Transfer-learning multi-input multi-output equalizer for mode-division multiplexing systems

Tianfeng Zhao, Feng Wen, Mingming Tan, Baojian Wu, Bo Xu, Kun Qiu

1 Key Laboratory of Optical Fiber Sensing and Communication, Ministry of Education, University of Electronic Science and Technology of China, Chengdu 611731, China
2 Aston Institute of Photonics Technologies, Aston University, Birmingham B4 7ET, UK

*Corresponding author: fengwen@uestc.edu.cn

Received March 11, 2024 | Accepted March 29, 2024 | Posted Online July 31, 2024

We propose a transfer-learning multi-input multi-output (TL-MIMO) scheme to significantly reduce the required training complexity for converging the equalizers in mode-division multiplexing (MDM) systems. Based on a built three-mode (LP₀₁, LP₁₁a, and LP₁₁b) multiplexed experimental system, we thoughtfully investigate the TL-MIMO performances on the three-typed data, collecting from different sampling times, launching optical powers, and inputting optical signal-to-noise ratios (OSNRs). A dramatic reduction of approximately 40%–83.33% in the required training complexity is achieved in all three scenarios. Furthermore, the good stability of TL-MIMO in both the launched powers and OSNR test bands has also been proved.

Keywords: mode division multiplexing; multi-input multi-output; transfer learning; training complexity.

DOI: 10.3788/COL202422.070602

1. Introduction

Spatial division multiplexing (SDM) technology has been widely studied to address the capacity bottleneck faced by the fiber-optic communication system, by the feature of considering different guide modes or fiber cores as independent channels [1,2]. In SDM systems, few-mode fiber (FMF) has been intensively investigated due to its high multiplexing density and easy implementation [3]. However, various mode-dependent distortions exist in FMF, such as mode-coupling (MC) induced crosstalk, differential mode group delay (DMGD), mode-dependent loss (MDL), and mode-dependent nonlinearity, which severely degrade the signal quality and limit the system transmission performance [4,5]. In order to improve the transmission performance of the SDM system, the digital signal processing (DSP)-based compensation scheme through multi-input multi-output (MIMO) equalizer is the crucial part at the optical receiver [6,7], which could mitigate the distortions across multi-spatial-channels simultaneously. Nevertheless, because of the sensitivity of the MIMO equalizers on the channel status, the retraining operation for MIMO is required for practical SDM systems when different operational conditions are applied, e.g., launched powers, optical signal-to-noise ratios (OSNRs), time-varying channel status, etc., resulting in massive expected computation and thereby hindering the real-time application of SDM technology.

To reduce the computational complexity, the current work mainly focuses on channel optimization, which involves carefully designing the optical fibers to achieve MIMO complexity reduction. On one hand, in earlier years, people focused on DMGD management to reduce MIMO complexity. Low MIMO complexity mode-division multiplexing (MDM) transmission was demonstrated with the 10.5 km low-DMGD four-mode fiber [8]. The maximum DMGD over the C + L band was controlled below 50 ps/km. In addition, to achieve more flexible DMGD management, nearly zero-, positive-, and negative-DMGD two-mode fibers were designed and fabricated [9]. On the other hand, reducing the MIMO scale is also an effective solution. For example, by ignoring the inter-mode coupling induced crosstalk in the weak-coupling scenario, the simplified MIMO scheme is only responsible for the intra-mode equalization [10,11]. This method indeed reduces the MIMO scale, but in practical implementation, the accumulated fusion will damage the original weak coupling property of the optical fiber.

Transfer learning (TL) has become a powerful tool for fast modeling of various algorithms with the training process [12]. When new tasks appear, TL exploits the similarity in feature distributions between new and existing tasks, thereby lowering the computational cost required for model reconstruction. In recent published literatures, the TL approach is first implemented in optical networks for optical performance monitoring (OPM), such as the quality of transmission (QoT) prediction [13], OSNR monitoring for 10-span standard single-mode fiber (SSMF) [14], and fast modulation format identification (MFI) [15]. In addition, TL has also been used in nonlinearity mitigation algorithms [16-18] by transferring compensation...
algorithm parameters between the fiber channels with different nonlinear features caused by the transmission length, the launched power, and the OSNR. Similar to the nonlinear fiber channel, the mode-dependent channel state in more sensitive FMF channels is also affected by the above factors. In addition, the time-varying nature of FMF also constitutes a crucial factor contributing to the dynamic changes in the channel state.

With the increase of the spatial modes considered in the MDM system (approaching 1000 modes already discussed\cite{19}), the massive computation demand for data recovery would be the major issue to this new multiplexing scheme in real industry implementation. It is necessary to reduce the training complexity required for frequent MIMO remodeling in FMF, the currently most sensitive fiber channel. To the best of our knowledge, there are still no works about using TL in the MIMO equalization process for MDM systems to reduce the computational complexity. Therefore, we propose the TL-aided MIMO equalization process for MDM systems to reduce the computational complexity.

In the context of FD-LMS, the least mean squares (FD-LMS), is adopted as the MIMO equalization algorithm due to its excellent stability and rapid computation speed. When employing FD-LMS, the received data of the MDM system comprises both training data and payload. The payload is recovered by the equalizer W trained with training data, the optimized step size $\mu$, and taps number $K$. It is worth noting that the computation cost of MIMO equalization primarily involves training $W$ and optimizing the $\mu-K$ combinations.

As illustrated in Fig. 1, we incorporate the MIMO training process into the TL framework. The upper part represents the source domain $D_S$ and the source task $T_S$, where $D_S$ comprises a group of received data and $T_S$ is set to recover the payload in $D_S$, requiring iterative training of $W$ with the training data from $D_S$ to ensure convergence. Then, the lower part of Fig. 1 contains the target domain $D_T$ and the target task $T_T$ of TL-MIMO. Various groups of received data with distinct channel states are placed in $D_T$, and $T_T$ focuses on recovering the payload in $D_T$. In the context of FD-LMS, $\mu$, $K$, and $W$ are the key parameters, determining the equalizer convergence speed and the bit error rate (BER) level\cite{20}. In order to reduce the computation cost required to achieve $T_T$, by leveraging the similarity in channel states between the received data in $D_S$ and $D_T$, TL-MIMO transfers these three well-trained parameters from $D_S$ to $D_T$ as initial values, accelerating the equalizers’ convergence speed of $D_T$.

### 2.2. FD-LMS algorithm in TL-MIMO

Figure 2 illustrates the structure of $2 \times 2$ FD-LMS-based MIMO equalization after transferring the equalization parameters ($\mu$, $K$, $W$) from $D_S$. As indicated by the three arrows in Fig. 2, the three parameters, respectively, affect the equalizer initialization, updating, and data-block size in MIMO equalization. The steps affected by each parameter are marked with their corresponding colors. Upon algorithm initiation, the twofold oversampled input sequences $x_1$ and $x_2$ undergo serial-to-parallel (S/P) conversion and are then divided into even and odd branches. The sequence in each branch is split into several data blocks of size $K$, denoted by $x_{1e}(n)$, $x_{1o}(n)$, $x_{2e}(n)$, and $x_{2o}(n)$, where $n$ represents the block index. These blocks are combined into new blocks with the 50% overlap-save method and are then converted to frequency-domain with fast Fourier transform (FFT) expressed

![Fig. 1. Schematic design of the proposed TL-MIMO.](image1)

![Fig. 2. $2 \times 2$ FD-LMS-based MIMO structure combined with TL.](image2)
as \( X_{im}(n) = \text{FFT}[x_{im}(n - 1), x_{im}(n)] \), where \( i \) and \( m \) represent the input port index and even/odd branch, respectively.

Because the number of equalizers corresponding to each input port is twice the number of input ports, the system with \( P \) input ports has \( 2P^2 \) equalizers. In the \( 2 \times 2 \) MIMO module, the \( W \) matrix consists of 8 FD-equalizers, namely \( W_{11e}, W_{11o}, W_{21e}, W_{21o}, W_{22e}, W_{22o}, W_{12e}, \) and \( W_{12o} \). These FD-equalizers, denoted as \( W_{ijm} \), are transformed from their corresponding time-domain (TD)-equalizers \( w_{ijm} \), that is, \( W_{ijm} = \text{FFT}[w_{ijm}, Z(K)] \), where \( Z(K) \) is a zero matrix with a size of \( 1 \times K \). Since the sizes of \( w_{ijm} \) and \( W_{ijm} \) are \( 1 \times K \) and \( 1 \times 2K \), respectively, the size of \( W \) should be \( 2P^2 \times 2K \). In TL-MIMO, the transferred \( W \) from \( D_8 \) serves as the initial values of the equalizers in \( D_T \) for subsequent training. The output frequency response \( Y_i(n) \) is summed from the products of both branches' data and the corresponding equalizers, as presented in Eq. (1).

The output vector \( y_{ij}(n) \) consists of the last \( K \) data points from the inverse fast Fourier transform (IFFT) of \( Y_i(n) \),

\[
Y_i(n) = \sum_{j=1}^{p} X_{je}(n) \cdot W_{ije}(n) + X_{jo}(n) \cdot W_{ijo}(n). \tag{1}
\]

The following is the training link. We define \( d_i(n) \) as the \( n \)th desired output block of the \( i \)th input port. The feedback error vector is then defined as \( e_i(n) = d_i(n) - y_i(n) \). After prefixed \( K \) zeros, \( e_i(n) \) is transformed to frequency-domain error vector \( E_i(n) \) by FFT. During the \( n \)th training time, the equalizers are updated according to the gradient error estimation method, as shown in Eq. (2):

\[
W_{ijm}(n + 1) = W_{ijm}(n) + \mu \Gamma_{im}(n), \tag{2}
\]

where \( \mu \) is the transferred step size factor and \( \Gamma_{im}(n) \) is calculated according to Eq. (3). \( r_{im}(n) \) in Eq. (3) is defined as the first \( K \) data in the IFFT results of the product of \( X_{im}(n) \) and \( E_i(n) \),

\[
\Gamma_{im}(n) = \text{FFT}[r_{im}(n), Z(K)]. \tag{3}
\]

In order to save the proportion of training data in the transmission data, we consider the self-recycling training scheme to extend a string of training data several times to fully extract valuable information.

We quantify the algorithm complexity by the times of complex multiplication. For each training time in the FD-LMS algorithm, each \( W_{im}(n) \) undergoes \( 2K \) complex multiplications with the input signal \( X_{im}(n) \), the same as their length, to yield the equalized signal. In our work, we set the number of input ports as equal to the excited modes in FMF. For a system with \( P \) input ports, it requires \( 4PK \) multiplications per port. Similarly, in gradient error estimation, the generation of \( r_{im}(n) \) per port involves additional \( 4PK \) complex multiplications. In addition, during the equalization, the data of each port are successively processed \( 8 \) times by FFT/IFFT, resulting in \( 8K\log_2(2K) \) times multiplication. Therefore, for a single training time, the number of complex multiplications \( C_{\text{single}} \) in FD-LMS-based MIMO equalization systems can be expressed as

\[
C_{\text{single}} = P \times [4PK + 4PK + 8K\log_2(2K)]
= 8P^2K + 8PK\log_2(2K). \tag{4}
\]

Moreover, the total number of training times, \( T_{\text{total}} \), can be expressed as

\[
T_{\text{total}} = T_{\text{recycling}} \times \frac{1}{L_{\text{data}}} = K = C_{\text{train}} / K, \quad \text{where} \quad T_{\text{recycling}} \quad \text{and} \quad L_{\text{data}} \quad \text{respectively, represent the self-recycling training times and the length of training data. Here,} \quad C_{\text{train}} = T_{\text{recycling}} \times L_{\text{data}} \quad \text{is defined as the training complexity. Therefore, the overall training complexity of the FD-LMS-based MIMO equalization system, denoted as} \quad C_{\text{total}}, \quad \text{is expressed in Eq. (5). This equation indicates that, while maintaining signal quality requirements, effective reduction of training complexity can be achieved through the optimization of training data length and training times.}
\]

\[
C_{\text{total}} = T_{\text{total}} \times C_{\text{single}}
= C_{\text{train}} / K \times [8P^2K + 8PK\log_2(2K)]
= T_{\text{recycling}} \times L_{\text{data}} \times [8P^2 + 8P\log_2(2K)]. \tag{5}
\]

For the payload in \( D_T \), let \( T_{\text{retrain}} \) and \( L_{\text{retrain}} \) denote the training times and training data length needed for training from scratch to achieve a specific BER, respectively. Under the same BER requirement, the necessary training times and training data length for using TL-MIMO are denoted as \( T_{\text{TL}} \) and \( L_{\text{TL}} \) respectively. The saved training complexity \( C_{\text{saved}} \) by TL-MIMO is expressed as Eq. (6). In Sec. 4, we investigate the performance of TL-MIMO by evaluating the reduction of training complexity.

\[
C_{\text{saved}} = \frac{(T_{\text{retrain}} \times L_{\text{retrain}} - T_{\text{TL}} \times L_{\text{TL}})}{(T_{\text{retrain}} \times L_{\text{retrain}})}. \tag{6}
\]

3. Experimental Setup

To verify the performance of the proposed TL-MIMO scheme, we built up an MDM coherent transmission system based on a 12-km-length three-mode fiber, depicted in Fig. 3. First, the two independent electrical non-return-to-zero (NRZ) signals generated by an arbitrary waveform generator (AWG) were used to drive an optical I/Q modulator (IQM). A continuous-wave (CW) light of 1552.52 nm as the optical carrier was also injected into the IQM. The data rate of the optical QPSK was 10 Gbit/s.

![Fig. 3. Coherent three-mode multiplexed experimental setup.](image-url)
An erbium-doped fiber amplifier (EDFA₁), as well as a variable optical attenuator (VOA₁), was responsible for adjusting the power level of the optical signal. In order to achieve the OSNR control in the system, an amplified-spontaneous emission (ASE) source was used to generate the noise, which coupled with the signal through the first optical coupler (OC₁) with a coupling ratio of 99:1. We monitored the input OSNR through the optical spectrum analyzer (OSA) received from the 1% port of OC₁. Then, the distorted signal was divided into three branches through three 3 dB optical couplers (OC₂), i.e., OC₂, OC₃, and OC₄. In each path, the VOAs were used to ensure the same input power for each branch before injecting into the mode-selective photonic lantern (MSPL₁). Due to the polarization sensitivity of the few-mode system, single-mode polarization controllers (PCs) were employed to maintain the few-mode system in a favorable polarization state and ensure similar output power for signals in each mode after demultiplexing. In order to de-correlate the three channels, the different delay was applied through three pieces of the single-mode fibers with different lengths placed at the input port of MSPL₁. Consequently, the data frames transmitted by the other two branches have different symbol offsets compared to that by the first branch. The mode conversion occurred at the MSPL₁, which also connected with the three-mode transmission fiber through its few-mode pigtail. The same three-mode graded-index fiber for the MSPL and the FMF channel was connected with the three-mode graded-index fiber through the OPA for the MSPL₁. Consequently, the data frames transmitted by the other two branches have different symbol offsets compared to that by the first branch. The mode conversion occurred at the MSPL₁, which also connected with the three-mode transmission fiber through its few-mode pigtail. The same three-mode graded-index fiber for the MSPL and the FMF channel was produced by YOFC. The three-mode signals, LP₀₁, LP₁₁a, and LP₁₁b propagated through the 12-km-length fiber and were injected into MSPL₁. Then, three single-mode signals were obtained after the MSPL₂ and detected by a coherent receiver (Co-Rx) separately. We used an optical switch (OS) to select the data each time for one channel. We calculated the relative symbol offsets among the channels based on the length differences of the delay lines placed before MSPL₁. The header of each frame was defined by cropping the respective symbol offset from the originally received frame of each branch. The real-time sampling was performed by an oscilloscope with a sampling rate of 50 GSa/s.

During the transmission in the FMF, besides the inherent distortion, such as the attenuation and the dispersion that already existed in the SSMF, the major degradation came from the mode-dependent distortions (e.g., MC and DMGD). So as to mitigate the influence of the mode-related distortions, the MIMO equalizer is an important module in DSP algorithms for MDM systems. In Fig. 3, the offline DSP processing flow is illustrated, wherein the signal successively undergoes IQ balancing, Gardner-algorithm-based time synchronization, Schmidt-algorithm-based frame synchronization, and quartic method-based frequency offset estimation before being processed by the MIMO module.

4. Results and Discussion

In order to investigate the performance of the proposed TL-MIMO scheme, we have measured the experimental results in three scenarios: different time moments, different launched powers, and different OSNRs, and we investigated the complexity reduction for each case.

4.1. TL-MIMO between different time moments

Just like the conventional SSMF-based communication system, the system performance is variable due to the slowly varying factors such as the state-of-polarization (SOP) evolution, which results in the equalizer retraining at the receiver. During parallel transmission in the FMF channel, time-dependent distortions, such as crosstalk induced by MC, can result in fluctuations in transmission performance. Therefore, in the MDM system, equalizer remodeling is an important step to adapt to the latest transmission conditions. It is necessary to investigate the features of the TL-MIMO scheme in this most practical scenario.

In this scenario, we have calculated the BER results of the data collected at different time moments, the results with retraining and two TL-MIMO methods, which are depicted in Fig. 4. For this test, the data length of each frame was 81,920, and the launched power and the input OSNR of the signals in both DS and DT were −4 dBm and 25 dB, respectively. First, taking a set of data as an example, Fig. 4(a) depicts the BER results with the number of self-recycling times Trecycling from 0 to 40 and the fixed length of training data Ldata of 16,384. The blue line represents the process of the training from scratch. The yellow line with the legend of TL w/o W (partial TL-MIMO method) means that the transferred parameters are the optimal μ-K combinations of DS, but the values of W in DT are initialized as zeros. The red line corresponds to the full TL-MIMO method. In this method, besides the optimal μ-K combination, the values of the well-trained W in DS are also transferred to the target training system. In addition, since the signals of three modes are generated by the same data source, the output three-channel signals are consistent after MIMO equalization. We can find that the BER trained from scratch requires at least 2 self-recycling times to meet the 7% HD-FEC threshold of 3.8 × 10⁻³, but whether the partial or full TL-MIMO method is used, only one self-recycling time is sufficient to meet this requirement. Therefore, according to Eq. (6), TL-MIMO reduced the training times by 50% with both lower initial BER and faster convergence speed compared to training from scratch. According to Fig. 4(a), the red dotted line initially decreased to its lowest point and then started...
increasing again with the increase of $T_{\text{recycling}}$, and the final BER was slightly higher than that of the retraining scenario. Two primary reasons account for this phenomenon: (1) During equalizer training, the overfitting of the equalizers led to degraded BER results; (2) The transferred $\mu$-$K$ combination is not optimal for the payload in $D_T$; thus, the BER results with TL-MIMO after sufficient training were slightly higher. As mentioned in Sec. 2, locating the optimal $\mu$-$K$ combination for each group of data requires multi-calls to the equalization algorithm, resulting in significant computational costs. The TL-MIMO scheme can avoid such computational costs with slight and affordable BER degradation. In addition, we have also demonstrated the constellations for the three methods with equalized BERs of around $1.7 \times 10^{-4}$. The similar constellation results indicate that TL-MIMO has a significant influence on the signal features.

The length of training data is another determining factor of the training complexity $C_{\text{train}}$ as discussed in Section 2. The BER results with $L_{\text{data}}$ are depicted in Fig. 4(b). The measured $L_{\text{data}}$ length was from 1024 to 16384 with a step of 1024, and each point in the figure was trained with 40 self-recycling times. In comparison to the necessary 4096 training data for the retraining process to meet the 7% FEC threshold, the shortest length of training data in TL-MIMO, which is 2048, results in a 50% reduction in training complexity.

In FMF, the evolution speed of the channel state is 1 order of magnitude faster than that in SSMF\cite{29}. To verify the time-varying characteristic of the experimental system built in Sec. 3, we demonstrate the BER distributions on the $T$-$D$ plane for the payload in $D_S$ and $D_T$, both under the same equalization conditions, as shown in Figs. 5(a) and 5(b). The diversity in BER distribution proves the channel state differences between $D_S$ and $D_T$.

To investigate the relationship between the BER and the parameters $T_{\text{recycling}}$ and $L_{\text{data}}$ both before and after applying TL-MIMO more accurately, we monitored the BER results with varying $L_{\text{data}}$ and $T_{\text{recycling}}$. The results, both without and with TL-MIMO, are depicted in Figs. 6(a) and 6(b), respectively. In these figures, color highlights areas where the BER is less than $3.8 \times 10^{-3}$. As per Eq. (5), training complexity $C_{\text{train}}$ is defined as the product of $T_{\text{recycling}}$ and $L_{\text{data}}$. Comparing Figs. 6(a) and 6(b), it is evident that the colored area extends toward lower $C_{\text{train}}$ values when the TL-MIMO scheme is applied. Specifically, the lowest $C_{\text{train}}$ through training from scratch was 26,624 ($T_{\text{recycling}} = 2$ and $L_{\text{data}} = 13,312$), marked in Fig. 6(a) with a red pentagram. However, the TL-MIMO scheme achieved a minimum $C_{\text{train}}$ of only 3072, marked in Fig. 6(b), corresponding to $T_{\text{recycling}} = 3$ and $L_{\text{data}} = 1024$. This represents an 88.46% reduction in $C_{\text{train}}$ achieved through TL-MIMO scheme.

We have also conducted a comparison between the TL-MIMO scheme and the variable step size FD-LMS (VSS-FD-LMS) algorithm\cite{30}, which is designed to accelerate equalizer convergence by optimizing the step size during training. The statistical results of 30 sets of independently received data are presented in Fig. 7, with dotted lines representing the average BER results and shadows covering the range of the tested results. In Fig. 7(a), compared to the VSS algorithm, the TL-MIMO scheme exhibits smaller initial BER values and converges to minimum values at a faster pace. Taking the average BER result as an example, the TL-MIMO scheme in Fig. 7(b) achieves a 60% reduction in $L_{\text{train}}$ compared to training from scratch and a 50% reduction compared to the VSS algorithm. These findings indicate the effectiveness of TL-MIMO scheme in reducing $C_{\text{train}}$ in MIMO equalization.

### 4.2. TL-MIMO between different launched powers

In this subsection, we measured the TL-MIMO results between different launched optical powers. In the experiment, the launched optical power was adjusted from $-15$ dBm to $-4$ dBm with the fixed input OSNR of 25 dB. Figure 8 demonstrates the BER versus $T_{\text{recycling}}$ and $L_{\text{data}}$ in two transferring cases between different launched powers,
i.e., transferring the equalization parameters from the lower OSNR of 15 dBm to the higher OSNR of 25 dBm (L-H case), and from 10 to 15 dBm (H-L case). The results in Fig. 8 are statistically counted from 30 groups of data. For the L-H case, as depicted in Figs. 8(a) and 8(b), $T_{\text{recycling}}$ and $L_{\text{data}}$ were reduced by 83.33% and 60%, respectively, by the full TL-MIMO method. For the H-L case, as depicted in Figs. 8(c) and 8(d), the $T_{\text{recycling}}$ and the $L_{\text{data}}$ were also significantly reduced by 80% and 40%, respectively.

To investigate the more detailed TL-MIMO performance for the scenario of the transferring parameters from different launched powers, we have transferred the equalization parameters from well-trained equalizers with different launched powers, i.e., with different $P_t$, to other power points of the test band and depicted the results in Fig. 9. The green, red, and yellow markers, respectively, represent the results with $P_t$ of −15, −10, and −4 dBm. In the test, the 16,384 training data and 40 self-recycling times were applied to all the datasets. Through using full TL-MIMO equalization, all experimental results in the testing range of −15 to −4 dBm were below the FEC threshold. The similar BER curves obtained by the three transferring cases further confirm the stability of the proposed TL-MIMO scheme. A small BER gap between the case of retraining and TL-MIMO came from the inherent optimal-value issue.

### 4.3. TL-MIMO between different OSNRs

In fiber-optic transmission systems, the OSNR is regarded as a significant parameter to directly judge the channel quality in the optical domain. Hence, it is necessary to analyze the compatibility of the TL-MIMO scheme under different input OSNRs. In the experimental setup of Sec. 3, we could adjust the OSNR of input signals through an ASE source and a power controllable device, i.e., VOA, in the experiment. The measured OSNR was in the range of 15 to 25 dB with the launched power of −4 dBm.

As mentioned in the previous subsection, measuring the results in two transferring cases, we transferred parameters here from the case of the input OSNR of 20 dB to the case of 25 dB (L-H case), or to the case of 15 dB (H-L case), also representing the two-way transferring behavior.

The statistical BER results for the two OSNR transferring cases are depicted in Figs. 10(a) to 10(d). The results prove that TL-MIMO has a significant improvement in reducing training complexity. For the case of transferring from the OSNR of 20 to 25 dB, 83.33% of the $T_{\text{recycling}}$ and 60% of the $L_{\text{data}}$ were saved by the full TL-MIMO scheme. For another case, the $T_{\text{recycling}}$ and the $L_{\text{data}}$ were, respectively, saved by 83.33% and 50%.

Additionally, in the scenarios corresponding to Figs. 8 and 10, TL-MIMO scheme remains more efficient in our measurements compared to the VSS-FD-LMS algorithm.

Figure 11 demonstrates the relationship between the BER and OSNR in different cases where the parameters transferred from the OSNRs of 15, 20, and 25 dB to each OSNR-testing point (see the yellow, red, and green markers). The blue circulars are
the tested results from the retraining MIMO. For each marker, it represents the average value of 30 BER data. Similar to Fig. 9, the TL-MIMO scheme for the three transferring cases shows similar results, confirming the stability of the proposed method used in the OSNR scenario. As in the other two scenarios, the small BER penalty is also observed.

5. Conclusion

We proposed a TL-MIMO scheme to reduce the equalizer training complexity in MDM transmission systems. Based on a 3-mode multiplexed experimental system with 12 km FMF, we carried out the investigation in three scenarios, i.e., transferring parameters between different time moments, launching optical powers, and inputting OSNRs to verify the performance of the TL-MIMO scheme. Experimental results show that under the premise of achieving the 7% HD-FEC threshold, 88.46% training complexity was reduced with the full TL-MIMO scheme in the first scenario. In the latter two scenarios, the training complexity was reduced by up to 83.33% and at least 40% according to the average results of 30 groups of data. Additionally, TL-MIMO scheme exhibited robust stability and compatibility across different launched powers and OSNR testing bands.

Acknowledgements

This work was supported by the National Key R&D Program of China (No. 2018YFB1801001) and the Royal Society International Exchange Grant (No. IEC/NSFC/211244).

References