Design and Analysis of Intelligent Control System for Bucket Wheel Stacker-Reclaimer Based on Multi-Source Data Fusion

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***Abstract*—**In view of the problems of variable working conditions under dynamic load conditions, low efficiency of traditional manual operation, and high energy consumption of equipment in bucket wheel stacker-reclaimers (BWRs), this paper proposes an intelligent control system design scheme based on multi-source data fusion. The system adopts a three-tier architecture design, integrating multi-source sensor data such as 3D laser scanning, RFID positioning calibration, and absolute value encoders to construct a full-time dynamic 3D digital twin model. Based on this, an improved repulsion model path planning algorithm is designed, effectively solving the problems of path oscillation and local optimum traps in dense obstacle environments. At the same time, fuzzy adaptive PID and PSO-GSA hybrid optimization strategies are adopted to achieve precise collaborative control of multiple motors. Experimental results show that the improved repulsion model algorithm achieves a path planning success rate of 94.7% under complex working conditions; the speed tracking difference of multiple motors is controlled within 3%; equipment energy consumption is reduced by 20% compared to before optimization; and the fluctuation range of reclaimer flow rate is controlled at ±1.9%.

Keywords*—*Bucket Wheel Reclaimer, Multi-Source Data, Intelligent Control, Collaborative Control

I. INTRODUCTION

As the core operational equipment in bulk material handling sites such as thermal power plants, coal mines, cement plants, and ports, BWR are responsible for the stacking and reclaiming of bulk materials. With the continuous growth in demand for bulk materials and the continuous improvement in industrial intelligence, higher requirements are placed on the operational efficiency, energy consumption level, and automation degree of BWR.

However, BWR face numerous technical challenges in practical operation: Firstly, the equipment operates under dynamic load conditions with variable working conditions, and the non-optimal operation of the drive system leads to frequent mechanical shocks and vibrations, resulting in high energy consumption; secondly, the traditional manual operation mode relies heavily on operators, who are exposed to harsh environments with high dust and strong noise for extended periods, and the consistency of manual operations is poor with delayed responses; thirdly, in coal yard environments with dense distribution of multiple obstacles, path planning algorithms are prone to falling into local optima or generating path oscillations, making it difficult to meet the reliability requirements of practical engineering. These issues severely restrict the development of BWR towards intelligent operations.

To address the aforementioned challenges, the academic and engineering communities have conducted extensive research. In terms of energy consumption optimization, Banke Bing proposed an optimization scheme for PLC-controlled frequency converters, achieving reduced equipment energy consumption through fuzzy speed regulation and multi-motor collaborative control. In path planning and control [1]. Zhang Chifei et al. proposed an integrated approach combining an improved repulsion model with GA-ACO fuzzy adaptive PID control, which addressed path oscillation issues in dense environments through a virtual coal pile obstacle mechanism. In unattended operation [2]. Zhang Jingjing et al. designed an intelligent control system based on 3D dynamic modeling and Dijkstra path planning, enabling fully automated operation of stacker-reclaimers throughout the entire process [3].

Although the aforementioned studies have made certain progress in their respective directions, most of the work still focuses on a single technical aspect, lacking systematic design and comprehensive analysis of the overall architecture of the intelligent control system for BWR. This paper proposes a comprehensive intelligent control scheme that integrates multi-source data fusion, 3D dynamic modeling, improved repulsion model path planning, and fuzzy adaptive PID control [4-5]. It systematically elaborates on system architecture design, core algorithm implementation, and experimental verification, providing a complete and feasible technical route for the intelligent upgrade of BWR.

II. OVERALL ARCHITECTURE DESIGN OF INTELLIGENT CONTROL SYSTEM

To achieve unattended operation of BWR, this paper designs an intelligent control system. The overall architecture of the system is shown in Fig. 1.

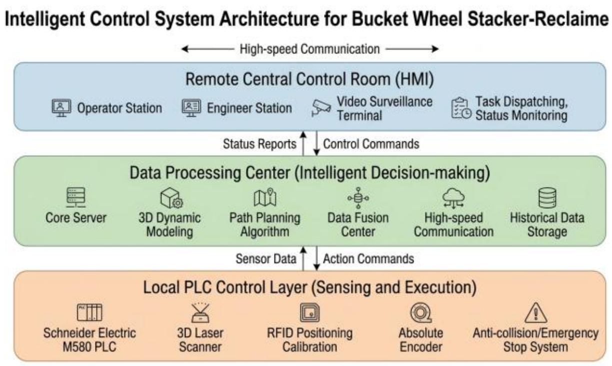

Fig. 1 The intelligent control system

The system consists of the following three levels: Remote centralized control room: Deploys operator stations and engineer stations to implement task assignment, monitor operational status, and intervene in emergency situations, forming a human-machine interface between operators and the intelligent system.

Data Processing Center: Deploys core servers responsible for real-time processing of massive data from multi-source sensors, full-time domain 3D dynamic modeling, path planning algorithm computation, and historical data storage. It is the core computing unit of the system.

Local PLC control layer: Schneider M580 PLC is used as the local controller, communicating with the data processing center through multimode fiber to achieve laser scanning data acquisition, positioning information fusion, and precise control of the actuator.

In terms of perception and positioning, the system integrates multiple high-precision sensors: an F5868 absolute encoderis used to monitor the crane's travel and rotation angles, an IS40 inclinometer detects the cantilever's pitch angle, and RFID passive tags are arranged every 20m along the track to achieve position calibration and eliminate cumulative errors. In terms of environmental perception, a LM5511 three-dimensional laser scanner is installed on each side of the cantilever head to achieve real-time scanning of the outer contour of the coal pile on the working surface

III. KEY ALGORITHM DESIGN

A. Full-Time Domain Dynamic 3D Modeling

Full-time domain dynamic 3D modeling serves as the data foundation for intelligent decision-making. The original point cloud data collected by the system through a laser scanner must undergo coordinate system transformation based on the real-time pose parameters of the stacker-reclaimer. A coordinate system is established with the rotation center as the origin, and a global yard coordinate system is established with a fixed point in the coal yard as the origin [6-7]. The transformation between the two coordinate systems is achieved through a translation transformation as expressed in Equation (1):

$$[X,Y,Z]=[X_e,Y_e,Z_e]+[X_{eo},Y_{eo},Z_{eo}] \tag{1}$$

where $[X,Y,Z]$ represents the coordinates of the point cloud in the global yard coordinate system; $[X_e,Y_e,Z_e]$ represents the coordinates of the point cloud in the rotation center coordinate system; $[X_{eo},Y_{eo},Z_{eo}]$ represents the real-time position of the rotation center in the global coordinate system.

To ensure the quality of 3D reconstruction, the system employs the Speeded Up Robust Features (SURF) algorithm for feature extraction. Initially, an image scale space is constructed through Gaussian filtering, and extreme points are detected using the Hessian matrix.

$$H(x,y,\sigma)=\begin{vmatrix} L_{xx} & L_{xy} \\ L_{xy} & L_{yy} \end{vmatrix} \tag{2}$$

Extreme points are identified by calculating the discriminant. Simultaneously, geometric feature keypoints are filtered using covariance analysis of the local neighborhood of the point cloud. The neighborhood covariance matrix is defined as:

$$\operatorname{cov}(p_i)=\sum_1^k w_{ij}\cdot(p_{ij}-\bar{p}_i)\cdot(p_{ij}-\bar{p}_i)^T \tag{3}$$

where p_i is the target point, $N(p_i)$ is the set of neighborhood points, k is the number of neighborhood points, $\bar{p}_i$ is the centroid of the neighborhood, and the weight is inversely proportional to the Euclidean distance, $w_{ij}=1/\|p_{ij}-\bar{p}_i\|$ is used to compensate for the influence of uneven point cloud density. By performing eigendecomposition on the covariance matrix, key feature points are filtered out, achieving efficient and accurate 3D reconstruction.

B. Improved repulsion model path planning algorithm

Addressing the issues of traditional artificial potential field methods easily getting trapped in local minima and generating path oscillations in dense multi-obstacle environments, this paper proposes an improved repulsion model path planning algorithm. By constructing a virtual coal pile obstacle mechanism, this algorithm clusters multiple densely distributed actual coal piles in space into an equivalent single virtual obstacle, effectively simplifying the potential field structure [8-9].

The improved model introduces a target distance adjustment factor and establishes a dynamic coupling mechanism between repulsion strength and target position. The improved repulsion calculation expression is:

$$\boldsymbol{F}_r=k_r\times\frac{1}{d^2}\times\frac{\boldsymbol{r}}{\|\boldsymbol{r}\|}\times\left(1-\frac{d_i}{d_i+d_0}\right) \tag{4}$$

where $\boldsymbol{F}_r$ represents the spatial repulsion vector; k_r represents the repulsion gain coefficient; d represents the minimum spacing between the equipment and the obstacle; $\boldsymbol{r}$ represents the displacement vector from the obstacle to the equipment; d_i represents the target distance; d_0 represents the adjustment coefficient. This mechanism ensures that the repulsion force decreases nonlinearly as the target distance decreases, ensuring that the repulsion force converges to zero as the target is approached. The goal-oriented mechanism is achieved by constructing a gravitational field.

$$\boldsymbol{F}_a=k_a\times d_t\times\frac{\boldsymbol{t}}{\|\boldsymbol{t}\|} \tag{5}$$

where $\boldsymbol{F}_a$ represents the gravitational vector; k_a represents the gravitational coefficient; d_t represents the distance between the device and the target; $\boldsymbol{t}$ represents the displacement vector.

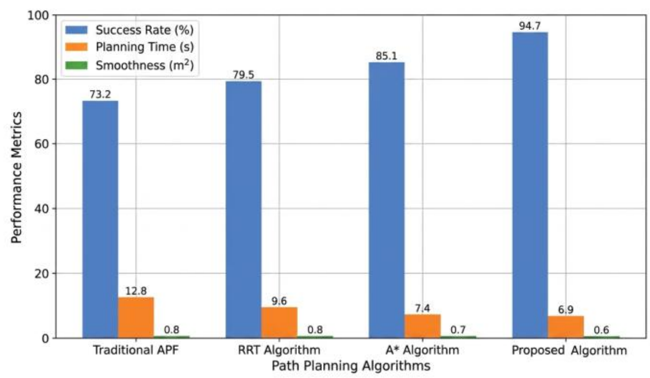

Fig. 2 Comparison of performance of different path planning algorithms

As can be seen from Fig. 2, the improved repulsion model algorithm outperforms traditional methods in terms of success rate, planning time, and path smoothness. The success rate is increased by 21.5% compared to the traditional artificial potential field method, the planning time is reduced by 46.1%, and the path smoothness is optimized to 0.62 /m, which is 8.8% to 27.1% lower than that of the comparative algorithm.

C. Fuzzy adaptive PID and multi-motor cooperative control

The BWR is a complex system involving multi-motor coordinated operation, and the coordinated control effect of each motor directly affects the energy consumption and operation quality of the equipment. In this paper, a fuzzy adaptive PID controller combined with a PSO-GSA hybrid optimization strategy is adopted to achieve precise coordinated control of multiple motors.

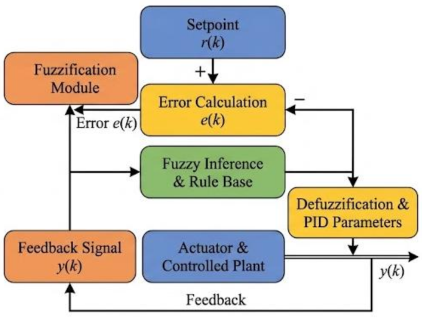

Fig. 3 Control schematic diagram

The fuzzy adaptive PID controller takes speed deviation and distance deviation as inputs, and outputs the online correction of PID parameters through fuzzy inference. The calculation formula for input deviation can be defined as follows:

$$D_t(k) = d_{des}(k) - d_{act}(k) \tag{6}$$

$$E_a(k) = v_r(k) - V_r(k) \tag{7}$$

where $d_{des}(k)$ represents the expected distance; $d_{act}(k)$ represents the actual distance; $v_r(k)$ represents the reference speed; and $V_r(k)$ represents the actual speed. The output defuzzification adopts the weighted average method.

$$a_{des}(k) = \frac{\sum_1^N \mu_i(E_a) \times y_i}{\sum_1^N \mu_i(E_a)} \tag{8}$$

where $a_{des}(k)$ is the expected acceleration; $\mu_i(E_a)$ is the membership degree; y_i is the output value corresponding to the fuzzy set; N is the total number of fuzzy rules.

The multi-motor speed monitoring model is based on the dynamic equation of the electric drive system.

$$T - T_L = \frac{R}{375} \times \frac{dn}{dt} \tag{9}$$

where T represents electromagnetic torque; T_L represents load torque; R represents flywheel torque; t represents time. By changing the number of motor pole pairs through a PLC frequency converter and adjusting the power frequency according to load changes, dynamic speed regulation is achieved.

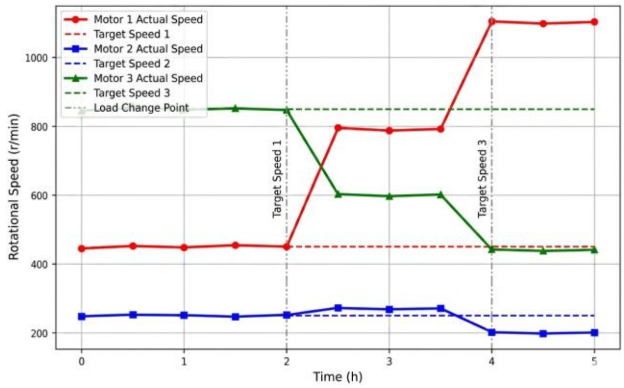

Fig. 4 Dynamic tracking effect of multi-motor speed

As can be seen from Fig. 4, under two load change disturbances, the actual rotational speeds of the three motors can track the target set rotational speeds, with the rotational speed difference remaining within 3%.

IV. EXPERIMENT AND RESULT ANALYSIS

A. Experimental platform configuration

The experiment selected the DQL1500/1500.55 cantilever bucket-wheel stacker-reclaimer as the experimental subject. It features a cantilever length of 35m, a turning radius of 35m, a bucket wheel diameter of 6.3m, and a rated stacking and reclaiming capacity of 1500t/h. The motor parameters are shown in Table 1. The simulation environment is based on Windows 11 system, using Unity3D 2022.3.11 as the core simulation engine, integrated with PhysX physics engine to achieve coal material discrete element simulation.

Table 1 Motor parameters of BWR

Parameter	Value
Rated voltage (V)	380
Rated current (A)	290
Rated power (kW)	160
Rated power factor	0.95
Rated frequency (Hz)	50

B. Analysis of energy consumption optimization effect

To verify the energy consumption reduction effect of the optimization method, experiments before and after optimization were compared, and the changes in equipment energy consumption over a period of 5 hours were recorded. The results are shown in Fig. 5.

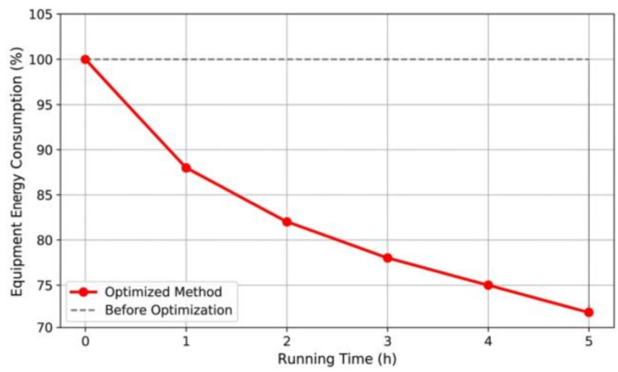

Fig. 5 Comparison of energy consumption before and after optimization

After optimization, the energy consumption of the equipment in this method is reduced by 20%, which is significantly better than the result before optimization. This is mainly due to the fuzzy adaptive control, which can dynamically adjust the motor speed according to real-time load, avoiding the motor operating in the low-efficiency zone for a long time.

C. Analysis of Material Handling Flow Stability

The set target flow rate is 800 t/h. The material handling flow stability of two BWRs was tested and compared with the delivery area analysis method and LiDAR technology. The results are shown in Fig. 6.

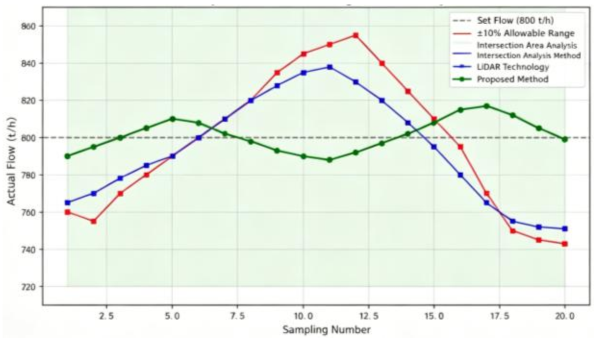

Fig. 6 Comparison of material withdrawal flow stability

Table 2 Comparison of results from different methods

Method	Fluctuation Range #1 (t/h)	Fluctuation Range #2 (t/h)	Fluctuation Magnitude (%)
Intersecting Area Analysis Method	743~859	763~828	±7.3%
LiDAR Technology	751~838	759~860	±6.4%
Proposed Method	**787~817**	**791~812**	**±1.9%**

As can be seen from Fig. 6 and Table 2, the fluctuation range of the material requisition flow in the method proposed in this paper is significantly smaller than that of other methods, with the fluctuation amplitude controlled within ±1.9%, effectively improving the accuracy of material requisition control.

D. 3D modeling performance and comprehensive operation efficiency

The performance of 3D modeling was tested and compared with the PSO-Kriging algorithm. In the modeling of 2,500 data points, the method proposed in this paper took 26~35ms for calculation and achieved an accuracy rate of over 98% for point location. Compared with PSO-Kriging, it exhibited higher computational efficiency and modeling accuracy.

Ten typical operation tasks were selected to compare the performance of intelligent control systems and manual operations. The results are presented in Table 3.

Table 3 Comparison of material handling efficiency between intelligent control and manual operation

No.	Manual method	Intelligent method	Improved (%)
1	105	89	15.2
2	98	83	15.3
3	112	95	15.2
4	107	91	15.0
5	103	87	15.5
6	99	84	15.2
7	108	92	14.8
8	104	88	15.4
9	101	86	14.9
10	106	90	15.1
Mean	104.6	88.5	15.1

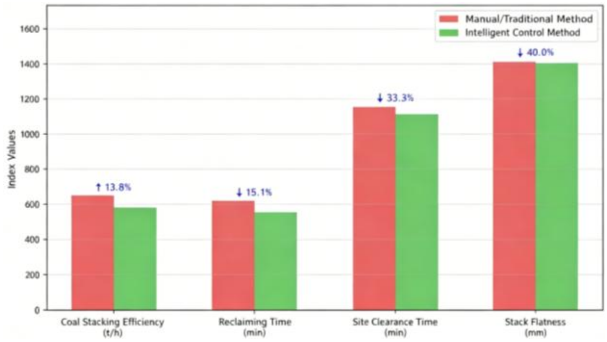

Fig. 7 Comparison of comprehensive performance between manual mode and intelligent control mode

As can be seen from Table 3 and Fig. 7, the intelligent control system saves an average of 15.1% of time in material retrieval operations, improves efficiency by 13.8% in coal stacking operations with better stacking quality, and reduces time consumption by 33.3% in site clearing operations. The efficiency improvement is mainly attributed to the application of all-terrain cruise path planning and bucket wheel irregular curved path control technology, which reduces non-effective operation time and mechanism idling.

CONCLUSION

This article focuses on the problems of high energy consumption, low manual operation efficiency, and difficult path planning of BWR under dynamic load conditions. A set of intelligent control system based on multi-source data fusion is designed, and the system architecture, algorithm design, and experimental verification are systematically explained. The main conclusions are as follows:

(1) Three layer system architecture: A three-layer architecture of "real-time perception intelligent decision-making precise control" has been constructed, which achieves high-precision environmental perception and equipment positioning in complex coal yard environments through multi-source sensor data fusion.

(2) Full time domain dynamic 3D modeling: using a combination of SURF feature extraction and covariance analysis, the calculation time is 26-35ms, and the point accuracy is over 98%, providing a high-quality data foundation for intelligent decision-making.

(3) Improved repulsive force model path planning: The virtual coal pile obstacle mechanism effectively solves the problem of path oscillation in dense environments, with a success rate of 94.7%, which is 21.5% higher than the traditional artificial potential field method, and still maintains a success rate of over 84.2% under extreme working conditions.

(4) Fuzzy adaptive PID and multi motor collaborative control: Combined with GA-ACO hybrid optimization strategy, precise tracking of multi motor speed has been achieved, equipment energy consumption has been reduced by 20%, and the fluctuation of material flow rate has been controlled within ± 1.9%.

(5) Comprehensive performance verification: The intelligent control system saves 15.1% in material retrieval operation time, improves coal stacking efficiency by 13.8%, and reduces cleaning operation time by 33.3%. It shows significant advantages in all three operation modes, providing a complete and feasible technical route for the intelligent upgrade of bulk material yards.

This study provides a complete technical solution for the intelligent transformation of coal yards in thermal power plants, which has important engineering application value for promoting unmanned operation of bulk material yards. Future work will focus on optimizing the real-time performance of algorithms, expanding their application to more complex working scenarios, and carrying out lightweight optimization design for the structure of BWRs.

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