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Resource Allocation Using Reconfigurable Intelligent Surface (RIS)-Assisted Wireless Networks in Industry 5.0 Scenario

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Abstract: Mobile communication networks evolved from first-generation (1G) to sixth-generation (6G) and the requirement for quality of services (QoS) and higher bandwidth increased. The evolvement of 6G can be deployed in industry 5.0 to fulfill the future industry requirement. However, deploying 6G in industry 6.0 is very challenging, and installing a reconfigurable intelligent surface (RIS) is an efficient solution. RIS contains the passive elements which are programmed for the tuning of a wireless channel. We formulate an optimization problem to allocate resources in the RIS-supported network. This article presents a mixed-integer non-linear programable problem (MINLP) considering the industry 5.0 scenario and proposes a novel algorithm to solve the optimization problem. We obtain the ϵ optimal solution using the proposed algorithm. The proposed algorithm is evaluated in energy efficiency (EE), throughput, latency, and channel allocation. We compare the performance of several algorithms, and the proposed algorithm outperforms all the algorithms.

Keywords: reconfigurable intelligent surface; optimization; 6G; industry 5.0; resource allocation

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1. Introduction

In the modern era of big data, the demand for higher data rates, low latency, and reliable communication is increasing daily [1]. In the past few years, the number of users is increasing drastically as mobile network communication evolved from first-generation (1G) to fifth-generation (5G) [2]. 1G supported voice calls only, 2G kept message services while 3G had internet support. 4G grew in the 2010s and supported mobile broadband (MBB). In the 2020s, 5G evolved and offered mobile broadband (eMBB), ultra-reliable low latency (URLLC), and massive machine-type communication (mMTC) services. Nowadays, the sixth generation (6G) is developing and offers intelligence and sensing technologies. These technologies require more bandwidth and data rates. Figure 1, shows the evolution of mobile communication from 2G to 6G.

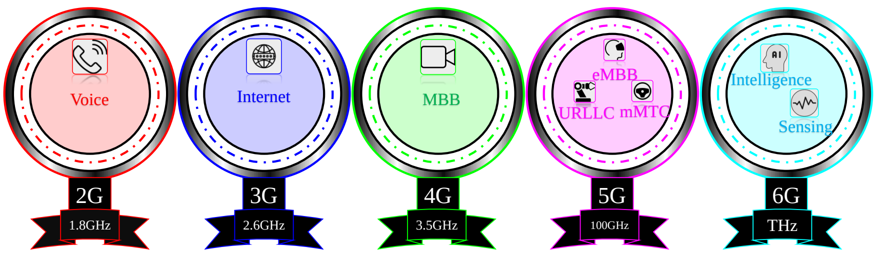

Figure 1. Evolution of mobile network from 2G to 6G.

Moreover, the use of mobile networks in the industry has also increased, and to fulfill the stringent requirements of industry 5.0 and beyond, the research to deploy next-generation (6G) networks has started. Industry 5.0 is based on human-centric solutions and supports mass customization. Figure 2 shows the industrial evolution. The primary requirements for industry 5.0 are high energy efficiency (EE), low latency, high spectral efficiency (SE), and high throughput [3]. The solution to fulfill all these requirements is deploying 6G in industry 5.0. However, the deployment of 6G in the industry is quite challenging. Due to non-line of sight (NLOS), the EE and throughput of the network decrease. NLOS also gives rise to multi-path fading, attenuation, and interference due to reflection and refraction. To overcome this problem, reconfigurable intelligent surface (RIS) is the primary solution [4]. RIS reduces attenuation and improves network performance [5].

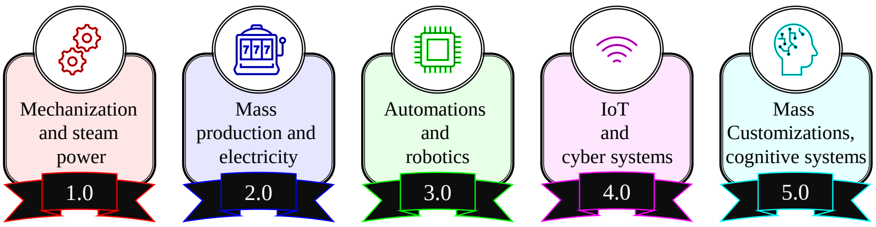

Figure 2. Evolution of industry from 1.0 to 5.0.

RIS consists of electromagnetic (EM) materials and possesses EM properties. These are thin sheets deployed on the buildings, walls, and machines. The EM nature of the RIS helps to monitor the medium of the whole network and the mode of operation of RIS, which is full-duplex [6]. The deployment of RIS is also cost-effective because it is a passive device. PIN diode controls the phase shift (Θ) of RIS [7] and helps to achieve a particular phase by switching function [8].

When the state of the PIN diode is low the incoming energy ($h\nu$) passes through it due to its installation on the frequency selective surface (FSS). Whereas, when the state of the diode is high most of $h\nu$ is reflected. A RIS-assisted network base station (BS) transmits a signal to RIS and RIS improves the characteristics of the incoming signal which helps in improving the overall performance of the network [9–13].

Inspired by the numerous benefits of RIS-assisted networks, we formulate an optimization problem to enhance EE, SE, throughput and minimize the latency of the network in an industry 5.0 scenario. We propose a novel algorithm to solve the optimization problem. Following are the primary contributions of this article.

1. We formulate an optimization problem in the RIS-assisted wireless network in the industry 5.0 scenario.
2. We propose a novel algorithm to solve the optimization problem and evaluate EE, SE, throughput, and latency.
3. We allocate resources and evaluate the channel mode.
4. We compare the performance of the proposed algorithm with others.

2. Related Work

RIS-assisted networks are widely deployed in the 6G. In [6], the authors studied the use of RIS and multiple-input single-output (MISO) technologies. They proposed an alternating minimization approach to increase EE of the system under constraints of no beamforming and NLOS between transmitter (T_x) and receiver (R_x). Similarly, in [14], the authors demonstrated the use of a RIS-assisted MISO network to increase the sum rate. They optimized the continuous Θ of RIS and beamformer of T_x.

The authors of [15] explored the use of RIS with single input single output (SISO) network assuming channel state information (CSI) and network achieved a higher signal-to-noise ratio (SNR). In [16], the authors also used RIS with MISO and maximized the signal-to-interference and noise ratio (SINR) of the network. In [17], the SNR of the network was improved using RIS in the single cell. Furthermore, Le et al. proposed an alternating descent gradient algorithm to maximize the EE of the network. The algorithm showed a significant gain in the EE of the cell-free network.

In [18], Lee et al. applied deep reinforcement learning (DRL) to improve the EE. They showed that the EE improved up to 77% by increasing the number of RIS elements. Similarly, in [19], the authors proposed the Dinkelbach method to enhance the EE of the device-to-device (D2D) network. The algorithm showed significant improvements in EE of the D2D network. In [20], the authors used RIS surface to enhance the security of the physical layer in the 6G wireless network. The performance showed a significant improvement in security using RIS. Similarly, Odeyemi et al. in [21] optimized the power of the wireless network using RIS surface. The use of RIS in next-generation wireless networks is surveyed in [22].

Moreover, You et al. in [23] used an accelerated projected gradient algorithm to achieve higher EE and SE in a RIS-assisted multiple-input multiple-output (MIMO) network. Similarly, in [24], the authors used the power consumption method to enhance the data rate and EE of the network. In [25], the authors used an optimization algorithm to enhance the throughput and EE of the RIS-assisted network. Similarly, in [26], a Q-learning based approach is adopted to manage interference in the heterogeneous networks (HetNets). In [27], the authors surveyed the game-theoretical approaches for the virtualization of the cellular network.

Table 1 summarizes the existing RIS-assisted networks. In this article, we propose an outer approximation algorithm (OAA) to maximize EE, SE, throughput and minimize the latency of the RIS-assisted network.

Table 1. Summary of Existing RIS-assisted Wireless Networks.

Research	Approach	Objective					Contributions
		EE	Throughput	SE	Latency	Channel Allocation	
[6]	Gradient descent search	✓	×	×	×	×	300% higher EE
[28]	Alternating descent algorithm	✓	×	×	×	×	Signification gain in EE of cell-free network
[18]	DRL	✓	×	×	×	×	EE improved up to 77% by increasing the number of RIS element
[19]	Dinkelbach method	✓	×	×	×	×	The algorithm provided a significant improvement in the EE of D2D network
[23]	Accelerated projected gradient	✓	×	✓	×	×	Achieved higher EE in MIMO network
[24]	Power consumption method	✓	×	×	×	×	RIS network surpasses relay one in terms of both rate and EE
[25]	Approximation Algorithm	✓	✓	×	×	×	Maximization of throughput and EE in the RIS-assisted wireless network
This paper	OAA	✓	✓	✓	✓	✓	Improved throughput, EE, SE of the network; minimized latency

3. Scenario and Problem Formulation

In this article, an industry 5.0 scenario in a company ABC Limited (Ltd) is supposed. In this scenario, a RIS-based wireless network is deployed. ABC Ltd has several departments and has more than 300 employees. The company also has automation and robotics support.

The company requires high throughput, low latency, and high EE. The complete network of ABC Ltd. is shown in Figure 3.

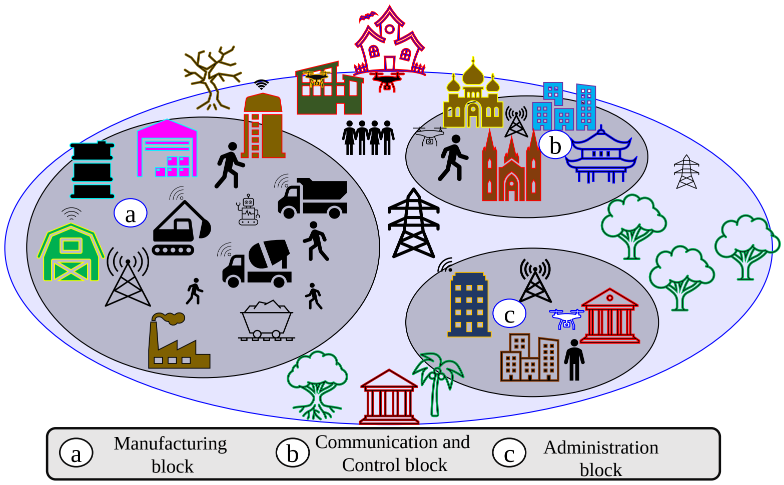

Figure 3. ABC Ltd. Scenario.

3.1. RIS-Assisted Scenario

Consider a manufacturing block of ABC Ltd. as shown in Figure 4, one BS has $\mathbb{N}$ antennas. RIS connects BS, and the plane of BS is YZ, whereas the plane of RIS is XZ. There are $\mathbb{K}$ reflecting elements of RIS. This surface serves $\mathbb{X}$ users. There is no line of sight (LOS) between the user (U_E) and the BS due to hurdles. $\mathbb{C}_1$ is the channel between BS and RIS, and $\mathbb{C}_2$ is the channel between the RIS and the ith U_E. Θ is the phase shift matrix of the RIS.

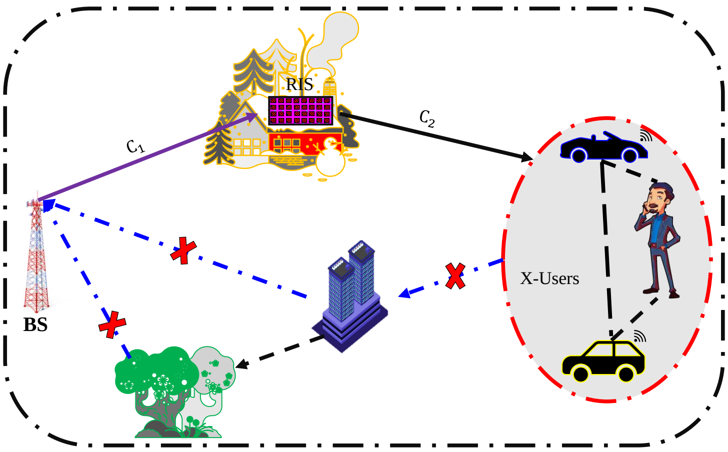

Figure 4. RIS-aided network scenario.

3.2. Problem Formulation

In the scenario shown in Figure 4, we have i users with $i = \{1, 2, 3, \ldots, \mathbb{X}\}$ and we can find the received signal with Equation (1) [6].

$$\mathbb{R}_u = \mathbb{H}_2 \times \Theta \times \mathbb{H}_{1\chi} + \eta_u \tag{1}$$

where $\mathbb{H}_1$ denotes the channel matrix between BS and the RIS and $\mathbb{H}_1 \in \mathbb{C}^{\mathbb{K}*\mathbb{N}}$, $\mathbb{H}_2 \in \mathbb{C}^{1*\mathbb{K}}$ denotes channel matrix between RIS and the user u. Θ represents the actual phase shift, and η_u denotes the noise. η_u is generated by transmission. χ represents the transmitted signal from the BS and can be evaluated by Equation (2) [6].

$$\chi = \sum_{u=1}^{\mathbb{X}} \sqrt{p_u \times g_u \times s_u} \tag{2}$$

where $g_u \in \mathbb{C}^{*1}$ denotes precoding vector. s_u denotes the unit-power from the discrete constellation set and p_u denotes the unit-power from total power (P_{Tx}). The SINR (γ) can be calculated by Equation (3) [6].

$$\gamma_i \triangleq \frac{p_i \times |h_{2,i} \times \Theta \times \mathbb{H}_1 \times g_i|^2}{\sum_{j=1,j\neq i}^{K} p_i \times |h_{2,i} \times \Theta \times \mathbb{H}_1 g_j|^2 + \sigma^2} \tag{3}$$

Using Equation (3), we can calculate the throughput of the network with help of Shannon capacity formula as in Equation (4).

$$Throughput\ (\Omega) = \sum_{i=1}^{\mathbb{X}} \log_2(1 + \gamma_i) \tag{4}$$

where γ_i is the SINR of ith users. The instantaneous power P_i can be calculated by (5).

$$\mathbb{P}_i = \mathbb{P}_{UE} + \mathbb{P}_{BS} + \mathbb{P}_{RIS} \tag{5}$$

Here $\mathbb{P}_{UE}$ denotes static power of U_E, $\mathbb{P}_{BS}$ represents the static power of BS and $\mathbb{P}_{RIS}$ shows total hardware static power absorbed by RIS. Equation (6) gives the power of RIS with $\mathbb{K}$ reflecting element.

$$P_{RIS} = \mathbb{P}(\theta) * \mathbb{K} \tag{6}$$

where $\mathbb{P}(\theta)$ is the dissipated power of phase-shifter. The total power (P_T) of the network can be calculated by Equation (7) [6].

$$\mathbb{P}_T = \sum_{i=1}^{\mathbb{X}} \mathbb{P}_{UE} + \sum_{i=1}^{\mathbb{N}} \mathbb{P}_{BS} + \sum_{i=1}^{\mathbb{K}} \mathbb{P}_{RIS} \tag{7}$$

The $\mathbb{EE}$ of the network can is the ratio of data rate and P_T. Mathematically it can written by Equation (8a). This objective function is subject to constraints from (8b) to (8g).

$$\mathbb{EE}_{max} = \frac{\Omega}{P_T} \tag{8a}$$

$$\text{subject to:} \quad P_{min} \leq P_c \tag{8b}$$

$$SINR_{min} \leq SINR_c \tag{8c}$$

$$0 \leq P_c \leq P^{max} \tag{8d}$$

$$R^c \geq R^{min} = \sum_{c \in C} X_c^u c p_c \geq \sum_{c \in C} X_c C p^u \tag{8e}$$

$$p_c^u \leq x_c^u P_c \quad c \in C; C = \{c1, c2\}, u \in U; U = \{1, 2, 3, ..., u\} \tag{8f}$$

$$p_c^u \geq 0 \tag{8g}$$

1. The power of cth connection must be greater than or equal to minimum power (8b).
2. The SINR of cth connection must be greater than or equal to minimum SINR (8c).
3. The power of cth connection must be greater than or equal to zero and less than or equal to maximum (8d).
4. The data rate of cth connection must be greater than or equal to minimum data rate (8e).

5. No power is allocated to non-connected U_E. P_c denotes the maximum transmission power of cth link while p_c^u represents the cth channel power having u U_E (8f).
6. The minimum power of cth U_E must be greater than or equal to 0 (8g).

The upcoming section briefly explains the proposed algorithm to optimize the problem in Equation (8a).

4. Proposed Method

We propose OAA to solve the problem in (8a). The algorithm starts by relaxing integer variables to obtain a non-linear (NLP) subproblem. Applying linearization to non-linear constraints converts the NLP subproblem into the master mixed-integer problem (MIP). Then the feasibility of the MIP is evaluated. If MIP is infeasible, the algorithm stops, and if it is feasible, then fix integer variables and solve the NLP problem again. Add the integer elimination constraints so that the same solution is not obtained in each iteration. The pseudo code of algorithm is shown in Algorithm 1.

Algorithm 1: OAA Algorithm

$k \leftarrow 1$
Initialize X
$\epsilon \leftarrow 10^{-3}$
$Convergence \leftarrow FALSE$
while $Convergence == FALSE$ **do**

$$y^k \leftarrow \begin{cases} \underset{y}{arg\,min} & -u(X,Y) \\ \text{s. t.} & \varphi_{C_1-C_6}(X,Y) \leqslant 0; \end{cases} \qquad Upper\ Bound \leftarrow u(X^k, Y^*)$$

$$(X^*, Y^*, \eta^*) \leftarrow \begin{cases} \underset{X,Y,\eta}{arg\,min} \quad \eta \\ \text{subject to} \\ \eta \geqslant -u(X^k, Y^k) \\ -\nabla u(X^k, Y^k)\left(Y \underset{0}{-} Y^k\right) \\ \varphi_{C1-C6}(X^k, Y^k) \\ -\nabla \varphi_{C1-C6}(X^k, Y^k)\left(Y \underset{0}{-} Y^k\right) \leqslant 0 \end{cases}$$

$Lower\ Bound \leftarrow \eta$
if $Upper\ Bound - Lower\ Bound \leqslant \epsilon$ **then**
  $Convergence \leftarrow TRUE$
end
else
  $k \leftarrow k+1$
  $X^k \leftarrow X^*$
end
end

4.1. Description of OAA Algorithm

Suppose U be the objective function as in (8a) subject to $\varphi_{C_1-C_6}$ (8b) to (8g) and $Y = \{\mathbb{P}_{UE}, \mathbb{P}_{BS}, \mathbb{P}_{RIS}\}$. Whereas $X = x \cup Y$. The following hypothesis are applied to (8a).

1. Y is the set with objective U. It possesses constraints $\varphi_{C_1-C_6}$.
2. U and $\varphi_{C_1-C_6}$ are continuous differentiable.
3. Optimal solution obtained by fixing the X satisfies all the constraints.
4. If we have solution of X, we can obtain the optimal solution of U.

All these hypotheses convert problem (8a) to NLP complex problem, and OAA gives ϵ-optimal solution at convergence. We can achieve the main problem by adjusting x. Integer variables of OAA are iterated κth times. The problem can be written as:

$$\begin{cases} \arg\min\limits_{Y} \quad -U(X,Y) \\ \text{s. t.} \quad \varphi_{C_1-C_6}(X,Y) \leqslant 0 \end{cases} \tag{9}$$

The solution of (9) is set to Y^{κ} and applying the upper and lower limit. We can get the master MIP problem by first converting (9) to integer space and then applying linearization. The problem in integer space X can be written as:

$$\begin{cases} \min\limits_{X}\min\limits_{Y} \quad -U(X^{\kappa},Y) \\ \text{s. t.} \quad \varphi_{C_1-C_6}(X^{\kappa},Y) \leqslant 0 \end{cases} \tag{10}$$

The master problem in (10) can be represented as:

$$\min_{X} \quad -\theta(X) \tag{11}$$

where

$$\begin{cases} \theta(X) = \min\limits_{Y} \quad -U(X^{\kappa},Y) \\ \text{s. t.} \quad \varphi_{C_1-C_6}(X^{\kappa},Y) \leqslant 0 \end{cases} \tag{12}$$

The equation in (11) is the projection of the (8a) with distinct variables. Then according to OAA linearization is applied to get master MIP problem. The master MIP problem can be written as:

$$\begin{cases} \min\limits_{X}\min\limits_{Y} - U(X^{\kappa},Y^{\kappa}) - \nabla U(X^{\kappa},Y^{\kappa})\begin{pmatrix} Y-Y^{\kappa} \\ X-X^{\kappa} \end{pmatrix} \\ \text{s. t.:} - \varphi_{C_1-C_6}(X^{\kappa},Y^{\kappa}) - \nabla\varphi_{C_1-C_6}(X^{\kappa},Y^{\kappa})\begin{pmatrix} Y-Y^{\kappa} \\ X-X^{\kappa} \end{pmatrix} \end{cases} \tag{13}$$

If the algorithm does not converge then a new variables are introduced and can be written as:

$$\min_{X,Y,\eta} \eta \text{ s. t.:} \begin{cases} \eta \geqslant -U(X^{\kappa},Y^{\kappa}) - \nabla U(X^{\kappa},Y^{\kappa})\begin{pmatrix} Y-Y^{\kappa} \\ X-X^{\kappa} \end{pmatrix} \\ -\varphi_{C_1-C_6}(X^{\kappa},Y^{\kappa}) - \nabla\varphi_{C_1-C_6}(X^{\kappa},Y^{\kappa})\begin{pmatrix} Y-Y^{\kappa} \\ X-X^{\kappa} \end{pmatrix} \leqslant 0 \end{cases} \tag{14}$$

OAA solves the MINLP problem (8a). For the resources allocation we use Algorithm 2.

4.2. Resource Allocation

For successful and reliable communication, each U_E needs better resources. We use the following Algorithm 2 to allocate optimal resources to the U_Es. Initially, the random base stations (BSs) are assigned to the U_Es, and U_Es discovers the nearest BS proximity. U_Es and BSs calculate the utility, and blocking is monitored. If the blockage is found, RIS resources are assigned. Then the U_Es sends the proposal to the optimal BS, and the utility is calculated if the utility increases the BSs accept proposals, and stable matching is achieved.

Algorithm 2: Resource Allocation Algorithm

1. *Assign random BSs to* $U_E s$
2. *Find the nearest BS proximity*
3. *Calculate utility*
4. *Utility improved* $\leftarrow$ *FALSE*

while *Utility improved* == *FALSE* **do**
  4*a*. *Observe blockage*
  if *Blockage* == *YES* **then**
    $U_E \leftarrow$ *RIS channel*
  end
  else
    $U_E \leftarrow$ *Without RIS channel*
  end
  4*b*. $U_E s$ *send proposals to nearest BSs*
  4*c*. *BSs calculate utility*
end
5. *Stable matching achieved.*

The next section shows the experimental results obtained with OAA.

5. Experimental Results

We simulated the network in MATLAB and solved the problem in Equation (8a) using OAA. The value of P_{BS} is 20 dBW. P_{UE} and P_{RIS} is 10 dBm. The minimum data rate (R_{min}) is 0.1 bits/s/Hz. The maximum number of users (max_{UE}) is 300 whereas the minimum number of users (min_{UE}) is 2. The simulation parameters for the network are summarized in Table 2.

Table 2. Simulation Parameters.

Parameter	Value	Unit
P_{BS}	20	dBW
P_{UE}	10	dBm
P_{RIS}	10	dBm
R_{min}	0.1	bits/s/Hz
min_{UE}	2	–
max_{UE}	300	–
$\mathbb{N}$	32	–
$\mathbb{K}$	16	–

The performance of the proposed algorithm is compared with the plethora of algorithms such as particle swarm optimization (PSO) [29], firefly algorithm (FA) [30], artificial bee colony (ABC) [31], cuckoo search (CS) [32], teaching learning-based optimization (TLBO) [33], basic open-source nonlinear mixed integer programming (BOMIN) [34], social group optimization (SGO) [35], mesh-adaptive-direct-search-algorithm (NOMAD) [36] and genetic algorithm (GA) [37] to compare and validate the results of the proposed algorithm. Figure 5 shows the complete performance analysis of the proposed algorithm. The throughput of the network for all the algorithms is shown in Figure 5a. The highest average Ω achieved by OAA is 90 Mbps. The proposed algorithm starts converging when the number of U_E is greater than 180. Figure 5a also shows that the performance of the OAA is better than other algorithms.

The EE and the latency of the network are also evaluated using several algorithms as shown in Figure 5b. Figure 5b shows that the performance of the OAA is better than other algorithms. OAA achieves optimal $\mathbb{EE}$ of 9 Mb/J whereas the highest $\mathbb{EE}$ achieved by the other algorithms, particularly NOMAD, is 8.5 Mb/J. OAA shows significant improvement in $\mathbb{EE}$. The optimal latency achieved by the OAA is 0.5 ms for 90 U_E, whereas the minimum latency achieved by NOMAD is 1 ms. The performance of NOMAD is better than other algorithms. However, OAA outperforms NOMAD.

We evaluated the channel efficiency ($\mathbb{CE}$) of the RIS channel and NLOS using OAA. Figure 5c shows the CE in the percentage of OAA with Ω. The $\mathbb{CE}$ of RIS-assisted network is 95%. However, the $\mathbb{CE}$ of the without RIS is 85% which signifies the importance of RIS surface in the network.

Figure 5d, shows the allocation of the RIS to the U_E. When the number of U_E increases, more U_E are shifted on RIS to avoid blockage caused by the NLOS. The minimum number of U_E that successfully communicates with RIS is 10. However, when the number of users increases from 10, the U_E is shifted on the RIS channel because the network exceeds the mobile communication network forecast limit. The forecast is predicted using Algorithm 2. The utility improvement makes the network stable and allocates optimal resources to all $U_E s$.

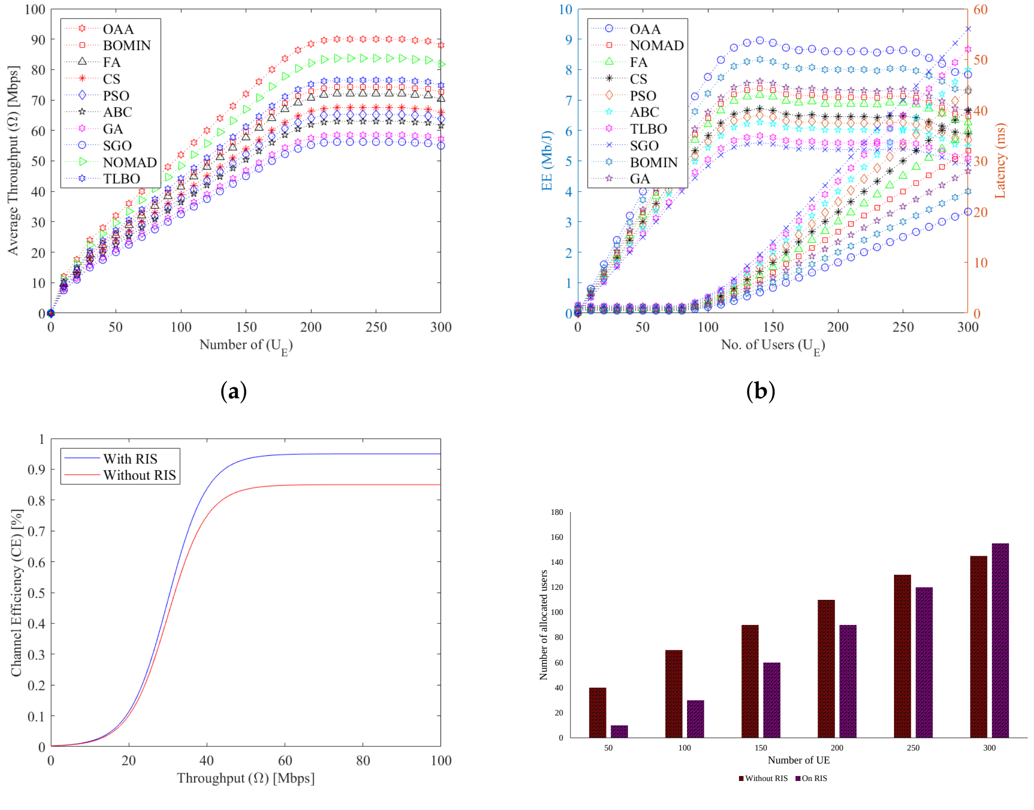

Figure 5. Performance analysis of the proposed algorithm. (**a**) Average Ω (Mbps) vs. No. of U_E; (**b**) No. of U_E vs. $\mathbb{EE}$ and Latency (ms); (**c**) Channel efficiency ($\mathbb{CE}$) vs. Ω; (**d**) Resource allocation to U_E.

The upcoming section presents the conclusion.

6. Conclusions

Mobile communication is increasing day by day, and the requirement for high EE and low latency is also growing, particularly in industry 5.0. 6G provides the solution to this problem; however, the deployment of 6G is challenging. RIS is the primary solution in deploying the 6G, and this article considers an industry scenario and formulates an MINLP optimization problem. We propose an OAA algorithm for the formulated problem. The performance of the proposed algorithm is evaluated in terms of EE, throughput, latency, and resource allocation. The optimal EE obtained by OAA is 9 MbJ^{-1}, whereas the optimal average Ω achieved by OAA is 90 Mbps. The latency of the network using the OAA algorithm is 0.5 milliseconds. We also compare the performance of the proposed algorithm with several optimization algorithms. The experimental results verify that the proposed OAA outperforms all the other algorithms. In we future, we aim to implement the proposed algorithm in other domains such as in a smart city, heterogeneous networks, human to robots communication.

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