Optimal control for a shield machine subject to multi-point earth pressure balance

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This paper discusses multi-point earth pressure balance (EPB) optimal control for EPB shield machine with five pressure sensors on its chamber clapboard. The predictive models taking into account advance speed, rotating speed of the cutter head, screw conveyor speed, and the earth pressure measurements are established for five shield chamber pressure points with the adaptive neuro-fuzzy inference system by minimizing the deviation between the corresponding point’s predicted pressures and the settings. Then, the ant colony system algorithm is employed to get the optimal screw conveyor speed to control the EPB during the tunnelling process. Simulation results show that the optimal control method gives better performance with small tracking error and fast tracking speed.

Keywords: shield machine; earth pressure balance; adaptive neuro-fuzzy inference system (ANFIS); ACS algorithm

1. Introduction

The earth pressure balance (EPB) shield is a large engineering machine widely applied in underground construction, such as metro tunnel, municipal construction, resources exploitation, hydraulic engineering, and so on. However, the imbalance of earth pressure in front of the tunnel face can lead to unpredictable and serious geological and hydrogeological accidents or even disasters, such as ground subsidence and heave. Thus, the stability of the tunnel face is a critical factor to ensure the safety of an excavating process.

Hongxin and Deming (2007) established a mathematical model for the excavating process based on physical analysis. However, a mathematical–physical model inevitably has some deviation from the practical condition. Then the analysis based on online measurement data and intelligent strategy is introduced in the study of EPB shield control. Cheng and Dongsheng (2012) designed a numerical method based on pressure field surface normal vector to judge the tunnel face stability, and optimal control with guarantee of tunnel face stability was suggested (2014). Yeh (1997) modelled earth pressure using back propagation neural network, which only considers the speed of the shield jack and the screw conveyor. Hu, Guofang, and Huayong (2008) applied adaptive fuzzy artificial neural network to EPB control based on a single point on the chamber pressure field. However, the studies mentioned above ignored other factors’ influences on the tunnel face, such as cutter speed and total thrust. Due to the complexity of the pressure distribution surface, only considering the pressure at one point cannot represent the working condition of the whole tunnel face and is hard to ensure the construction safety and stability.

The pressure balance between the tunnel face and the shield chamber is mainly controlled by adjusting the shield’s advance speed, the cutter head rotating speed and the speed of the screw conveyor which discharges the excavated soil out of the chamber. Given that the advance speed and cutter head speed need to be designed according to the local geological and hydrogeological conditions, the rotating speed of the screw conveyor is chosen as the control variable.

This paper proposes an optimal EPB control method based on the ant colony system (ACS) algorithm for the screw conveyor rotating speed to keep the chamber pressure following its set values and ensure the stability of the tunnel face. Previous studies on EPB control are generally based on the central pressure point which cannot give the characteristic of pressure distribution on the whole pressure field. In this case, this paper, considering multiple pressure monitoring points, establishes an ANFIS predictive model for each of the five pressure points which facilitates a more comprehensive understanding of the pressure field before applying proper control strategy. Compared with the data of four sensors analysed by Kairu, Yan, and Cheng (2014), a new set of data measured in a practical construction project is introduced. This certain type of EPB shield has five pressure sensors on its chamber clapboard. Additionally, all of the five relative variables, including advance speed, total thrust, cutter speed, screw conveyor

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speed, and the real-time earth pressure, are considered in the ANFIS model. Then, with online measurement data from pressure sensors, the ACS algorithm is used to find the optimal screw conveyor speed, which aims to minimize the difference between the earth pressure in the chamber and the corresponding pressure set value. Finally, simulation results are presented to demonstrate the effectiveness of the proposed method.

2. Optimal control of multi-point EPB in pressure chamber

2.1. Control strategy for multi-point EPB

Generally, the EPB in the pressure chamber is only controlled by monitoring the sensor on the centre horizontal line in the chamber clapboard. In this paper, the control of EPB is based on five sensors on different points on the chamber clapboard. Figure 1 shows the distribution of the five pressure sensors on the chamber clapboard of a certain type of EPB shield which is used in a real tunnel construction project.

When a shield machine excavates a homogeneous and stable soil layer, the EPB in the chamber is controlled by adjusting the advance speed or screw conveyor speed based on the discharge control mode. The cutter speed, total thrust, and advance speed decide the amount of earth charged, and the screw conveyor speed influences the discharge. They directly influence the balance of earth pressure in the chamber.

Based on the consideration above, this paper proposes an optimal control strategy for EPB: firstly, the ANFIS pressure predictive model is established, taking advance speed $v_a$, total thrust $F$, cutter speed $v_c$, screw conveyor speed $v_s$, and the real-time earth pressure $p_i(k)$ as the inputs and next time earth pressure $p_i(k + 1)$ as the output variable; secondly, the optimal output variable (the screw conveyor speed) is obtained by using the ACS algorithm which uses the minimization of the pressure deviation between the real-time pressures and corresponding set values. The control strategy is as shown in Figure 2, where $p_i(k) (i = 1, \ldots, 5)$ is the real-time earth pressure, $p_i(k + 1) = f (v_a, F, v_c, v_s, p_i(k))$ is the next time earth pressure; and $p_{d1}, p_{d2}, p_{d3}, p_{d4}, p_{d5}$ are the set earth pressures of the points of sensors.

2.2. Establishment of ANFIS model for chamber earth pressure

Due to the complexity of the tunnelling process, the earth pressure is hard to be accurately predicted based on physical mechanism analysis. Fuzzy inference system (FIS) is a non-linear, strong coupling system. It is an effective method to predict systems that are hard to be modelled. The selection of a fuzzy membership function and the generation of fuzzy rules in the FIS generally depend on expert experience. However, insufficient expert experience and wrong judgements may strongly influence the prediction. Thus, a Takagi-Sugeno-Kang fuzzy inference model (Michio & Kang, 1988; Tomohiro & Michio, 1985) is applied to build an adaptive neuro-fuzzy inference system (ANFIS) for identifying parameters. In the ANFIS system, the learning mechanism of a neural network is used to obtain the fuzzy membership function and fuzzy rules instead of depending on expert experience, which could overcome the deficiency of a fuzzy system and make the model more objective.

The ANFIS model is based on a multilayer feed-forward neural network. Each layer has a certain task, and then transfers information to the next layer.

The first layer receives the data of five input parameters, including total thrust, advance speed, cutter speed, screw conveyor speed, and real-time earth pressure.

The second layer completes the blurring process and transfers the numerical value to fuzzy value, a membership belonging to a certain fuzzy subset.

The third layer and the fourth layer complete the fuzzy inference process together. The third layer completes the rule antecedent; the fourth layer completes the rule consequently and output fuzzy value after fuzzy inference.

The fifth layer completes defuzzification and then output results.

Based on this theory, five ‘five-input and single-output’ ANFIS systems are obtained. The input values, screw conveyor speed, total thrust, thrust speed, cutter speed, and real-time earth pressure $p_i(k) (i = 1, 2, \ldots, 5)$, are obtained by data training. The outputs, next time earth pressures, are $p_i(k + 1)$. $p_{d1}, p_{d2}, p_{d3}, p_{d4}, p_{d5}$ are the set earth pressures of the five sensors on the chamber.

ANFIS is a Sugeno fuzzy non-linear model. It can be used to indicate the dynamic response of complicated
systems. The most common fuzzy inference rule is: if $v_s$ is $A_1$, $F$ is $A_2$, $v_a$ is $A_3$, $v_c$ is $A_4$, $p_i(k)$ is $A_5$, then $p_i(k+1) = f(v_s, F, v_a, v_c, p_i(k))$, where $A_1, \ldots, A_5$ are fuzzy sets. Finally, $p_i(k+1) = f(v_s, F, v_a, v_c, p_i(k))$, the model of each pressure point is obtained.

2.3. Optimal control mechanism and solution

2.3.1. Establishing the optimization model

To realize dynamic balance control of the earth pressure, an EPB optimal control strategy is proposed in this paper. The control object is to make the pressure in the chamber track the desired value in the future, which we can achieve through the optimization function

$$
\min \sum_{i=1}^{5} |p_i(k+1) - p_d|,
$$

s.t. $V_{\text{min}} \leq V_S(k) \leq V_{\text{max}}, \quad (1)$

where $V_{\text{min}}, V_{\text{max}}$ are the minimum and maximum values of screw conveyor speed, respectively, and $p_d$ is the set earth pressure of the point of a sensor.

2.3.2. The solution of the optimization model

Because the optimization model (1) is smooth, non-convex, and constrained, it is difficult to solve by using the conventional numerical optimization method. However, the ant algorithm can be easily implemented with fewer parameters to adjust, and it is very suitable for solving the complicated non-linear problems and can get the global optimal solution (Haibin, Daobo, & Xiufen, 2005). Therefore, an ACS algorithm is employed to solve the optimization model (1). The specific process for searching the optimal solution is as follows:

2.3.2.1. Formation of the ant moving path. The optimal screw conveyor speed is represented by $V_S(k)$. Because the rotating speed of the screw conveyor is usually less than 22.4 rpm, each of them is represented by three decimal significant figures and, according to actual values, two figures are placed in front of the decimal point and the third one after the decimal point. In order to use the ACS algorithm conveniently, we express the values on the plane. As shown in Figure 3, $x_i (i = 1, 2, 3)$ represents the significant digit of the values of the control variables from the first one to the third one, respectively. $y_{ij} (i = 0, 1, \ldots, 9)$ represents the possible value of each significant digit. Especially, taking the dimension parameters of the shield machine into consideration, the screw conveyor rotational speed is usually less than 22.4 rpm, which means that the value of the first digit of each control value may be 0, 1, or 2; therefore, there are only 3 nodes on line $L_i$ as shown in Figure 3. We use $(x_i, y_{ij})$ to denote the node $j$ on line $L_i$, whose value is $y_{ij}$. Let an ant depart from the starting point 0. In each step forward, it chooses a node from the next line $L_i$ and then moves to this node along the straight line. The ant travels through in turn $L_1, L_2, L_3$; when it arrives at any node on line $L_3$, it completes one tour which is also called a cycle. Its moving path is expressed as

$$
\text{Path } k = \{0, (x_1, y_{1j}), (x_2, y_{2j}), (x_3, y_{3j})\}.
$$

Obviously, the values of the control variable on this path can be computed according to the following formula:

$$
V_S(k) = y_{1j} \times 10^1 + y_{2j} \times 10^0 + y_{3j} \times 10^{-1}. \quad (2)
$$
2.3.2.2. Selecting nodes on a moving path. Ants decide their direction according to the pheromone intensity on each node. $p^k_{ij}(t)$ denotes the state transition probability from position $i$ to $f$ for ant $k$ at time $t$:

$$p^k(x_i, y_{ij}, t) = \frac{[\tau(x_i, y_{ij}, t)]^\alpha}{\sum_{w \in \text{allowed}_k} [\tau(x_i, y_{iw}, t)]^\alpha} \quad \text{if} \quad j \in \text{allowed}_k,$$

$$= 0 \quad \text{else}, \quad (3)$$

where allowed$_k$ is the set of nodes that are allowed to choose in the next step for ant $k$, and $\alpha$ is a parameter that weighs the relative importance of the pheromone values.

2.3.2.3. Updating the pheromone intensity. After $n$ steps, each ant has travelled all lines and completed a cycle. The pheromone intensity of each node on the best tour is updated according to the following formula:

$$\tau(x_i, y_{ij}, t + n) = (1 - \rho)\tau(x_i, y_{ij}, t) + \Delta \tau(x_i, y_{ij}, t + n), \quad (4)$$

where $\rho (0 < \rho < 1)$ is the evaporation factor, $\tau(x_i, y_{ij}, 0) = \tau_0$, and $\Delta \tau$ is the increment of pheromone on the node $(x_i, y_{ij})$, which is calculated in term of the following rule:

$$\Delta \tau(x_i, y_{ij}, t + n) = \begin{cases} \frac{Q}{F_k} & \text{if} \quad (x_i, y_{ij}) \ \text{belongs to the best tour}, \\ 0 & \text{otherwise}, \end{cases}$$

where $Q$ is a constant and $F_k$ is the objective function value corresponding to the optimal path done by the best ant $k$. To avoid the algorithm converging to a non-global optimization solution prematurely, the pheromone intensity on each path is limited in $[\tau_{\text{min}}, \tau_{\text{max}}]$.

The procedures of the ACS algorithm used in this paper are summarized as follows:

Step 1: Establish a free solution space for the ant searching the path as shown in Figure 3, and define a one-dimensional array

$$\text{Path} \ k = \{0, (x_1, y_{ij}), (x_2, y_{ij}), (x_3, y_{ij})\}$$

with four elements to store the ordinate values of the nodes that the ant $k$ passes through in a tour.

Step 2: Define the number of ants $m$ and the maximum number of iterations $NC_{\text{max}}$; set time counter $t = 0$ and the number of cycle $N = 0$; specify the values of parameters $\alpha, \rho, \tau_0, \tau_{\text{min}}, \tau_{\text{max}},$ and $Q$; and then place all the $m$ ants at the start point 0.

Step 3: Set $i = 0$, $k = 1$.

Step 4: Ant $k$ selects a node on line $L_i$ to move according to Equations (3–5) and the path rule shown in Figure 3; then, store the ordinate value $y_q$ of this node into the $i$th element of Path $k$.

Step 5: Set $k = k + 1$, if $k \leq m$, then go to step 4; otherwise, continue.

Step 6: Set $i = i + 1$, if $i \leq 3$, then go to step 4; otherwise, continue.

Step 7: According to the array path $k$ of each ant $k$, we can obtain the ordinate values $y_q$ of the nodes that it passes through, and compute the values of $V_5(k)$ by using Equation (2).

Step 8: For all the $m$ ants, compute the objective function values according to Equation (1), find the minimum $F_k$ which corresponds to the optimal path done by the best ant $k$, and then update the pheromone intensity according to Equation (4).

Step 9: Define path$_b$ as the optimal path till the previous iteration $N - 1$, compare the path$_b$ with the optimal path $k$ obtained at this iteration to $N$ and find the optimal one, and then save the nodes of the optimal path into path$_b$.

Step 10: Set each element of path $k$ to 0, and $t = t + d, N = N + 1$; if $N > NC_{\text{max}}$ or $m$ ants make the same tour, the iteration is over, then output the optimal path path$_b$ and its corresponding control value $V_5(k)$; otherwise, return to step 3.

3. Simulation

3.1. Simulation of the ANFIS model

The simulation is based on a set of practical excavation data measured from an EPB shield of a construction project. A total of 100 groups of monitoring data are taken as the training data, and the other 100 groups of data are taken as the testing data. Then sub-clustering is used...
to initialize FIS, using Gauss subordination function. The model is trained for 10 times based on a hybrid algorithm. As in Figures 4–8, the black curves represent the real-time monitoring data, while the blue curves show the model outputs of the five points’ earth pressures, and the mean square errors of model outputs are detailed in Table 1. It is observed that the ANFIS model has small errors, which indicate a high precision for the proposed model.

3.2. Effect simulation of optimal control algorithm

A certain type of EPB shield is used to train and test the control model in order to verify the effectiveness of the control method. The diameter of the shield cutter is 9.75 m and the tunnel length is 3.065 km. The first 50 groups of data are obtained when tunnelling in sand pebble. Correspondingly, the set pressures of each point are as follows: $p_{d1} = 0.07$ MPa, $p_{d2} = p_{d5} = 0.10$ MPa,

| Pressure point | Mean square error |
|----------------|-------------------|
| $P_1$          | 0.004636          |
| $P_2$          | 0.004867          |
| $P_3$          | 0.005158          |
| $P_4$          | 0.005039          |
| $P_5$          | 0.004723          |
$p_{d3} = p_{d4} = 0.15 \text{ MPa}$. The second 50 groups of data are obtained when tunnelling in silty clay; in this condition, the set pressures of each point are as follows: $p_{d1} = 0.10 \text{ MPa}, p_{d2} = p_{d5} = 0.15 \text{ MPa}, p_{d3} = p_{d4} = 0.20 \text{ MPa}$. The control simulation results as in Figures 9–13 show that the method proposed in this paper has better control effect than that without optimization. It is confirmed that the presented method has good tracking performance even when the geological condition is changed. Through simulation analysis, the effectiveness of the presented method is verified.

4. Conclusions and future work

The five-point pressure data of an EPB shield chamber is used to learn and train the parameters of fitness function and fuzzy rules of the fuzzy system by means of a hybrid algorithm in ANFIS, and then the five points’ earth pressure prediction models are established. Later, an optimal control strategy of multi-point EPB for EPB shield is presented. The optimization function is established and solved by ACS algorithms. The simulation results show that the prediction model established by ANFIS has small errors and can achieve high precision, and the optimal control method has better control performance even if the geological conditions are changed, which indicates that the method has better tracking control performance than that without optimization.

Currently, only the discharge system is controlled in this paper to obtain the balance of an earth pressure field. However, the pressure balance is also influenced by the thrust system and cutter head system. Although the advance speed and the cutter head speed are usually decided based on the local geological and hydrogeological conditions, a coordinating optimization control of all the three systems with an integration of a geological identification system could be researched in the future to obtain a more accurate control performance of the tunnelling process.

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References
Cheng, S., & Dongsheng, L. (2012). Tunnel face stability analysis based on pressure field surface’s normal vector for earth pressure balanced shield. International Journal of Modelling, Identification and Control, 17(2), 143–150.
Cheng, S., & Dongsheng, L. (2014). Optimal control of an earth pressure balance shield with tunnel face stability. Automation in Construction, 46(10), 22–29.
Haibin, D., Daobo, W., & Xiufen, Y. (2005). Research on the optimum configuration strategy for the adjustable parameters in ant colony algorithm. Journal of Communication and Computer, 2(9), 32–35.
Hongxin, W., & Deming, F. (2007). Theoretical and test studies on balance control of EPB shields. China Civil Engineering Journal (in Chinese), 40(5), 61–68.
Hu, S., Guofang, G., & Huayong, Y. (2008). Control model of EPB shield machine. Journal of Coal Science & Engineering (in Chinese), 33(3), 343–346.
Kairu, L., Yan, Z., & Cheng, S. (2014). Earth pressure multipoint forecasts and optimal control for EPB shield. The 20th IEEE International Conference on Automation and Computing (ICAC), 272–276.
Michio, S., & Kang, G. T. (1988). Structure identification of fuzzy model. Fuzzy sets and systems, 28(1), 15–33.
Tomohiro, T., & Michio, S. (1985). Fuzzy identification of systems and its applications to modeling and control. IEEE Transactions on Systems, Man and Cybernetics, 15(1), 116–132.
Yeh, I.-C. (1997). Application of neural networks to automatic soil pressure balance control for shield tunneling. Automation in Construction, 5(5), 421–426.