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Machine Learning and Optoelectronics for Automated Decision Support in Engineering Project Management

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Abstract

With the development of science and technology, the emergence of machine learning methods such as neural networks has brought new ideas to cost management, and machine learning technology can greatly improve the efficiency of cost management. In addition, due to the extremely high raw bandwidth and fast signal transmission characteristics of optical systems, integrated photonics has been considered for the design of computing platforms. In this paper, we propose an optoelectronic hybrid neural network-based machine learning approach to support automated decision making in engineering project management. Specifically, based on the transmission method of optoelectronic hybrid computation, we plan the overall structure of the computational architecture, including the computing unit, the storage method and the interconnection module, and we plan the timing design of the FPGAs as well as the structural evaluation and selection of each module. The results show that the machine learning method based on optoelectronic hybrid neural network can effectively support the decision-making of project management.

Keywords: Machine Learning; Neural Network; Optoelectronics; Automated Decision Support; Engineering Project Management

1 INTRODUCTION

Through the construction of the project to obtain which maximize the benefits is the most fundamental purpose of the construction unit into the construction, but also to ensure that the construction unit of the long-term sound development of the enormous power. With the deep change of the market economic system of the project, the competition market is more and more equal and open, the company should be more serious about the construction cost investment and management, in order to greatly save the project cost to ensure that their own benefit optimization. The accurate prediction of direct cost as the core task of the company helps the reasonable apportionment of various costs and work arrangements, and finally achieves the reasonable and controllable cost. Therefore, the forecasting decision of direct cost is of great significance to the construction unit [1,2].

Forecasting the direct costs of a project means making a reasonable prediction of the direct costs to be invested in the project in the early stage of preparation. Regarding the method of forecasting the direct cost of the project, since the construction unit enterprises usually still have to make a rough analysis and estimation of the direct cost of the construction of the proposed project, but most of them still rely on personal experience, so it is not thorough. Therefore, in order to effectively strengthen the competitive strength of construction enterprises in the entire engineering industry, and to obtain a greater return on investment in the project, it is required that our enterprises make a reasonable and accurate prediction of the direct cost of the project. As neural networks [4-6] can be modeled to find out the complicated relationship embedded between inputs and outputs, and further expand this relationship, analyze and predict similar data, and model the variance required to predict highly variable data and predict rare events, which makes neural networks capable of engineering project management in a variety of complex problems, especially in recent years with the development of photovoltaic technology, based on the photovoltaic technology, neural networks based on photovoltaic technology have enhanced this capability.

Therefore, in order to continuously enhance the construction unit's automated decision-making ability of the project, the prediction link of the direct cost of the construction phase naturally can not be ignored, so it has a positive significance to build the direct cost prediction model of the construction phase by adopting a scientific and reasonable method.

2. OPTOELECTRONIC HYBRID NEURAL NETWORK

2.1. Optical neural network

Convolutional neural networks do reduce the amount of data compared to fully-connected neural networks, but for a complex, multi-layer neural network, the amount of data in the network is still significant, and it still consumes a lot of computational resources in the electrodynamic system, increasing the latency of the whole network and making the computational speed decrease [7]. However, as Moore's Law is gradually coming to an end, the performance of the electrical system itself is very limited, and it is difficult to meet the increasing demand for neural network scale, for this reason, researchers have begun to turn to the study of optical neural networks.

The optical chip is a device with ultra-high arithmetic power, as shown in Figure 1, the optical chip is cascaded with multiple Mach-Zönder interferometers (MZI) on top of the chip, which is capable of fast matrix operations, and its essence is to utilize the phase of the light for the operation of the data, and because the speed of the light is faster than the speed of the electronic movement, the calculation speed of the optical is much faster than that of the electrical system. On this basis, there is the research of using light to participate in neural network computation, because the convolution belongs to the matrix computation, so the light can be very good to complete the calculation required by the convolution layer, and there are a large number of convolutional calculations in the convolutional neural network, improve the speed of convolutional calculations can be very good to improve the speed of the whole neural network calculations.

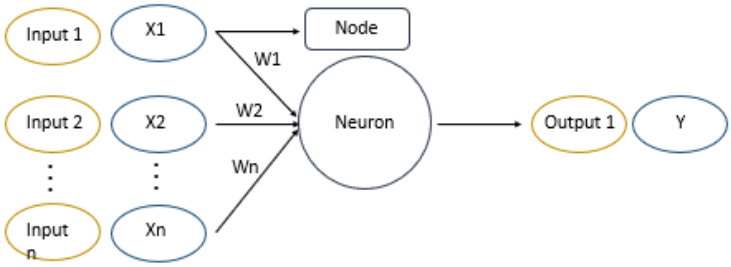

Figure 1.Schematic diagram of optical chip operation

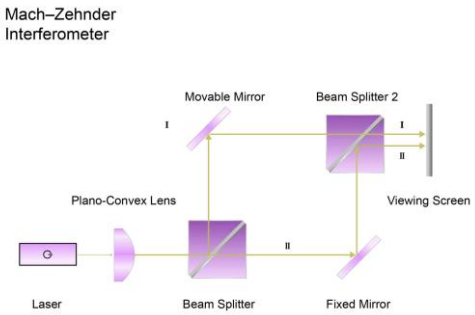

Figure 2: Schematic diagram of MZI.

To simplify Figure 2 into a $2 * 2$ MZI, as shown in Figure 3, this MZI has two input ports to input optical signals, to two optical signals are coherent as a prerequisite, then the input phase difference can be set to ϕ and 2ϕ, so that the two beams of light with different phases of the phase length or phase cancellation, the phase length will make the output light intensity increase, phase cancellation of the output light intensity is reduced, the use of this feature can be accomplished by a second-order conjugate The operation of a second-order conjugate matrix can be accomplished by utilizing this property. Assuming that there exists a matrix of size $i \times j$, its singular value decomposition, can be decomposed into a you matrix, a diagonal matrix and a you matrix conjugate multiplication, that is:

$$X_{ij} = U_{ii} \times \sum_{ij} V_{jj}^{T} \quad (1)$$

Since the MZI can realize the identity matrix and the optical amplifier or attenuator can realize the diagonal matrix with the presence of imaginary parts, the optical computation can be and is further accomplished by all the matrix computations according to the above matrix decomposability property for neural network computation.

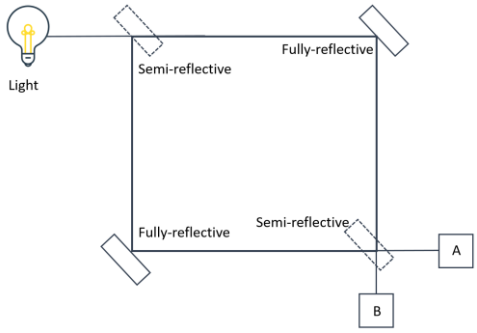

Figure 3: MZI Principles of Matrix Operations.

2.2 Motivation for Optical Hybrid Neural Networks

Optical computation can be accomplished with MZI arrays for matrices, but there is more than just matrix computation in neural networks. Matrix computation is a kind of linear computation, and currently neural networks are often used to solve more complex problems, which means that the input and output of the network is not a simple linear relationship, and therefore must be introduced into the nonlinear to increase the fit of the neural network, and this means that the light can not be independently complete a large-scale complex neural network computation, it must be undertaken by the electrical computation of the nonlinear computation part[8,9].

For the electrical design, the design difficulty of the optoelectronic hybrid neural network lies in the understanding and integrated analysis of both optical and electrical computing, which needs to be adapted to the characteristics of optical computing for the design of the electrical computing part, and on the basis of which the functions to be undertaken by the electrical are planned. More specifically, to realize the design of electrical computation on FPGA, firstly, it is necessary to clarify the process and characteristics of the convolutional neural network through optical computation, clarify the ability range of optical computation, reasonably disassemble the neural network computation, and reasonably plan the part that can not be accomplished by optics to electrical computation; secondly, due to the photoelectricity conversion of photoelectricity hybrid neural network, therefore, in addition to computation, it is also necessary to consider the transmission between optoelectricity and optics in the design.

3 SOFTWARE AND HARDWARE PLATFORM

In order to complete the optoelectronic hybrid neural network operation with optical computing, it is necessary to select a suitable electrical platform for the construction of neural network hardware computing unit. In this paper, an FPGA is selected as the electrical platform for the computational hardware support design. FPGA is essentially a hardware integrated circuit that can be programmed by the user to perform one or more logical operations. One of the major advantages of FPGAs is that there are no physical changes to the configuration, i.e., complex analog transformations. All changes are made digitally, and the user can create hardware interactions with the code-based operations, which can be reconfigured multiple times. multiple reconfigurations[10,11]. The classic FPGA architecture consists of three main types of modules, the configurable logic unit, the interconnect architecture, and the I/O unit.

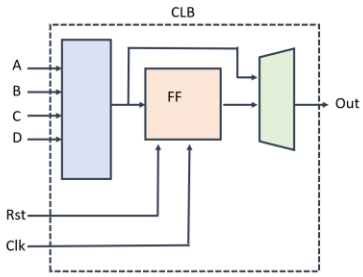

Figure 4.MZI Principles of Matrix Operations.

A configurable logic cell is often called a (CLB) or LE. As shown in Figure 4 is a classic configurable logic cell structure, there are multiple configurable logic cells in an FPGA, each configurable logic cell generally has multiple inputs and outputs, between the inputs and outputs is the configurable logic part, the designer can program this part to achieve the desired logic function, it consists of three basic It consists of three basic elements, lookup tables, multiplexers, and flip-flops.

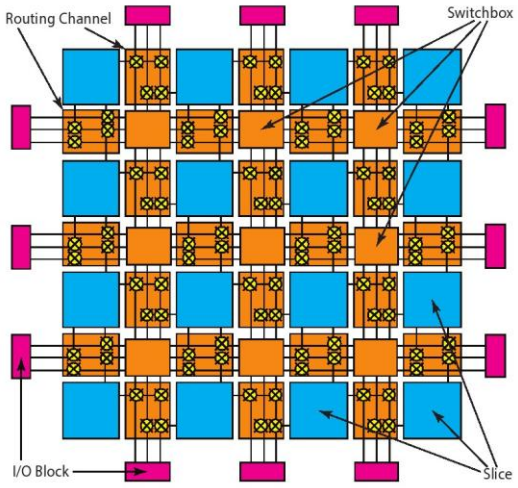

Figure 5. MZI Principles of Matrix Operations.

The lookup table (LUT) is one of the most important elements of the FPGA architecture, it is the main element that realizes the logic functions and is the core of the FPGA architecture. The basic principle of the lookup table is to create an internal logic function generator, consisting of a data selector and a SRAM cell, which contains the corresponding outputs based on the selected lines, i.e., it holds the values of the truth table derived from the Boolean functions, and can look up the corresponding outputs based on the inputs. A typical three-input lookup table structure is shown in Figure 5. In order to make the picture look uncluttered, the multiplexer, i.e., the data selector, is labeled with Mux, and it can be seen that the number of input ports to the lookup table determines its size, and the output values corresponding to the different inputs are stored in the SRAM, and when the input arrives, the input value is sent to the enable port of the data selector, which controls the data coming from the SRAM's When the input comes, the input value is sent to the enable port of the data selector to control the path of the data coming from the SRAM, and for one of these data, it will be sent to the output only if all the three layers of the selector are selected to complete the lookup process.

On the basis of the optoelectronic hybrid neural network transmission structure for the optoelectronic hybrid neural network computation part of the hardware support design, as shown in Figure 6, in the PL to add a neural network computing unit, used to complete the neural network computation in addition to the optical computation part of the increase in the computation of the computing support structure has a high degree of flexibility, can be combined with the optical neural network to complete a more complex neural network computation. For a complete neural network calculation, the ARM core can be unified scheduling, assuming that a certain convolutional neural network consists of multiple convolutional layers, multiple pooling layers, and multiple fully connected layers, when dealing with certain extremely large data volume convolutional layer calculations, the ARM core calls the optical chip to carry out the calculations, while the other layers call the electrical calculation unit to carry out the calculations.

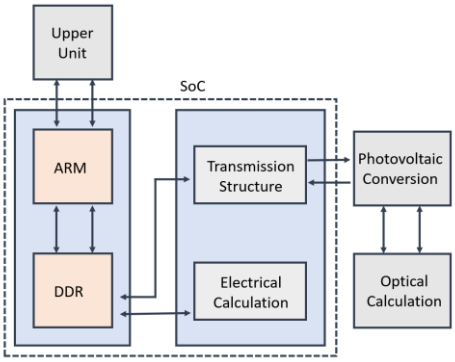

Figure 6.General Structure of Optical Hybrid Neural Network Computing.

For the design of the computational architecture, based on the basic structure of convolutional neural networks, the basic intermediate computational layers included are convolutional layer, pooling layer, and fully connected layer. The above is the

optoelectronic hybrid neural network proposed in this paper, which can be used to support automated decision making in engineering project management.

4 EXPERIMENT AND RESULTS

4.1 Engineering Project Case

The project has a building area of up to 32,211 square meters, two underground floors for parking and equipment rooms, etc., three floors above ground for offices and laboratories, a height of about 20 meters, is a scientific research and development building and garden, the structure is diverse and complex, cost control has a certain degree of difficulty. The general plan is shown in Figure 7.

The project is very large in scale when viewed comprehensively, and there are many major players, the required construction period is also long, and the complexity is quite obvious. The entire construction project is often composed of many sub-projects, with an intricate structure that makes it difficult to manage in a uniform manner. Also, the underground space is large, the excavation depth is large, and the foundation is affected by the length, width, depth and other factors in the process of construction, which makes the difficulty factor larger. There are also more complicated components in the whole project, and the most critical work for the construction unit is to ensure the completion of the whole project within the specified date and to minimize the funds required for the whole project. Therefore, in the construction stage of the whole project, it is necessary to correctly allocate various important resources such as labor, construction materials and machines on site, and to reasonably arrange the inputs of each stage, especially Before the start of construction, it is necessary to make a scientific and reasonable estimation of the construction cost, in order to better implement effective management of the cost during construction.

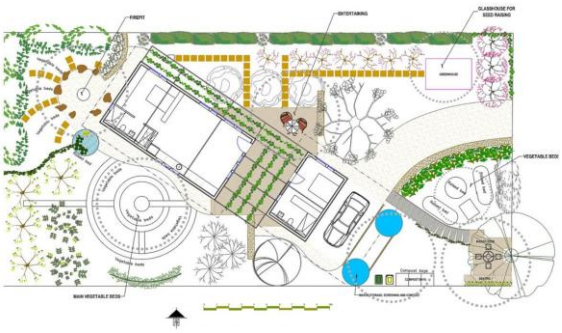

Figure 7.The rendering of the project design.

4.2 Experimental results of cost control decision making

In this paper, the direct cost automated control decision-making using photoelectric hybrid neural network prediction is applied in real engineering projects to predict the direct cost of engineering projects, and the prediction process is shown in Figure 8.

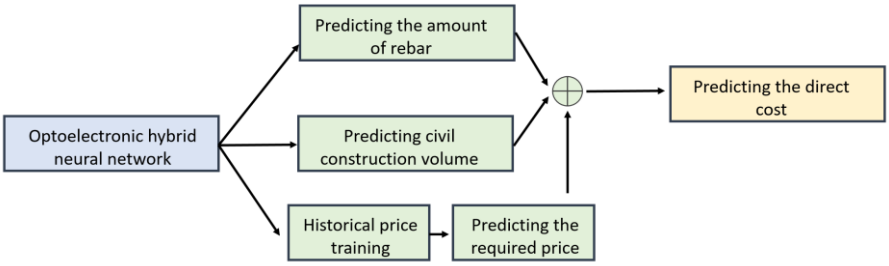

Figure 8. Schematic diagram of the prediction process.

Taking the price of HPB300 12mm diameter steel bar, the price of 42.5 grade cement and the price of 40mm gravel, which are the main materials required for the project, as an example, in the training of photoelectric hybrid neural network, we collect the price data of steel bar, cement and gravel of the local area in each month from 2018 to 2023 as a sample, construct the model of photoelectric hybrid neural network, and input the historical price sample data into the prediction model for learning training and simulation, so as to predict the required price at the corresponding time. The historical price sample data are input into the prediction model for learning training and simulation, so as to predict the required price at the corresponding time. The collected

prices of HPB300 12mm diameter steel bar was shown in Table 1. Although there may be some minor errors in the information prices in the table due to market changes and other factors, they will not affect the overall trend of the prices, nor will they have a significant impact on the overall trend of the price prediction. In addition, Tables 4 was obtained after applying Equation 2 to normalize the data in Tables 1.

$$y_i = \frac{x_i - \min[x_i]}{\max[x_i] - \min[x_i]} \quad (2)$$

Table1. Price Information of HPB300 Diameter 12mm Reinforcing Steel 2018-2023(USD/t).

Month/Year	2018	2019	2020	2021	2022	2023
1	600	610	580	580	610	615
2	600	610	570	580	610	615
3	600	610	570	580	610	615
4	600	610	560	580	600	635
5	600	610	560	590	615	615
6	600	605	565	580	615	605
7	605	605	560	590	615	605
8	605	610	565	590	615	605
9	605	610	565	590	615	615
10	610	610	555	595	615	605
11	600	610	555	600	605	615
12	605	590	560	590	610	605

Table2. Normalization of rebar price data.

Month/Year	2018	2019	2020	2021	2022	2023
1	0.5625	0.6875	0.3125	0.3125	0.6875	0.7500
2	0.5625	0.6875	0.1875	0.3125	0.6875	0.7500
3	0.5625	0.6875	0.1875	0.3125	0.6875	0.7500
4	0.5625	0.6875	0.0625	0.3125	0.5625	1
5	0.5625	0.6875	0.0625	0.4375	0.7500	0.7500
6	0.5625	0.6250	0.0125	0.3125	0.7500	0.6250
7	0.6250	0.6250	0.0625	0.4375	0.7500	0.6250
8	0.6250	0.6875	0.0125	0.4375	0.7500	0.6250
9	0.6250	0.6875	0.0125	0.4375	0.7500	0.7500
10	0.6875	0.6875	0	595	0.7500	0.6250
11	0.5625	0.6875	0	0.5625	0.6250	0.7500
12	0.6250	0.4375	0.0625	0.4375	0.6875	0.6250

After the learning training, the prediction results of the prices of steel, cement and gravel are shown in Figures 9, 10 and 11. It can be seen that the prices predicted by the photoelectric hybrid neural network are closer to the actual prices, which fully

demonstrates that the machine learning method based on the photoelectric hybrid neural network can effectively support the decision-making of the project management.

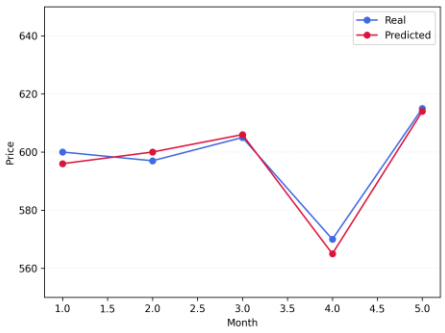

Figure 9.Prediction results of rebar price.

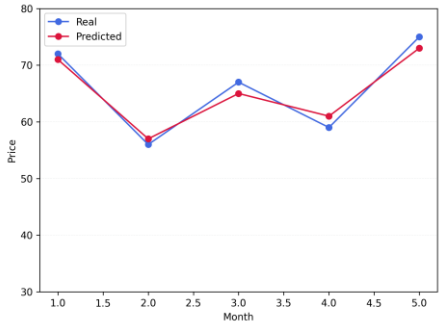

Figure 10. Prediction results of cement price.

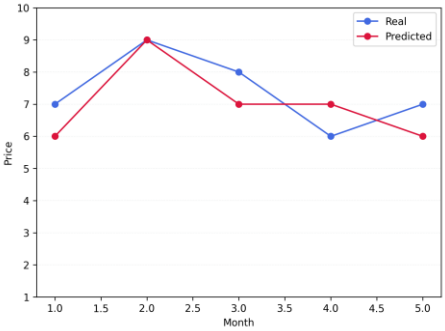

Figure 11. Prediction results of gravel price.

5 CONCLUSION

In this paper, it is considered that with the development of science and technology, the emergence of machine learning methods, such as neural networks, has brought new ideas to cost management, and machine learning techniques can greatly improve the efficiency of cost management. In addition, integrated photonics has been considered for the design of computing platforms due to the extremely high raw bandwidth and fast signal transmission characteristics of optical systems. In this paper, we propose an optoelectronic hybrid neural network-based machine learning approach to support automated decision making in engineering project management. Specifically, based on the transmission method of optoelectronic hybrid computing, the overall structure of the computational architecture, including the computational units, storage methods and interconnect modules, is planned, and the timing design and structural evaluation of FPGAs are planned. and the selection of each module. The results show that the machine learning method based on optoelectronic hybrid neural network can effectively support project management decisions.

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