed sensing, making it among the best approaches. In summary, several channel estimation methods have been proposed, out of which super-resolution turns out to be the best method due to its enhanced accuracy, putting it ahead of LS, OMP, and DNN-based methods.

Optimization

The IRS's comparable benefits lie in optimizing its phase shifts, offering the desired passive beamforming. In [47]- [50], iterative optimization schemes are presented for improved performance. Although they are shown to increase the EE and SE significantly, they are limited by time constraints, especially when many iterations are needed. The scheme proposed by [50] offers the best iterative optimization, leading to a 200% increase in energy efficiency and at least 400% gains in sum rate.

Moving from iterative methods, authors in [58]-[62] use hybrid techniques that include SDR, iterative methods, and other numerical methods highlighted herein. As described in section c(ii), these hybrid methods help to solve the imitations associated with SDR and iterative methods. Out of the highlighted techniques, the scheme presented in [54] gives the most practical scenario where the secrecy rate is improved despite not having perfect CSIs of the eavesdroppers.
Machine learning techniques have emerged as the best solutions to IRS beamforming optimization as they introduce flexibility and enable the system to adapt to changing variables. In [51]-[57], several machine learning approaches are discussed. Among these, the ISL method proposed in [55] offers the best solution due to improved inference accuracy while maximizing the SINR without increasing the system's complexity. This offers better performance than the other optimization techniques presented in [63] and [64], which leads to suboptimal solutions.

Trends and Industry Applications of the IRS

Due to the IRS' reconfigurability and low power consumption, while providing full-duplex operation, it has found application in other key areas, including radar, IoT, smart manufacturing, and industry 5.0, as highlighted in [65]-[70]. The potential application of IRSs in cybertwin 6G vehicular networks has been investigated in [71] and shown to be a potential solution that can aid vehicular communications, particularly in high-traffic scenarios. However, despite these performance improvements, authors in [11] compare the IRS's performance with the relay under imperfect hardware conditions and reveal that the IRS can never outperform the full-duplex relaying system in non-ideal hardware conditions of the transmitter. Acquiring perfect transmitter hardware properties is quite challenging, implying that more research needs to be done to optimize the passive beamforming gains of the IRS without sacrificing channel estimation accuracy, energy and spectral efficiency, and time.

Another interesting industrial application that has been examined in literature is the use of IRS in power grids to relay wireless power [72]. This concept is closely related to simultaneous wireless and information power transfer that has been investigated in [66] and has been found to be vital for future communications by [73] and [74]. Similar concepts of wireless power transmission have been identified and explored by [75] and [76]. While current approaches necessitate accurate CSI estimation, analyses done by [77] and [78] show great potential for achieving wireless transfer in the future without the need for channel state information. With these potential solutions, the industry is moving to a place where IRSs can be effectively deployed on power grids to facilitate wireless power and information transmission.

The use of IRSs in sensing and monitoring is another possible industrial application that is expected to transform industrial processes significantly. Following the research by [79] - [82], it is evident that IRSs can provide not only localization but also monitoring, making it possible to achieve machine monitoring and environmental monitoring effectively and at a low-cost. Lastly, the rise of Extended Reality (XR), described in [83] - [86], is expected in future mobile communications, a trend that will be made possible by the deployment of IRSs, as shown in [87].

Open Issues

While authors have widely examined how the IRS can be optimized and applied in various wireless communication settings and in industry, little has been done towards its commercialization. Commercializing the IRS with require standardization by Standard Development Organizations (SDO), like the IEEE and 3rd Generation Partnership Project (3GPP), as noted by [88] . In addition, while current research treats the IRS-User channels as LoS, it is expected that in actual industrial implementations, this link will contain NLoS components dues to reflections, this reveals the need for more complex channel design and larger databases to characterize such channels [88] .

Further, since the number of IRS elements needs to be significantly large to outperform relay technologies, it is shown that more efficient technologies for tunability and reconfigurability are needed to balance performance, cost, and reliability [89] . Security and privacy concerns for UAV technologies have been addressed in [90]- [92] . Similarly, authors have derived technologies for interference mitigation in satellite communication [93] - [94]. However, it is noted in [95] that privacy challenges associated with IRS systems cannot be addressed by simply considering the presence of transmissions. This implies that for the IRS to be industrialized in the UAV and satellite communication systems, more research is need to mitigate the risks associated with privacy breach which could have severe consequences.

As the application of IRS in future mobile communications shows a great promise of high efficiency and low latency, the issue of handover becomes critical. Although several propositions have been offered in [96] - [99], these are formulated under the premise of an available LoS. Therefore, in NLoS, effective handover mechanisms need to be developed as highlighted in [100]. In summary, challenges associated with privacy, integration with other communication infrastructures, standardization, and handover remain critical issues that will significantly determine the industrial application of intelligent reflecting surfaces in the future.

CONCLUSIONS

In this review paper, we have presented a comprehensive assessment of the IRS, its structure and hardware requirements and open issues, channel estimation approaches, optimization methods, and various key applications in the industry. We have categorized the channel estimation and optimization techniques into several sections for easy comparison. With this paper, one can understand the benefits and challenges that remain unaddressed in the context of the IRS.

Accurate channel estimation is crucial for IRS performance optimization. Several channel estimation techniques have been addressed herein, having different outcomes and challenges. The LS method is the most commonly used in CSI acquisition, while several approaches such as On/Off, element-grouping, machine learning, and compressive channel estimation are applied. While the On/Off method is straightforward, it is limited by high overhead, making it unsuitable, especially when the IRS has many elements. Machine learning techniques are the most suitable as they provide reliability and flexibility.

The main contribution of the IRS is in optimizing key parameters such as the achievable rate, energy efficiency, spectral efficiency, sum rate, and power minimization. All these parameters are optimized by working on the phase shifts of the IRS to ensure constructive or destructive passive beamforming. While the iterative methods are easy to implement and can significantly improve the system's achievable rates, the ISL approach provides a better solution due to its unmatched role in maximizing the SINR without increasing the system's complexity.

The IRS's reconfigurability has made it an attractive solution to many communication system challenges. In addition to improving secrecy rates, reducing transmission losses, and offering a higher system throughput, it has been applied in radar, IoT, smart manufacturing, and industry 5.0. As the IRS continues to gain application in these areas, it is important to consider the challenges highlighted herein including secrecy, handover mechanisms, and standardization. More research is needed on overcoming the challenges highlighted herein to ensure optimal IRS performance is achieved without sacrificing the channel estimation accuracy and system reliability.

ACKNOWLEDGMENT

The authors thank the Dedan Kimathi University of Technology for this research's financial and material support

REFERENCES

[1] A. Gashtasbi, M. M. Silva, and R. Dinis, "An Overview of Intelligent Reflecting Surfaces for Future Wireless Systems," in *2022 13th International Symposium on Communication Systems, Networks, and Digital Signal Processing, CSNDSP 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 314–319, doi: 10.1109/CSNDSP54353.2022.9907933.

[2] D. Pérez-Adán, Ó. Fresnedo, J. P. Gonzalez-Coma, and L. Castedo, "Intelligent reflective surfaces for wireless networks: An overview of applications, approached issues, and open problems," *Electron. Switz.*, vol. 10, no. 19, 2021, doi: 10.3390/electronics10192345.

[3] S. Hassouna *et al.*, "A survey on reconfigurable intelligent surfaces: Wireless communication perspective," *IET Commun.*, vol. 17, no. 5, pp. 497–537, Mar. 2023, doi: 10.1049/cmu2.12571.

[4] F. C. Okogbaa *et al.*, "Design and Application of Intelligent Reflecting Surface (IRS) for Beyond 5G Wireless Networks: A Review," *Sensors*, vol. 22, no. 7, Apr. 2022, doi: 10.3390/s22072436.

[5] I. Alamzadeh, G. C. Alexandropoulos, N. Shlezinger, and M. F. Imani, "A reconfigurable intelligent surface with integrated sensing capability," *Sci. Rep.*, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-99722-x.

[6] Y.-C. Liang, R. Long, Q. Zhang, J. Chen, H. V. Cheng, and H. Guo, "Large intelligent surface/antennas (LISA): Making reflective radios smart," *J. Commun. Inf. Netw.*, vol. 4, no. 2, pp. 40–50, 2019.

[7] Z.-Q. He and X. Yuan, "Cascaded channel estimation for large intelligent metasurface assisted massive MIMO," *IEEE Wirel. Commun. Lett.*, vol. 9, no. 2, pp. 210–214, 2019.

[8] S. Gong *et al.*, "Toward Smart Wireless Communications via Intelligent Reflecting Surfaces: A Contemporary Survey," *IEEE Commun. Surv. Tutor.*, vol. 22, no. 4, 2020, doi: 10.1109/COMST.2020.3004197.

[9] J. Wu and B. Shim, "Power minimization of intelligent reflecting surface-aided uplink IoT networks," in *IEEE Wireless Communications and Networking Conference, WCNC*, Institute of Electrical and Electronics Engineers Inc., 2021, doi: 10.1109/WCNC49053.2021.9417397.

[10] X. Peng, X. Hu, and C. Zhong, "Distributed Intelligent Reflecting Surfaces-Aided Communication System: Analysis and Design," *IEEE Trans. Green Commun. Netw.*, vol. 6, no. 4, pp. 1932–1944, Dec. 2022, doi: 10.1109/TGCN.2022.3186543.

[11] M. H. N. Shaikh, V. A. Bohara, A. Srivastava, and G. Ghatak, "Intelligent Reflecting Surfaces Versus Full-Duplex Relaying: Performance Comparison for Non-Ideal Transmitter Case," in *IEEE International Symposium on Personal, Indoor, and Mobile Radio Communications, PIMRC*, Institute of Electrical and Electronics Engineers

Inc., Sep. 2021, pp. 513–518. doi: 10.1109/PIMRC50174.2021.9569598.

[12] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, "Intelligent Reflecting Surface Aided Wireless Communications: A Tutorial." arXiv, Jul. 06, 2020. Accessed: Jun. 11, 2023. [Online]. Available: http://arxiv.org/abs/2007.02759

[13] X. Ma, Z. Chen, L. Yan, C. Han, and Q. Wen, "Joint hardware design and capacity analysis for intelligent reflecting surface enabled terahertz MIMO communications," *ArXiv Prepr. ArXiv201206993*, 2020.

[14] C. You, B. Zheng, W. Mei, and R. Zhang, "How to Deploy Intelligent Reflecting Surfaces in Wireless Network: BS-side, User-side, or Both Sides?," Dec. 2020, [Online]. Available: http://arxiv.org/abs/2012.03403

[15] A. A. Boulogeorgos and A. Alexiou, "How much do hardware imperfections affect the performance of reconfigurable intelligent surface-assisted systems?," *IEEE Open J. Commun. Soc.*, vol. 1, pp. 1185–1195, 2020.

[16] A. M. Tota Khel and K. A. Hamdi, "Effects of Hardware Impairments on IRS-Enabled MISO Wireless Communication Systems," *IEEE Commun. Lett.*, vol. 26, no. 2, 2022, doi: 10.1109/LCOMM.2021.3134815.

[17] M. H. N. Shaikh, V. A. Bohara, A. Srivastava, and G. Ghatak, "Performance Analysis of Intelligent Reflecting Surface-Assisted Wireless System with Non-Ideal Transceiver," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 671–686, 2021, doi: 10.1109/OJCOMS.2021.3068866.

[18] M. H. N. Shaikh, V. A. Bohara, A. Srivastava, and G. Ghatak, "A Downlink RIS-Aided NOMA System With Hardware Impairments: Performance Characterization and Analysis," *IEEE Open J. Signal Process.*, vol. 3, pp. 288–305, 2022, doi: 10.1109/OJSP.2022.3194416.

[19] D. Mishra and H. Johansson, "Channel estimation and low-complexity beamforming design for passive intelligent surface assisted MISO wireless energy transfer," presented at the ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2019, pp. 4659–4663.

[20] A. M. Elbir, A. Papazafeiropoulos, P. Kourtessis, and S. Chatzinotas, "Deep channel learning for large intelligent surfaces aided mm-wave massive MIMO systems," *IEEE Wirel. Commun. Lett.*, vol. 9, no. 9, pp. 1447–1451, 2020.

[21] Y. Yang, B. Zheng, S. Zhang, and R. Zhang, "Intelligent reflecting surface meets OFDM: Protocol design and rate maximization," *IEEE Trans. Commun.*, vol. 68, no. 7, pp. 4522–4535, 2020.

[22] H. Alwazani, A. Kammoun, A. Chaaban, M. Debbah, and M.-S. Alouini, "Intelligent reflecting surface-assisted multiuser MISO communication: Channel estimation and beamforming design," *IEEE Open J. Commun. Soc.*, vol. 1, pp. 661–680, 2020.

[23] T. L. Jensen and E. De Carvalho, "An optimal channel estimation scheme for intelligent reflecting surfaces based on a minimum variance unbiased estimator," presented at the ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2020, pp. 5000–5004.

[24] B. Zheng and R. Zhang, "Intelligent Reflecting Surface-Enhanced OFDM: Channel Estimation and Reflection Optimization," Sep. 2019, doi: 10.1109/LWC.2019.2961357.

[25] C. You, B. Zheng, and R. Zhang, "Channel Estimation and Passive Beamforming for Intelligent Reflecting Surface: Discrete Phase Shift and Progressive Refinement," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 11, pp. 2604–2620, Nov. 2020, doi: 10.1109/JSAC.2020.3007056.

[26] Y. Lin, S. Jin, M. Matthaiou, and X. You, "Channel Estimation and User Localization for IRS-Assisted MIMO-OFDM Systems," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 4, pp. 2320–2335, Apr. 2022, doi: 10.1109/TWC.2021.3111176.

[27] W. Chen, Z. Chen, and X. Ma, "Channel estimation for intelligent reflecting surface aided multiuser MISO terahertz system," *Terahertz Sci. Technol.*, vol. 13, no. 2, pp. 51–60, 2020.

[28] C. Liu, X. Liu, D. W. K. Ng, and J. Yuan, "Deep residual network empowered channel estimation for IRS-assisted multiuser communication systems," presented at the ICC 2021-IEEE International Conference on Communications, IEEE, 2021, pp. 1–7.

[29] Z. Zhang, T. Ji, H. Shi, C. Li, Y. Huang, and L. Yang, "A Self-Supervised Learning-Based Channel Estimation for IRS-Aided Communication Without Ground Truth," *IEEE Trans. Wirel. Commun.*, 2023.

[30] Z. Li, Z. Chen, X. Ma, and W. Chen, "Channel Estimation for Intelligent Reflecting Surface Enabled Terahertz MIMO Systems: A Deep Learning Perspective."

[31] Y. Liu, I. Al-Nahhal, O. A. Dobre, and F. Wang, "Deep-Learning Channel Estimation for IRS-Assisted Integrated Sensing and Communication System," *IEEE Trans. Veh. Technol.*, May 2022, doi: 10.1109/TVT.2022.3231727.

[32] S. Liu, M. Lei, and M. J. Zhao, "Deep Learning Based Channel Estimation for Intelligent Reflecting Surface Aided MISO-OFDM Systems," in *IEEE Vehicular Technology Conference*, Institute of Electrical and Electronics Engineers Inc., Nov. 2020. doi: 10.1109/VTC2020-Fall49728.2020.9348697.

[33] G. López-Lanuza, K. Chen-Hu, and A. G. Armada, "Deep Learning-Based Optimization for Reconfigurable Intelligent Surface-Assisted Communications," in *2022 IEEE Wireless Communications and Networking Conference (WCNC)*, Apr. 2022, pp. 764–769. doi: 10.1109/WCNC51071.2022.9771876.

[34] S. Zhang, S. Zhang, F. Gao, J. Ma, and O. A. Dobre, "Deep Learning Optimized Sparse Antenna Activation for Reconfigurable Intelligent Surface Assisted Communication," *IEEE Trans. Commun.*, vol. 69, no. 10, pp. 6691–6705, Oct. 2021, doi: 10.1109/TCOMM.2021.3097726.

[35] P. Wang, J. Fang, H. Duan, and H. Li, "Compressed Channel Estimation and Joint Beamforming for Intelligent Reflecting Surface-Assisted Millimeter Wave Systems," Nov. 2019, doi: 10.1109/LSP.2020.2998357.

[36] Z. Wan, Z. Gao, and M.-S. Alouini, "Broadband channel estimation for intelligent reflecting surface aided mmWave massive MIMO systems," presented at the ICC 2020-2020 IEEE International Conference on Communications (ICC), IEEE, 2020, pp. 1–6.

[37] V. K. Gorty and A. Chattopadhyay, "Channel estimation for double IRS assisted communication for a mobile user," 2023.

[38] A. Taha, M. Alrabeiah, and A. Alkhateeb, "Enabling Large Intelligent Surfaces with Compressive Sensing and Deep Learning," Apr. 2019, [Online]. Available: http://arxiv.org/abs/1904.10136

[39] X. Ma *et al.*, "Joint Channel Estimation and Data Rate Maximization for Intelligent Reflecting Surface Assisted Terahertz MIMO Communication Systems," *IEEE Access*, vol. 8, pp. 99565–99581, 2020, doi: 10.1109/ACCESS.2020.2994100.

[40] Y. Wang, H. Lu, and H. Sun, "Channel Estimation in IRS-Enhanced mmWave System with Super-Resolution Network," *IEEE Commun. Lett.*, vol. 25, no. 8, pp. 2599–2603, Aug. 2021, doi: 10.1109/LCOMM.2021.3079322.

[41] Z. Chen, J. Tang, X. Y. Zhang, D. K. C. So, S. Jin, and K. K. Wong, "Hybrid Evolutionary-Based Sparse Channel Estimation for IRS-Assisted mmWave MIMO Systems," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 3, pp. 1586–1601, Mar. 2022, doi: 10.1109/TWC.2021.3105405.

[42] S. Ma, W. Shen, J. An, and L. Hanzo, “Wideband Channel Estimation for IRS-Aided Systems in the Face of Beam Squint,” *IEEE Trans. Wirel. Commun.*, vol. 20, no. 10, pp. 6240–6253, Oct. 2021, doi: 10.1109/TWC.2021.3072694.

[43] Z. Wang, L. Liu, and S. Cui, “Channel Estimation for Intelligent Reflecting Surface Assisted Multiuser Communications: Framework, Algorithms, and Analysis,” *IEEE Trans. Wirel. Commun.*, vol. 19, no. 10, pp. 6607–6620, Oct. 2020, doi: 10.1109/TWC.2020.3004330.

[44] Y. Wei, M. M. Zhao, M. J. Zhao, and Y. Cai, “Channel Estimation for IRS-Aided Multiuser Communications With Reduced Error Propagation,” *IEEE Trans. Wirel. Commun.*, vol. 21, no. 4, pp. 2725–2741, Apr. 2022, doi: 10.1109/TWC.2021.3115161.

[45] C. Peng, H. Deng, H. Xiao, Y. Qian, W. Zhang, and Y. Zhang, “Two-Stage Channel Estimation for Semi-Passive RIS-Assisted Millimeter Wave Systems,” *Sensors*, vol. 22, no. 15, 2022, doi: 10.3390/s22155908.

[46] J. An, Q. Wu, and C. Yuen, “Scalable Channel Estimation and Reflection Optimization for Reconfigurable Intelligent Surface-Enhanced OFDM Systems,” *IEEE Wirel. Commun. Lett.*, vol. 11, no. 4, pp. 796–800, Apr. 2022, doi: 10.1109/LWC.2022.3145885.

[47] X. Xie, F. Fang, and Z. Ding, “Joint Optimization of Beamforming, Phase-Shifting and Power Allocation in a Multi-Cluster IRS-NOMA Network,” *IEEE Trans. Veh. Technol.*, vol. 70, no. 8, pp. 7705–7717, Aug. 2021, doi: 10.1109/TVT.2021.3090255.

[48] Q. Wu and R. Zhang, “Beamforming Optimization for Wireless Network Aided by Intelligent Reflecting Surface With Discrete Phase Shifts,” *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1838–1851, Mar. 2020, doi: 10.1109/TCOMM.2019.2958916.

[49] M. Shi, X. Li, T. Fan, J. Liu, and S. Lv, “Multiuser beamforming optimization for IRS-aided systems with discrete phase shifts,” *IET Commun.*, vol. 16, no. 13, pp. 1523–1530, 2022.

[50] D. Zhao, H. Lu, Y. Wang, and H. Sun, “Joint passive beamforming and user association optimization for IRS-assisted mmWave systems,” presented at the GLOBECOM 2020-2020 IEEE Global Communications Conference, IEEE, 2020, pp. 1–6.

[51] H. Yang *et al.*, “Deep Reinforcement Learning Based Intelligent Reflecting Surface for Secure Wireless Communications,” in *2020 IEEE Global Communications Conference, GLOBECOM 2020 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., Dec. 2020. doi: 10.1109/GLOBECOM42002.2020.9322615.

[52] X. Guan, Q. Wu, and R. Zhang, “Joint Power Control and Passive Beamforming in IRS-Assisted Spectrum Sharing,” *IEEE Commun. Lett.*, vol. 24, no. 7, pp. 1553–1557, Jul. 2020, doi: 10.1109/LCOMM.2020.2979709.

[53] M. Cui, G. Zhang, and R. Zhang, “Secure wireless communication via intelligent reflecting surface,” *IEEE Wirel. Commun. Lett.*, vol. 8, no. 5, pp. 1410–1414, Oct. 2019, doi: 10.1109/LWC.2019.2919685.

[54] H.-M. Wang, J. Bai, and L. Dong, “Intelligent reflecting surfaces assisted secure transmission without eavesdropper’s CSI,” *IEEE Signal Process. Lett.*, vol. 27, pp. 1300–1304, 2020.

[55] B. Yang, X. Cao, C. Huang, C. Yuen, L. Qian, and M. Di Renzo, “Intelligent spectrum learning for wireless networks with reconfigurable intelligent surfaces,” *IEEE Trans. Veh. Technol.*, vol. 70, no. 4, pp. 3920–3925, 2021.

[56] T. Jiang, H. V. Cheng, and W. Yu, “Learning to Reflect and to Beamform for Intelligent Reflecting Surface with Implicit Channel Estimation,” Sep. 2020, [Online]. Available: http://arxiv.org/abs/2009.14404

[57] J. Gao, C. Zhong, X. Chen, H. Lin, and Z. Zhang, “Unsupervised learning for passive beamforming,” *Ieee Commun. Lett.*, vol. 24, no. 5, pp. 1052–1056, 2020.

[58] S. Zhang and R. Zhang, “On the Capacity of Intelligent Reflecting Surface Aided MIMO Communication,” in *2020 IEEE International Symposium on Information Theory (ISIT)*, Jun. 2020, pp. 2977–2982. doi: 10.1109/ISIT44484.2020.9174375.

[59] C. He and J. Xiao, “Joint Optimization in Intelligent Reflecting Surface-Aided UAV Communication for Multiaccess Edge Computing,” *Wirel. Commun. Mob. Comput.*, vol. 2022, p. 5415562, Mar. 2022, doi: 10.1155/2022/5415562.

[60] X. Yu, D. Xu, and R. Schober, “MISO wireless communication systems via intelligent reflecting surfaces,” presented at the 2019 IEEE/CIC International Conference on Communications in China (ICCC), IEEE, 2019, pp. 735–740.

[61] J. J. L. Quispe, T. F. Maciel, Y. C. B. Silva, A. Klein, and J. Beamforming, “Selection for Energy-Efficient Communications via Aerial-RIS,” 2021.

[62] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” *IEEE Trans. Wirel. Commun.*, vol. 18, no. 11, pp. 5394–5409, 2019.

[63] Y. Han, W. Tang, S. Jin, C. -K. Wen, and X. Ma, “Large Intelligent Surface-Assisted Wireless Communication Exploiting Statistical CSI,” *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 8238–8242, Aug. 2019, doi: 10.1109/TVT.2019.2923997.

[64] M. M. Zhao, Q. Wu, M. J. Zhao, and R. Zhang, “IRS-Aided Wireless Communication with Imperfect CSI: Is Amplitude Control Helpful or Not?,” in *2020 IEEE Global Communications Conference, GLOBECOM 2020 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., Dec. 2020. doi: 10.1109/GLOBECOM42002.2020.9348255.

[65] K. K. Nguyen, A. Masaracchia, V. Sharma, H. V. Poor, and T. Q. Duong, “RIS-assisted UAV communications for IoT with wireless power transfer using deep reinforcement learning,” *IEEE J. Sel. Top. Signal Process.*, vol. 16, no. 5, pp. 1086–1096, 2022.

[66] C. Pan *et al.*, “Intelligent reflecting surface aided MIMO broadcasting for simultaneous wireless information and power transfer,” *IEEE J. Sel. Areas Commun.*, vol. 38, no. 8, pp. 1719–1734, 2020.

[67] W. Wu *et al.*, “IRS-Enhanced Energy Detection for Spectrum Sensing in Cognitive Radio Networks,” *IEEE Wirel. Commun. Lett.*, vol. 10, no. 10, pp. 2254–2258, Oct. 2021, doi: 10.1109/LWC.2021.3099121.

[68] Md. Noor-A-Rahim *et al.*, “Towards Industry 5.0: Intelligent Reflecting Surface (IRS) in Smart Manufacturing,” Jan. 2022, [Online]. Available: http://arxiv.org/abs/2201.02214

[69] Z. Esmaeilbeig, K. V. Mishra, and M. Soltanalian, “IRS-aided radar: Enhanced target parameter estimation via intelligent reflecting surfaces,” presented at the 2022 IEEE 12th Sensor Array and Multichannel Signal Processing Workshop (SAM), IEEE, 2022, pp. 286–290.

[70] X. Shao, C. You, W. Ma, X. Chen, and R. Zhang, “Target Sensing with Intelligent Reflecting Surface: Architecture and Performance,” Jan. 2022, [Online]. Available: http://arxiv.org/abs/2201.09091

[71] M. A. Javed, T. N. Nguyen, J. Mirza, J. Ahmed, and B. Ali, “Reliable Communications for Cybertwin-Driven 6G IoVs Using Intelligent Reflecting Surfaces,” *IEEE Trans Industr Inform*, vol. 18, no. 11, pp. 7454–7462, 2022, doi: 10.1109/TII.2022.3151773.

[72] H. Li, S. Shen, M. Nerini, and B. Clerckx, “Reconfigurable Intelligent Surfaces 2.0: Beyond Diagonal Phase Shift Matrices,” *IEEE Communications Magazine*, vol. 62, no. 3, pp. 102–108, 2024, doi: 10.1109/MCOM.001.2300019.

[73] H. Ren, Z. Chen, G. Hu, Z. Peng, C. Pan, and J. Wang, “Transmission design for active RIS-aided simultaneous wireless information and power transfer,” *IEEE Wireless Communications Letters*, vol. 12, no. 4, pp. 600–604, 2023.

[74] F.-B. Ueng, H.-F. Wang, and H.-W. Shen, “Reconfigurable Intelligent Surfaces Assisted Simultaneous Wireless Information and Power Transfer,” *Wirel Pers Commun*, vol. 133, no. 3, pp. 1963–1985, 2023.

[75] C. Kumar and S. Kashyap, “On the power transfer efficiency and feasibility of wireless energy transfer using double IRS,” *IEEE Trans Veh Technol*, 2023.

[76] Q. Yue, J. Hu, K. Yang, and Q. Yu, “Joint transceiving and reflecting design for intelligent reflecting surface aided wireless power transfer,” *IEEE Trans Wirel Commun*, 2023.

[77] M. Fu, W. Mei, and R. Zhang, “Multi-active/passive-IRS enabled wireless information and power transfer: Active IRS deployment and performance analysis,” *IEEE Communications Letters*, 2023.

[78] C. Luo, J. Hu, L. Xiang, K. Yang, and K.-K. Wong, “Massive Wireless Energy Transfer without Channel State Information via Imperfect Intelligent Reflecting Surfaces,” *IEEE Trans Veh Technol*, 2024.

[79] M. Hwang *et al.*, “Environment-Adaptive Reconfigurable Intelligent Surface for Dynamic Channel Conditions,” *IEEE Communications Magazine*, vol. 61, no. 11, pp. 152–158, 2023, doi: 10.1109/MCOM.001.2300314.

[80] S. P. Chepuri, N. Shlezinger, F. Liu, G. C. Alexandropoulos, S. Buzzi, and Y. C. Eldar, “Integrated sensing and communications with reconfigurable intelligent surfaces: From signal modeling to processing,” *IEEE Signal Process Mag*, vol. 40, no. 6, pp. 41–62, 2023.

[81] R. Liu, M. Li, H. Luo, Q. Liu, and A. L. Swindlehurst, “Integrated sensing and communication with reconfigurable intelligent surfaces: Opportunities, applications, and future directions,” *IEEE Wirel Commun*, vol. 30, no. 1, pp. 50–57, 2023.

[82] Z. Zhang, T. Jiang, and W. Yu, “Localization with Reconfigurable Intelligent Surface: An Active Sensing Approach,” *IEEE Trans Wirel Commun*, 2023.

[83] A. Alhakamy, “Extended Reality (XR) Toward Building Immersive Solutions: The Key to Unlocking Industry 4.0,” *ACM Comput Surv*.

[84] B. K. Burian *et al.*, “Using extended reality (XR) for medical training and real-time clinical support during deep space missions,” *Appl Ergon*, vol. 106, p. 103902, 2023.

[85] J. Ratcliffe, F. Soave, N. Bryan-Kinns, L. Tokarchuk, and I. Farkhatdinov, “Extended reality (XR) remote research: A survey of drawbacks and opportunities.” *Proceedings of the 2021 CHI conference on human factors in computing systems*. 2021.

[86] E. Anastasiou, A. T. Balafoutis, and S. Fountas, “Applications of extended reality (XR) in agriculture, livestock farming, and aquaculture: A review,” *Smart Agricultural Technology*, vol. 3, p. 100105, 2023.

[87] T. Ma, Y. Xiao, X. Lei, and M. Xiao, “Integrated Sensing and Communication for Wireless Extended Reality (XR) With Reconfigurable Intelligent Surface,” *IEEE J Sel Top Signal Process*, vol. 17, no. 5, pp. 980–994, 2023, doi: 10.1109/JSTSP.2023.3304846.

[88] R. Liu, Q. Wu, M. Di Renzo, and Y. Yuan, “A Path to Smart Radio Environments: An Industrial Viewpoint on Reconfigurable Intelligent Surfaces,” *IEEE Wirel Commun*, vol. 29, no. 1, pp. 202–208, 2022, doi: 10.1109/MWC.111.2100258.

[89] R. Flamini *et al.*, “Toward a Heterogeneous Smart Electromagnetic Environment for Millimeter-Wave Communications: An Industrial Viewpoint,” *IEEE Trans Antennas Propag*, vol. 70, no. 10, pp. 8898–8910, 2022, doi: 10.1109/TAP.2022.3151978.

[90] S. Li, B. Duo, M. D. Renzo, M. Tao, and X. Yuan, “Robust Secure UAV Communications With the Aid of Reconfigurable Intelligent Surfaces,” *IEEE Trans Wirel Commun*, vol. 20, no. 10, pp. 6402–6417, 2021, doi: 10.1109/TWC.2021.3073746.

[91] S. Fang, G. Chen, and Y. Li, “Joint Optimization for Secure Intelligent Reflecting Surface Assisted UAV Networks,” *IEEE Wireless Communications Letters*, vol. 10, no. 2, pp. 276–280, 2021, doi: 10.1109/LWC.2020.3027969.

[92] W. Wang, H. Tian, W. Ni, and M. Hua, “Intelligent Reflecting Surface Aided Secure UAV Communications,” *ArXiv*, vol. abs/2011.04339, 2020, [Online]. Available: https://api.semanticscholar.org/CorpusID:226282490

[93] S. Xu, J. Liu, T. K. Rodrigues, and N. Kato, “Envisioning Intelligent Reflecting Surface Empowered Space-Air-Ground Integrated Network,” *IEEE Netw*, vol. 35, no. 6, pp. 225–232, 2021, doi: 10.1109/MNET.011.2100007.

[94] Q. Ngo, T. Khoa, A. Mahmood, and W. Xiang, *Physical Layer Security in IRS-Assisted Cache-Enabled Hybrid Satellite-Terrestrial Networks*. 2022. doi: 10.36227/techrxiv.20224296.

[95] F. Naeem, M. Ali, G. Kaddoum, C. Huang, and C. Yuen, “Security and Privacy for Reconfigurable Intelligent Surface in 6G: A Review of Prospective Applications and Challenges,” *IEEE Open Journal of the Communications Society*, vol. 4, pp. 1196–1217, 2023, doi: 10.1109/OJCOMS.2023.3273507.

[96] H. Zhang and H. Wei, “Discrete-Time Modeling and Handover Analysis of Intelligent Reflecting Surface-Assisted Networks,” *arXiv preprint arXiv:2403.07323*, 2024.

[97] H. Zhang and H. Wei, “Analysis of Intelligent Reflecting Surface-Enhanced Mobility Through a Line-of-Sight State Transition Model,” *arXiv preprint arXiv:2403.07337*, 2024.

[98] K. W. S. Palitharathna, A. M. Vegni, P. D. Diamantoulakis, H. A. Suraweera, and I. Krikidis, “Handover Management through Reconfigurable

Intelligent Surfaces for VLC under Blockage Conditions," *arXiv preprint arXiv:2402.16873*, 2024.

[99] O. S. Faragallah, H. S. El-Sayed, and M. G. El-Mashed, "High mobility transmission system under intelligent reflecting surface," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 7, p. e4495, 2022.

[100] S. Basharat, M. Khan, M. Iqbal, U. S. Hashmi, S. A. R. Zaidi, and I. Robertson, "Exploring reconfigurable intelligent surfaces for 6G: State-of-the-art and the road ahead," *IET Communications*, vol. 16, no. 13, pp. 1458–1474, 2022.