Effect of Adaptive Intelligent Reflective Surfaces on SINR in a Wireless Communication System

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***Abstract*—It has been determined that Intelligent Reflecting Surfaces (IRS) are a revolutionary technology that can create a smart, optimizable environment for wireless communication. This work examines an adaptive IRS-assisted communication system that uses multi-hop signal reflection to help a Base Station (BS) communication. A multi-hop cascaded Line-of-Sight (LOS) link between the Base Station (BS) and the user is created by employing LOS link between neighboring IRSs. A group of IRSs are chosen to reflect the BS's signal in turn, increasing the received signal strength at the user. The work presents a closed-form solutions for the best active and cooperative passive beamforming at the BS and particular IRSs, respectively, in order to improve channel communication. Bit Error Rate (BER) and Signal to Interference Plus Noise Ratio (SINR) is calculated considering different number of IRSs and base stations. This, should uncover a key issue between minimizing the multi-reflection path loss and maximizing the multiplicative passive beamforming gain in the ideal beam routing design. The obtained results through simulation, showed an increase in SINR and reduction in BER as a function of increasing transmitter power, reflection coefficient, and number of intelligent reflecting surfaces. Mathematical models are also established relating transmitter power to both reflection coefficient and number of reflecting surfaces.**

***Keywords*—intelligent reflecting surface, beamforming, beam routing, data transmission, communication, Signal to Interference Plus Noise Ratio (SINR), Bit Error Rate (BER)**

I. INTRODUCTION

The method known as intelligent reflecting surface, or IRS, has shown great promise for wireless networks. IRS greatly improves the wireless signal transmission rate and reliability by allowing for variable wireless channel control and construction through the dynamic tuning of the reflection amplitudes and phase shifts of a large number of passive devices [1–4].

Although there is a wealth of literature on the design and optimization of various IRS-assisted wireless systems, previous research has primarily concentrated on improving wireless links with single signal reflection only by one or more IRSs. This may not be enough to increase the wireless link capacity in certain challenging propagation conditions, such as an indoor environment with dense blockages or obstructions. Using two or more IRSs to support each wireless link and collaboratively utilizing their single as well as multiple signal in addition to several signal reflections across them [5–8].

By adjusting signal reflections, the Reconfigurable Intelligent Surface (RIS), also known as the Intelligent Reflecting Surface (IRS), is a newly developed wireless network technology that promises to enhance wireless environments [9–11]. Due to its significantly lower cost and energy consumption, IRS can offer a substitute for small base-stations and relays for improving throughput, reducing Bit Error Rate (BER), and enhancing Signal to Interference Plus Noise Ratio (SINR). This leads to better coverage, and more reliable connection in upcoming industrial wireless networks. Early research focused on a single IRS, but multi-IRS cooperation is becoming more and more common [12–15].

Channel characterization is mainly possible in some simple settings, such as when there are two IRSs or when the multi-hop reflected channels are entirely ignored, due to the exponential increase in the number of IRSs.

A number of studies, such as the two-timescale optimization and deep learning methods, focus on reducing the overhead and computational complexity associated with channel characterization in IRS systems [16, 17].

Intelligent Reflecting Surfaces (IRS) [18, 19] and their various equivalents, such as Reconfigurable Intelligent Surfaces (RIS) [20–22], have gained popularity recently as a promising method for proactively controlling the radio propagation environment through intelligent signal reflection, greatly improving wireless communication performance. In particular, IRS is a digitally controlled meta-surface made up of several passive reflecting components, each of which has the ability to independently alter the incident signal's phase and/or amplitude [23–25]. When IRSs are placed correctly in wireless networks, the reflecting elements of all IRSs can be collaboratively tuned to maximize the throughput of wireless communications, allowing the wireless channels to be dynamically modified.

The IRS or RIS method differs significantly from conventional wireless systems, which can only adjust or compensate for the fading of the wireless channel while the channels themselves remain mainly random and uncontrollable. IRS can be used to improve the multi-antenna/multiuser channel condition, adjust wireless channels distributions, and avoid signal obstruction in

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wireless channels [26, 27]. Moreover, IRS significantly improves spectral efficiency over active relays since it just uses passive reflection to function in full-duplex mode, eliminating signal amplification and processing noise [28].

Intelligent Reflecting Surfaces (IRSs) have gained attention in recent years as a potential remedy for mm-wave 5G network performance issues and coverage issues [29–30]. A planar array of reflecting cells that can be independently constructed to regulate the amplitude and/or phase of the reflected wave makes up an IRS. Since the IRS only reflects incident signals without actively processing them, it can be widely installed at a lower cost, with minimal environmental impact (since it is fixed on walls and its flat surface means that it uses no energy) and minimal energy consumption [31, 32].

In this research, simulation and analysis of parameters affecting communication in an environment system with Intelligent Reflecting Surfaces (IRSs) and Wireless Nodes (WNs). The analyzed system makes use of adaptive beamforming and reflection control techniques. The implemented closed loop control, updates the patterns of the IRSs repeatedly through a feedback loop, and evaluates the system's performance in terms of Bit Error Rate (BER), and signal-to-interference-plus-noise ratio. Analysis of effect of transmitter power, reflection coefficient and number of IRSs provides a design approach and representation of the adaptive process that can be used to achieve optimum communication.

The rest of this paper is divided as follows: Related Works, Methodology, Results and Discussion, Conclusions, References.

II. Related Works

Intelligent Reflecting Surfaces (IRS) improve wireless device performance in propagation scenarios, according to a recent study [33]. The study looks on cognitive radio's spectrum sensing skills in situations where wireless propagation is aided by IRS. Monte Carlo simulation was employed in the study to confirm IRS's efficacy.

In addition to highlighting the significance of communication channel fading and the use of SNR as a calibrating parameter, researchers in Ref. [34] endorsed the work done by Kumar and Singh [33]. In the field of cognitive radio networks, they strive to address communication problems between primary and secondary users. According to the experts, new research indicates that Intelligent Reflecting Surfaces (IRS) may be utilized to control the wireless device's propagation channel. IRS alters the channel, which impacts the cognitive radio networks' spectrum sensing. Ref. [35, 36] focused on energy harvesting and confirming the results of Ref. [34], the work in Ref. [34] demonstrates the efficacy of employing IRS.

The reconfigurable intelligent surface devices were examined by researchers in Ref. [37]. In cognitive radio-based dynamic spectrum management, they believed that spectrum sensing played the most significant role in the cognitive cycle. According to the work in Ref. [37], reconfigurable smart surfaces have a lot of potential for providing smart radio environments because they enhance spectrum management and signal coverage. In order to alleviate the rising demand for wideband services and the dispersion of spectrum resources, work in Ref. [38] further examined the number of elements required to provide optimal signal detection, supporting the assumptions in Kumar *et al.* [37]. The lack of readily available spectrum may be addressed via cognitive radio, as the researchers in Ref. [39] recognized.

Intelligent Reflecting Surfaces (IRS) can improve wireless devices' performance in a variety of signal propagation scenarios, according to research backed by [39]. The study in [39] used a statistical model in order to assess cognitive radio's spectrum-sensing capabilities in wireless environments enhanced by IRS technology.

SINR and BER are used as main parameters in the work simulation to assess the performance of IRS systems, as stated by Alhamad and Boujemaa [40]. The researchers in [40] carried out work to enable optimized design and application of intelligent reflecting surfaces with adaptive transmit power. There work covered different power levels, with the conclusion that an increase in throughput is realized as adaptive power is used with general energy stability.

There work is supported by researchers in Ref. [41], where they used SINR and BER as the main factors to characterize intelligent reflecting surfaces and their effect on interference. The authors investigated through simulation the interference problem. They concluded that by creating and resolving an optimization problem to set up the phase shift parameters of 100 IRS elements for the maximum received Signal-to-Interference-Plus-Noise Ratio (SINR), adaptive passive beamforming is accomplished. Bit Error Rate (BER) curves show five times increased reliability across multiple Signal-to-Noise Ratio (SNR) regimes. Their MATLAB simulations show enormous performance gains from implementing an IRS. Radiation pattern plots show a directed beamforming gain enhancement. The outcomes unequivocally confirm that IRS-based paradigms are beneficial for managing interference in developing networks in a dynamic and effective manner.

Practical design considerations are carried out by researchers in Ref. [42] to enable optimized implementation. The study expanded on the body of research showing the significance of IRS in wireless communication network design. The authors looked at IRS applications, such as, An Unmanned Aerial Vehicle (UAV) mounting, vehicular communications, among others. They concluded that IRS has the ability to support the cooperative optimization of the transmitter, receiver, and propagation channel, and it is a crucial technology in creating a smart radio environment.

The work in Ref. [42] is supported by the work presented by researchers in Ref. [43]. The researchers concluded that, it is evident that additional study and technological development are required to resolve a number of outstanding problems in order to eventually move toward a genuine consolidation of IRS-assisted communication systems. IRS-aided systems are therefore anticipated to yield greater performance gains over the current state-of-the-art approaches by addressing a large number of practical issues regarding mobility, scheduling, and coding, even though notable performance improvement can be realized.

Effect and requirements of hardware for practical implementation of IRS systems is discussed by researchers in Ref. [44]. They considered the negative effects of in-phase and quadrature-phase imbalance in order to assess the reduced performance of realistic RIS-assisted systems. The authors used closed-form formulations for outage probability and ergodic capacity to describe the primary system performance parameter. They assessed how well the system performs when the number of meta-surfaces, channel characteristics, and Signal-to-Noise Ratio (SNR) are taken into account. Their results show that the RIS scheme under consideration improves outage probability significantly at high SNR and high meta-surface number at both dual-hop and single-hop.

Effect of using more than one IRS in design and practical applications, is discussed by researchers in Ref. [45]. In the study, they present a basic overview of multi-IRS assisted wireless networks, which, under some circumstances, are demonstrated to offer potential performance advantages over the traditional single-IRS assisted system. These networks use two or more IRSs to help each wireless link. In order to achieve this, the researchers first introduce the overall system paradigm for a wireless network with multi-IRS assistance. Then, they examine the most recent findings on the double- and multi-IRS-aided systems, respectively, emphasizing open problems and crucial avenues for further study while tackling their novel and distinct design challenges in IRS reflection optimization and channel acquisition. In addition to IRS-assisted communications, the multi-IRS-assisted wireless network can be used for other intriguing and promising wireless applications, including wireless power transfer, RF sensing/localization, spatial modulation, among others.

None of the previous works, carried out neural networks with particular application of backpropagation algorithm, with incorporation of noise and interference as part of a modeling process for multi IRS devices. Backpropagation is unique in comparison to other deep learning algorithms, in terms of ease of weight modification, learning rate, and the overall behavior, as an intelligent and adaptive closed loop controller. This is achieved in this work presented in the following sections.

III. Materials and Methods

Effective planning, which necessitates a set of objectives and requirements to be met, is the foundation of any successful wireless deployment. Almost always, the network needs list includes the minimum signal strength requirements for the coverage area. The number of clients on the network, background noise levels, intended data rates, and the applications being utilized are just a few of the variables that affect the ideal signal strength for best performance.

The energy that a wireless transmitter emits is known as transmit power. It is desired that the wireless node or access point to have the ability to adapt the transmit power dynamically to the surroundings, resulting in a dynamic transmission control of power, which will determine the transmitter power level of the wireless node. This depends on a number of variables, including the unwanted interference, the communication channel that is being used, and the signal strength of the close by wireless access points.

Adaptive beamforming reduces interference and directs beams in desired directions to improve antenna array performance in wireless communication systems. It does this by using sophisticated algorithms, which lowers noise and interference and raises system efficiency as a whole. Additionally, the incorporation of machine learning methods, such as deep neural networks, provides dependable and quicker substitutes for conventional beamforming algorithms, guaranteeing high accuracy levels and quick response times [46–49].

When selecting transmitter power, the normal range of operation for wireless node or access point is between 8–13 dBm for 2.4 GHz and 10–17 dBm for 5GHz. Thus, this work selected a range of 8–16 to enable covering both frequencies and establish design and placement criteria for wireless nodes.

The Signal-to-Interference-Plus-Noise Ratio (SINR) is a quantity used in to provide theoretical upper bounds on channel capacity, or the rate at which information is transferred, in wireless communication systems like networks. Similar to the Signal-to-Noise Ratio (SNR), which is frequently used in wired communications systems, the SINR can be defined as the power of a particular signal of interest divided by the total power of background noise and interference.

In wireless communication, SINR is frequently used to gauge the strength of wireless links, in particular energy consumption during transmission in using a particular route. In wireless networks, the energy of a transmission usually decreases with distance; this phenomenon is known as a route loss. Other considerations need to be made when using a wireless network, such as background noise and the power of other transmissions.

The learning rate parameter determines how much the model is altered each time the model weights are changed in response to the updated IRSs patterns in a feedback loop similar to backpropagation. Selecting the right learning rate is important, as a high value could lead to an unstable control process and to a suboptimal set of weights too quickly. A value that is too small could cause a lengthy iterative process that may not result in a significant optimization of weights.

The approach in this work is determined through the following steps with Table I showing definition of used variable.

TABLE I. NOMENCLATURE

Symbols/Acronyms	Meaning
$\boldsymbol{d(t)}$	Desired output
$\boldsymbol{r(t)}$	Real output
BP	Back Propagation Algorithm (A neural Networks algorithm used in deep learning)
$\boldsymbol{\Delta w_{ji}}$	Weights change function
$\boldsymbol{\alpha}$	Learning rate
$\boldsymbol{IRS(t)}$	Intelligent reflecting surface and its time dependence
$\boldsymbol{WN(t)}$	Wireless node and its time dependence
$\boldsymbol{IRS_{ref}}$	Reference or initial intelligent reflective surface value.
$\boldsymbol{RC_{ref}}$	Reflection coefficient initial value
$\boldsymbol{WN_{ref}}$	Wireless node reference and initial value
$\boldsymbol{P_{ref}}$	Reference and initial transmitter power value
P_{TX}	Transmitter power
RC	Reflection Coefficient
BER	Bit Error Rate

A. Parameter Setting

1. Parameters of the Wireless Nodes ($\boldsymbol{WNs}$), Intelligent Reflecting Surfaces ($\boldsymbol{IRSs}$), and the required setting are defined.
2. Maximum number of rounds or iterations is selected
3. Learning Rate ($\boldsymbol{\alpha}$) is specified.
4. Reference transmission power (Maximum) for wireless nodes ($\boldsymbol{P_{ref}}$) is selected.
5. Reference Reflection Coefficient (Maximum) for IRSs ($\boldsymbol{RC_{ref}}$) is determined.
6. IRSs initial reflection coefficients is chosen.
7. Wireless nodes initial beamforming weight vectors are specified.
8. At each iteration compute, SINR, and BER are computed.
9. IRSs reflecting patterns are updated based on the current beamforming of WNs.
10. WNs beamforming weights are updated based on the feedback from the IRSs.

Eq. (1) shows the overall error function. This allows optimization of the system response using BP by reducing the error function through minimization of the error function.

$$\boldsymbol{Error(t)} = \frac{1}{2}\left(\boldsymbol{d_{k(t+1)}} - \boldsymbol{r_{k(t+1)}}\right)^2 \quad (1)$$

where:

$\boldsymbol{d(t)}$: ***Desired output***

$\boldsymbol{r(t)}$: ***Real output***

Weight change can be described by Eq. (2)

$$\boldsymbol{\Delta w_{ji}} = \boldsymbol{\alpha}\left(\frac{\boldsymbol{d_{k(i+1)}} - \boldsymbol{r_{k(i+1)}}}{\boldsymbol{\partial w_{k(j+1),k(j)}}}\right) \quad (2)$$

where:

α: Learning rate

$\boldsymbol{k}$: **IRS layer**

where:

$$\alpha_{increment} = \alpha(t) + \left(\alpha(t+1) - \alpha(t)\right)\left(\frac{iterations(t+1) - iterations(t)}{iterations(t+1)}\right) \quad (3)$$

$$\alpha_{decrement} = \alpha(t) - \left(\alpha(t+1) - \alpha(t)\right)\left(\frac{iterations(t+1) - iterations(t)}{iterations(t+1)}\right) \quad (4)$$

Considering Eqs. (1) to (4), Eqs. (5), and (6) are obtained.

$$\Delta w_{ji_{increment}} = \alpha_{increment}\left(\frac{d_{k(t+1)} - r_{k(t+1)}}{\partial w_{k(j+1),k(j)}}\right) \quad (5)$$

$$\Delta w_{ji_{decrement}} = \alpha_{decrement}\left(\frac{r_{k(t+1)} - d_{k(t+1)}}{\partial w_{k(j+1),k(j)}}\right) \quad (6)$$

Eqs. (5) and (6) represent the carried out bidirectional process to reach optimal, balanced, and converged stable solution. This model is applied to achieve an intelligent adaptive control for the wireless arrangement comprising WN and IRSs.

To apply the model in Eqs. (1)–(6), the initial state of the network is first considered, as in Eqs. (7) and (8).

$$\boldsymbol{IRS(t)} = \left(\frac{\boldsymbol{IRS_{initial}}}{\boldsymbol{IRS_{ref}*RC_{ref}}}\right) \quad (7)$$

where:

$$\boldsymbol{WN(t)} = \left(\frac{\boldsymbol{WN_{initial}}}{\boldsymbol{WN_{ref}*P_{ref}}}\right) \quad (8)$$

Updating the reflecting patterns for each IRS based on the beamforming of the WN is carried out using the model in Eqs. (3) and (4). The mathematical expression for the process of updates is presented in Eqs. (9)–(14).

$$\boldsymbol{IRS_{update}} = \boldsymbol{\alpha}\left(\frac{\boldsymbol{(WN(t+1) - IRS(t+1))}}{\boldsymbol{IRS_{ref}*RC_{ref}}}\right) \quad (9)$$

$$\boldsymbol{IRS_{update}} = \left(\frac{\boldsymbol{IRS(t)}}{\boldsymbol{IRS_{ref}*RC_{ref}}}\right) + \boldsymbol{\alpha}\left(\frac{\boldsymbol{(WN(t+1) - IRS(t+1))}}{\boldsymbol{IRS_{ref}*RC_{ref}}}\right) \quad (10)$$

Simplifying Eq. (10), results in Eq. (11)

$$\boldsymbol{IRS_{update}} = \left(\frac{\boldsymbol{IRS(t) - \alpha IRS(t+1) + \alpha WN(t+1)}}{\boldsymbol{IRS_{ref}*RC_{ref}}}\right) \quad (11)$$

$$\boldsymbol{WN_{update}} = \boldsymbol{\alpha}\left(\frac{\boldsymbol{(IRS(t+1) - WN(t+1))}}{\boldsymbol{WN_{ref}*P_{ref}}}\right) \quad (12)$$

$$\boldsymbol{WN_{update}} = \left(\frac{\boldsymbol{WN(t)}}{\boldsymbol{WN_{ref}*P_{ref}}}\right) + \boldsymbol{\alpha}\left(\frac{\boldsymbol{(IRS(t+1) - WN(t+1))}}{\boldsymbol{WN_{ref}*P_{ref}}}\right) \quad (13)$$

Simplifying Eq. (13), results in Eq. (14):

$$\boldsymbol{WN_{update}} = \left(\frac{\boldsymbol{WN(t) - \alpha WN(t+1) + \alpha IRS(t+1)}}{\boldsymbol{WN_{ref}*P_{ref}}}\right) \quad (14)$$

Signal-to-noise-plus-interference ratio (SNIR) is calculated based on the beamforming weights of the WNs, the reflecting patterns of the IRSs, and a random noise component, as shown in Eq. (15).

$$\boldsymbol{SINR} = \left(\frac{\boldsymbol{\sum_{t=1}^{t=q} WNs*IRSs}}{\boldsymbol{Noise+Interference}}\right) = \left(\frac{\boldsymbol{\sum_{t=1}^{t=q} WNs*IRSs}}{\boldsymbol{0.1*v+0.01}}\right) \quad (15)$$

where;

$\boldsymbol{q}$**: Maximum number of iterations.**

$\boldsymbol{v}$:**Random variable**

IV. Result and Discussion

A. *Effect of Varying Maximum Transmitting Power*

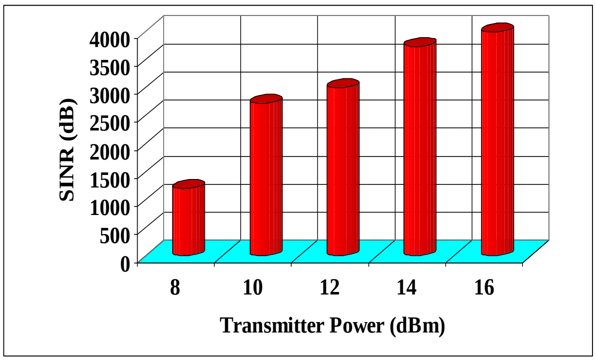

Fig. 1. Relationship between transmitter power and SINR.

Fig. 1 shows effect of varying transmitter power on SINR after 150 iterations. The plot clearly proves that as transmitter power increases, so does the value of SINR. The power range covered both 2.4 GHz and 5 GHz.

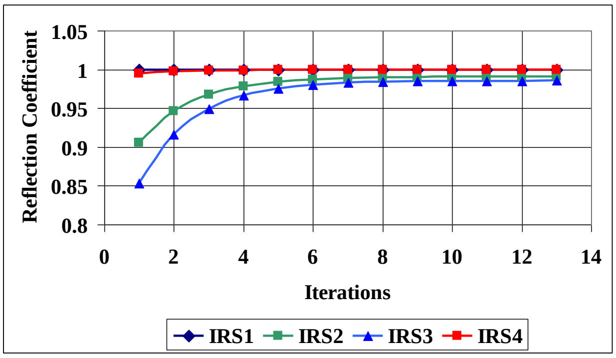

Fig. 2. Update of IRSs reflection coefficients for maximum power of 8 dBm.

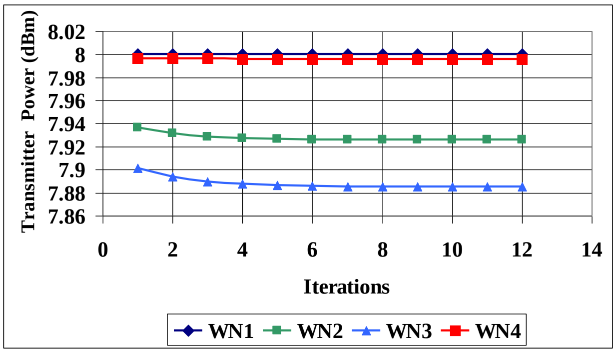

Fig. 3. Update of WNs reflection coefficients for maximum power of 8 dBm.

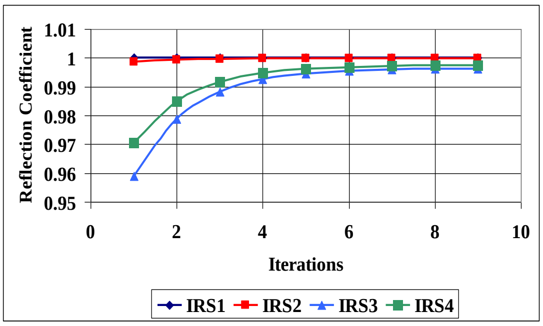

Fig. 4. Update of IRSs reflection coefficients for maximum power of 10 dBm.

Figs. 2–11 show the convergence of the reflective surfaces to a steady state close to the maximum reference value of 1, and the adaptive change in the transmitter power, through changes in the weight matrix as iterations progress to enable more effective and optimized communication channel. These closed loop relationship between IRSs and WNs the core of the adaptive process.

From the plots, it is evident that as the power increase, resulting in higher energy of transmission, leads to a conversion of IRSs reflection coefficient to higher values, which is consistent with increases, in transmitted data, thus a corresponding increase in transmitted energy and power corresponding to increase in the number of transmitted bits. Thus, a reduction in energy levels and power is observed, as shown when comparing pairs of Figs. 2–11. This is consistent with Eqs. (3), (4), and their corresponding Eqs. (9)–(12).

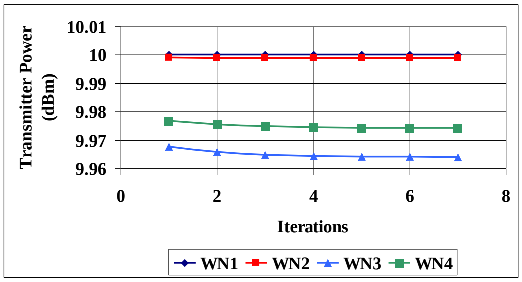

Fig. 5. Update of WNs reflection coefficients for maximum power of 10 dBm.

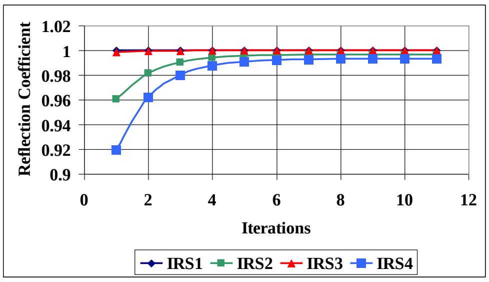

Fig. 6. Update of IRSs reflection coefficients for maximum power of 12 dBm.

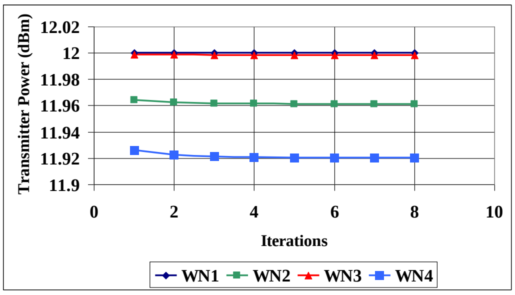

Fig. 7. Update of WNs reflection coefficients for maximum power of 12 dBm.

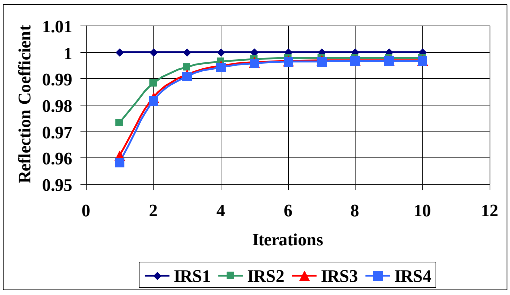

Fig. 8. Update of IRSs reflection coefficients for maximum power of 14 dBm.

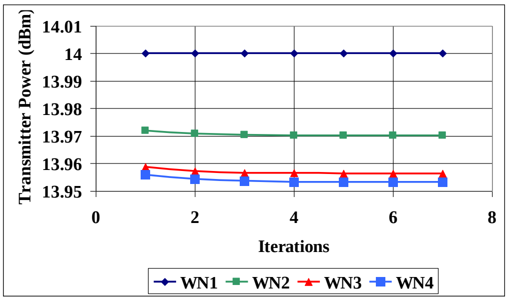

Fig. 9. Update of WNs reflection coefficients for maximum power of 14 dBm.

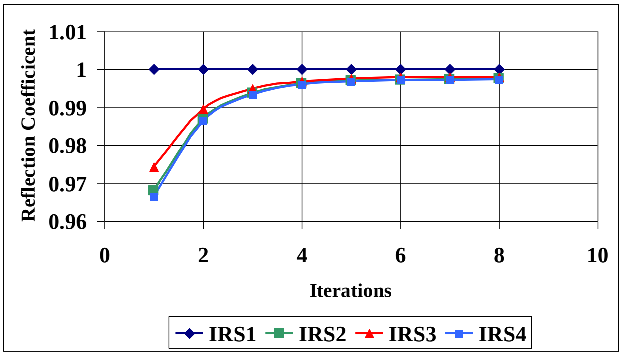

Fig. 10. Update of IRSs reflection coefficients for maximum power of 16 dBm.

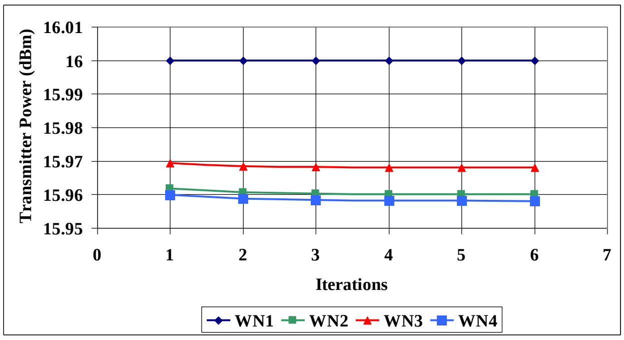

Fig. 11. Update of WNs reflection coefficients for maximum power of 14 dBm.

B. Effect of Varying Reflection Coefficient

Fig 12 shows effect of the reflection coefficient on SINR after 150 iterations. The plot clearly proves that as the reflectivity increases, so does the value of SINR. The reflection coefficient represents both material properties and directivity as a lumped component in the simulation.

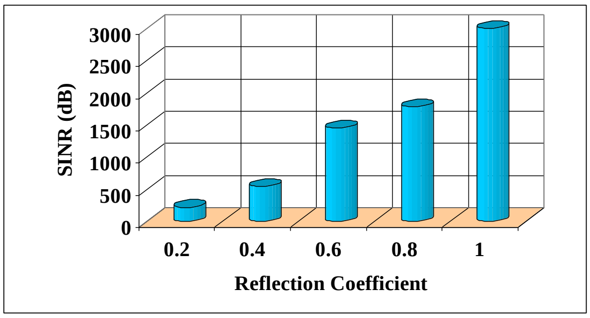

Fig. 12. Relationship between reflection coefficient and SINR.

Figs. 13–22 show the convergence of the reflective surfaces to a steady state close to the maximum reference value of 1, and the adaptive change in the transmitter power, as a function of reflectivity and reflection coefficient, through changes in the weight matrix as iterations progress to enable more effective and optimized communication channel.

From the plots, it is evident that as the IRSs reflective coefficient increases, more data is transmitted, thus a corresponding increase in transmitted energy and power corresponding to increase in the number of transmitted bits. Thus, a reduction in energy levels and power is observed, with linear behavior up to RC=0.6, as shown when comparing pairs of Figs. 13– 22. This is consistent with Eqs. (3) and (4), and their corresponding Eqs. of (9)–(12).

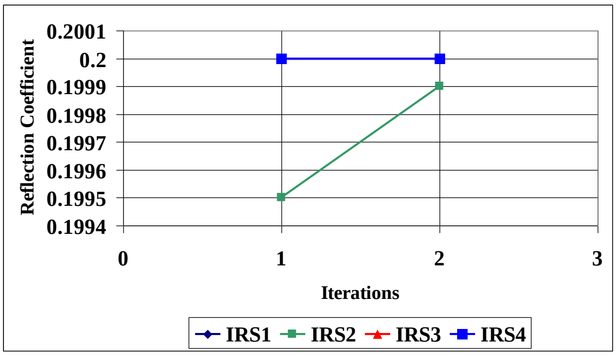

Fig. 13. Update of IRSs reflection coefficients for 0.2 reflection coefficient.

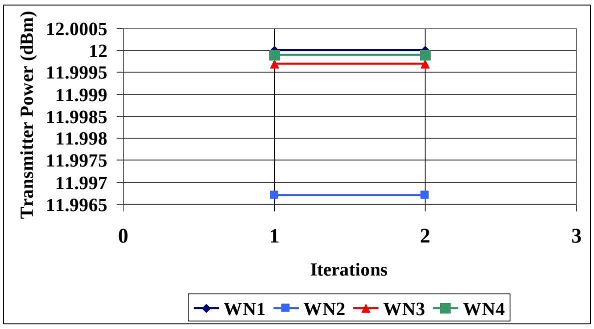

Fig. 14. Update of WNs reflection coefficients for 0.2 reflection coefficient.

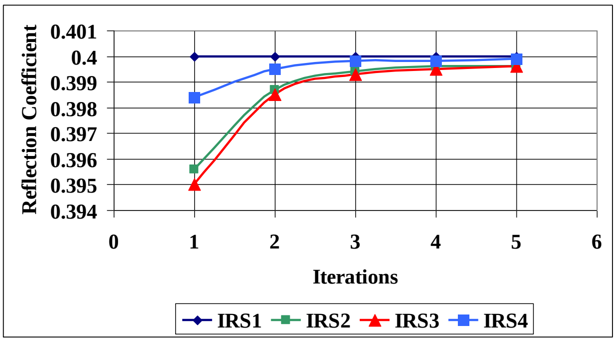

Fig. 15. Update of IRSs reflection coefficients for 0.4 reflection coefficient.

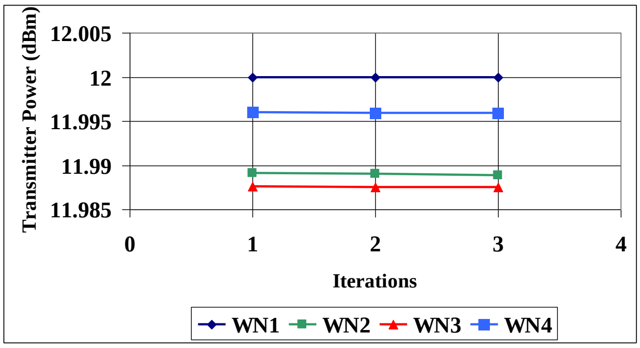

Fig. 16. Update of WNs reflection coefficients for 0.4 reflection coefficient

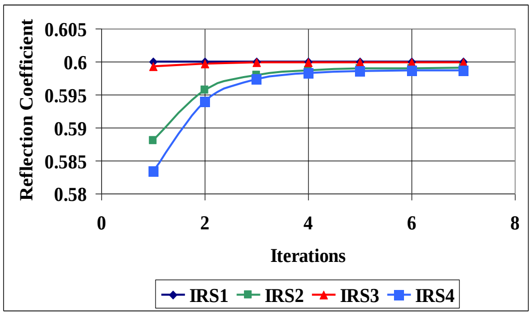

Fig. 17. Update of IRSs reflection coefficients for 0.6 reflection coefficient.

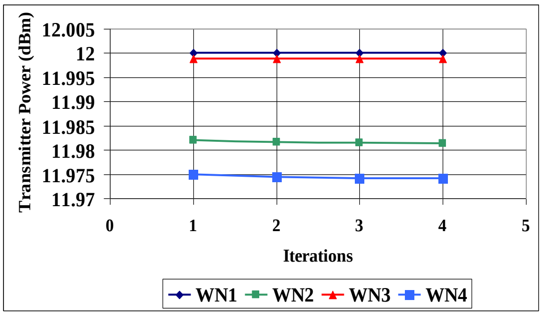

Fig. 18. Update of WNs reflection coefficients for 0.6 reflection coefficient.

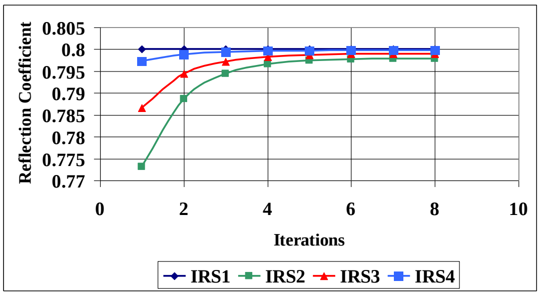

Fig. 19. Update of IRSs reflection coefficients for 0.8 reflection Coefficient.

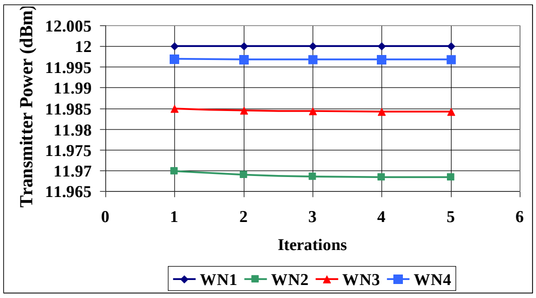

Fig. 20. Update of WNs reflection coefficients for 0.8 reflection coefficient.

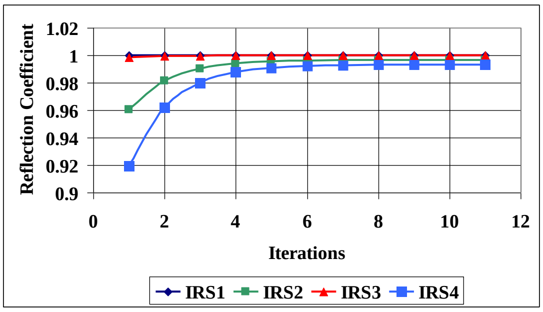

Fig. 21. Update of IRSs reflection coefficients for 1.0 reflection coefficient.

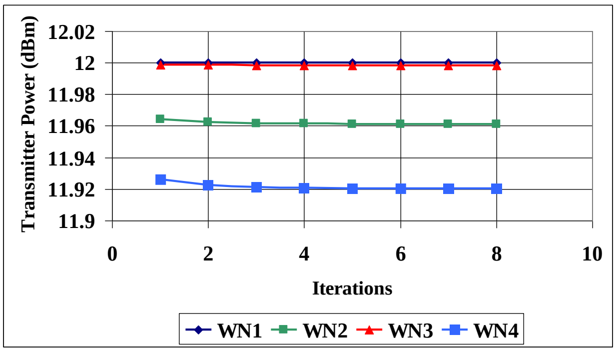

Fig. 22. Update of WNs reflection coefficients for 1.0 reflection coefficient.

C. Effect of Varying Reflecting Surfaces

Fig. 23 shows effect of the number of reflecting surfaces on SINR after 150 iterations. The plot clearly proves that as the number of surfaces increases, so does the value of SINR. This is due to the beam forming effect, which results in a constructive interference with more targeted transmission wave and higher energy and power and further reachability.

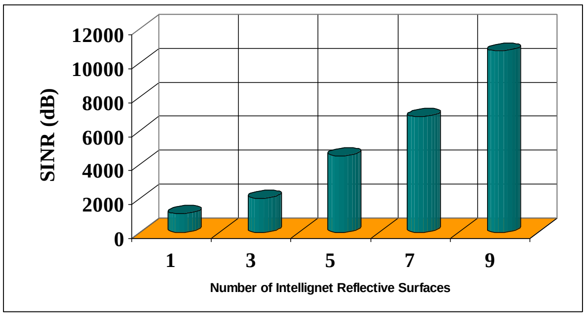

Fig. 23. Relationship between number of reflecting surfaces and SINR.

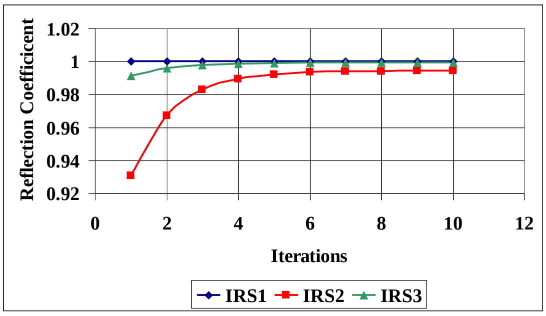

Fig. 24. Update of IRSs reflection coefficients for 3 reflective surfaces.

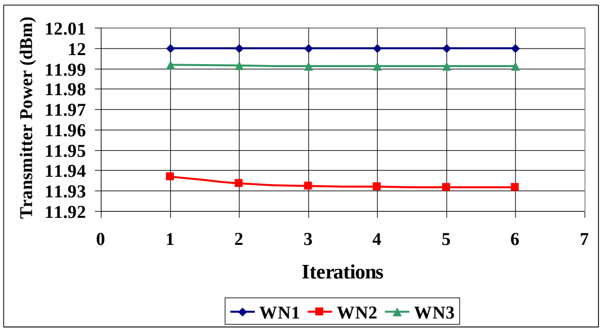

Fig. 25. Update of WNs reflection coefficients for 3 reflective surfaces.

Figs. 24–29 show the convergence of the reflective surfaces to a steady state close to the maximum reference value of 1, and the adaptive change in the transmitter power, as a function of number of IRSs.

From the plots, it is evident that as the IRSs number increases, higher data transmission rate is enabled, thus a corresponding increase in transmitted energy and power corresponding to increase in the number of transmitted bits. Thus, a reduction in energy levels per transmitting node, and power is observed.

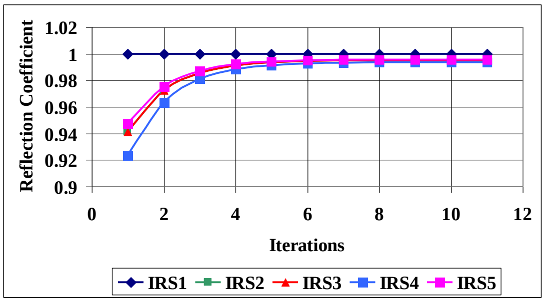

Fig. 26. Update of IRSs reflection coefficients for 5 reflective surfaces.

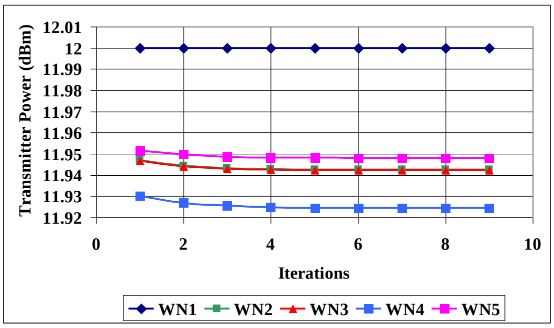

Fig. 27. Update of WNs reflection coefficients for 5 reflective surfaces.

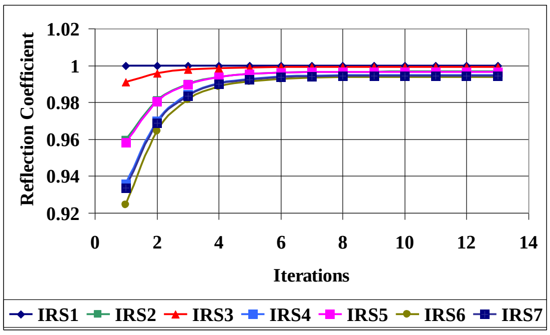

Fig. 28. Update of IRSs reflection coefficients for 7 reflective surfaces.

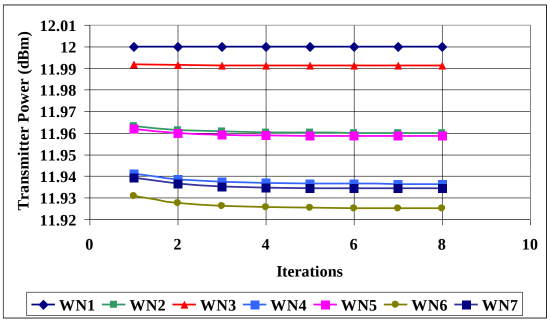

Fig. 29. Update of WNs reflection coefficients for 7 reflective surfaces.

From Figs. 2, 13, and 24, it's clear that there is a relationship connecting SINR, P_{TX}, RC, and number of reflecting surfaces, as presented in Eq. (16).

$$\boldsymbol{SINR(P_{TX}) \propto SINR(RC) \propto SINR(IRS)} \quad (16)$$

Thus, by curve fitting of simulation data, the following functions (Eqs. (12–14)) are obtained.

$$\boldsymbol{SINR = \theta \log_e (P_{TX}) - \phi} \quad (17)$$

where;

$$\boldsymbol{\theta \leq 4000}$$
$$\boldsymbol{\phi \leq 6650}$$

$$\boldsymbol{SINR = \eta RC^{\mu}} \quad (18)$$

where;

$$\boldsymbol{\eta \leq 2845}$$
$$\boldsymbol{\mu \leq 1.63}$$

$$\boldsymbol{SINR = \delta exp(\lambda * IRS)} \quad (19)$$

where;

$$\boldsymbol{\delta \leq 882}$$
$$\boldsymbol{\lambda \leq 0.3}$$

From Eqs. (17) and (18), Eq. (20) is obtained.

$$\boldsymbol{\theta \log_e (P_{TX}) - \phi \ = \ \psi \ (\eta RC^{\mu})} \quad (20)$$

where;

$\boldsymbol{\psi}$**:** correlating parameter

Thus; Eq. (21) is obtained.

$$\boldsymbol{P_{TX} \ = exp \left(\frac{(\psi \ (\eta RC^{\mu}))+\phi}{\theta}\right)} \quad (21)$$

From Eqs. (17) and (19), Eq. (22) is obtained.

$$\boldsymbol{\theta \log_e (P_{TX}) - \phi \ = \ \delta exp(\kappa * IRS_i)} \quad (22)$$

From Eqs. (22), Eq. (23) is obtained.

$$\boldsymbol{P_{TX} \ = exp\left(\frac{(\gamma(\delta exp(\lambda * IRS)))+\phi}{\theta}\right)} \quad (23)$$

Eqs. (22) and (23) show that the general relationship between transmitter power and both reflection coefficient and number of reflecting surfaces is exponential. This can be used as design mathematical models, which assists in selecting the number of relative surfaces and their associated reflection coefficient. In addition, the bidirectional relationship between the reflecting surfaces and the wireless nodes can be further optimized with the number of iterations parameter and the learning rate parameter.

Figs. 30–32 show effect of transmitter power, reflection coefficient values, and number of reflective surfaces on the bit error rate. The plots show that as transmitter power increases, reflection coefficient, which corresponds to an increase in the number of reflective surfaces increases, BER decreases. However, the impact is most when the transmitter power is increased, followed by number of reflective surfaces, and then the reflection coefficient. Thus, combining the three parameters together, would result in an excellent optimization to the communication channel transmission characteristics.

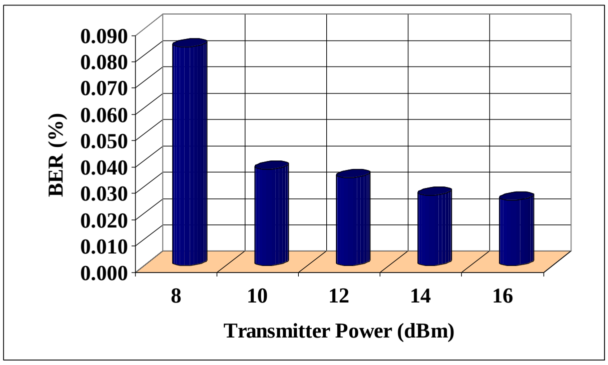

Fig. 30. Relationship between transmitter power and BER.

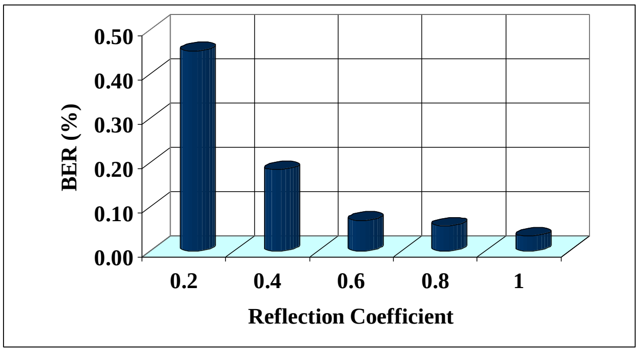

Fig. 31. Relationship between reflection coefficient and BER.

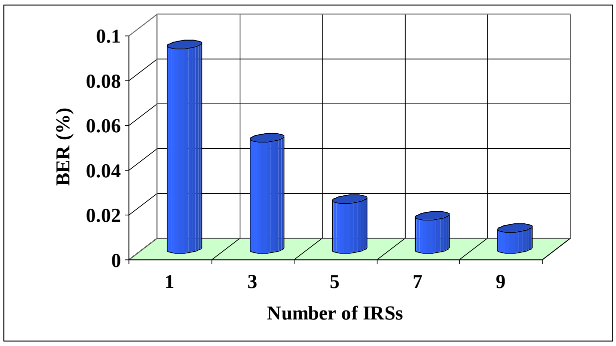

Fig. 32. Relationship between number of IRSs and BER.

The obtained results agrees with published work as in Ref. [40], where IRS with adaptive power is used to determine the secondary throughput, For N = 8, 16, 32, 64, and 128 reflectors, IRS permits gains of 14, 20, 26, 32, and 38 dB in comparison to the lack of IRS, which compares with the obtained results of this work of maximum of 16 dBm. The work in Ref. [40], also showed an increase in throughput and better SINR. Other works [41], used 100 IRS elements with maximum power of 30 dBm, which also compares well with the values obtained in this work. BER of maximum of 0.5 is observed in the work carried out by Liu *et al.* [50], which is higher than the values obtained in this work of 0.09. However, it does agree in terms of range, which is less than 1 with the published work. A closer value of BER is observed in the work published in [51], with BER having values of 0.1. Such value is optimized using Long-Short Term Memory based algorithms.

V. Conclusion

The work investigated effect of transmitter power, reflection coefficient, and number of reflective surfaces on both SINR and BER. The simulation used intelligent reflective surfaces with continuous feedback loop, which is equivalent to backpropagation. A backpropagation model is used to model the system process. The successful simulation work showed an evidence of improving SINR and BER as a result of optimizing the use and setting of the mentioned parameters. In addition, mathematical modeling relating transmitter power to both reflection coefficient and number of reflective surfaces are presented. An exponential relationship relating transmitting power to both reflecting surface coefficient and number of reflecting surfaces is established. This type of relationship is very important to consider during the design process, due to the behavior of the exponential function, and its effect on the transmitting power.

Conflict of Interest

The author declare no conflict of interest.

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References

[1] F. Xu, J. Yao, W. Lai, K. Shen, X. Li, X. Chen, and Z. Luo, "Coordinating multiple intelligent reflecting surfaces without channel information," *IEEE Transactions on Signal Processing*, vol. 72, pp. 31–46, 2023.

[2] W. Mei, B. Zheng, C. You, R. Zhang, "Intelligent reflecting surface-aided wireless networks: From single-reflection to multireflection design and optimization," in *Proc. IEEE*, vol. 10, no. 9, 2022, pp. 1380–1400.

[3] E. Martinez-de-Rioja, Á. Vaquero, M. Arrebola, E. Carrasco, J. Encinar, and M. Achour, "Passive intelligent reflecting surfaces based on reflectarray panels to enhance 5G millimeter-wave coverage," *International Journal of Microwave and Wireless Technologies*, vol. 15, pp. 3–14, 2022.

[4] F. Okogbaa, Q. Ahmed, F. Khan, W. Abbas, F. Che, S. Zaidi, T. Alade, "Design and application of intelligent reflecting surface (IRS) for beyond 5G wireless networks: A review," *Sensors*, vol. 22, no. 2436, pp. 1–24, 2022.

[5] P. Huang, Y. Zhou, K. Wang, B. Wang, "Placement optimization for Multi-IRS-Aided wireless communications: An adaptive differential evolution algorithm," *IEEE Wireless Communications Letters*, vol. 11, no. 5, pp. 942–946, 2022.

[6] S. Bazzi and W. Xu, "IRS parameter optimization for channel estimation MSE minimization in double-IRS aided systems," *IEEE Wireless Communications Letters*, vol. 11, no. 10, pp. 2170–2174, 2022.

[7] S. Ren, K. Shen, Y. Zhang, X. Li, X. Chen, and Z. Luo, "Configuring intelligent reflecting surface with performance guarantees: Blind beamforming," *IEEE Transactions on Wireless Communications*, vol. 22, no. 5, pp. 3355–3370, 2022.

[8] E. Björnson, H. Wymeersch, B. Matthiesen, P. Popovski, L. Sanguinetti, E. Carvalho, "Reconfigurable intelligent surfaces: A signal processing perspective with wireless applications," *IEEE Signal Processing Magazine*, vol. 39, no. 2, pp. 135–158, 2022.

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

[10] Y. Xu, G. Gui, H. Gacanin, and F. Adachi, "A survey on resource allocation for 5G heterogeneous networks: Current research, future trends, and challenges," *IEEE Commun. Surveys Tuts*., vol. 23, no. 2, pp. 668–695, Feb. 2021.

[11] J. Yao, F. Xu, W. Lai, K. Shen, X. Li, X. Chen, and Z.-Q. Luo, "Blind beamforming for multiple intelligent reflecting surfaces," in *Proc. IEEE Int. Commun. Conf. (ICC)*, May 2023, pp. 1–5.

[12] W. Mei, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surfaceaided wireless networks: From single-reflection to multireflection design and optimization," in *Proc. IEEE*, vol. 110, no. 9, 2022, pp. 1380–1400.

[13] V. K. Gorty, "Channel estimation for double IRS assisted broadband single-user SISO communication," in *Proc. IEEE Int. Conf. Signal Process. Commun (SPCOM)*, Jul. 2022, pp. 1–18.

[14] B. Zheng, C. You, and R. Zhang, "Efficient channel estimation for double-IRS aided multi-user MIMO system," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 3818–3832, Jun. 2021.

[15] S. Bazzi and W. Xu, "IRS parameter optimization for channel estimation MSE minimization in double-IRS aided systems," *IEEE Wireless Commun. Lett*., vol. 11, no. 10, pp. 2170–2174, Oct. 2022.

[16] 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. Wireless Commun*., vol. 22, no. 8, pp. 5446–5460, 2023.

[17] X. Pei, H. Yin, L. Tan, L. Cao, Z. Li, K. Wang, K. Zhang, and E. Bj¨ornson, "RIS-aided wireless communications: Prototyping, adaptive beamforming, and indoor/outdoor field trials," *IEEE Trans. Commun*., vol. 69, no. 12, pp. 8627–8640, Dec. 2021.

[18] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, Jan. 2020.

[19] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surface aided wireless communications: A tutorial," *IEEE Trans. Commun*., vol. 69, no. 5, pp. 3313–3351, May 2021.

[20] J. Wang, Y. Liang, Y. Pei, X. Shen, "Reconfigurable intelligent surface as a micro base station: A novel paradigm for small cell networks," *IEEE Transactions on Wireless Communications*, vol. 22, no. 4, pp. 2338–2351, 2023.

[21] G. Trichopoulos, P. Theofanopoulos, B. Kashyap, A. Shekhawat, A. Modi, T. Osman, S. Kumar, A. Sengar, A. Chang, and A. Alkhateeb, "Design and evaluation of reconfigurable intelligent surfaces in real-world environment," *IEEE ComSoc*, vol. 3, pp. 462–474, 2022.

[22] B, Rana, S. Cho, I. Hong, "Review paper on hardware of reconfigurable intelligent surfaces," *IEEE Access*, vol. 11, pp. 29614–29634, 2023.

[23] Q. Bie, Y. Zhang, Y. He, Y. Lin, "Joint base station selection and power allocation design for reconfigurable intelligent surface-aided cell-free networks," *Electronics*, vol. 13, no. 1688, pp. 1–17, 2024.

[24] S. Hassouna, M. Jamshed, J. Rains, J. Kazim, M. Rehman, M. Abualhayja, L. Mohjazi, T. Cui, M. Imran, and Q. Abbasi, "A survey on reconfigurable intelligent surfaces: Wireless communication perspective," *IET Communications*, vol. 17, pp. 497–537, 2023.

[25] M. Zain Siddiqi, T. Mir, "Reconfigurable intelligent surface-aided wireless communications: An overview," *Intelligent and Converged Networks*, vol. 3, no. 1, pp. 33–63, 2022.

[26] Z. Huang, B. Zheng, and R. Zhang, "Transforming fading channel from fast to slow: IRS-assisted high-mobility communication," in *Proc. IEEE Int. Conf. Commun.*, Montreal, Canada, pp. 1–6, 2021.

[27] O Zdogan, E. Bjornson, and E. G. Larsson, "Using intelligent reflecting surfaces for rank improvement in MIMO communications," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Barcelona, Spain, pp. 9160–9164, 2020.

[28] M. Di Renzo *et al.*, "Reconfigurable intelligent surfaces vs. relaying: Differences, similarities, and performance comparison," *IEEE Open J.Commun. Soc.*, vol. 1, pp. 798–807, Jun. 2020.

[29] H. Alwazani and A. Chaaban," IRS-enabled ultra-low-power wireless sensor networks: scheduling and transmission schemes," *Sensors*, vol. 22, no. 9229, pp. 1–24, 2023.

[30] D. Brilhante, J. Manjarres, R. Moreira, L. Veiga, J. de Rezende, F. Müller, A. Klautau, L. Mendes, and F. Figueiredo, "A literature survey on ai-aided beamforming and beam management for 5G and 6G systems," *Sensors*, vol. 23, no. 4359, pp. 1–61, 2023.

[31] S. Motie, H. Zayyani, and M. Korki, "IRS-Aided received signal strength localization using a wireless sensor network," *IEEE Communications Letters*, vol. 28, no. 5, pp. 1039–1042, 2024.

[32] N. Ghattas, A. Ghuniem, A. Abdelsalam, and A. Magdy, "Planar antenna arrays beamforming using various optimization algorithms," *IEEE Access*, vol. 11, pp. 68486–68500, 2023.

[33] R. Kumar and S. Singh, "Intelligent reflecting surface framework for ED based spectrum sensing," *International Journal of Wireless Information Networks*, vol. 31, pp. 155–162, 2024.

[34] A. Nasser, H. Hassan, A. Mansour, K. Yao, L. Nuaymi, and M. Pineda, "Intelligent reflecting surfaces and spectrum sensing for cognitive radio networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 8, no. 3, pp. 1497–1511, 2022.

[35] R. Alhamad, "Spectrum sensing using intelligent reflecting surfaces with multi-antennas energy harvesting," *Wireless Personal Communications*, vol. 135, pp. 1103–1116, 2024.

[36] R. Alhamad, "Cognitive radio networks using intelligent reflecting surfaces," *Computer Systems Science & Engineering*, vol. 43, no. 2, pp. 751–765, 2022.

[37] M. Saber, R. Saadane, A. Chehri, A. El Rharras, Y. Al Hafid, and M. Wahbi, "Reconfigurable intelligent surfaces improved spectrum sensing in cognitive radio networks," *Procedia Computer Science*, vol. 207, pp. 4113–4122, 2022.

[38] H. Xie, D. Li, and B. Gu, "Enhancing spectrum sensing via reconfigurable intelligent surfaces: Passive or active sensing and how many reflecting elements are needed?" *arXiv*, vol. 2306, no.13874v2, pp. 1–13, 2023.

[39] R. Kumar, S. Singh, S. Chauhan, A. Anand, and A. Kumar, "ED based spectrum sensing over IRS-assisted Rayleigh-FTR fading channels," *AEU–International Journal of Electronics and Communications*, vol. 171, no. 154908, pp. 1–7, 2023.

[40] R. Alhamad and H. Boujemaa, "Intelligent reflecting surfaces with adaptive transmit power for underlay cognitive radio networks," *Sensors*, no. 2787466, pp. 1–7, 2022.

[41] M. Shukur, "Exploiting intelligent reflecting surfaces for interference mitigation in heterogeneous 6G," *J. Res. Technol. Eng.*, vol. 5, no. 3, pp. 78–96, 2024.

[42] F. Okogbaa, Q. Khan, W. Abbas, F. Che, S. Zaidi, and T. Alade, "Design and application of intelligent reflecting surface (IRS) for beyond 5G wireless networks: A review," *Sensors*, vol. 22, no. 2436, pp. 1–24, 2022.

[43] D. Pérez-Adán, Ó. Fresnedo, J. Gonzalez-Coma, L. Castedo, "Intelligent reflective surfaces for wireless networks: An overview of applications, approached issues, and open problems," *Electronics*, vol. 10, no. 2345, pp. 1–28, 2021.

[44] N. Nguyen, A. Le, M. Munochiveyi, F. Afghah, and E. Pallis, "Intelligent reflecting surface aided wireless systems with imperfect hardware," *Electronics*, vol. 11, no. 900, pp. 1–18, 2022.

[45] W. Mei, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surface aided wireless networks: From single-reflection to multi-reflection design and optimization," *arXiv*, vol. 2109, no. 13641v2, pp. 1–18, 2022.

[46] Z. Yigit, E. Basar, and I. Altunbas, "Over-the-air beamforming with reconfigurable intelligent surfaces," *Front. Comms. Net.*, vol. 3, no. 016270, pp. 1–12, 2022.

[47] H. Al Kassir, Z. Zaharis, P. Lazaridis, N. Kantartzis, T. Yioultsis, and T. Xenos, "A review of the state of the art and future challenges of deep learning-based beamforming, "*IEEE Access*, vol. 10, pp. 80869–80882, 2022.

[48] F. Ahamad, N. Malek, F. Roslan, R. Islam, and N. Qasem," Enhanced antenna performance at 3.5 Ghz with a compact and intelligent reflecting surface," *IIUM Engineering Journal*, vol. 25, no. 2, pp. 179–195, 2024.

[49] R. Hazim, N. Qasem, A. Alamayreh, "OAM beam generation, steering, and limitations using an intelligent reflecting surface,"

Progress In Electromagnetics Research M, vol. 118, pp. 93–104, 2023.
[50] S. Liu, L. Xiao, M. Zhao, X. Xu, and Y. Li, "Performance analysis of intelligent reflecting surface in multi-user MIMO systems," *Journal of Physics: Conference Series*, vol. 1575, no. 012078, pp. 1–11, 2022.
[51] R. Tabassum, M. Sejan, M. Rahman, M. Aziz, and H. Song, "Intelligent reflecting surface-assisted wireless communication using RNNs: Comprehensive insights," *Mathematics*, vol. 12, no. 2973, pp. 1–20, 2024.