Performance Analysis and Enhancement of STAR-RIS-NOMA Using Neural Networks

Presented by

BATCH -21

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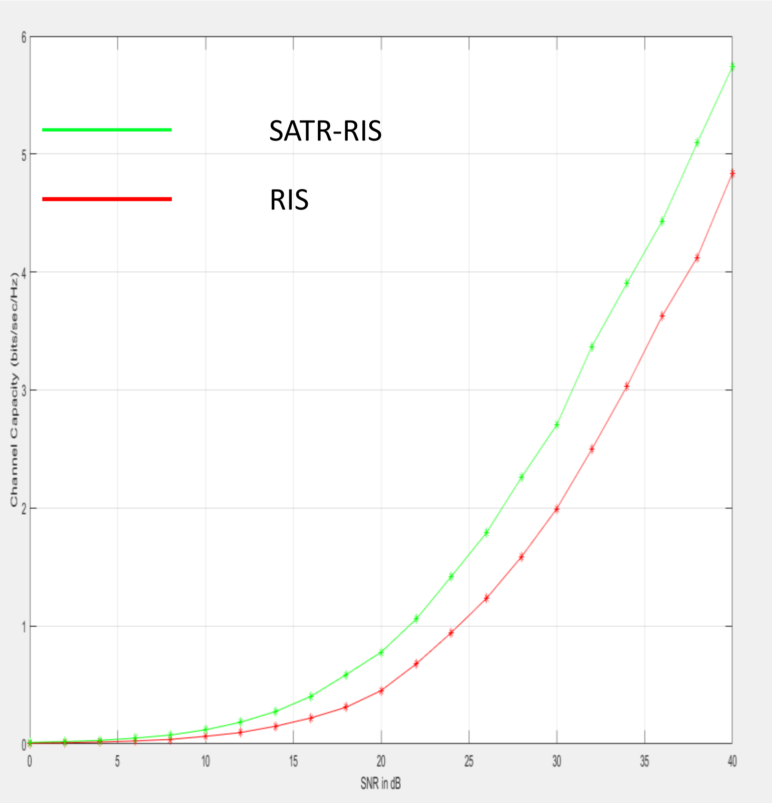
Outline

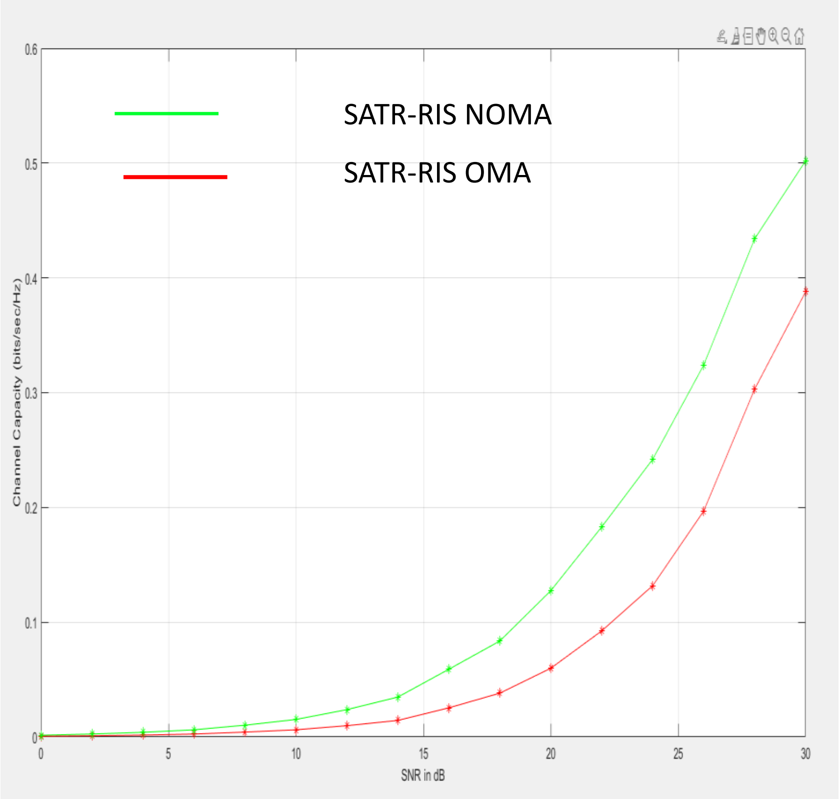
- Past work
- Introduction
- Literature Survey
- STAR-RIS
- System model
- Methodology
- Adam’s algorithm
- Loss Function
- Neural network architecture
- Weight updates
- Conclusion
- References

Past Work

Channel capacity vs SNR graphs Comparisons



RIS vs STAR-RIS



STAR-RIS OMA vs STAR-RIS NOMA

Introduction :

- STAR-RIS channel capacity estimation using Stochastic gradient descent algorithm in neural networks.

Literature Survey on STAR-RIS

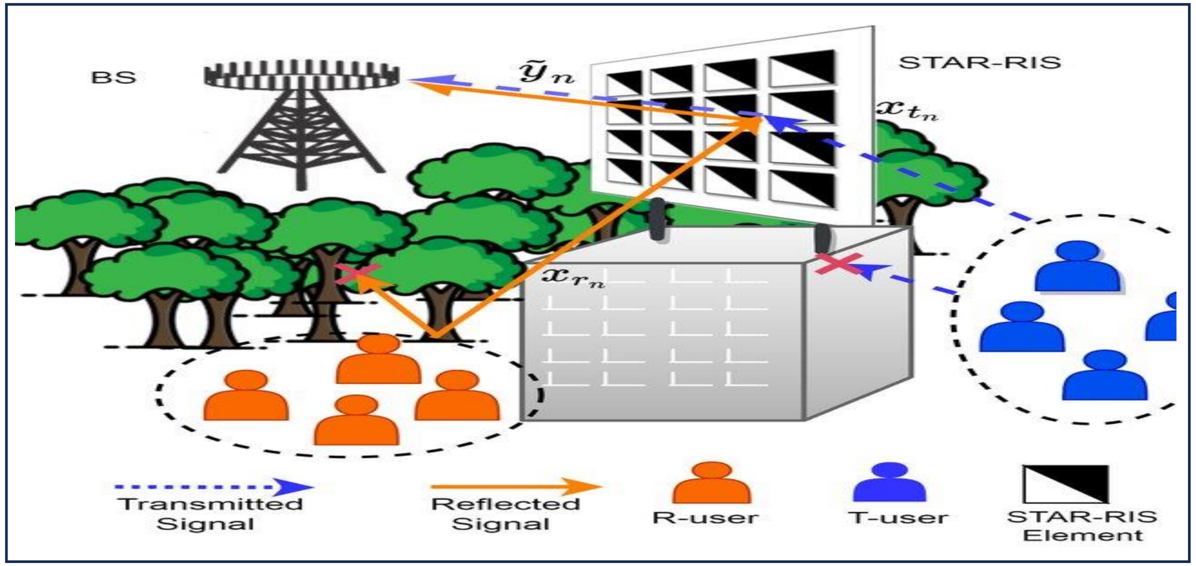
S.No.	Author Name	Title & Publication	Contribution & Remarks
1	Han Wen; Ahmad Massud Tota Khel; Khairi Ashour Hamdi	Phase Shift Configuration Strategies for Unbalanced T&R Users in STAR-RIS-Aided NOMA IEEE COMMUNICATIONS LETTER 2023	This citation includes STAR RIS and it's strategies, and shows substantial improvement in high power scenarios such as mm wave and Tera hertz wireless communication.
2	Jiagao Chen and Xiangbin Yu	Ergodic Rate Analysis and Phase Design of STAR-RIS Aided NOMA With Statistical CSI, IEEE 2022	In this letter, we consider a STAR RIS-aided non-orthogonal multiple access downlink . This simulation results validate the validity of the theoretical analysis and the design of the phase shift matrices
3	Xidong Mu; Yuanwei Liu; Li Guo; Jiaru Lin; Robert schober	Simultaneously Transmitting and Reflecting (STAR) RIS Aided Wireless Communications, IEEE, 2022	The numerical results reveal that: 1) the TS and ES operating protocols are generally preferable for unicast and multicast transmission, respectively; and 2) the required power consumption for both scenarios is significantly reduced by employing the proposed.
4	Anastasios Papazafeiropoulos; Zaid Abdullah; Pandelis Kourtessis; Steven Kisseleff; Ionnis Krikidis	Coverage Probability of STAR-RIS-Assisted Massive MIMO Systems With Correlation and Phase Errors, IEEE WIRELESS COMMUNICATIONS LETTERS, VOL. 11, NO. 8, AUGUST 2022	In this citation they derived a closed-form expression for the coverage probability of a STAR-RIS assisted massive MIMO system while accounting for correlated fading and phase-shift errors.
5	Jiakuo Zuo; Yuanwei Liu; Zhiguo Ding; Lingyang Song	Simultaneously Transmitting And Reflecting (STAR) RIS Assisted NOMA Systems GLOBECOM 2021 - 2021 IEEE Global Communications Conference	This citation explains STAR RIS assisted NOMA system. The main objective is to maximize the achievable sum rate by jointly optimizing the decoding order, power allocation coefficients, active beamforming, transmission and reflection beamforming.

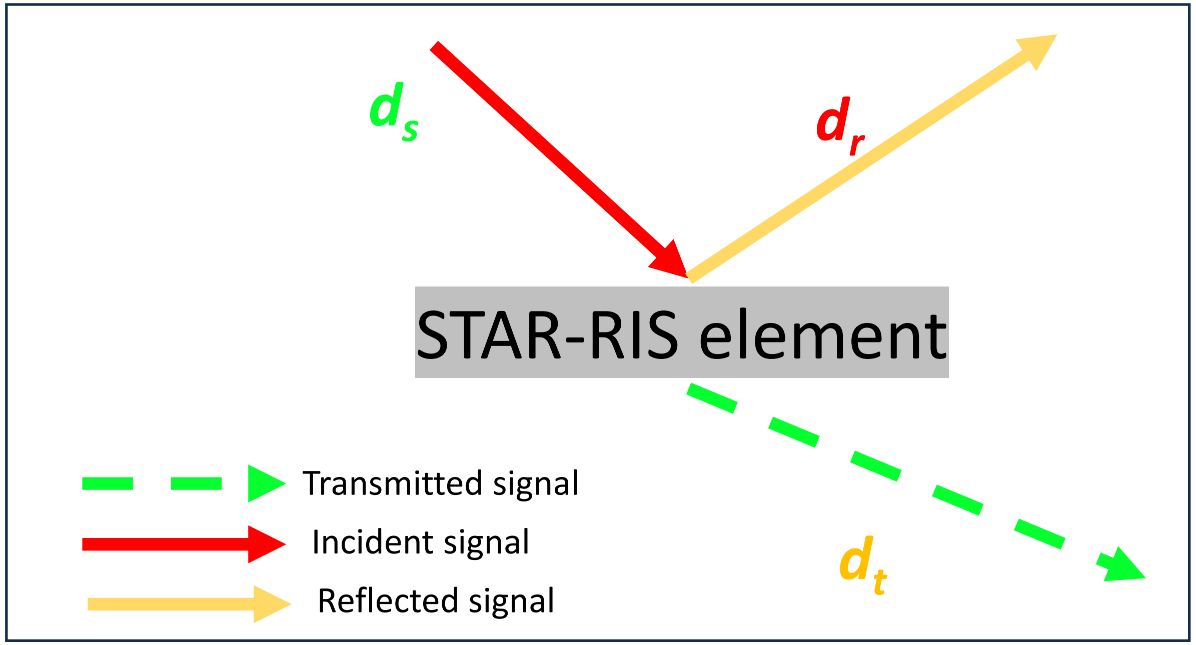
Why STAR-RIS?

- RIS are only able to reflect the incident signal , which restrict it to operate in only one side the RIS i.e.(180°).
- To overcome this geographical restriction we use STAR-RIS.
- Low power consumption.
- Increased channel capacity.

Simultaneously Transmitting and Reflecting RIS (STAR-RIS)

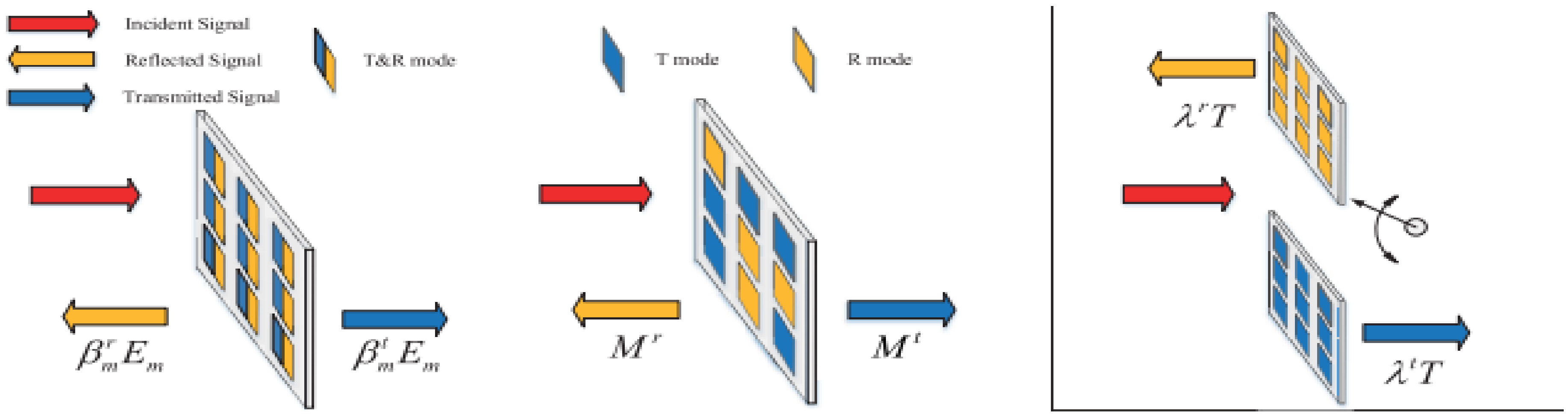
- **STAR-RIS** is a software-defined surface, which can customize the propagation of the radio waves appearing upon it towards the destination.
- Unlike conventional reflecting-only RISs, a STAR-RIS provides full-space coverage for users located on both sides of the STAR-RIS.
- Cost-Efficiency and Element Composition
- Simultaneous Service Provision
- Advancements in Wireless Networks
- **Easy to deploy**
- **Spectral efficiency enhancement**
- **Environment friendly**
- **Compatibility**





Signal Model

- Energy splitting (ES)
- Mode switching (MS)
- Time switching (TS)



(a) Energy splitting (ES). (b) Mode switching (MS). (c) Time switching (TS).

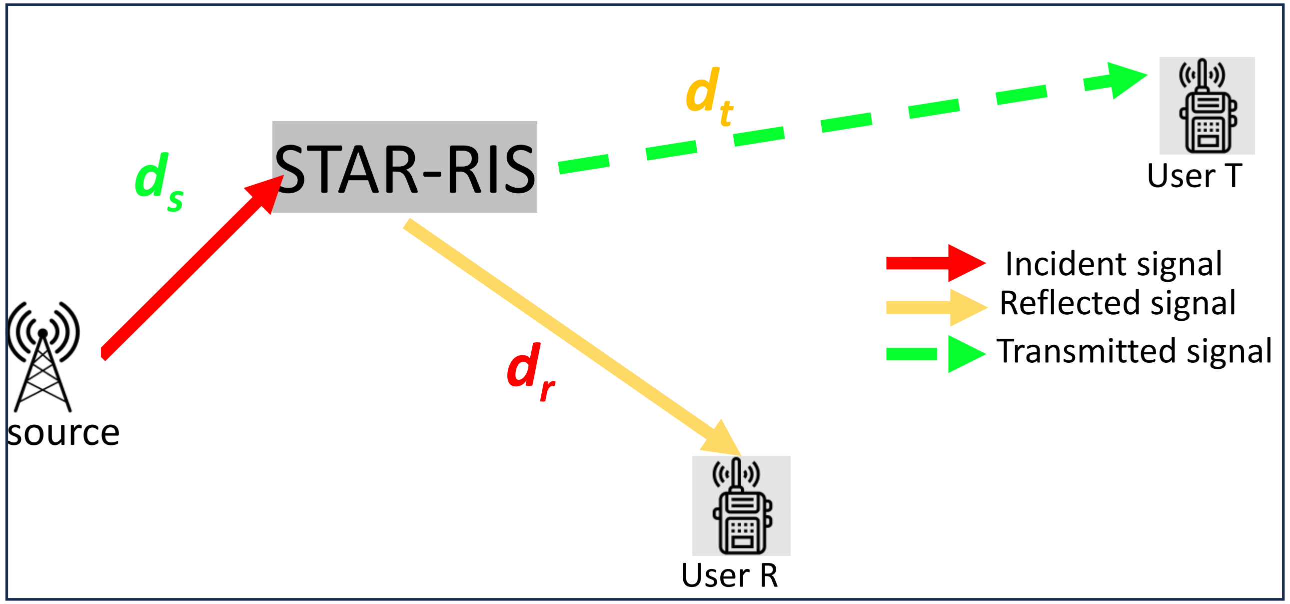
Various modes

- T mode
  $\beta_n^t = 1$; $\beta_n^r = 0$
- R mode
  $\beta_n^t = 0$; $\beta_n^r = 1$
- T & R mode
  β_n^t , $\beta_n^r \epsilon$ [0,1]

Constraints of practical operating protocols

Optimization Variables	ES	MS	TS
Phase-shift coefficients	θ^t_n , θ^r_n $\in [0,2\pi)$		
Amplitude coefficients	β^t_n , $\beta^r_n \in [0,1]$, $\beta^t_n + \beta^r_n = 1$	β^t_n , $\beta^r_n \in \{0,1\}$, $\beta^t_n + \beta^r_n = 1$	—
Time allocation	—	—	λ^t_n , $\lambda^r_n \in [0,1]$, $\lambda^t_n + \lambda^r_n = 1$

System Model



$$y_k = \sqrt{P_s}[d_k^T \psi_k d_s]s_c + n_k$$

$$\gamma_k = \frac{P_s |d_k^T \psi_k d_s|^2}{\sigma_k^2}$$

$$C_k = log_2(1 + \frac{P_s |d_k^T \psi_k d_s|^2}{\sigma_k^2})$$

Signal Model

- S_n → incident signal on n^{th} element
- Transmitted signal by n^{th} element

$$t_n = (\sqrt{\beta^t{}_n}\, e^{j\theta_n^t})\, S_n$$

$$\sqrt{\beta^t{}_n} \in [0,1], \qquad \theta_n^t \in [0, 2\pi)$$

- Reflected signal by n^{th} element

$$r_n = (\sqrt{\beta^r{}_n}\, e^{j\theta_n^r})\, S_n$$

$$\sqrt{\beta^r{}_n} \in [0,1], \qquad \theta_n^r \in [0, 2\pi)$$

- By energy conservation

$$t_n^2 + r_n^2 = S_n^2$$

$$\beta_n^t + \beta_n^r = 1 \qquad \text{(ideal condition)}$$

Due to path loss

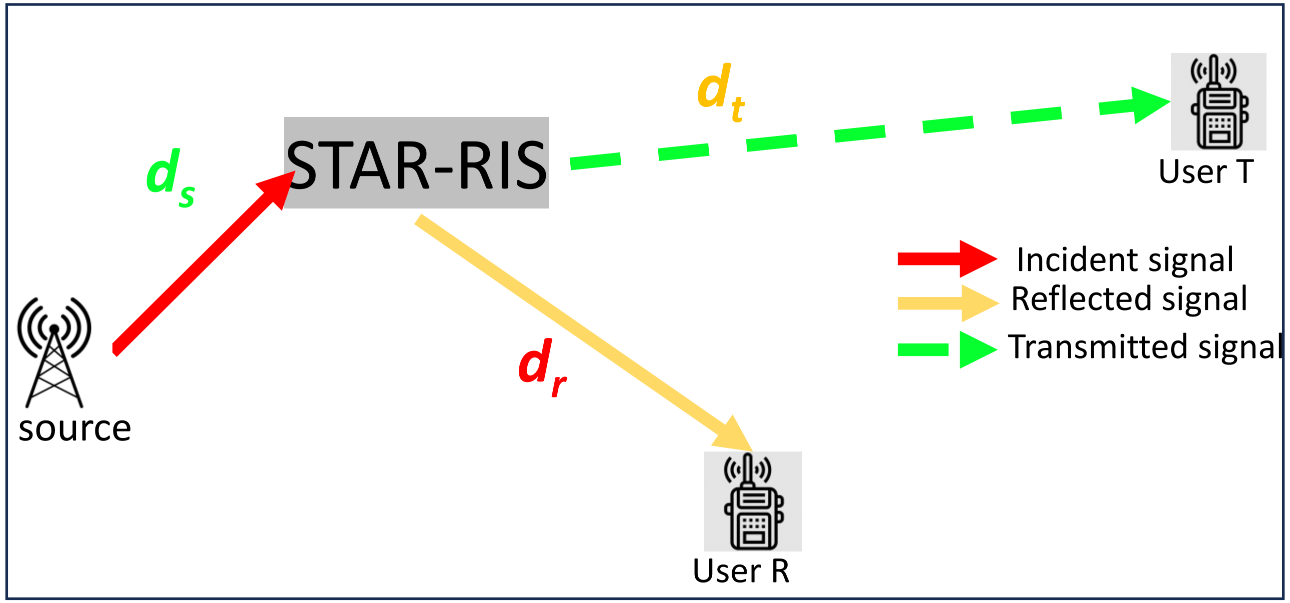
$$\beta_n^t + \beta_n^r = c \quad , \quad 0 < c < 1 \quad \text{(practical case)}$$

Transmission & Reflection coefficients

$$\psi_t = diag(\sqrt{\beta_1^t}\, e^{j\theta_1^t}, \sqrt{\beta_2^t}\, e^{j\theta_2^t}, \ldots\ldots, \sqrt{\beta_n^t}\, e^{j\theta_n^t})_{nxn}$$

$$\psi_r = diag(\sqrt{\beta_1^r}\, e^{j\theta_1^r}, \sqrt{\beta_2^r}\, e^{j\theta_2^r}, \ldots., \sqrt{\beta_n^r}\, e^{j\theta_n^r})_{nxn}$$

System Model of STAR-RIS aided NOMA



$$X=\sqrt{a_t P}\, x_t + \sqrt{a_r P}\, x_r, \quad a_t + a_r = 1,\ a_t > 0.5$$

$$\gamma_r = a_r \frac{P_s |\, d_r^T\, \psi_r d_s|^2}{N_0}$$

$$\gamma_t = \frac{a_t P_s |\, d_t^T\, \psi_t d_s|^2}{a_r P |\, d_t^T\, \psi_t d_s|^2 + N_0}$$

$$\gamma_{star\_noma} = \min(\gamma_t, \gamma_r)$$

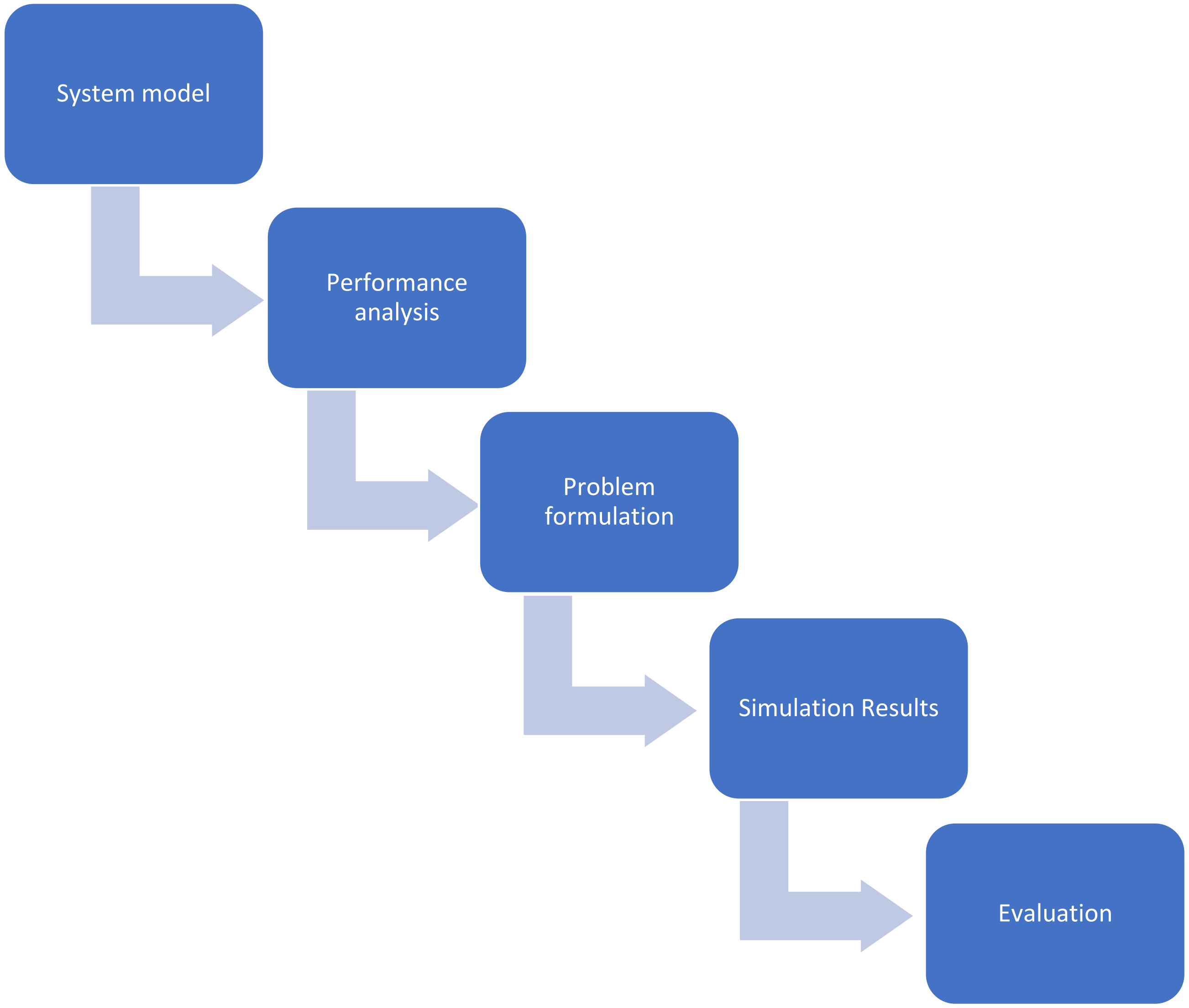
$$C_{star\_noma} = log_2(1 + \gamma_{star\_noma})$$

System Model of STAR-RIS aided OMA

- In OMA systems the power is equally distributed for near-users and far-users i.e. $p_i = p/n \quad i=1,2,..,n$
- Hence in this 2 user system

$$p_1 = p/2;\ p_2 = p/2 \quad \text{i.e. } a_r = a_t = 0.5$$

Methodology



Python Libraries used:

- pandas
- numpy
- matplotlib.pyplot
- sklearn.model_selection
- sklearn.preprocessing
- sklearn.metrics(MSE,MAE,R2)
- tensorflow

Sample Dataset:

alpha_t	alpha_r	SNR_STAR(dB)	SNR_OMA(dB)	SNR_STAR	SNR_OMA	C_STAR	C_OMA
0.755676	0.244324	4.86194	4.939349	0.326442	0.320675	0.407562	0.200638
0.799398	0.200602	2.90011	1.814684	0.512848	0.658463	0.597267	0.364924
0.795321	0.204679	0.90295	4.346186	0.812279	0.367605	0.857805	0.225826
0.725061	0.274939	11.46254	8.865203	0.071408	0.129861	0.099508	0.088073
0.769054	0.230946	7.607259	8.649606	0.17349	0.136471	0.230805	0.09228
0.737612	0.262388	6.072604	3.272339	0.247024	0.470724	0.31849	0.278263
0.792728	0.207272	4.813729	5.075463	0.330086	0.31078	0.41152	0.195213
0.755316	0.244684	7.964704	9.000207	0.159783	0.125887	0.213854	0.085531
0.742649	0.257351	11.47121	12.86827	0.071265	0.051662	0.099316	0.036336
0.77436	0.22564	0.927117	4.334964	0.807771	0.368556	0.854212	0.226327
0.739045	0.260955	2.906446	1.48676	0.512101	0.710107	0.596554	0.387043
0.768994	0.231006	5.845308	6.405409	0.260297	0.228802	0.333764	0.148626
0.73836	0.26164	0.998376	3.768591	0.794625	0.419895	0.843683	0.252892
0.784757	0.215243	7.950811	9.149731	0.160295	0.121626	0.214491	0.082796

Adam Algorithm

- Input: γ(lr), β_1 , β_2(betas) , θ_0(params) , $f(\theta)$(objective)
- Initialize: m_0 0(firstmoment), v_0 0(secondmoment)
- For t=1 to ….do

$$x_{t+1} = x_t + \Delta t v_{t+1}$$
$$v_{t+1} = v_t + \Delta t a_{t+1}$$
$$a_{t+1} = a_t + \Delta t(f_{t+1} - \nabla U(x_t))$$
$$f_{t+1} = f_t + \Delta t(g_{t+1} - f_t)$$
$$g_{t+1} = m_1 v_t + (1-m_1)g_t + (1-m_2)\ \Delta t\ \nabla U(x_t)$$
$$m_1 = \beta_1(1- \beta_1)^{-1}$$
$$m_2 = \beta_2(1- \beta_2)^{-1}$$

Objective Function

- $f(a) = -(SNR)_{min}$
- $a_t + a_r = 1$, $a_t > 0.5$

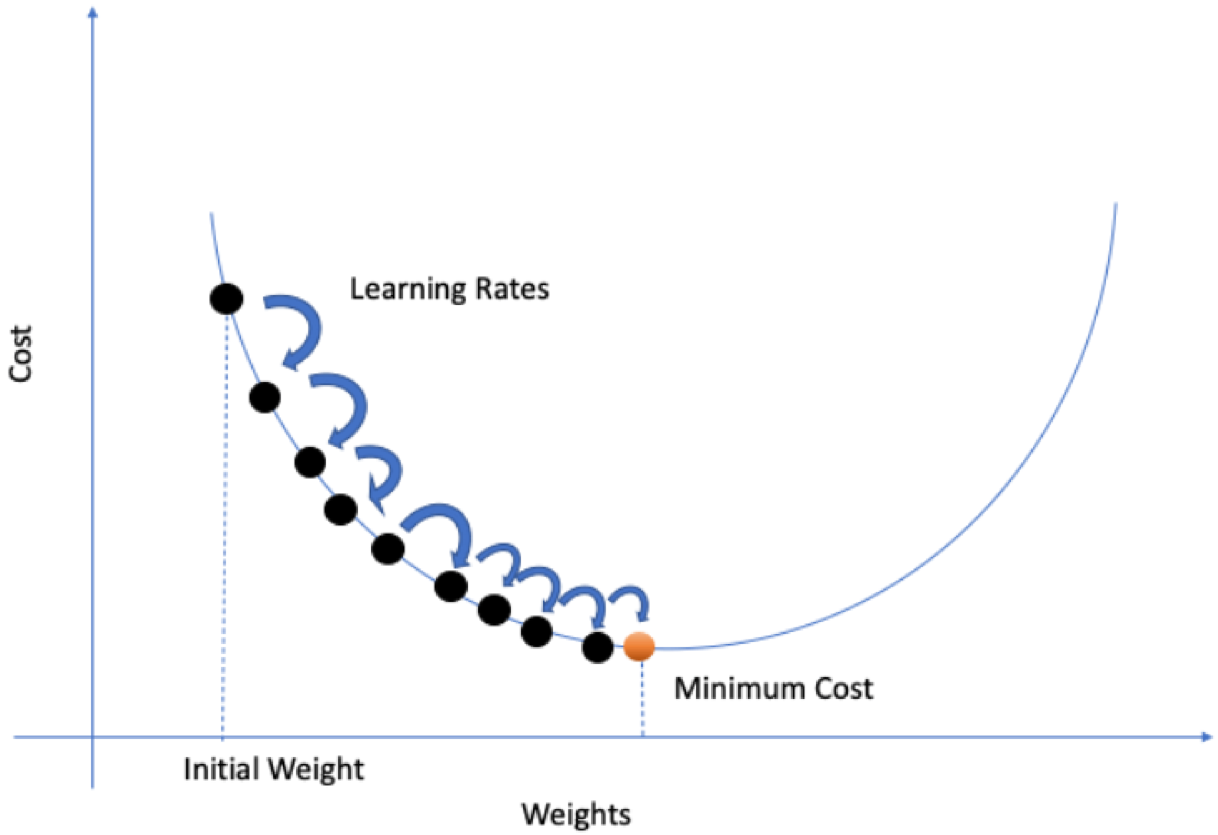
Simulation attributes

Attributes	Values
Sigma (noise power)	1
SNR range (dB)	0-30 dB
Number of iterations	1000
d_si (distance between source and RIS)	30 km
d_it (distance between user T and RIS)	15 km
d_ir (distance between User R and RIS)	5 km
V (path loss component)	2.0
a_t (power allocation coefficients)	0.7
a_r(power allocation coefficients)	0.3
Channel	Rician small scale fading

Simulation attributes

Attributes	Values
Trainable parameters	2401(9.38KB)
Total parameters	2401(9.38KB)
Number of Epochs	20
Non-trainable parameters	0
Mean square error(MSE)	0.006024936504379367
Mean absolute error(MAE)	0.0710162161443786
R2	0.8962111924982294
Dataset features	10000
Sigma (noise power)	1
SNR range (dB)	0-30 dB
d_si (distance between source and RIS)	30 km
d_it (distance between user T and RIS)	15 km
d_ir (distance between User R and RIS)	5 km
V (path loss component)	2.0

Point of Convergence



https://www.researchgate.net/figure/Stochastic-Gradient-Descent_fig4_344544069

Stochastic Gradient Descent (SGD)

- Input
  - Training dataset $\left\{\left(x^{(i)}, y^{(i)}\right)\right\}_{i=1}^{N}$ where $x^{(i)}$ is the input feature vector for the ith sample and $y^{(i)}$ is the corresponding target output.
  - Learning rate η.
- Initialization
- Repeat until convergence
  - Sample selection
    - Randomly select a mini batch from training dataset.
  - Forward Propagation
  - Loss calculation
    - Root mean square error.
  - Backward Propagation
  - Parameter update using SGD
  - Convergence check

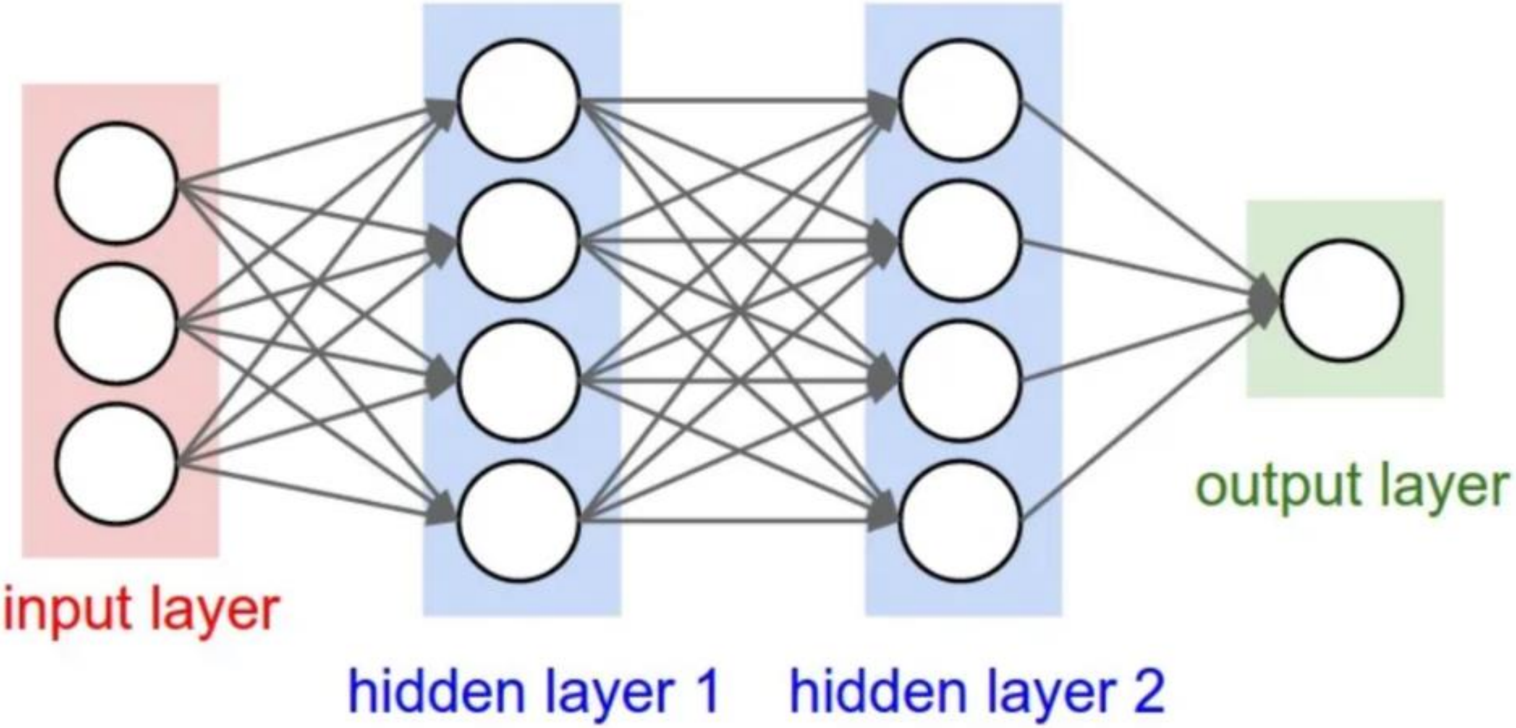
Loss Function

The RMSE loss function can be expressed mathematically as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

- N is the number of samples.
- y_i is the actual value of the target variable of i^{th} sample.
- $\hat{y}_i$ is the predicted value of the target variable of i^{th} sample.

Neural Network Architecture



Weights Update

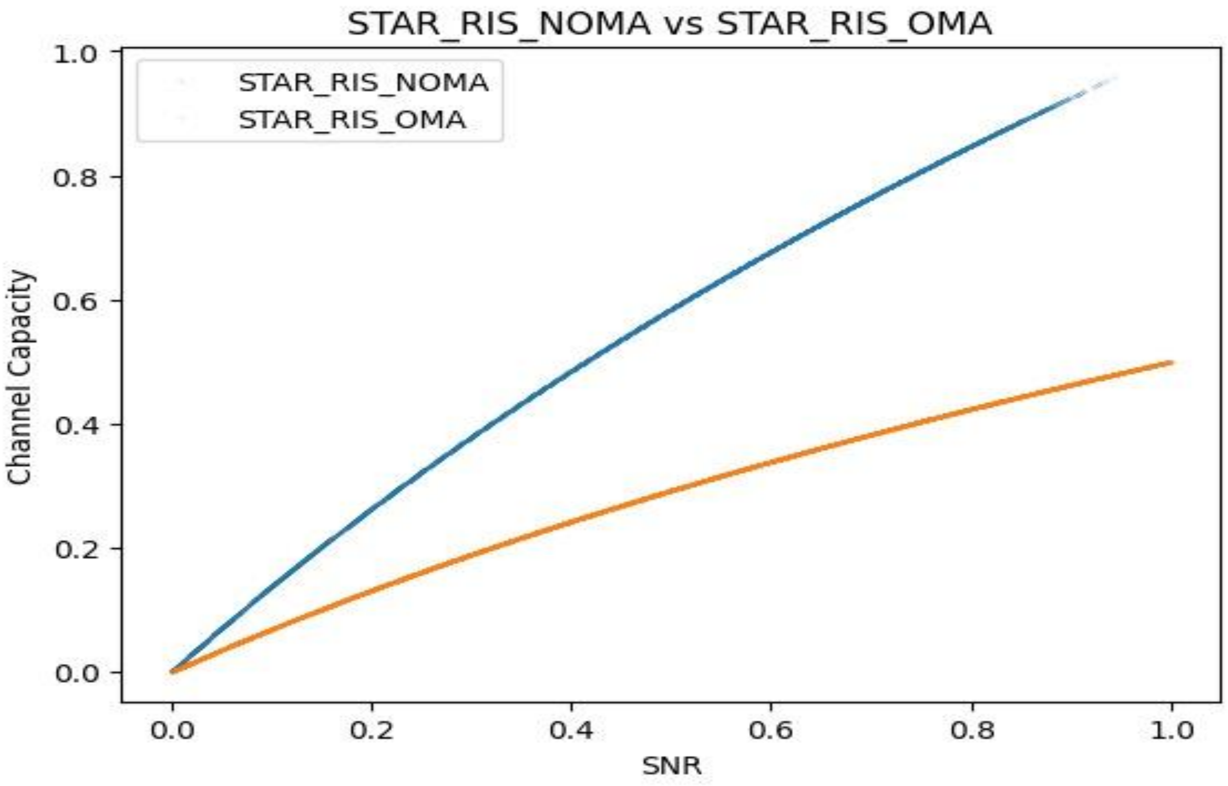
- $w^{(t+1)} = w^{(t)} - \eta * \frac{1}{m} * x^T * (x * w^t + bias^t - y)$
- $bias^{t+1} = bias^t - \eta * \frac{1}{m} * mean(x * w^t + bias^t - y)$

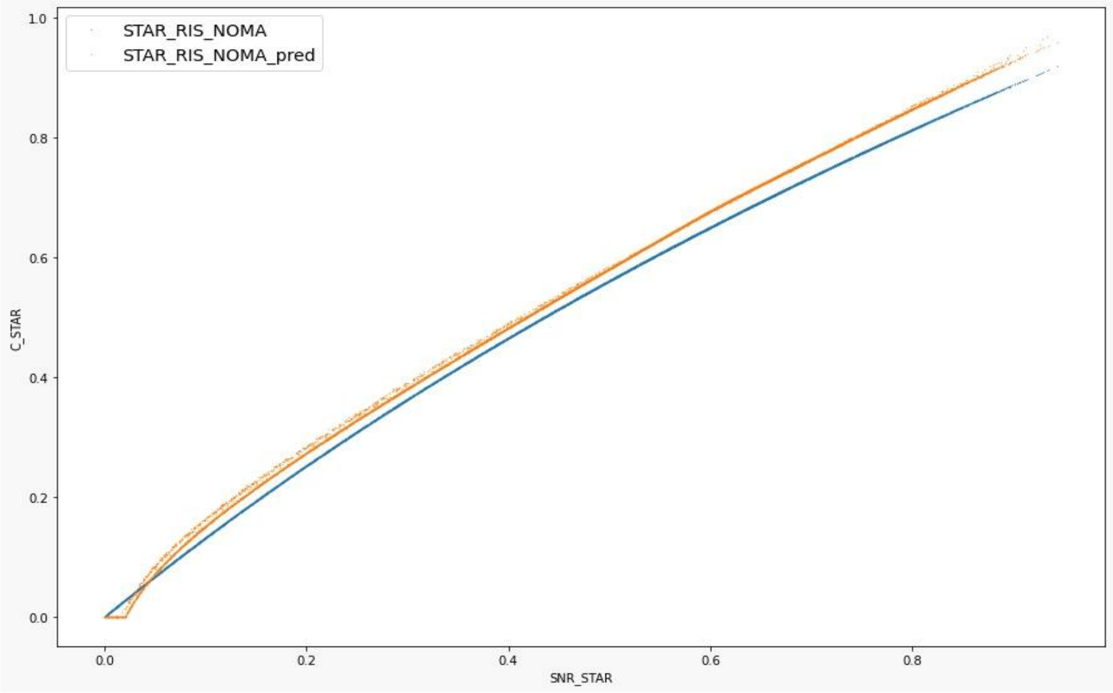
  - x = input feature matrix for mini batch.
  - y = channel capacity matrix for mini batch.
  - m = mini batch size.
  - η = learning rate parameter.
  - n = number of input parameters.

$$x_{mxn} = \begin{bmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{bmatrix}_{mxn}$$

$$y = [\quad \cdots \quad]_{1xn}$$

Training Results





Validation Results

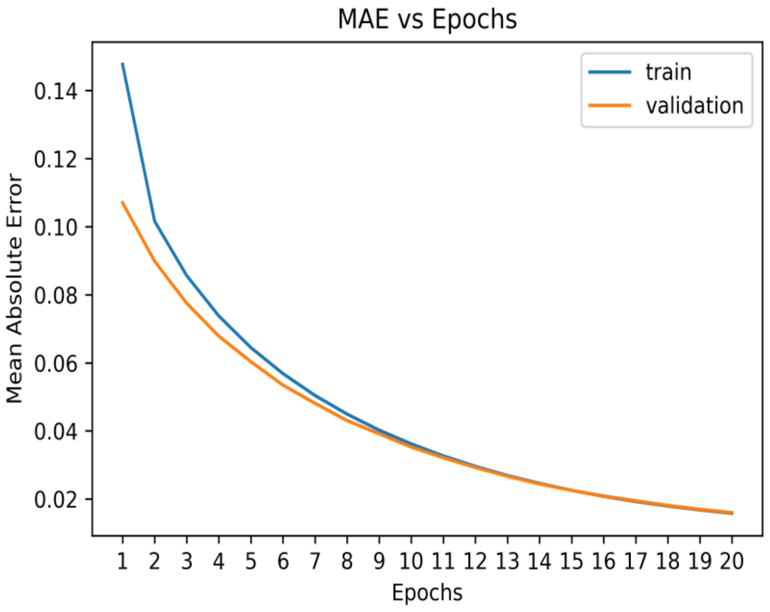


Fig.1 Mean absolute error

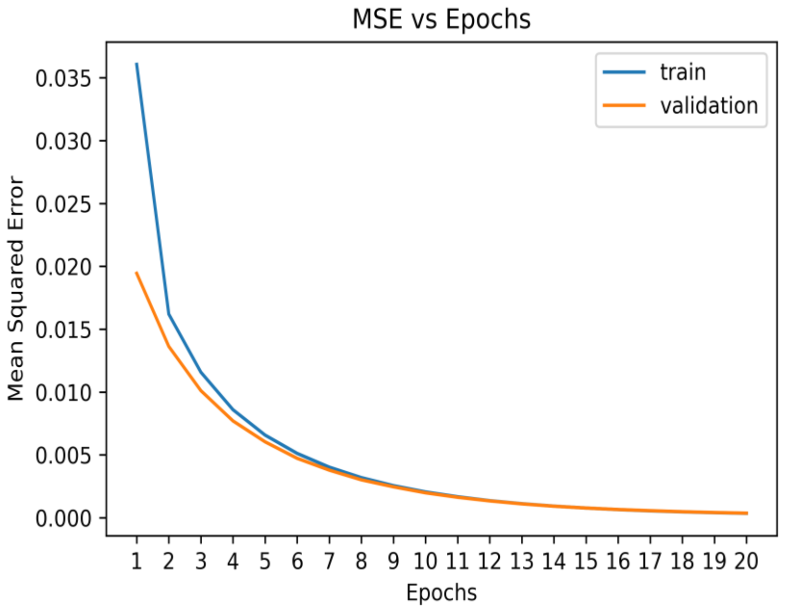


Fig.2 Mean square error

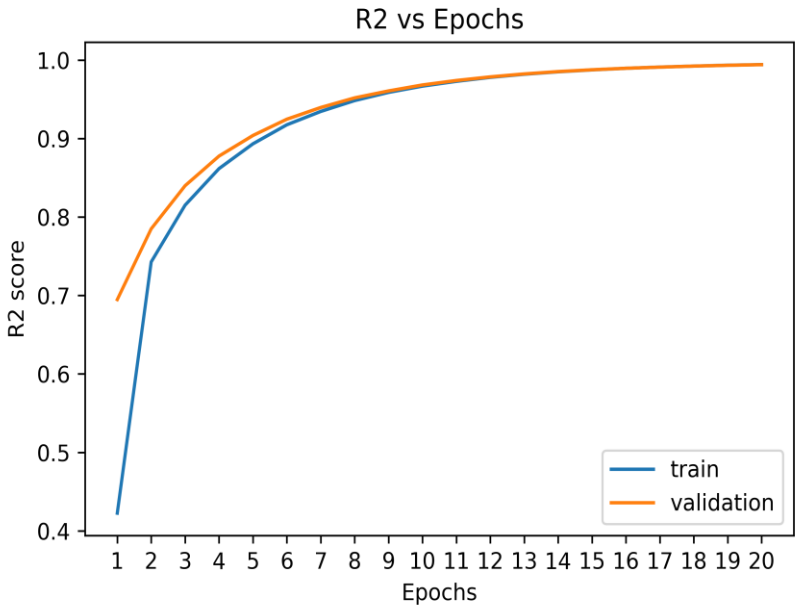


Fig.3 R2

Observations

- Enhancing Channel Capacity
- Achieving high SNR
- Maximizing the data rate
- Increasing the outage probability
- Increasing Spectral Efficiency

Conclusion

- By using STAR-RIS we can both transmit and reflect the signals.More efficiency.
- High channel capacity.
- High SNR.
- We can operate through different protocol modes.

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Thank You