A Semi-Markov Decision Process (SMDP)-based Channel Allocation Model for Unreliable Terahertz (THz) Reconfigurable Intelligent Surfaces (RIS)

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Abstract—Terahertz (THz) communications and reconfigurable intelligent surfaces (RISs) have been recently proposed to enable various powerful indoor applications, such as wireless virtual reality (VR). For an efficient servicing of VR users, an efficient THz channel allocation solution becomes a necessity. Assuming that RIS component is the most critical one in enabling the service, we investigate the impact of RIS hardware failure on channel allocation performance. To this end, we study a THz network that employs THz operated RISs acting as base stations, serving VR users. We propose a Semi-Markov decision Process (SMDP)-based channel allocation model to ensure the reliability of THz connection, while maximizing the total long-term expected system reward, considering the system gains, costs of channel utilization, and the penalty of RIS failure. The SMDP-based model of the RIS system is formulated by defining the state space, action space, reward model, and transition probability distribution. We propose an optimal iterative algorithm for channel allocation that decides the next action at each system state. The results show the average reward and VR service blocking probability under different scenarios and with various VR service arrivals and RIS failure rates, as first step towards feasible VR services over unreliable THz RIS.

Index Terms—SMDP, channel allocation, virtual reality, reconfigurable intelligent surfaces, reliability.

I. INTRODUCTION

Virtual Reality (VR) applications are envisioned as one of the key technologies that will advance the human to machine interactions where a user is present and acts in a virtual world [1]. In order to satisfy the high demand of data rates that VR applications require, the THz frequency band is currently one of the most promising communications technology to provide a high quality VR experience. As THz communication is characterized by directional and sensitive to attenuation beams, a new technology called Reconfigurable Intelligent Surfaces (RIS) is used to enhance the performance of THz wireless communications [2], [3]. In an indoor setting, the usage of RIS in THz communications is rather critical, since by controlling the reflective properties of the underlying channels, we can mitigate various THz transmission impairments [4].

It is known that RIS array elements, so called meta-surfaces, are vulnerable to failures, which can cause deterioration of the antenna radiation pattern, and in severe cases, the RIS failures can affect the functioning of RIS meta-surface elements [5]. In addition, THz links can also be blocked between the user and RIS, due to various obstacles. In order to design reliable RIS based networks in practical environments, it is becoming essential to develop channel allocation schemes that are aware of RIS meta-surface failures, as well as link failure between RISs and users. The resource allocation problem in RIS networks is indeed one of the key problems to solve for any efficient RIS design, where several sub-problems can be investigated, including channel allocation, power allocation, RIS-to-user assignment, and phase shifts design. Few works studied resource allocation problems, but no work to date considered the problem of channel allocation under faulty RIS scenarios. To the best of our knowledge, channel allocation of VR over THz RIS, considering the unreliability of RIS devices has not yet been investigated.

In this paper, we consider channel resource allocation in the VR applications over RIS network with controlled access of VR users request by Semi-Markov decision Process (SMDP). We introduce an optimal channel allocation scheme to ensure the reliability and maximize the system reward in a set of RISs, in which a RIS device and its meta-surface elements are vulnerable to failures, as are the THz links between RISs and users. We formulate the problem of RIS-unreliability-aware channel allocation as an SMDP model considering multiple RIS devices in an indoor environment used to allocate THz meta-surfaces to VR users. Following the definition of SMDP [6], the decision is taken at the event occurrence, while an iterative algorithm proposed maximizes the total long-term reward of the VR over RIS system, considering the factors of user’s income of the accepted services, the costs for occupying channels, and penalty of RIS and meta-surface failures. We make realistic assumptions on the reference THz network model, where a set of backup RIS devices are used to ensure the reliability of the system, for cases where a RIS device or a meta-surface in a RIS fails. When a RIS or a meta-surface fails, the corresponding backup RIS is allocated to transfer the existing services, which allows the RIS network to operate in a reliable fashion.

Numerical results show the average reward and blocking probability with various service arrival and RIS failure rates, and under different network configurations. Our proposed solution can compute corresponding policies to each service request arrival rate to ensure the reliability and maximize long-term rewards. The proposed scheme is generally applicable, dynamic and provides an efficient solution to the channel al-
location problem. We also show that our scheme improves the QoS of THz communication with regard to the request arrival rate, and RIS meta-surfaces availability. Moreover, when VR users request arrival rate is high, the channels are allocated with the minimum requirements for a VR service to operate, which decreases the blocking probability, and allows more users to join the RIS network overall. Since each RIS device can be used to provide a connection to various VR users, we show that a shared solution allows for more flexibility to the system. The results show that increasing the number of RISs and meta-surfaces does not always improve the performance in terms of long-term reward and service blocking for service arrival rates below a certain threshold. Hence, our model can help dimensioning RIS THz networks in terms of costs and performance based on the expected service rate. We show that future work can benefit from a large-scale solution based on reinforcement learning that could to solve value iteration algorithm, which is known to grow exponentially.

The rest of this paper is organized as follows. Section II discusses the related work. Section III presents the SMDP based channel allocation model in indoor THz network, with unreliable RIS. Section IV describes the proposed optimal iterative-based solution. Section V evaluates the performance. We conclude the paper in Section VI.

II. RELATED WORK

VR communication has been recently investigated in several seminal works [7]–[9], focusing on studying the VR Quality of Service (QoS). In [7], a VR model was studied that detect the tracking and delay components of VR QoS. The work in [8] analysed the spectrum resource allocation problem, considering a brain-aware QoS constraint. In [9] the downlink of VR requests over RISs network, operating over the terahertz (THz) frequency bands, was considered, and a solution was proposed to the problem of associating RISs to virtual reality users.

Due to the importance of hardware failures, the baseband complex received signal from a RIS element has been modeled in [10], considering faulty reflecting elements of RIS. Thus, in order to design reliable RIS based networks in practical environments, it is essential to develop resource allocation schemes aware of RIS array failures. The optimal number of reflecting elements in a RIS has been studied theoretically in [11] to maximize the transmission rate in a point-to-point link, emphasizing the importance of RIS configuration (e.g., channel allocation scheme), and the resulting overhead due to channel estimation. Motivated by this work, which concluded that new, sophisticated resource allocation schemes are needed, we use a model of a VR over THz RIS network under the similar failure assumptions to solving channel allocation problem.

Recent works studied the resource allocation problem in THz RIS networks specifically. Paper [12] studied different types of active RISs (active and passive), considering their hardware architectures, operation modes, and applications in communications, and also highlighted the need of developing efficient resource allocation solutions, which is still an open challenge. In [13] a downlink multi-user multi-input single-output (MISO) system was studied, where a RIS is used to support a base station to ensuring a reliable communication when the signal is affected by obstacles. The resource allocation problem is tackled by an iterative algorithm based on alternating optimization, in order to solve the sum-rate maximization problem, addressed by optimizing the digital beamforming at the base station and the discrete phase shifts at the RIS. The main focus of the work was the rate optimization over a signal RIS component, under the assumption that RIS devices are reliable, and a user is assigned to a single channel.

In [9], a virtual reality network was considered and a solution was proposed to the problem of associating RISs to virtual reality users operating over the terahertz frequency bands. In particular, the paper formulates a risk-based framework based on the entropic value-at-risk and optimize the transmission rate and reliability. A single RIS device was considered and the formulated problem aims at achieving higher order statistics of the queue length, in order to guaranteeing continuous reliability. Lyapunov optimization, deep reinforcement learning, and recurrent neural network were adopted to solve the optimization problem. We adopt a similar VR over RIS model as in [9], however our focus is not on optimizing the transmission rate by adjusting the queue length. Instead, we assume the existence of multiple RISs that can provide the same set of VR users, as well as the possibility to allocate multiple channels for the same VR user request, while considering the failure possibility of RISs and meta-surfaces.

A few other related works are notable including [14], that focused on energy-efficient design for transmit power allocation and the phase shifts of the surface reflecting elements. In [15], an optimal scheme was proposed that maximizes the system sum-rate using a modulation scheme compatible with RIS system and a resource allocation scheme that control the transmission power and modulation. The studied system has not considered channel allocation, considering the user arrival rates, service rates, or the faulty RISs.

Paper [16] studied the resource allocation problem in RIS systems focusing on power allocation and proposed a resource allocation framework in multi-cell downlink RIS-nominal-orthogonal multiple access (NOMA) networks, where a joint optimization problem was solved to maximize the achievable sum-rate of user association, sub-channel assignment, power allocation, phase shifts design, and decoding order determination; a single RIS was considered assuming that RIS devices cannot fail. In [17], joint active and passive beamforming problem and the user-RIS association problem was investigated in a multi-RIS assisted multi-user communications. The authors mapped the problem of max-min signal-to-interference-plus-noise ratio (SINR) into a user-RIS association problem, and proposed greedy search algorithm as a solution, tuning the RIS to serve a certain user.

It should be noted that channel allocation problem has been well investigated in other contexts such as in vehicular networks. In [18], an SMDP-based channel allocation scheme was
proposed in vehicular ad-hoc networks to maximize the overall system rewards, while servicing user requests through roadside units. The paper concluded that due to the high mobility of users, an SMDP policy for the channel allocation problem can improve the QoS. Motivated by this work, we could see the VR over RIS network as a cognitive-enabled vehicular ad-hoc networks, where VR users can be mapped to vehicle users, RISs could replace the roadside units (RSUs), and the allocation of meta-surfaces can be seen as channel allocation, which is our approach in this paper. SMDP-model was also proposed in [19] to solving channel allocation problem in order to maximizing throughput in the context of vehicular networks.

The related work is primarily based on linear programming which is known to be an NP hard problem, and that it works for off-line processing, whereas our proposed model works for online channel assignment to users using an iterative solution, that assumes the knowledge about some system statistics, such as the RIS failure, service arrival, and service departure. Moreover, our approach assumes that the system statistics are known, and that the RIS configuration such as phase shift and power control are managed by other algorithms independently. Thus, our approach is focused on channel allocation only, as a function of VR user’s THz channel request behavior. We also do not consider the dependency between RIS failures, which is a limitation, as is the intrinsic limitation of SMDP to scale to larger systems.

III. SMDP based Channel Allocation of VR over THz RIS

In this section, we model a RIS-based wireless indoor reference THz network in an indoor area, provide the channel model, analyze the channel states and actions, as well as transmission probabilities, and rewards analysis.

A. The reference network and assumptions

The reference THz network is illustrated in Figure 1. The reference network consists of a set of RISs, small base station (SBS) operating over THz frequency, RIS controller, and VR users. RISs are classified into two categories: main RIS, used to servicing a set of mobile wireless VR users, and a backup RIS used to servicing the users when a main RIS fails. The SBS is responsible for receiving requests from VR users and servicing them via RIS components. The uplink of VR service requests is adopting an ultra reliable low latency communications (URLLC) scheme, similar to [9]. In this study, we consider the downlink of the RIS-based network only, where each RIS is covering the indoor environment and can provide THz communication channel to VR users. The users are assumed to be mobile and can have different locations in the environment, and requesting VR services. The VR user end-devices can send several of service requests through the RIS network.

Each RIS can reflect the beams received from a main THz SBS, which generally uses a MIMO system. The information sent from the SBS is encoded in the phase of the signal reflected by the reconfigurable elements that compose the RIS. A RIS contains of a very large number of passive reflective elements called meta-surfaces, capable of reconfiguring properties of electromagnetic (EM) waves impinging upon them. We assume that all RISs are connected to the RIS Controller responsible for channel tuning by changing the phase of the reflected signal [14]. A RIS containing several meta-surfaces connected to a THz SBS can be represented as a multi channel system. The channels can be allocated based on the system availability. In order to ensure the reliability of the system, where RIS failure is considered, we pre-reserve a backup RIS to each operating RIS. We assume that services can be transferred from the operating RIS to the backup RIS when operating RIS or a single meta-surface failure occurs. Figure 1 illustrates three failure scenarios. First, when a meta-surface fails, we assume the failure of meta-surface will affect at most one user, while all other channels remain unaffected. To insure the reliability, we transfer one connection from the main RIS to the backup RIS. On the other hand, when an entire RIS fails, all connections will be affected, thus we transfer all of them to the backup RIS. Finally, a THz link between RIS and users can also fail.

For the generality of our model, we assume that the RIS network can include heterogeneous RIS devices, of various sizes and containing different number of meta-surfaces, and thus servicing different number of channels. When a requested VR services from VR users is detected, the RIS controller accepts or rejects it based on the availability of the channel resources.

In this paper, we assume that the THz link between the VR user and the RIS can be blocked and fail with a certain probability, and the link between RIS and the THz SBS is reliable and cannot be disrupted by obstacles. A VR user-RIS failure caused by an obstacle block will result in a failure of the transmission channel and creates a delay, which affects the QoS. We assume that a RIS and a meta-surface can face a hardware failure, and for the downlink connection we propose a novel channel allocation scheme.

B. Channel Model

This model focuses on the THz link between VR users and the RIS, where the VR user is mobile. The user movements can cause signal blocking due to self blocking, or due to other mobile or fixed obstacle in the indoor environment, as described in [9]. We assume the time slots indexed by $t$ have a period duration $\tau_0$. We denote by $L_{r,n,u,t}$ a binary random variable, which is equal to 1 when the Line-of-Sight (LoS) link between the meta-surface $n$ of the RIS $r$ and the user $u$ at time slot $t$ is available and 0 otherwise. The corresponding random channel gain is defined as in [9] as:

$$h_{r,n,u,t} = \begin{cases} \left(\frac{c}{4\pi d_{r,u,t}}\right) (e^{-k(f)d_{r,u,t}})^2, & \text{if } P(L_{r,n,u,t} = 1), \\ 0, & \text{if } P(L_{r,n,u,t} = 0), \end{cases}$$

where $c$ is the speed of light in the vacuum, $d_{b,u,t}$ is the distance between RIS $r$ and the VR user at time slot $t$,
Figure 1: The reference indoor THz RIS network.

\( f \) is the operating frequency, \( k(f) \) is the overall molecular absorption coefficients of the medium at THz band, available from HITRAN database \[20\]. The transmission rate between RIS \( r \) and the VR user \( u \) at time slot \( t \) is given by:

\[
c_{r,u,t} = W \cdot \log_2 \left( 1 + P_{RIS} h_{r,u,t} \sum_{n=1}^{N} \left| e^{j(\phi_{r,n,u,t} - \psi_{r,n,u,t})} \right|^2 L_{r,n,u,t} \right)
\]

where \( W \) is the total bandwidth, \( P_{RIS} \) is the transmit power related to each RIS, \( \psi_{r,n,u,t} \) is the phase shift of the channel between meta-surface element \( n \) of RIS \( r \) with respect to user \( u \) at time slot \( t \), \( \phi_{r,n,u,t} \) is the phase shift of the channel between meta-surface element \( n \) of RIS \( r \) with respect to user \( u \) at time slot \( t \), \( N(d_{r,u,t}, p, f) = N_0 + \sum_{r=1}^{R} P_{RIS} A_0 d_{r,u,t}^{-2} (1 - e^{-K(f)d_{r,u,t}}) \), \( T_0 \) is the temperature in Kelvin, \( A_0 = \frac{1}{106.77} \) \[21\].

The obtained transmission rate can be used to calculate the service rate of a specific VR service \( s \), given by:

\[
C_{r,u,t,s} = \frac{c_{r,u,t}}{O_s}
\]

where \( O_s \) is the size of the object related to the service \( s \), such as the size of a VR image.

C. Problem Formulation

We consider a RIS-based THz network including two sets of RISs, e.g., a set of operating RISs \( R = \{r_1, ..., r_i, ..., r_R\} \) and a set of backup RISs \( B = \{b_1, ..., b_i, ..., b_R\} \), managed by the RIS Controller. We study the channel allocation problem regarding different RIS components, where VR users are requesting service connections. The RIS \( r_i \) and \( b_i \) contain \( N(i) \) meta-surfaces that can be allocated as transmission channels. A service request can occupy \( k \) channels/meta-surfaces based on the resource availability, where \( K \) represents the maximum number of channel a RIS can allocate to a single service, whereby \( K \leq \min_{i \in [1,R]} \{N(i)\} \). In other words, for any service, all RIS has enough maximum capacity \( N(i) \) to satisfy its capacity requirements. We model the arrival and service processes of VR service requests from a user as a Poisson process with mean rates \( \lambda_s \) and \( \mu_s \), respectively, where \( \mu_s \) can be concluded from eq. (5) for different services.

To address reliability issue, we assume failures of RISs, meta-surfaces and THz links between meta-surface and VR user. We assume that the THz link fails due to either a permanent obstacle between meta-surface and VR user with probability \( \phi_i \) or a failure of the meta-surface. Any meta-surface can fail with probability \( p_i \) due to hardware or software failure. We assume any operating RIS as not available, when at least one operating meta-surface of this RIS fails. Moreover, operating and backup RIS can fail due to hardware or software failure with probability \( \eta_i \) and results in unavailability of all meta-surfaces. In case of any disruption of operating THz channel, a service migration to backup RIS is required, i.e., the THz connection will be maintained by a backup RIS. Thus, the probability of a maintaining a THz channel available to ensure VR services can be expressed as follows:

\[
R = (1 - \eta_i)(1 - p_i)^k(1 - \phi_i)^k.
\]

\[
\cdot \left[1 + \eta_i(1 - \eta_i)\left[(1 - (1 - p_i)^k)(1 - (1 - \phi_i)^k)\right]\right]
\]

Our unreliability-aware resource allocation model assumes that all RISs and all meta-surfaces are spatially separated from each other. Thus, there is no failure dependency i.e. if a meta-surface in a certain RIS fails, there is no direct effect on the availability of other meta-surfaces that belong to the same or other RISs.

Next, we provide an SMDP model described by the components \( \{S, A(s), p(s'|s, a), r(s|a)\} \), where \( S \) is the state space, \( A(s) \) is the set of feasible actions at the state \( s \in S \), \( p(s'|s, a) \) is the transition probability from the state \( s \) to the state \( s' \) when an action \( a \) is chosen, and \( r(s|a) \) is the reward of the system at the state \( s \) when choosing the action \( a \).
D. System States

The system state $s$ represents the number of VR service requests with different number of allocated channels $k$ in a RIS $r_i$, the availability of the RIS and the next event that can happen in the system:

$$S = \{ s | s = (\Delta^M, \Delta^B, X, e) \},$$

(5)

where a set $\Delta^M = \delta^{r_1}, ..., \delta^{r_n}$ collects all subsets $\delta^{r_i}$, which describe a state $s$ and indicate a number of VR services transferred to backup RISs $\delta^{b_i} = \{ \delta_1(b_i), ..., \delta_k(b_i), ..., \delta_K(b_i) \}$. The variable $\delta_k(r_i)$ denotes the number of VR services allocated with $k$ channels in the main RIS $r_i$, $\Delta^B = \delta^{b_1}, ..., \delta^{b_n}$ collects all subsets $\delta^{b_i}$, which describe a state $s$ and indicate a number of VR services transferred to backup RISs $\delta^{b_i} = \{ \delta_1(b_i), ..., \delta_k(b_i), ..., \delta_K(b_i) \}$. The variable $\delta_k(b_i)$ denotes the number of VR services allocated with $k$ channels in the backup RIS $b_i$.

A set $X = \{ X^{r_1}, ..., X^{r_n} \}$ describes the availability of RIS devices and indicates the number of available meta-surfaces:

$$X^{r_i} = N(i)$$

if all the elements of the RIS $r_i$ are available, $X^{r_i} = N(i) - j$ if $j$ elements are failed and $X^{r_i} = 0$ if all the elements are failed or the RIS hardware fails. The failure of the backup RIS is not considered in our work.

The variable $e$ describes an event that occurs in the VR over THz RIS network, such as $e = \{ Ar, D^r, D^b, F^r, F^m, R^c, R^m \}$, where a set $Ar$ denotes the arrival of any VR service request, a set $D^r = \{ D^{r_1}, ..., D^{r_n} \}$, and a subset $D_i^{r} = \{ D_i^{r_1}, ..., D_i^{r_k}, ..., D_i^{r_K} \}$ collects the set of departure events of a VR service from a main RIS $r_i$, and $D_i^{b}$ defines the departure of a VR service allocated in $k$ channel from a RIS $r_i$, a set $D^b = \{ D^{b_1}, ..., D^{b_k}, ..., D^{b_n} \}$, and a subset $D_i^{b} = \{ D_i^{b_1}, ..., D_i^{b_k}, ..., D_i^{b_K} \}$ collects the set of departure events of a VR service from a backup RIS $b_i$, and $D_i^{b}$ defines the departure of a VR service allocated in $k$ channel from a backup RIS $b_i$, an event $F^r_i$ denotes the failure of the controlled RIS ($r_i$), a set $F^m = \{ F^m_i, ..., F^m_i, ..., F^m_n \}$ and a variable $F_i^m$ define the failure process of a meta-surface in the RIS $r_i$, an event $R^c_i$ denotes the return process of a RIS $r_i$ to the working state after a failure, similar, a set $R^m = \{ R^m_i, ..., R^m_i, ..., R^m_n \}$ and a variable $R_i^m$ define the return of a channel/meta-surface in the RIS $r_i$ to working state after a failure.

The channel allocation scheme in RIS network has the following capacity constraints:

$$\forall i \in [1, R]: \sum_{k=1}^{K} k \cdot \delta_k(r_i) \leq N(i),$$

(6)

E. Actions

The system controller has several possibilities of actions a to take when it receives a service request, whether to accept or reject it. The action space $A(s)$ is described as follows:

$$A(s) = \begin{cases} 
\{0, (i, k)\}, & e = Ar, \\
\{k \in {0, 1, 2, ..., K}, i \in {1, ..., R}\}, & e = D^r, D^b, R^c, R^m \\
\{-1\}, & e = F^r_i, F_i^m \\
\{-2, T\}, & e = F^r_i, F_i^m 
\end{cases}$$

(7)

where $a(s) = (i, k), \forall k \in {1, ..., K} \forall i \in {1, ..., R}$ when a VR service request is accepted and $k$ channels are allocated in RIS $r_i$, $a(s) = 0$ denotes the action of rejecting a service request. When a service completes and departs the RIS system, a RIS node or channel/meta-surface returns into the state after a failure, no action is required, and the controller needs only to update the system state, we represent the action as $a(s) = -1$. When a RIS fails, all the allocated channels are transferred to the backup RIS, and when a meta-surface (channel) fails, a corresponding channel will be allocated in the backup RIS, we denote the information update and the transfer action as $a(s) = (-2, T)$, where $T$ is the transfer vector from main RIS to backup RIS.

Definition 1. we define a mapping $\psi(.)$ in $\mathbb{N}$ as follows:

$$\psi(x) = \begin{cases} 0, & \text{if} \ x = 0 \\
1, & \text{if} \ x > 0 
\end{cases}$$

(8)

F. Transition Probabilities

We assume that the time period between two continuous decision epochs follows an exponential distribution and denoted as $\tau(s, a)$, given the current state $s$ and action $a$. Thus the mean rate of events for a specific state $s$ and action $a$ denoted as $\gamma(s, a)$, is the sum of the rates of all events in the RIS system, which is expressed as follows:

$$\forall i \in [1, R], \forall k \in [1, K]: \tau(s, a) = \gamma(s, a)^{-1} =$$

$$
\begin{cases} 
\lambda_s + \lambda^r + \lambda^m + \Theta^c + \Theta^m + \Theta + k\mu_s, & \text{e = Ar, a = (i, k)}, \\
\lambda_s + \lambda^r + \lambda^m + \Theta^c + \Theta^m + \Theta, & \text{e = Ar, a = 0}, \\
\lambda_s + (\lambda^r - \lambda^c) + \lambda^m + (\Theta^c + \mu^r) + \Theta^m + \Theta, & \text{e = R^c, a = -1}, \\
\lambda_s + \lambda^r + (\lambda^m - \lambda^c) + \Theta^c + (\Theta^m + \mu^m) + \Theta, & \text{e = R^m, a = -1}, \\
\lambda_s + \lambda^r + \lambda^m + \Theta^c + (\Theta^m + \Theta - k\mu_s), & \text{e = D^c_i | D^b_k, a = -1}, \\
\lambda_s + \lambda^r + (\lambda^m + \lambda^c) + \Theta^c + (\Theta^m - \mu^m) + \Theta, & \text{e = F^m_i, a = (-2, T)}, \\
\lambda_s + (\lambda^r + \lambda^c) + (\Theta^m + \Theta^c) + \Theta^m + \Theta, & \text{e = F^r_i, a = (-2, T)}, 
\end{cases}
$$

(9)
where \( \lambda_s \) is the arrival rate of VR service requests, \( \lambda^r \) and \( \mu^r \) denotes the arrival rate (return of RIS to operating after a failure) and the departure rate (failure) of a RIS, \( \Lambda^r = \lambda^r \sum_{i=1}^{R}(1 - \psi(X^r_i)) \) is the arrival rate of non available RISs, \( \Theta^r = \mu^r \sum_{i=1}^{R} \psi(X^r_i) \) is the failure rate of available RISs, \( \Lambda^m = \lambda^m \sum_{i=1}^{R} N(i) - X^r_i \) is the arrival rate of non available RIS meta-surfaces, and \( \Theta^m = \mu^m \sum_{i=1}^{R} N(i) \) is the failure rate of available RIS meta-surfaces.

When an arriving service request is rejected, or a RIS or a meta-surface/channel returns to system, the total number of existing services allocated in RISs is \( \sum_{i=1}^{R} \sum_{k=1}^{K} \delta_k(r_i), \) so the departure rate of a VR service in RIS system is \( \Theta = \sum_{i=1}^{R} \sum_{k=1}^{K} \delta_k(r_i) \), when a service request is accepted and \( k \) channels are allocated, one more service is added to the system, thus the departure rate becomes \( \Theta + k \mu_s \). When a departure of a VR service from a RIS \( r_i \) allocated in \( k \) channels occurs, the departure rate becomes \( \Theta - k \mu_s \). When a RIS meta-surface/channel fails, the arrival rate and failure rate of the RIS channels in the system are adjusted such that the failed channel can return in the future and cannot fail again while it is already failed. All services admitted in the case of a failed RIS channel are transferred to the backup RIS, so it should be accounted in the departure rate, which ensures the system reliability, and thus the number of existing services remains equal to \( \Theta \). When a RIS fails, the arrival rate and failure rate of RIS in the system are also adjusted, and all services are transferred to the backup RIS, thus the service rate remains the same.

The transition probability in our markov decision model from state \( s \) to state \( s' \) when an action \( a \) is selected is denotes as \( p(s' | s, a) \), which can be determined under different events.

- State \( s = (\hat{\Delta}^m, \Delta^B, X, Ar) \), and \( a = 0 \). This state describes the system in terms of number of channels allocated in a RIS \( r_i \), RIS and RIS meta-surfaces availability, and the next event, which is in this case a service arrival. The service arrival event can have two actions accept or reject. The following equation shows the transition probability when the service is blocked, where the number of channels allocated in the RISSs and in the backup RISs, and RIS and RIS meta-surfaces availability remain the same, and possible events can occur in the future.

\[
p(s' | s, a) = \begin{cases} 
\frac{\lambda_s}{\tau(s,a)} & s' = (\hat{\Delta}^m, \Delta^B, X, Ar) \\
\frac{k\delta_k(r_i)\mu_s}{\tau(s,a)} & s' = (\hat{\Delta}^m, \Delta^B, X, D^b_i) \\
\frac{k'\delta_{k'}(r_i)\mu_s}{\tau(s,a)} & s' = (\hat{\Delta}^m, \Delta^B, X, D^b_{i'}) \\
\frac{\lambda^m}{\tau(s,a)} & s' = (\hat{\Delta}^m, \Delta^B, X, Re_i^m) \\
\frac{\mu^m}{\tau(s,a)} & s' = (\hat{\Delta}^m, \Delta^B, X, F_i^m) 
\end{cases}
\]

(10)
where \( \Delta^B = \delta^{b_1}, \ldots, \delta^{b_i} - I_k, \ldots, \delta^{b_d} \).

- State \( s = (\Delta^M, \Delta^B, X, Re^{r_i}) \), \( a = -1 \). This state describes the system in terms of number of channels allocated in all RISs, RIS and RIS meta-surfaces availability, and the next event, which is a return of a RIS \( r_i \) to working state after a failure, where \( X^r_i = 0 \).

\[
p(s'|s,a) = \begin{cases} 
\frac{\lambda_s}{\tau(s,a)} & s' = (\Delta^M, \Delta^B, X, Ar) \\
\frac{k\delta_k(b_i)r_mu_s}{\tau(s,a)} & s' = (\Delta^M, \Delta^B, X, D_k^{b_i}) \\
\frac{\mu^c}{\tau(s,a)} & s' = (\Delta^M, \Delta^B, X, F_i^{r_i}) \\
\mu^m & i' \neq i \\
\end{cases}
\]

(13)

- State \( s = \Delta^M \), \( a = -1 \). This state describes the system in terms of number of channels allocated in all RISs, RIS and RIS meta-surfaces availability, and the next event, which is the failure process of a RIS \( r_i \), where \( X^r_i = N(i) - j \geq 1 \). The vector \( T \) transfers the allocated channels in \( r_i \) to \( b_i \).

\[
p(s'|s,a) = \begin{cases} 
\frac{\lambda_s}{\tau(s,a)} & s' = (\Delta^M, \Delta^B, \tilde{X}, Ar) \\
k\delta_k(b_i)r_mu_s & s' = (\Delta^M, \Delta^B, \tilde{X}, D_k^{b_i}) \\
\mu^c & i' \neq i \\
\mu^m & s' = (\Delta^M, \Delta^B, \tilde{X}, F_i^{r_i}) \\
\end{cases}
\]

(16)

where \( \tilde{X}^r_i = N(i) \)

- State \( s = (\Delta^M, \Delta^B, X, Re^{r_i}) \), \( a = -1 \). This state describes the system in terms of number of channels allocated in all RISs, RIS and RIS meta-surfaces availability, and the next event, which is a return of a meta-surface in the RIS \( r_i \), to the working state after a failure, where \( X^r_i = N(i) - j \), and \( j \) is the number of failed meta-surfaces.

\[
p(s'|s,a) = \begin{cases} 
\frac{\lambda_s}{\tau(s,a)} & s' = (\Delta^M, \Delta^B, \tilde{X}, Ar) \\
k\delta_k(b_i)r_mu_s & s' = (\Delta^M, \Delta^B, \tilde{X}, D_k^{b_i}) \\
\mu^c & i' \neq i \\
\mu^m & s' = (\Delta^M, \Delta^B, \tilde{X}, F_i^{r_i}) \\
\end{cases}
\]

(17)

where \( \tilde{X}^r_i = N(i) - j \)

\( G. \text{Rewards} \)

Given the system state \( s \) and the corresponding action \( a \), the system reward of the VR over THZ RIS system is denoted by

\[
r(s,a) = w(s,a) - g(s,a)
\]

(18)
Algorithm 1 Finding Service Transfer Vector

1: Input: $s = (\Delta^M, \Delta^B, X, F^m_i)$
2: Initialization: $T = T^1, ..., T^R$, $T^1 = \{T^{i_1}, ..., T^{i_k}, ..., T^{i_K}\}$,
3: $T_k^i = 0, \forall i \in \{1, ..., R\}, \forall k \in \{1, ..., K\}$.
4: $k = 1$
5: while $\delta_k(r_i) = 0$ do
6: $T_k^i = 0$
7: $k = k + 1$
8: end while
9: $T_1^i = 1$
10: Return $T$

where $w(s) = \text{net lump sum incomes of VR users at state } s \text{ when action } a \text{ is taken and an event } e \text{ occurs, and } g(s) = \text{expected system costs}$.

$$w(s,a) = \begin{cases} R_k & e = Ar, a = (i,k) \\ 0 & e = Ar_k, a = 0 \\ 0 & e = Re^{\nu_1} or Re^{m}, a = -1 \\ 0 & e = D^i_k or D^{m}_k, a = -1 \\ -\epsilon N(i) & e = F^r, a = (-2, T) \\ -\epsilon \sum_{k=1}^{k_k} kT_k^i, e = F^{m}_i, a = (-2, T) \\ \end{cases}$$

where the variable $R_k = Q - \frac{2}{k}$ denotes the reward of the RIS system for accepting of the requested service and allocating $k$ channels. $Q$ denotes the income reward from VR user satisfaction, $\frac{2}{k}$ denotes the transmission cost of occupying $k$ channels. The constant $\epsilon$ denotes the penalty of a meta-surface failure. We penalize the failure of a RIS as a summation of the penalties of all meta-surfaces as $-\epsilon N(i)$. When a meta-surface fails, a number of services are transferred to the backup RIS, and thus we consider a penalty proportional to the number of re-allocated channels as $-\epsilon \sum_{k=1}^{k_k} kT_k^i$. In our work, we don’t penalize rejected services, neither reward accomplished services or returned RISs or returned meta-surfaces.

The expected system cost $g(s,a)$ is defined as:

$$g(s,a) = c(s,a) \cdot \tau(s,a)$$

where $\tau(s,a)$ is the expected service time defined by eq. [3].

$$\text{from the state } s \text{ to the next state in case that action } a \text{ is chosen and } c(s,a) \text{ is the service holding cost rate when the RIS system is in state } s \text{ in case that action } a \text{ is selected. Furthermore, } c(s,a) \text{ can be described by the number of occupied channels in the RIS system, as follows:}$$

$$c(s,a) = \sum_{k=1}^{k} \sum_{k} c \cdot k \cdot (\delta^r_k + \delta^b_k)$$

where $c$ represents the utilization cost of a channel unit.

IV. SMDP-BASED CHANNEL ALLOCATION MODEL

In this section, we develop an SMDP-based channel allocation model to study the performance of a RIS system considering the unreliability of RIS devices. We aim to take optimal decisions at every decision epochs: arrival of new service request, departure of a service, failure of a RIS, failure of a meta-surface, return of a RIS, or return of a failed meta-surface, where our goal is to maximize the long-term expected system rewards. The expected discounted reward is given based on the model in [6] as follows:

$$r(s,a) = w(s,a) - c(s,a) \cdot E \left[ \int_0^\tau e^{-\alpha t} dt \right]$$

$$= w(s,a) - c(s,a) \cdot E \left[ \frac{1 - e^{-\alpha \tau}}{\alpha} \right]$$

$$= w(s,a) - \frac{c(s,a)}{\alpha + \tau(s,a)}$$

where $\alpha$ is a continuous-time discount factor.

Using the defined transition probabilities eq. [10], [11], [12], [13], [14], [15], [16], [17], we can obtain the maximum long-term discounted reward using a discounted reward model defined in [6] as

$$\nu(s) = \max_{a \in A(s)} \left\{ r(s,a) + \lambda \sum_{s' \in S} p(s'|s,a)\nu(s') \right\}$$

where $\lambda = \tau(s,a)/(\alpha + \tau(s,a))$. In the SMDP model, the value of $\nu(s)$ in a strategy $\psi$ is computed based on the value $\nu(s')$ obtained in the strategy $\psi - 1$, and as an initial value, the discounted reward can be set to zero for all states to initialize the computation, which will converge afterwards to the optimal solution.

To simplify the computation of the reward, let $\rho$ be a finite constant, where $\rho = \lambda + \lambda'R + \lambda^m \prod_{i=1}^{R} N(i) + \mu'R + \mu^m \prod_{i=1}^{R} N(i) + \mu_s + \sum_{i=1}^{R} N(i) < \infty$. We define $\overline{p}(s'|s,a), \bar{\nu}(s), \bar{\tau}(s,a)$ as the uniformed transition probability, long-term reward, and reward function, respectively, and given by:

$$\bar{\tau}(s,a) = r(s,a) \frac{\tau(s,a) + \alpha}{\rho + \alpha}, \overline{\lambda} = \frac{\rho}{\rho + \alpha}$$

$$\overline{p}(s'|s,a) = \left\{ \begin{array}{ll}
1 - \frac{1 - (1 - \nu(s'|s,a))\tau(s,a)}{\rho} & s' = s \\
\nu(s'|s,a) & s' \neq s
\end{array} \right.$$}

After uniformization, the optimal reward is given by:

$$\nu(s) = \max_{a \in A(s)} \left\{ r(s,a) + \overline{\lambda} \sum_{s' \in S} \overline{p}(s'|s,a)\nu(s') \right\}$$

In order to solve our SMDP-based Channel Allocation (CA) model, we consider an iterative algorithm described as follows:

After obtaining the optimal policy from Algorithm 2, the steady states probabilities are computed using the following system of equations:

$$\pi(P - J) = 0, \sum_{s \in S} \pi(s) = 1$$
Algorithm 2 Iterative SMDP-CA Algorithm

1: Step 1 (Initialization): \( \pi^0(s) = 0, \) for all \( s \in S. \) Set the value of \( \epsilon > 0, \) and iteration \( t = 0. \)

2: Step 2: Using eq. [26], compute the discounted reward for each state \( s: \)

\[
\pi^{t+1}(s) = \max_{a \in A(s)} \left\{ \pi(s,a) + \lambda \sum_{s' \in S} P(s'|s,a)\pi^t(s') \right\}
\]

3: Step 3:

4: if \( |\pi^{t+1} - \pi^t| > \epsilon \) then \( t \leftarrow t + 1, \) go to Step 2
5: else go to Step 4
6: end if
7: Step 4: Compute the optimal policy for all \( s \in S \)

\[
d^*_s(s) \in \max_{a \in A(s)} \left\{ \pi(s,a) + \lambda \sum_{s' \in S} P(s'|s,a)\pi^{t+1}(s') \right\}
\]

where \( \pi(s) \) represents the steady state probability at state \( s, \) \( P \) is the transition probability matrix, considering the optimal policy \( d^*_s, \) and \( J \) denotes the all-ones matrix.

V. Numerical Results

In this section, we validate and evaluate the proposed SMDP-based unreliability-aware channel allocation for VR over THz RIS system using a Python simulator to implement the model and the algorithms proposed. The parameters used for simulation are summarized in Table I. To investigate the performance of the RIS system under different settings, the simulation results present a function of the discount factor \( \alpha \), the reward provided for a new service request, which decreases the average reward of the RIS system reduced by failed RISs. The highest acceptance probability of around 68% could be reached in scenario 3 with 3 RISs and low RIS failure rate. This can be explained by the fact that the high RIS channel availability with 4 RISs and 4 backup RISs, where hardware failure is managed by the backup RISs. The RIS system configured based on the scenario 1 and 2 show the highest acceptance probability for the higher RIS failure rate starting from \( \mu' = 0.1 \) and decreases from 45% to 30%. The RIS system in scenario 4 shows the lowest service acceptance probability up to 37%, as the RIS system can not always satisfy the amount of VR user requests with the limited amount of RISs and additional RIS failures.

Next we investigate the average system reward as a function of different arrival rates of service requests and different RIS failure rates. Fig. 3 illustrates that the highest and the lowest average reward could be provided in scenario 1, and in scenarios 3 and 4 with \( \lambda_s > 9 \), respectively. In general, the average reward decreases with increasing arrival rate of service requests, which is a result of the limited channel capacity of RIS system. Additionally, in scenarios 3 and 4, the service requests can be blocked, when available RIS do not provide enough meta-surfaces/channels for the requested service. When the service arrival rate increases, the overall capacity needed to provide all service requests is higher than the RIS capacity. As a result, the system rejects any new incoming service requests, which decreases the average reward.

![Figure 2: Action probabilities with different RIS failure rates for each defined scenario (\( \lambda_s = 1 \)).](image)
value. The average reward is a good metric for future work to compare an optimal channel allocation policy with heuristic or machine learning based allocation algorithms.

Fig. 4 shows an average reward as a function of the RIS failure rate. In our settings we highly penalize the RIS failure, which explains the drastic decrease of the average reward, since the probability of accepting services becomes lower, and where we increased the number of RIS. In Fig. 4 the average reward follows a convex decreasing function in terms of RIS failure rates, with service arrival rate \( \lambda_s \) equal to 1. The figure shows that with low failure rate the reward is the same under all scenarios, and then it becomes the worst with scenarios that have more RIS. The minimum reward for scenario 1 is 0, which means that the single RIS has failed and no service is accepted, while for scenario 3, the system can have failed RIS and still accepts service which will have a high probability to be lost in the case of failure, causing a negative reward value.

Finally we illustrate in Fig. 5 the blocking probabilities with different arrival rates of services and with different RIS failure rates under different scenarios. We maintain the same configuration defined in table I where \( \mu' = 0.01 \) when varying the service arrival rate and \( \lambda_s = 1 \) when varying the RIS failure rate. The blocking probability is very low with low arrival rates, less than 0.001. It increases sharply after reaching the value \( \lambda_s = 5 \), in scenario 1, due to the lack of channels to allocate of a single RIS system and reaches the value 0.31 when \( \lambda_s = 10 \). For high service arrival rate, the more we increase the number of RISs the more stable our system gets. However, for low and medium arrival rates, scenario 1 with less RISs performs better than scenario 4 with 3 RISs, thus increasing the number of RISs and meta-surfaces does not always improve the performance in terms of service blocking and long-term reward. In Fig. 6 we fix the service arrival rate to 1 and we vary the RIS failure rate, we remark that the blocking probability is equal to 0 all values under \( \mu' = 0.1 \) which shows the stability of our channel allocation algorithm. For \( \mu' = 0.5 \), the blocking increases then to reach a maximum of 0.14, 0.03 and 0.01 for scenarios 1, 2 and 3, respectively. We see that increasing the number of RISs and meta-surfaces highly improves the performance of RIS network in terms of service blocking.
VI. Conclusion

We considered channel resource allocation in the virtual reality (VR) applications over RIS network with controlled access of VR users request by Semi-Markov decision Process (SMDP). We introduced an optimal channel allocation scheme to ensure the reliability and maximize the system reward in a set of RISs, in which a RIS device and its meta-surface elements are vulnerable to failures. We formulated the problem of RIS-unreliability-aware channel allocation as an SMDP model considering multiple RIS devices in an indoor environment used to provide services to VR users. Numerical results showed the average reward and blocking probability with various service arrival and RIS failure rates, and under different network configurations. The system computed corresponding policies to each service arrival rate to ensure the reliability and maximize long-term rewards. We showed that the proposed scheme was generally applicable, dynamic and provided an efficient solution to the channel allocation problem. Our proposed model works for online channel assignment to users using an iterative solution, that assumes the knowledge about some system statistics, such as the RIS failure, service arrival, and service departure. We also showed that our scheme improved the QoS of VR users with regard to their arrival rate and RIS meta-surfaces availability. Moreover, when VR user arrival rate were high, the channels were allocated with the minimum requirements for a VR service to operate, which decreased the blocking probability. We showed that increasing the number of RISs and meta-surfaces does not always improve the performance in terms of service blocking and long-term reward, for low and medium service arrival rate. Such finding allows us to better dimensioning RIS networks based on the expected service rate, in order to improve costs and performance at the same time. In our future work, a large-scale solution based on reinforcement learning can be proposed to solve value iteration algorithm, which is known by its exponential growth. Also, the RIS system can consider VR users location to prioritize RIS associations before allocating channels. Finally, failure dependency between RIS devices can be considered in future system design.

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