ADDITIONAL SIMULATION RESULTS

A. Simulation results on pre-trained scheme by varying the number of training samples

In our manuscript, it can be confirmed from the simulation results that the pre-trained scheme in which the transmit power and energy harvesting (EH) ratio are derived using our deep neural network (DNN) model with the pre-training but without the unsupervised training, provides lower spectral efficiency (SE) and higher outage probability compared to all considered schemes except the fixed scheme. The main reason for having such behavior is that the DNN model is trained using only few channel samples with iterative algorithm (IA) solutions. One of main reason for such low performance is that only 2000 channel samples with corresponding IA solution are used for training and consequently the DNN cannot be fully trained to mimic IA scheme due to the lack of training samples.

In Fig. 1, we show the average spectral efficiency (SE) of pre-trained scheme by varying the number of channel samples used for training. As can be confirmed from the simulation results, the average SE of pre-trained scheme increases as the number of channel samples increases, which validates our conjecture that the lack of channel sample deteriorates the performance of the pre-trained scheme. It should be noted that we have used small number of channel samples for pre-training because it is used as a means of initialization of DNN model and reducing the overhead caused by the pre-training is more important than achieving high performance with pre-training.

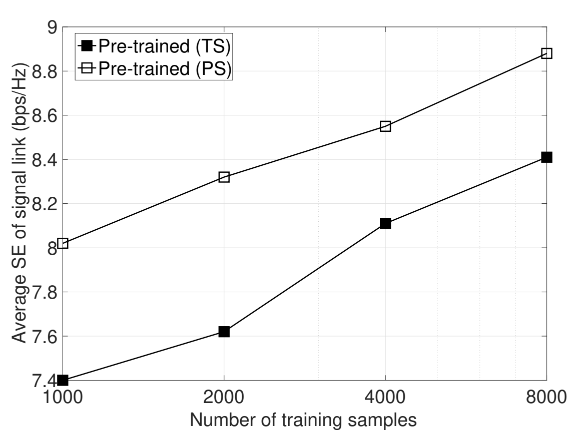
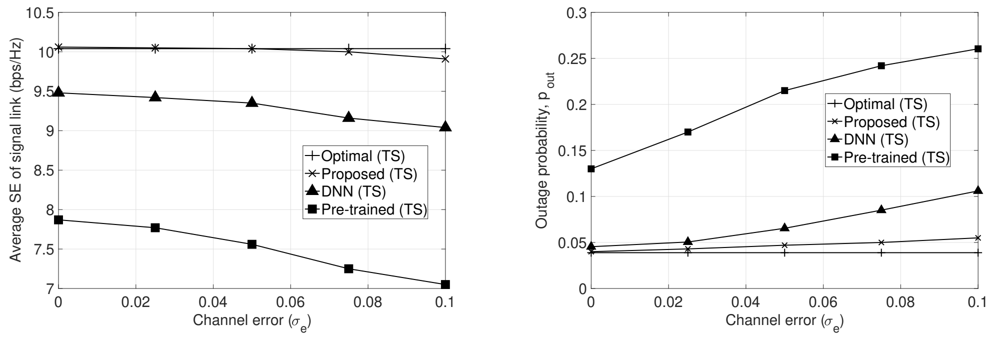


Fig. 1. Average SE vs. the number of training channel samples



(a) Average SE vs. σ_e for TS.

(b) Outage probability vs. σ_e for TS.

Fig. 2. Performance comparison against channel error (σ_e) for TS.

B. Simulation results with imperfect channel information

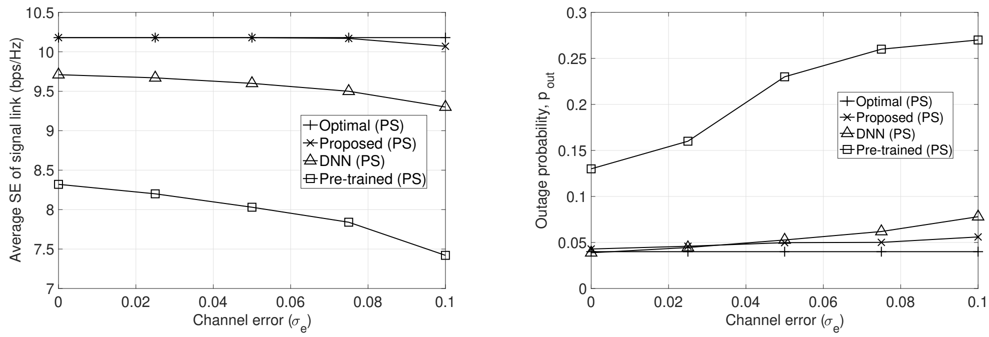
In the performance evaluation of our manuscript, we have assumed that the global perfect channel state information (CSI) is available in our proposed scheme. However, in practice, the perfect CSI is hard to obtain due to the dynamic nature of wireless channels and high signaling overhead. In order to find the effect of having imperfect CSI in the performance of the DNN, we have performed additional simulation by taking into account the error in CSI. To this end, we let the channel gain be composed of two components which are path-loss ($L_{i,j}$) and multi-path fading ($f_{i,j}$), such that $h_{i,j} = \sqrt{L_{i,j}} \cdot f_{i,j}$ for $i, j \in \mathbb{N}$. In this simulation, we assume that the path-loss can be estimated accurately while the acquisition of exact value of multi path fading, $g_{i,j}$, is infeasible due to the dynamic nature of wireless channels, such that the relation between the estimated value of multi path fading, which we denote as $\hat{g}_{i,j}$, and its actual value is formulated based on the first-order Gauss–Markov process as follows [R1], [R2]:

$$g_{i,j} = \sqrt{1 - \sigma_e^2}\hat{g}_{i,j} + \sigma_e e_{i,j}, \qquad \forall i, j \in \mathbb{N}. \tag{1}$$

In (1), $e_{i,j}$ indicates the error of $g_{i,j}$, which follows a complex Gaussian distribution such that $e_{i,j} \sim \mathcal{CN}(0, 1)$. Moreover, the coefficient σ_e quantifies the accuracy of channel estimation with the range of $0 \le \sigma_e \le 1$, such that the CSI becomes more accurate as $\sigma_e \to 0$.

Consequently, the imperfect channel gain from the transmitter of the i-th Tx-Rx pair to the receiver of the j-th Tx-Rx pair, $\hat{h}_{i,j}$, can be written as follows:

$$\hat{h}_{i,j} = \hat{g}_{i,j}\sqrt{G_{i,j}}, \qquad \forall i, j \in \mathbb{N}. \tag{2}$$



(a) Average SE vs. σ_e for PS.

(b) Outage probability vs. σ_e for PS.

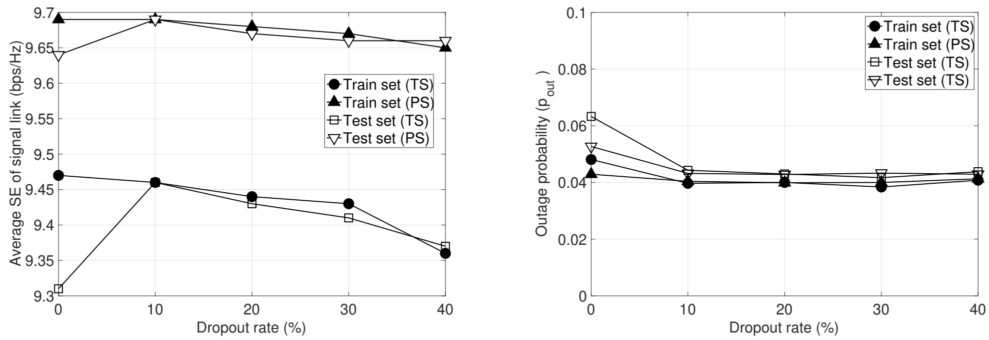
Fig. 3. Performance comparison against channel error (σ_e) for PS.

In Figs. 2 and 3, the average SE of signal link and the outage probability of the schemes which utilize DNN, is shown for varying the level of inaccuracy in CSI, σ_e. For comparison, the performance of optimal scheme is also shown which is invariant according to σ_e. As can be confirmed from the simulation results, the performance of all considered schemes utilizing DNN, which are the proposed hybrid scheme, DNN scheme, and pre-trained scheme, deteriorates as σ_e increases, which coincides with our intuition. However, we can find that the level of deterioration is smallest in the proposed hybrid scheme compared to the DNN and pre-trained schemes. For examples, when $\sigma_e = 0.1$, the decrease of average SE for proposed hybrid scheme is 1.3% and 1.1% for time switching (TS) and power splitting (PS), respectively, where that for DNN scheme is 4.87% and 4.41% for TS and PS. This result validates the robustness of our proposed scheme against the channel error.

C. Simulation results by varying dropout rate

In order to justify the use of dropout and to determine the dropout rate, we evaluate the average SE and outage probability of DNN scheme with TS and PS by varying the drouput rate for train and test data set in Fig. 4. As can be confirmed from the simulation results, the overfitting can be mitigated[1] by utilizing the dropout and the improvement of average SE is maximized when the dropout rate is set to 10%, in which the average SE is improved by 1.6% for TS. This result justifies the use of dropout for reducing the overfitting.

[1]However, given that we have used large training data, the effect of overfitting is not significant, as shown in the simulation results.



(a) Average SE vs. dropout rate.

(b) Outage probability vs. dropout rate.

Fig. 4. Performance of DNN scheme against dropout rate for train and test set.

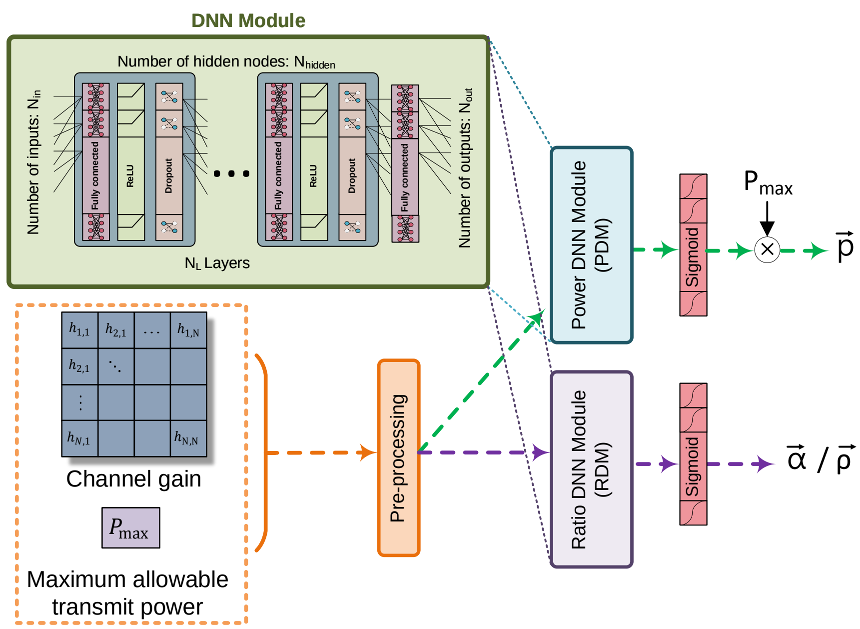
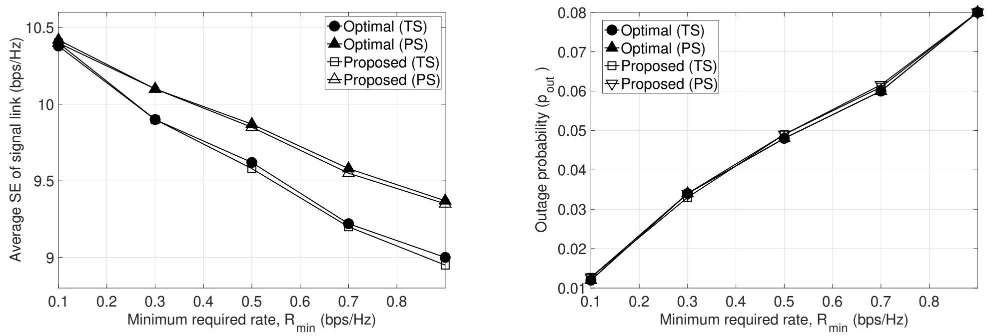


Fig. 5. Revised DNN structure to cope with varying transmit power.

D. Simulation results for varying P_{max}

In the performance evaluation of our manuscript, P_{max} is fixed during training, such that the DNN model which is trained for specific P_{max} cannot be applied for the environment with different value of P_{max}. In order to cope with the varying P_{max}, we have modified the DNN structure such that the maximum allowable transmit power, P_{max}, becomes the input of DNN model along with channel gain, as depicted in Fig. 5. Note that during training, the value of P_{max} is also varied such that the DNN model can learn the resource allocation strategy for varying



(a) Average SE vs. $R_{\min}$ for TS and PS.

(b) Outage probability vs. $R_{\min}$ for TS and PS.

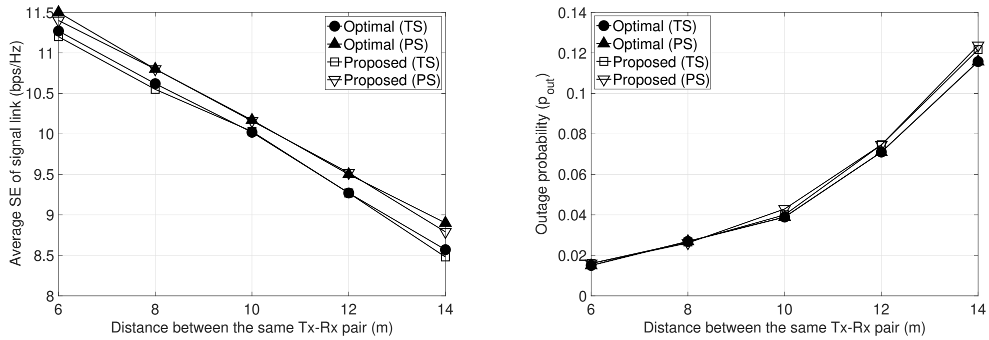
Fig. 6. Performance of optimal and proposed hybrid scheme against $R_{\min}$.

$\mathrm{P}_{\max}$. It should be stressed that although we only consider the case of varying $\mathrm{P}_{\max}$, the revised DNN structure in Fig. 5 can cope with other system parameters as well, e.g., $R_{\min}$.

In Fig. 6, we depict the average SE of the signal link and the outage probability (p_{out}) as a function of the minimum required rate for response link, where the $\mathrm{P}_{\max}$ is randomly chosen from 17 dBm to 29 dBm. For the brevity, we only show the performance of optimal scheme and proposed hybrid scheme. As can be confirmed from the simulation results, the proposed hybrid scheme with revised DMN structure can achieve optimal performance even for varying $\mathrm{P}_{\max}$. From the simulation result, we can verify that our DNN model can cope with varying system parameters through modification.

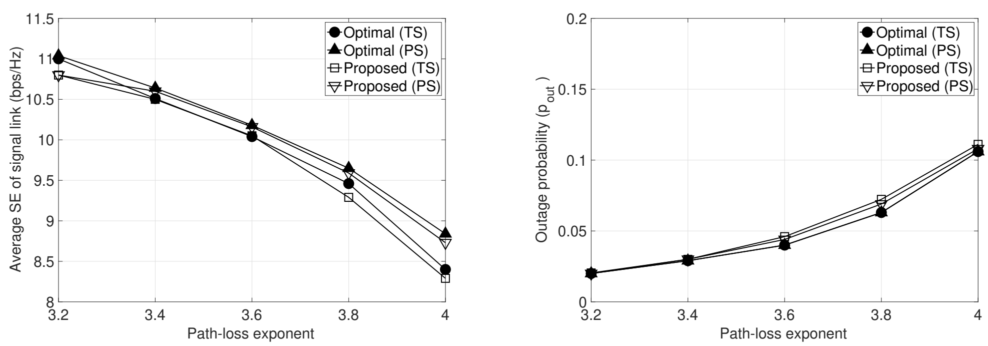
E. Simulation results by varying system parameters

In order to confirm the robustness of the proposed schemes with respect to varying system parameters, we have evaluated the performance, i.e., average SE and outage probability, of the proposed hybrid scheme by varying the distance and path-loss exponent. More specifically, the performance of the proposed hybrid scheme and the optimal scheme is shown in Figs. 7 and 8, where the distance between the same Tx-Rx pair and the path-loss exponent is varied. Note that the distance between the same Tx-Rx pair and the path-loss exponent are set to 10 m and 3.6 during the training of the proposed hybrid scheme. From the simulation results, we can observe that the performance of the proposed scheme is slightly deteriorated as the system parameters deviate from the values which are used during training, as expected. However we can find that



(a) Average SE vs. distance between the same Tx-Rx pair for TS and PS. (b) Outage probability vs. distance between the same Tx-Rx pair for TS and PS.

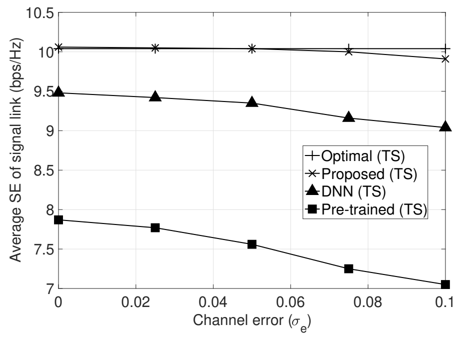
Fig. 7. Performance of optimal and proposed hybrid scheme against distance between the same Tx-Rx pair.



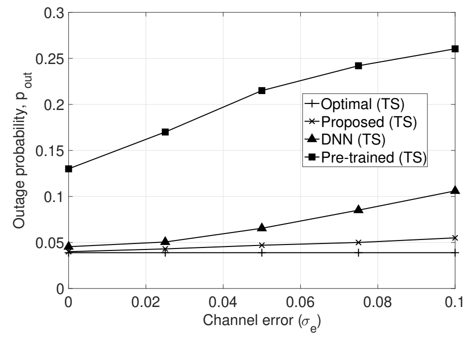
(a) Average SE vs. path-loss exponent for TS and PS. (b) Outage probability vs. path-loss exponent for TS and PS.

Fig. 8. Performance of optimal and proposed hybrid scheme against path-loss exponent.

the level of deterioration is less than 3% in all considered case, which validates the robustness of the proposed hybrid scheme against varying system parameters.

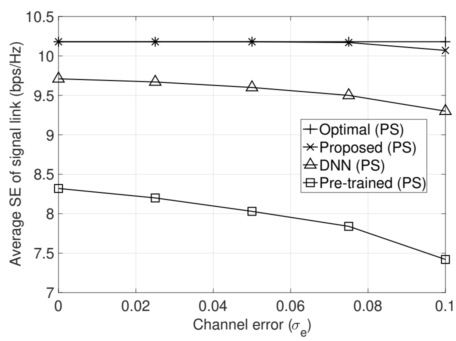


(a) Average SE vs. σ_e for TS.

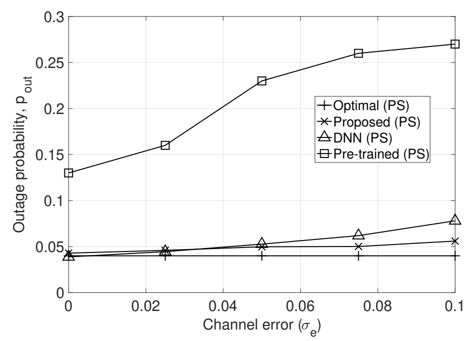


(b) Outage probability vs. σ_e for TS.

Fig. 9. Performance comparison against channel error (σ_e) for TS.



(a) Average SE vs. σ_e for PS.



(b) Outage probability vs. σ_e for PS.

Fig. 10. Performance comparison against channel error (σ_e) for PS.

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