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Power compensation study to optical communication on improved control model with time-delay

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This paper mainly presents the self-tuning PID controller based on improved BP neural network for a networked control system (NCS) with the presence of network transmission time-delay and power compensation at amplifiers' node firstly. In this study, the function of the standard control plane of the automatically switched optical network is enhanced to perceive transmission impairments and control tunable physical impairment compensators in the physical layer. A link level power control model is introduced to the dynamic adjustment for learning rate and adjusts the OSNR value of the signals toward channel OSNR optimization. Control algorithms continuously update their channel powers in response to dynamic information from the network links. And the controller could achieve the on-line adaptive power compensation without changing the parameters of PID controller. The results of simulation show that the proposed new PID controller is better to adjust channel power independently at the transmitter sites and achieve channel optical signal-to-noise ratio (OSNR) optimization with network time-delays.

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1. Introduction

Optical Wavelength-Division Multiplexing (WDM) communication networks with arbitrary topologies are widely enabled by technological advances in optical devices such as optical add/drop MUXes (OADM), optical cross connects (OXC) and dynamic gain equalizer (DGE). But fiber optic cables are spread out over vast surface areas in applications, propagation delays of corresponding signals cannot be avoided practically. When the time-delay becomes sufficiently large, the networked control algorithm may become unstable if the time-delay is not appropriately handled. Transparent transmission in the optical networks mainly depends on the optical signal-to-noise ratio (OSNR). Core networks in the future will have a translucent and eventually transparent optical structure. Ultra-high-speed end-to-end connectivity with high quality of service and reliability will be realized through the exploitation of optimized protocols and light-path routing algorithms. These algorithms will complement flexible control and a management plane integrated in most proposed solutions. Conventional off-line OSNR optimization is done by adjusting channel input power at transmitter (Tx) to equalize the dominant impairment of noise accumulation in chains of optical amplifiers.

However, for optical networks, where different channels can travel via different optical paths, it is more desirable to implement on-line decentralized iterative algorithms to accomplish such adjustment. Physical layer impairments and optical performances are monitored and incorporated in impairment-aware light-path routing algorithms in [1-2]. The research on OSNR optimization and power impairment has been active, which is accomplished by maximizing the channel OSNR. A non-cooperative game formulation for the OSNR optimization is presented by Pavel in [3]. This approach abstracts the channels in the network as players in a game, where an increase in the signal power (increase in OSNR) of a channel causes increase in noise (decrease in OSNR) in other channels. Pavel's work also devises a network-level power control algorithm at the signal sources to ensure the channel powers to converge to the unique Nash equilibrium point. Dynamic link pricing is introduced in [4], associated with a control algorithm. Because of the many sources of information in a network and the existing information transmission problems, it inevitably causes delays in information transmission. Stefanovic and Pavel further analyzed the effects of time-delays in optical communication networks in [5]. They suggested a link-level power control which adjusts the OSNR value of the signals toward channel OSNR optimization along with a game-theory-based control algorithm. However, they did not analyze the performance degradation in optical networks as a result of time-delays. Huang and Heritage develop intelligent impairment-aware routing and wavelength assignment (RWA) algorithms in [6], which automatically consider the effects of high-speed transmission impairment when setting up a light-path. But these algorithms implement flexible control and a management plane integrated in the proposed solution without considering the influence of time-delays.

Research on time-delay neural network in networks is an active area. El Bakry proposed fast time delay neural networks use cross correlation in the frequency domain between the tested data and the input weights of neural networks. It is proved mathematically and practically that the number of computation steps required for the presented time delay neural networks is less than that needed by conventional time delay neural networks[7][8]. In recent years, the application of neural networks in control system has improved the information-processing capabilities and the intelligence of the systems. So, the combination of the PID control and the neural network has become a new direction for intelligent controller, attracting many researchers[9][10]. Yang Xue presented new kind of intelligent PID control method based on BP neural network and a complex neural network PID controller is designed. The controller has strong self-adaptability and self-learning abilities[11]. The self-tuning PID can use the BP neural networks to get the parameters on line. After introducing the PID controller structure based on BP neural network, this paper firstly presents a PID controller based on improved BP neural network to adjust the gain of amplifiers and compensate the transmission impairment with time-delay. The controller model adaptive to disturbance based on neural network has the ability of self-learning. So the controller could achieve the power compensation without changing the controlling factors of PID controller.

2. Optical link model

Consider a generic optical network model (Figure 1), with a set of optical links= $\{1,\cdots,L\}$ connecting the optical nodes (for channel add/drop (ROADM) or cross connection (OXC)). Consider also an optical link composed of *N* cascaded optical amplifiers and optical fiber spans. A set $M = \{1, \cdots, m\}$ of channels are transmitted across the same optical fiber by wavelength-multiplexing. We denote by $u_i = [u_1,\cdots,u_m]$ as the vector of input powers for all channels at the i^{th} node.

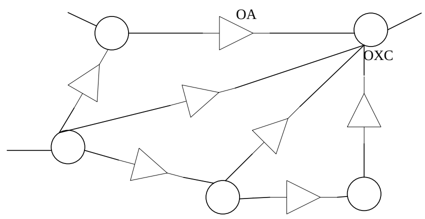

Fig.1. Mesh Optical Network.

For a fiber link in every few tens of km, an optical amplifier is used to compensate the impairment of the previous optical span. Such an amplifier simultaneously boosts the optical power of all channels, each with gain G_i , at the expense of introducing amplified spontaneous emission (ASE) noise, with power ASE_i , $i \in M$. Optical amplifiers are operated to maintain a constant total power at their output. The compensation method is to have variations in optical span impairment across each link. Then, at the input of the node, through each intermediary optical span we have the following condition:

$$OSNR_i(t) = \frac{u_i\left(t - t'_{i,i}\right)}{n_{0,i} + \sum_{j\in\mu}\Gamma_{i,j}u_j\left(t - t'_{i,j}\right)} \quad (1)$$

Here, $\Gamma = \left[\Gamma_{i,j}\right]$ is the system matrix with

$$\Gamma_{i,j} = \sum_{v=1}^{N}\frac{G_j^v}{G_i^v}\frac{T_i}{T_j}\frac{ASE_i}{P_0} \quad (2)$$

We denote this time-delay as $t'_{i,i}$ in the *i*th channel and $t'_{i,T}$ as the cumulative delay time ahead of $i-1$ nodes, as shown in Fig. 2, where t is the signal arrival time to the node.

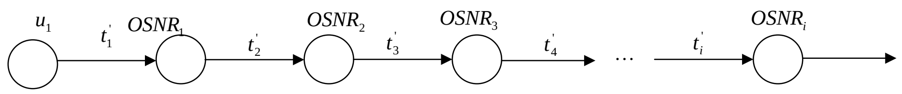

Fig.2. Example of optical link.

It is important that channel transmission performance and quality of service (QoS) be optimized and maintained. At the physical transmission level, channel performance and QoS are directly determined by the bit error rate (BER), which in turn depends on optical signal to noise ratio (OSNR), dispersion and nonlinear effects. Thus, OSNR is considered as the dominant performance parameter in link-level optimization. Channel OSNR is affected by noise accumulation in optical amplifiers, which depends on all channel powers at the input. Based on this model, an adaptable adaptive control model can be formulated towards the compensation and optimization of power impairment. Meanwhile, we should consider transmission performance limits. Accumulating OSNR must be greater than the minimum OSNR at a specific bit error rate because useful information will "flooded" to the noise and cannot be identified correctly if the OSNR is too small. The total power target needs to be selected below the threshold of nonlinear effects. System residual dispersion should be set between the minimum tolerate negative dispersion and the maximum tolerance positive dispersion. If it exceeds the positive and negative dispersion tolerance ranges, it will show that the pulse broaden excessively the resulting error rate. In this paper, we suppose that dispersion can be compensated in optical fiber transmission links, so we only consider OSNR and nonlinear effects are changed after regulation compensation.

3. PID Controller on BP Neural Network for Compensation

3.1 Structure of PID Controller Based on BP Neural Network

The structure of the control system is shown in Figure 3, which includes the classic PID controller and a BP neural network modular. The PID controller is used to handle input value and the BP neural network is used to further amend the PID control parameters indirectly via self-learning and adjusting weighted coefficient in order to compensate power through adjusting the gain of amplifiers. When the traditional control system is used in the network system, we only connect an adaptive scale factor of BP neural network to PID controller to achieve the power compensation.

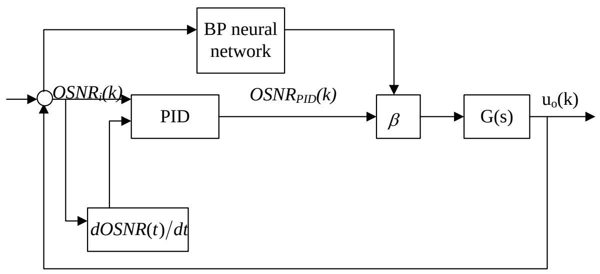

Fig.3. Structure of PID controller based on BP neural network.

Controlling model based on the BP neural network:

$$OSNR_{PID}(k)=OSNR_i(k)+K_p[e(k)-e(k-1)+K_ie(k)+K_d[e(k)-2e(k-1)+e(k-2)] \quad (3)$$

$$e(k-1)=OSNR_o(k-1)-OSNR_{min} \quad (4)$$

$$e(k)=OSNR_o(k)-OSNR_{min} \quad (5)$$

$$e(k-2)=OSNR_o(k-2)-OSNR_{min} \quad (6)$$

Where, K_p is the proportional parameter, K_i is integral coefficient and K_d is differential coefficient. And $OSNR_{min}$ is the tolerant minimum OSNR value with a particular BER. $OSNR_o(k)$ is the output OSNR after adjustment and compensation at the k^{th} node. $u_o(k)$ is the controlling output at the k^{th} node and β is adjustable factor.

3.2 BP Algorithm

BP neural network is a more layers hierarchical neural network with upper neurons full associated with lower neurons. When a couple of learning samples is supplied to the network, the transferred value is propagated from the input layer through middle layer to the output layer, and we can get neural network input response from neurons in output layer. Along the direction of reducing the error between expected value and actual output, connection weights are adjusted from the output layer to every middle layer, and ultimately to the input layer. With the ongoing amendment by this back-propagation, the correct rate for the network response to input also increases continuously. As BP algorithm implements middle hidden layer and has a corresponding learning rules to follow, it has the ability to identify the non-linear pattern. Especially to those learning that has clear calculation methods, well-defined steps, BP algorithm has more extensive applications. Typical BP network has three layers, input layer, hidden layer (middle layer) and output layer. Full connection is applied between layers.

The BP neural network of three inputs and a single output is shown in Figure 4. X_1, X_2 and X_3 are inputs related to $e(k)$, $e(k-1)$ and $e(k-2)$ respectively. $O^{(3)}$ is the threshold of the output; β is the output.

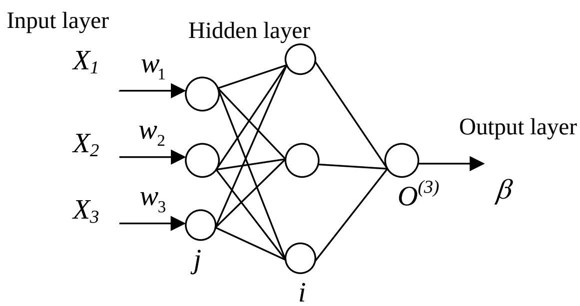

Fig. 4. Structure of BP neural network.

The input of the input layer is $O_j^{(1)}=X(j)$ $(j=1,2,3)$. The input and output of hidden layer are partitioned as:

$$net_i^{(2)}(k)=\sum_{j=0}^{M}W_{ij}^{(2)}O_j^{(1)} \quad (7)$$

$$O_i^2(k)=f\left(net_i^2(k)\right) \qquad (i=1,2,\ldots,n) \quad (8)$$

W_{ij}^2 is the connection weight vector of hidden layer. The activation function in the hidden layer is the sigmoid function.

$$f(x)=\tanh(x)=e^{x}-e^{-x}/e^{x}+e^{-x} \quad (9)$$

The input and output of output layer are partitioned as:

$$net^{(3)}(k)=\sum_{i=0}^{n}W_{1i}^{(3)}O_i^{(2)}(k) \quad (10)$$

$$O^{(3)}(k)=g\left(net^{(3)}(k)\right) \quad (11)$$

Where the elements $O^{(3)}(k)$ are defined as:

$$O^{(3)}(k)=\beta \quad (12)$$

Because k_p, k_i, k_d could not be negative, the activation function of the output layer is expressed as:

$$g(x)=(1+\tanh(x))/2=e^{x}/e^{x}+e^{-x} \quad (13)$$

The performance function is expressed as:

$$E(k)=\frac{1}{2}\left(OSNR_O(k)-OSNR_i(k)\right) \quad (14)$$

The weight coefficients are adjusted by using the gradient descent method. It is to say that they are adjusted in the negative gradient of the $E(k)$ with an inertia item, expressed as Eq (15).

$$\Delta W_{1i}^{(3)}(k)=-\eta\frac{\partial E(k)}{\partial W_{1i}^{(3)}}+\alpha\Delta W_{1i}^{(3)}(k-1) \quad (15)$$

Where, η is the learning rate, α is the inertia coefficient.

$$\frac{\partial E(k)}{\partial W_{1i}^{(3)}}=\frac{\partial E(k)}{\partial OSNR_o(k)}\bullet\frac{\partial OSNR_o(k)}{\partial OSNR_c(k)}\bullet\frac{\partial OSNR_c(k)}{\partial O^{(3)}(k)}\bullet\frac{\partial O^{(3)}(k)}{\partial net^{(3)}(k)}\bullet\frac{\partial net^{(3)}(k)}{\partial W_{1i}^{(3)}(k)} \quad (16)$$

and while , $\frac{\partial net^{(3)}(k)}{\partial W_{1i}^{(3)}(k)}=O_i^2(k)$. Because $\partial OSNR_o(k)/\partial OSNR_c(k)$ is unknown, it could be replaced by $\mathrm{sgn}(\partial OSNR_o(k)/\partial OSNR_c(k))$. The replacement can result in the worse accuracy which can be compensated by the learning rate η . And $\partial OSNR_c(k)/\partial O^{(3)}(k)$ is equal to *e(k)-e(k-1),* and $\partial OSNR_c(k)/\partial O_2^{(3)}(k)$ = *e(k),* and $\partial OSNR_c(k)/\partial O_3^{(3)}(k)$ = *e(k)-2 e(k-1)+ e(k-2).*

From the above analysis, the adjustment of the weight coefficients in the output layer is expressed as:

$$\Delta W_{1i}^{(3)}(k)=\alpha\Delta W_{1i}^{(3)}(k-1)+\eta\delta^{(3)}O_i^{(2)}(k) \quad (17)$$

$$\delta^{(3)}=e(k)\bullet OSNR_{PI}(k)\bullet\mathrm{sgn}\left(\frac{\partial OSNR_o(k)}{\partial OSNR_c(k)}\right)g'\left(net^{(3)}(k)\right) \quad (18)$$

Similarly, the adjustment of the weight coefficients in the hide layer is expressed as:

$$\Delta W_{ij}^{(3)}(k)=\alpha\Delta W_{ij}^{(2)}(k-1)+\eta\delta^{(2)}O_j^{(1)}(k) \quad (19)$$

Where, $\delta_i^{(2)}$ is equal to

$f'\left(net^{(2)}(k)\right)\bullet\delta^{(3)}\bullet W_{ij}^{(3)}(k)$, ($i$=1, 2,⋯), and

$$g'(\bullet)=g(x)\bullet(1-g(x)) \quad (20)$$

$$f'(\bullet)=\frac{1-f^2(x)}{2} \quad (21)$$

3.3 An improved neural network model

BP algorithm is tested in a lot of determinacy problems, the result is satisfying in most cases. However, BP algorithm has still some limitations, such as:

(1) Because some application’s essence is non-linear optimization, then inevitably, the Local minimum problem will exist. And the best solution of the problem can’t be obtained.

(2) The learning algorithm [12] [13] has a slow convergence speed.

(3) The selection of the number of hidden neurons has no strict theoretical basis[14][15], so the selection is usually based on experiences.

(4) While learning the new sample, BP tends to forget the old ones. In addition, the number of characteristics for specifying each sample is required to be the same.

Focusing on the defects of traditional BP algorithm which are specified above, researchers improve the algorithm from different points of view. Especially the convergence speed is slow while multilayer network of basic BP neural network is trained. Therefore, improving the back propagation to speed up the training is one of key issues which need to be solved urgently in practice.

The major methods to speed up convergence change the learning efficiency in this paper. In order to speed the learning procedure of the BP neural network, dynamic adjustment for learning rate is proposed as following.

In the steepest descent of the BP algorithm, the learning rate η is a constant. However, the performance of learning algorithm is very sensitive to the learning rate. In the special applications it is very difficult to choose the best learning rate. In fact, during the learning procedure the learning rate can be changed according to the change tendency of the performance function $E(k)$. In order to make the network stable and shorten the learning time, the learning rate η can be multiplied by the incremental factor k_{inc} in the learning procedure, when the error trends to the excepted value in the positive direction. While when the error trends to the excepted value in the negative direction, it can be multiplied by the reduction factor k_{dec} in order to decrease the learning rate. The learning rate η is changed according to the Eq (22).

$$\eta(k+1)=\begin{cases} k_{inc}\eta(k) & E(k+1)<E(k) \\ k_{dec}\eta(k) & E(k+1)>E(k) \end{cases} \tag{22}$$

It is an efficient measure to speed the BP neural network, also has the character of global convergence.

3.4 PID Control based on Improved BP Neural Network

The self-tuning PID control based BP neural network by using the improved method includes the following steps:

(1) Initialize the neural network, giving the values of the weight coefficients, setting the value of η.
(2) Compute the $e(k)$, $e(k-1)$ and $e(k-2)$.
(3) Adjust the parameters of the improved method according to the Eq (22).
(4) Compute the output of the PID control.
(5) Compute the outputs of the neural network.
(6) Adjust the weight coefficients of the BP neural network according to the improved method.
(7) If the output doesn't meet the transmission requirement, then returns to step (2). Otherwise, the iteration is terminated.

4. Simulation and analysis

Transfer function about the optical link is given by Eq(23) and (24),

$$OSNR(s)\left[n_{o,i}+\sum_{j\in\mu}\Gamma_{i,j}U_j(s)\right]=U_{i,o}(s) \tag{23}$$

$$G(s)=n_{o,i}+\sum_{j\in\mu}\Gamma_{i,j}U_j(s) \tag{24}$$

Here, $u_{i,o}(k)$ is the output power after adjustment and compensation at the i^{th} node.

One controller's input of PID regulator is:

$$\frac{dOSNR_i(t)}{dt}=\frac{u_i\left(t-t_{i,i}^{'}-t_{i,T}^{'}\right)}{n_{0,i}+\sum_{j\in M}\Gamma_{i,j}u_j\left(t-t_{i,i}^{'}-t_{i,T}^{'}\right)} \tag{25}$$

A MATLAB simulation was used for the control model with ten nodes, nine amplified spans per link, each optical amplifier with variable gain. We assume that the link dispersion is compensated at last, so we do not consider the influence of dispersion. All spans in a link have an equal length and all the amplifiers in a link have the same spectral shape and are operated in automatic power control mode. Each optical amplifier adjusts its power towards this goal in the presence of all other channels.

During the simulation, the three parameters initial value of the PID control was k_p=0.1, k_i=0.25, k_d=0.05. The learning rate η and the inertia coefficient α are respectively 0.15 and 0.06. And the field of initial value on the weight coefficients is [-0.5, 0.5]. Minimum $OSNR_i$ is 20 dB. And the delay time is [0,20]ms.

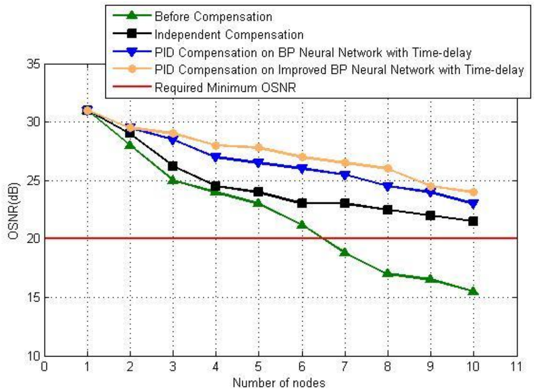

Fig.5. OSNR of ten nodes in the optical link, time-delay 10ms.

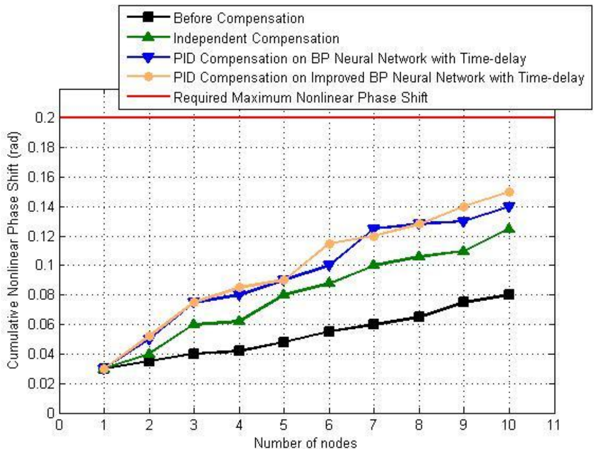

Fig.6. Nonlinear phase shift of ten nodes in the optical link, time-delay 10ms.

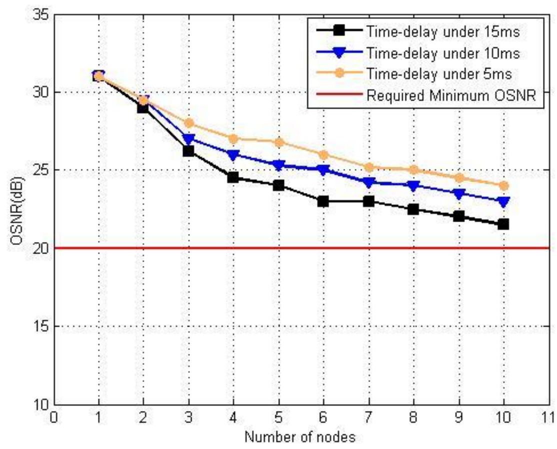

Fig.7. OSNR of ten nodes in the optical link, delay time under 15ms, 10ms and 5ms.

From Fig. 5 and Fig. 6, we compare four curves when the control system adjust and compensate the power at the node. The OSNR is better than others to adjust transmission power because the improved BP model has a better convergence speed and a better precision. We can see that channel OSNR levels converge to new steady state values, and the OSNR is always greater than the present minimum OSNR after compensation and optimization. But variable power adjustment on line must inevitably lead to the impact of nonlinear and make the accumulated nonlinear phase-shift signal larger with more accurate adjustment. And the nonlinear phase shift is still less than the maximum. From Figure 7 the control algorithms could adjust OSNR with delay time under 15ms, 10ms and 5ms to meet performance requirement respectively. The method of considering the time-delays to compensate impairment power by adjusting the OA gain is more appropriate than not considering it. Therefore, the PID controller based on improved BP neural network with time-delay can make the transmission signal quality meet the system requirements.

5. Conclusions

A self-tuning PID control based BP neural network is proposed. The PID controller based on BP neural network can complete the power adjustment well under different delay time. The results of simulation show that the controller has good dynamic and effective performances for compensation of transmission power at the device nodes. The controller can achieve the on-line adaptive power compensation and optimization of the transmission signal quality meeting the system requirement in practice. There are several directions for future research. Another topic of research is to analyze other strategies of setting parameters of dynamic power compensation, as well as development of real-time power control model, also better meeting transmission performance.

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